Dynamic Pricing Behavior in Perishable Goods Markets: Evidence from Secondary Markets for Major League Baseball Tickets

Andrew Sweeting*

Duke University

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Abstract

A perishable good seller typically has a fixed number of units to sell, as well as limited time in which to sell them. This creates incentives to price dynamically, and in particular, to cut prices as future selling opportunities disappear. I use data from secondary markets for MLB tickets to show that sellers behave in the way that theory predicts. They cut prices significantly, by 60% or more in the final month before a game, and these price cuts are explained by dynamic incentives, rather than changes in demand or competition. Dynamic pricing is valuable, increasing expected revenues by 24%.

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1 Introduction

The pricing problem of a perishable good seller is typically characterized by having a fixed number of units to sell, as well as a limited time in which to sell them before the good's value disappears. Prominent examples include seats for a specific flight, hotel rooms for a particular night, seats for an event, sold either by the event organizer or a broker, or any type of seasonal or fashion good sold by a retailer who wants to switch the shelf space to other products at the end of the season.[1] In an environment where customers arrive stochastically, these characteristics create incentives to price dynamically even if static features of the environment, such as demand and the degree of competition, do not change. For example, as future selling opportunities disappear the seller's optimal price should fall. In this paper, I use data from the two largest online secondary markets (eBay and Stubhub) for regular-season Major League Baseball (MLB) tickets, to test whether sellers - who are a mixture of fans and ticket brokers - price dynamically. I find that sellers do respond to dynamic incentives, consistent with sellers using dynamic profit-maximizing strategies, even though most sellers in these markets are small and might be assumed to be relatively unsophisticated. The incentive to cut prices leads to a striking aggregate pattern, and a dynamic violation of the 'law of one price', where prices fall by 30% or more in the month leading up to a game, controlling for both ticket quality and demand shocks. Moreover, I show that it is dynamic incentives alone that cause sellers to cut prices, because the static environment faced by a seller, summarized by his residual demand curve, changes very little as a game approaches. The seller's problem therefore corresponds very closely to the one described by a class of standard dynamic pricing models that underpin the field of Revenue (or Yield) Management, and for which there has been no previous empirical illustration.

These models, described by McAfee and te Velde (2006), Gallego and van Ryzin (1994) and Bitran and Mondschein (1993), have the following stylized structure that I will refer to as the 'standard dynamic model' in what follows. The seller begins with an exogenous inventory that will perish at a known time in the future. The seller sets a list price at each point in time and, as inventory cannot be replenished, the seller's aim is revenue-maximization.[2] Consumers with unit demands arrive stochastically with valuations drawn from a known time-invariant distribution, and they must

[1] Most fashion goods have to be ordered several months in advance of the season when they are sold, so stores cannot replace sold inventory.

[2] Dana (1998), Dana (1999) and Gale and Holmes (1993) consider models where a seller chooses a (price, quantity) schedule before demand is realized. Prices are not a function of time, so prices tend to rise as more units are sold. Of course, in some settings firms may want to commit not to reduce prices by using this type of strategy. For example, airlines and large retailers interact with the same customers repeatedly, and this may create an incentive to commit not to reduce prices in order to affect future consumer behavior. This incentive is absent in the standard model. The sellers in my setting are small and relatively anonymous, so this type of incentive should not be important.

buy at once or exit the market.[3] If there are no changes in the competitive environment, these assumptions lead to a (residual) demand or probability of sale function that depends on the seller's current price and is constant over time. Of course, stable demand is not necessary for sellers to have dynamic incentives, but I will show that it is actually a fairly accurate description of the environment facing a reseller of MLB tickets. I also consider why this is the case given that it seems natural to assume that some buyers can choose when to purchase.

In the framework of the standard dynamic model, the optimal price is determined by the distribution of consumer valuations, just as it would be in a static model, and the probability that a current sale precludes a future one because of a stockout. A lower inventory increases the optimal price, but this effect is largely absent in my setting because most sellers have only one set of similar tickets (e.g., a pair of seats for a particular game with a particular face value). On the other hand, as the end of the selling horizon approaches, the probability that unsold units will be sold in the future tends to decline. This reduces the 'opportunity cost' of a current sale, lowering the optimal price. McAfee and te Velde show that a 'robust prediction' of the model is that declining opportunity costs cause expected prices to fall, and given stable demand, this should also cause the probability of sale to increase.

Consistent with this prediction, I show that secondary market prices fall significantly as a game approaches. Transaction prices fall by about 30% in the month before a game, a pattern that holds across different types of mechanism (fixed prices and auctions). Listed fixed prices fall by a similar amount in both markets, while auction start prices fall by around 40%. Individual sellers cut prices of unsold listings even more dramatically, by 60% or more. At the same time, the probability of sale tends to increase. Another feature which is consistent with the standard dynamic model is that the price declines accelerate as one moves closer to the game.[4] The exceptionally large size of the datasets (the smaller eBay dataset contains over 600,000 listings) allow me to show that these patterns are robust to controlling in different ways for ticket and game quality, and that the same patterns are found for different types of seat and games with quite different levels of demand.

The observed price declines are consistent with dynamic pricing, but they could also be explained by changes in demand or competition as a game approaches, possibilities that are ruled out only by assumption in the standard dynamic model. I examine whether these changes are important by

[3] Lazear (1986) and Pashigan (1988) study a simple pricing problem where sellers change prices as they learn about the level of demand. I will provide evidence that the price declines that I observe are not driven by seller learning. Deneckere and Peck (2009) provide a related model with learning on both sides of the market.

[4] For example, Figure 1 in McAfee and te Velde (2006).

estimating a seller's static residual demand curve (probability of sale function) that will reflect both the distribution of consumer preferences and competition. I show that the residual demand curve changes only a little as a game approaches. I further show that sellers cut prices because of dynamic incentives (falling opportunity costs) rather than because of these small changes in residual demand by computing the opportunity cost of each listing, using a pricing first-order condition implied by either static or dynamic profit-maximization, and calculating the counterfactual prices that sellers would set if static demand and competition conditions did not change at all. These counterfactual prices are very similar to observed prices, consistent with sellers cutting prices only because of dynamic concerns, while the distribution of opportunity costs shifts downwards monotonically as a game approaches. One reason why sellers may use dynamic strategies is that the returns to doing so are quite large: under some plausible additional assumptions, the estimates imply that dynamic pricing raises a seller's expected revenues by 24%. The profitability of using a dynamic strategy reflects the fact that product differentiation gives each seller some degree of market power even though the market structure of these resale markets is quite fragmented.

These empirical results are important for several reasons. First, they provide the first empirical evidence that a set of dynamic pricing models that are central to the field of Revenue Management accurately describe seller behavior.[5] The evidence in favor of these models is made more impressive by the fact that ticket resellers do not use automated systems to set prices.[6] Previous tests have used price data from airlines (e.g., McAfee and te Velde (2006)), where automation is normal. However, for airlines the declining price prediction is rejected because prices tend to rise over time, probably because the incentive to price discriminate between different types of buyer (Borenstein and Rose (1994)) dominates the dynamic incentive to cut prices.[7] This contrasts with my finding that residual demand changes very little over time in resale MLB markets. The conclusion that prices are determined dynamically may also have important implications for how secondary market data is used to assess the welfare consequences of allowing resale. For example, Leslie and Sorensen (2009) estimate the welfare effects of allowing the resale of event tickets, under the assumption that secondary market prices are determined by one-shot market clearing, consistent with the assumptions of the related theoretical

[5] Former American Airlines CEO Robert Crandall described Revenue Management as "single most important technical development in transportation management since we entered the era of airline deregulation in 1979."

[6] Some large ticket brokers told me that they use 'rules of thumb' that reflect dynamic considerations in setting prices. Stubhub does give sellers the option of setting a price that declines linearly up to the game, but, as described in Section 3, this option is rarely used.

[7] 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.

literature (Courty (2000, 2003a, 2003b) and Karp and Perloff (2005)).

Second, and more generally, the paper shows that small sellers tend to behave in a way consistent with dynamic profit-maximization.[8] This contrasts with the fairly mixed evidence found in static settings (e.g., Hortacsu and Puller (2008), Levitt (2006), Genesove and Mayer (2001)) and Asplund (2007)'s rejection of dynamic profit-maximization by the Swedish Tobacco monopoly.

Finally, the paper provides an example where the 'law of one price' does not hold in a dynamic setting. Sorensen (2000) shows that its failure in a static, retail setting is likely to be due to search costs, while the literature on declining prices in sequential auctions has focused on particular features of the auction mechanism being used and unobserved object heterogeneity (Ashenfelter (1989), Ashenfelter and Genesove (1992), McAfee and Vincent (1993), Beggs and Graddy (1997), Ginsburgh (1998) and van den Berg et al. (2001)). In contrast, I identify a declining price pattern that is not specific to a particular sales mechanism or a particular market, and which can be explained by the dynamic pricing strategies of sellers. This naturally raises the question of whether buyers, some of whom can presumably choose when to purchase, can be behaving optimally when prices decline so much. In the final part of the paper (Section 6) I present empirical evidence that is consistent with a model where early buyers have similar ticket preferences to people who wait, but face additional costs to buying at the last minute. Irrational or uninformed buyers are not required to explain what is observed.[9]

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, while the probability of sale increases. Section 5 shows that sellers lower prices because of dynamic incentives. The analysis uses fixed price listings, with a similar analysis for auction listings in Appendix B. Section 6 examines evidence of consumer sorting, and shows that the data on buyer behavior is consistent with the price declines being driven by the dynamic pricing concerns of sellers rather than changes in demand. Section 7 concludes.

[8] I do find that there is a subset of sellers who prefer, maybe for ethical reasons, to set prices around face value.

[9] An earlier working paper investigated how risk-averse buyers would have to be to explain early purchase decisions. Many early purchases could be explained by quite small levels of risk-aversion, but some required levels of risk-aversion that seem implausible given the stakes involved. Section 2 contains a discussion of why product differentiation may hinder a short-selling strategy to exploit the price decline.

2 Institutional Background

MLB teams sell season tickets and single game tickets in the *primary market* to a combination of fans and professional resellers.[10] 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. Discussions with people in the industry indicate that there is a higher proportion of fans selling tickets for MLB games, compared to NFL games or rock concerts, because few season ticket holders attend all 81 home games. In contrast to some concert promoters, MLB teams do not hold back tickets to build demand and there are also only one or two minor examples of teams experimenting with dynamic pricing in the primary market.[11]

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, the sources of my data. 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 in the resale market, and they also sometimes 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.

Ticket listings are differentiated products: listings to the same game can differ in the number of seats included and the quality of the section or row, and on eBay the reputation of the seller may also be important (Hortacsu and Cabral (2008)). Differentiation may play at least two roles in supporting declining prices as an equilibrium outcome. First, differentiation will lead to sellers having some degree of market power, even when many listings are posted. As a result, sellers can charge a mark-up that can be adjusted over time. Second, differentiation may prevent strategies that would exploit, and arbitrage away, price declines. For example, suppose that someone sells a promise to supply a

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

[11] The Colorado Rockies have used limited dynamic pricing for certain sections for several years and the San Francisco Giants experimented with dynamic pricing for some less expensive seats in 2009. The Colorado Rockies are excluded from the specifications in this paper because I lack information on ticket face values for this team.

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 exactly which tickets will be available later on. In practice I observe that if listings posted with missing row information are sold, their prices are typically 15-20% below those of other seats in the same section (coefficients reported in Table A1 columns (7) and (8)). This discount 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 focus is on 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.[12] Tickets can only be listed within three 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 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 it is clear from the data that prices are often changed by creating a new listing: on almost 66% of occasions where I observe a listing ID exiting the data, a new listing ID appears for the same game, section and row on the following day.

[12] In 2007 shipping cost $11.95 for transactions more than 14 days before the game and $16.95 for transactions thereafter. Price declines look very similar whether or not shipping costs are included in the price. Since 2007 the use of electronic tickets, with lower shipping and handling costs, has increased greatly.

I only use listings in Stubhub's fixed price format, which comprises 99.5% of listings in the data. An auction-format, which is no longer available, accounts for the remainder. I drop a small proportion of listings (0.4%) in a format that has a linearly-declining fixed price as the game approaches. The fact that Stubhub offers this option is informative about the direction in which sellers may want to change prices. 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 were purchased from an official data reseller, Advanced E-Commerce Research Systems (AERS). Tickets on eBay can be listed in several different 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 (hybrid) 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 I only observe these being used in 4% of the auction listings in my sample. Sellers pay a small listing fee and commissions that 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. Reputations may matter because there is no equivalent of the Stubhub guarantee.

The data includes all event ticket listings from January 1 to September 30, 2007.[13] I use the data on regular season MLB games, but the complete data is used to impute missing data on feedback scores and zipcodes by using the score or zipcode associated with the buyer or seller's previous appearance in the data. 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 (an indicator for a secret reserve price), 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. I use the seller's identity number to identify listings sold by the same seller, although it is obviously possible that a single person may be using several different identities on eBay. I also observe several additional listing characteristics such as whether the listing was highlighted or contained additional information such as pictures. For all bids, the data 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.

[13] 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 was not available for the Colorado Rockies and for some season ticket-only sections for other teams (3.6% of the sample). The specifications in this paper will use only listings where face values are observed, although the qualitative results are very similar if all listings are used and variables based on face values are defined in different ways.

Demand for tickets can vary significantly across games and it may also vary for a particular game over time as the performance of the teams involved changes. I control for demand in the descriptive analysis in Section 4 by including game fixed effects and a set of measures for the performance of each team both on their own and interacted with the number of games remaining in the season: the team's record (proportion of games won), 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 were constructed using historical game results from Retrosheet.org.

I will also make some use of a measure of expected attendance at 22 different dates before the game (which correspond to the days-to-go dummies used in the specifications below), based on an estimated censored normal regression model using data from the 2000 to 2007 seasons. The dependent variable in the model is the realized attendance of the game, reported by Retrosheet, measured as a proportion of stadium capacity.[14] The explanatory variables are the team performance measures on the day in question, the home team's average realized attendance so far during the season, home team*year dummies, home team*month dummies, home team*day of week (of game) dummies and dummies for the type of game being played (interleague and same region (e.g., AL East vs. NL East), interleague and different regions, within-league but across division, within-league and within-division).

[14] I use the highest realized attendance as a measure of capacity as this frequently exceeds the stadium capacity reported by teams. As the exact attendance can vary even when a game is sold out, I top-code the attendance variable at 0.98 and use this value as the censoring point.

The correlation between the realized attendance and the model's predicted attendance immediately prior to the game is 0.9. The correlation declines monotonically as one moves further from the game, but remains very high (0.87 90 days before the game).

3.3 Summary Statistics

Tables 1(a) and (b) and Figure 1 present statistics which summarize some important features of the market. Appendix C presents more detailed summary statistics for different groups of tickets.

Table 1(a) shows some statistics on the number of listings in the sample and the average eBay transaction price by team. Stubhub has many more listings than eBay for every team, and the difference in the average number of listings available on a particular day is larger because Stubhub listings are available for an average of 16 days compared with 4.5 days for eBay listings. There are more listings for teams with higher attendances and also for the games which are likely to have the highest demand. This pattern continues up until the game and shows that high demand is not associated with scarcity in secondary ticket markets, although prices tend to be high. For example, two days before a Boston Red Sox home game against the New York Yankees (the combination that my attendance model predicts has the greatest excess demand) there are on average 79 listings available on eBay, compared with 31 listings for Boston home games against other teams (all of which were also sold out).[15] Average secondary market prices also differ substantially across teams, with Red Sox tickets having the highest prices relative to face values. 87% of eBay listings and 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. When commissions are excluded, average posted fixed prices on the two sites are quite similar (99% above face value on Stubhub and 104% on eBay), suggesting that returns to listing on either site may be similar.[16]

The reported Herfindahl-Hirschman Indices (HHI) show that market structure is fragmented, particularly for the teams with the most listings. 63% of sellers list only one or two listings on eBay during the entire season, and 90% of sellers have less than 15 listings. On the other hand, there are some large sellers: 139 sellers have more than 500 listings each and they account for approximately 30% of all listings. These sellers are likely to be professional traders. The buyers' side of the market is even less concentrated, with 89% of buyers purchasing only one or two listings during the season.

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

[16] Of course, to measure sellers' returns precisely would require knowing the probability of making a sale on Stubhub. Ellison and Fudenberg (2003) and Ellison et al. (2004) show that competing marketplaces can co-exist with different market shares, if the ratio of buyers to sellers is similar. Brown and Morgan (2009) show that this condition did not hold for eBay and Yahoo!'s auction sites prior to Yahoo!'s departure from the market.

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 an individual does this on eBay he makes a loss. However, many of the profitable trades are made by the largest buyers presumably because they have some ability to identify listings that are underpriced. Table 1(b) compares the types of ticket purchased and sold by different types of buyer and seller. It also reports the proportion of each type's transactions accounted for New York Yankees' tickets, the most traded tickets in the data. While the largest sellers, who are likely to be brokers, offer slightly higher quality tickets on average, the differences in mean characteristics between the groups are very small relative to the within group variation.

[TABLE 1 ABOUT HERE]

Figure 1 illustrates several dynamic features of these markets. 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, although 50% of transactions happen more than 10 days before the game. The probability that a listing results in a sale tends to increase as a game approaches, except for single unit auction listings which experience a slight decline in the final 10 days. In Section 5 I will show that the sale probabilities increase because sellers are moving down a fairly stable demand curve rather than because demand is changing. The mix of mechanisms used on eBay also changes over time, with a shift towards pure auctions and then hybrid BIN auctions.[17] While this paper does not study the choice of sales mechanism, it may be affected by a seller's dynamic considerations (opportunity cost) as well as the preferences of buyers and I will make use of this logic when defining instruments for price. For example, an auction is likely to be attractive for a seller who wants to sell immediately (low opportunity cost of sale) because a low start price will make a sale very likely while also providing some possibility of a high price if multiple bidders enter the auction. On the other hand, a fixed price prevents a sale at a low price and may be preferred by sellers who do not have to sell at once, especially if some buyers prefer the certainty of buying a fixed price listing over entering an auction.

[FIGURE 1 ABOUT HERE]

[17] 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.

Figure 1(d) shows that the observed quality of available and transacted tickets, measured by face value and the row of the ticket within the seating section, is quite stable as a game approaches, with a small increase in average face value in the last few days. The pattern that observable ticket quality is so stable suggests that the observed price declines across listings are unlikely to be driven by declines in unobserved ticket quality.

4 Evidence for Declining Prices

The standard dynamic model predicts that sellers should cut prices as a game approaches. In this Section I show that this prediction holds in my data, for both listed and transaction prices and both across and within sellers. Appendix A shows that I find similar declines when I restrict the sample to particular kinds of ticket such as cheap or expensive seats, or high or low demand games, and when I vary the definition of price or the definition of fixed effects used to control for seat quality.

Since there is considerable variation in quality across tickets, I estimate the quality-adjusted path of prices using a regression model

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

where p_{it} is the log price per seat of listing i on date t and F are the controls for the performance of the home and away teams, which should control for demand shocks that affect the value of a ticket. C includes 20 variables that control for the amount of competition from other listings posted on both eBay and Stubhub.[18,19] Some of these variables are based on face values so tickets without face values are excluded, although the time effects are similar if the competition variables are excluded and all tickets are used. Q and fixed effects (FE) are used to control for observable features of ticket and listing quality. All of the results reported in the text include game-section (or richer) fixed effects, which group 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). Five 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 include dummies for the number of seats

[18] Separate variables are defined to measure competition from listings with the same or different numbers of seats, and from listings for tickets in the same section or 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.

[19] Both the form and competition variables are jointly significant at any standard significance level.

in the listing (interacted with a dummy for if fewer seats are available) and other seat characteristics. For example, I include dummies for whether the text provided with the listing indicates that parking is included, some of the seats are behind rather than next to each other (piggy-back) or include aisle seats. The eBay specifications control for the level of the seller's feedback score using four dummies[20] and they include additional dummies for the exact type of the listing (e.g., a store fixed price or a non-store fixed price) and additional listing characteristics (whether the listing was highlighted or included pictures). Conditional on these controls, the time path of prices is measured by the coefficients on a set of 22 dummies (D, days-to-go dummies) for different time intervals prior to a game.

Listed Prices. The standard dynamic model assumes that sellers use fixed prices. Figure 2(a) shows the path of listed fixed prices on eBay and Stubhub (the exact coefficients are reported in Appendix A).[21] The Stubhub coefficients are calculated using a 5% random sample of game-sections. The eBay sample includes all fixed prices, including BIN prices in hybrid auctions, with dummies controlling for the type of listing. Prices fall significantly, and almost perfectly monotonically, as a game approaches. The plotted coefficients show that list prices are 29% higher on Stubhub and 42% higher on EBay one month before the game than they are immediately before the game. Evaluated at average prices 0-2 days before a game, the differences are \$17 and \$22 per seat respectively. The price declines accelerate as a game approaches. This is also true in the standard dynamic model, because, with a stable probability of sale function, the seller chooses a sequence of lower *additional* mark-ups as she moves away from the game.[22]

While the standard dynamic model assumes fixed prices, one would also expect that sellers would lower start prices in auctions if they become keener to sell, under the assumption that lower start prices increase the probability of sale but lower expected revenues if a sale occurs. Figure 2(b) also shows the estimated path of start prices on eBay, based on a specification that includes a dummy for listings with a secret reserve as well as observations from hybrid BIN auctions.[23] In percentage terms, auction start prices fall even more dramatically than fixed prices in the three months leading up to the game, although in dollar terms the decline in the final month is smaller (\$11) because, on

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

[21] An eBay observation is a listing (and the date is the date the posting is first listed). A Stubhub observation is a listing available on a particular date, and the same listing may be available at the same price on multiple days. I treat Stubhub listings in this way because the listing identification numbers provide only an imperfect measure for when a listing is posted.

[22] This mirrors what happens in a vertical chain of monopolies, where at each higher stage in the chain a smaller additional mark-up is chosen.

[23] For auction listings the date is the end of the auction.

average, start prices are lower than fixed prices. Average start prices do not decline in the final week before the game. One explanation for this pattern is that many sellers with higher opportunity costs switch from using fixed prices into using some type of auction listing in the final week as they become keener to sell, so the mix of sellers using auction listings changes.

[FIGURE 2 ABOUT HERE]

Within-Seller-Listing Price Changes. Dynamic pricing predicts that individual sellers will cut prices as their future selling opportunities disappear. Figure 2(c) shows the path of prices when I include seller-game-section-row fixed effects for eBay listings and listing ID fixed effects for Stubhub listings so that the coefficients reflect how individual sellers change the prices of unsold tickets.[24] As noted in Section 3, Stubhub sellers may change prices by posting a new listing with a new listing ID, so the Stubhub coefficients will reflect only cases where this does not happen. As a game approaches, sellers cut prices significantly for all types of listing. The proportion of price changes which are price cuts, 0.89 on Stubhub and 0.81 for both auction and fixed price listings on eBay, confirm that sellers tend to cut prices. Individual sellers continue to cut auction start prices through the week before the game, which shows that the flat pattern of start prices across sellers must reflect a change in the set of sellers using auctions. Time effects also explain quite a large proportion of the within-listing price variation: the within-R^2s when only time dummies are included are 0.44 on Stubhub and 0.20 on eBay.

Transaction Prices. While dynamic pricing models are focused on sellers, one can also look at what happens to prices paid by buyers. Figure 2(d) shows the path of transaction prices on eBay for fixed price and auction sales, controlling for game-section fixed effects. The price is measured by the final price paid by the buyer which includes shipping costs, and the set of fixed price transactions includes sales at a BIN price in a hybrid auction. For both types of sale, buyers pay roughly 30% more one month before the game.

Price Distributions. Figures 2(a)-(d) show that *mean* quality-adjusted prices decline as a game approaches. However, changes in other features of the price distribution may be important for explaining equilibrium behavior. For example, if the upper percentiles of the price distribution tend to increase as a game approaches because tickets sometimes become more valuable due to either

[24] The Stubhub sample contains all observations with a new listing id or a continuing listing id with a price change.

demand or supply shocks, then strategic consumers with risk-averse preferences who know that they want to attend a game may choose to purchase early even though average prices are falling.[25] Figures 2(e) and (f) show how quality-adjusted price distributions for list prices on Stubhub and transaction prices on eBay change in the 60 days leading up to a game. These distributions are formed by taking the residuals from the log(price) regression excluding the time dummies and the form and competition variables so that the estimated price distributions reflect how these demand and supply shifters may change. A flatter CDF reflects a more dispersed price distribution. In both cases, dispersion increases as a game approaches, but not enough to increase the upper percentiles of the price distribution. This shows that the declining price pattern almost always dominates the effect of shocks that can increase the value of tickets.

Probability of Sale. If, consistent with the standard dynamic model, sellers are moving down a stable residual demand curve when they lower prices then the probability that a listing is sold should increase. On the other hand, if prices are cut because there is less demand or more competition, then the probability of sale may fall as well. I estimate how the probability of sale changes, using eBay data, and specification (1) with an indicator for whether the listing results in a sale as the dependent variable (i.e., I estimate a fixed effects linear probability model).

Figure 3 shows how the probability of sale changes for auction and fixed price listings, for a specification with game-section fixed effects, for pure auction listings, hybrid auction listings (which can result in either an auction or a fixed price sale) and pure fixed price listings. The mean sale probabilities for listings posted 0-2 days before the game are 0.58, 0.48 and 0.44 respectively. The estimated coefficients show that, conditional on controls, the probability that fixed price and hybrid auction listings sell rises by 23 and 14 percentage points respectively in the final month before a game. For auction listings, the probability of sale increases until around 20 days before a game but is flat thereafter. However, because auction prices are also flat close to the game, this result should not be interpreted as necessarily implying that the demand curve is moving.

5 Do Dynamic Incentives Cause Sellers To Cut Prices?

While the observed price declines are consistent with dynamic pricing, sellers are only pricing dynamically if they cut prices because of falling opportunity costs, rather than some factor that the dynamic

[25] See an earlier working paper, Sweeting (2009), for an examination of the degree of risk-aversion required to explain early purchasing.

model ignores. In this section I estimate a seller's residual demand curve, which summarizes a seller's static environment, and use the estimates to show that dynamic incentives, rather than changes in demand or competition, cause sellers to cut prices.

To understand why both falling opportunity costs and changes in residual demand may affect prices, suppose that a risk-neutral seller i can post a listing in two time periods ($t = 1, 2$) before a game using fixed prices p_{it}. i receives a payoff of $\$v_i \geq 0$ from attending the game himself if the ticket is unsold after period 2. In period t, the residual probability of sale function $Q_{it}(p_{it})$ $\left(\frac{\partial Q_{it}(p_{it})}{\partial p_{it}} < 0\right)$ determines the probability that the listing is sold in period t, and it will reflect both the preferences of consumers looking for tickets in period t and competition from other differentiated listings. For simplicity, assume that $Q_{i2}(p_{i2})$ is known in period 1 and does not depend on p_{i1}. A payoff-maximizing 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, optimal prices will be

$$p_{i2}^* = \underbrace{v_i}_{\text{Opp. Cost of Sale in Period 2}} - \frac{Q_{i2}(p_{i2}^*)}{\frac{\partial Q_{i2}(p_{i2}^*)}{\partial p_{i2}}} \tag{3}$$

$$p_{i1}^* = \underbrace{p_{i2}^* Q_{i2}(p_{i2}^*) + v_i(1 - Q_{i2}(p_{i2}^*))}_{\text{Opp. Cost of Sale in Period 1}} - \frac{Q_{i1}(p_{i1}^*)}{\frac{\partial Q_{i1}(p_{i1}^*)}{\partial p_{i1}}} \tag{4}$$

The first term in each first-order condition is the opportunity cost of sale. The opportunity cost in period 1 is the expected payoff from having tickets in period 2, and the opportunity cost must fall because $p_{i2}^* \geq v_i$. In a slightly more general set-up the opportunity cost in period 1 would also reflect any cost of relisting unsold tickets in period 2. The second term, which determines the mark-up over the opportunity cost, reflects the current elasticity of the residual demand curve. A seller would also want to set a lower price if his residual demand curve is more elastic in the second period. In particular, it would also cause prices to fall for a seller who behaves statically in the sense of ignoring his ability to relist an unsold ticket when choosing his period 1 price.

I use estimates of residual demand to quantify the relative importance of falling opportunity costs and changes in residual demand in causing sellers to cut prices. The first step is to estimate the residual demand function faced by sellers, allowing it to change as a game approaches. This provides some direct evidence on whether the demand curve is changing, but I can also use the estimates to quantify what is happening to opportunity costs. Specifically, suppose that the seller sets a price to solve the following pricing problem

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

where o_{it} is the seller's value to holding onto the ticket at time t (the opportunity cost of a sale). Assuming standard regularity conditions hold, the estimate of the residual demand function $Q_{it}(p_{it})$, the pricing first-order condition and the observed price can be used to calculate the implied opportunity cost for each posting. This calculation is similar to the calculation of a firm's marginal costs from an estimated demand system in an oligopoly model or the calculation of a bidder's valuation from his observed bid and an estimate of the distribution of rival bids in a first-price auction. If sellers are behaving dynamically, and not just maximizing static expected revenues, then the opportunity costs implied by the first-order condition should be falling as a game approaches. On the other hand, if sellers price to maximize their static payoffs, so that it is only changes in residual demand that cause prices to drop, then the implied opportunity costs should not fall at all. Note that for a dynamic seller we would not necessarily expect o_{it} to be zero immediately before the game (the seller's last chance to sell) because people who are listing tickets may still have some value to attending the game themselves or some costs to completing a transaction (e.g., booking a Fedex pick-up).

In practice I find that residual demand is quite stable and that implied opportunity costs fall significantly. To show that the small changes in residual demand that I do find do not drive the observed price declines I calculate the prices that sellers would set if the residual demand curve did not move at all, given the opportunity costs implied by their actual pricing decision. These counterfactual prices are very similar to those that are observed, showing that it is falling opportunity costs that cause sellers to cut prices.

To keep the exposition as clear as possible, I focus on fixed price listings in the main text. The standard dynamic model assumes that sellers use fixed prices. Appendix B presents results using single unit, pure auction listings. In both cases I only use eBay listings, as I need to observe transactions, as well as listings, to estimate demand.

5.1 Empirical Residual Demand Specification for Fixed Price Listings

A seller's residual demand curve $Q_{it}(p_{it})$ is specified as a flexible parametric function of a ticket's price, characteristics and the prices and characteristics of competing listings. I use a probit because the observed dependent variable (whether a listing is sold or not) is binary. This specification reflects the fact that each seller will face a downward sloping residual demand curve, as a function of his own price, because of product differentiation and heterogeneous consumer tastes for different types of ticket.[26]

I define the dependent variable as equal to 1 if the listing is sold within seven days of posting. A listing's own price is defined per seat, including shipping costs, and it is normalized by the face value of the ticket.[27] To allow for the demand function to change as a game approaches, I define four 'time periods': 0-10, 11-20, 21-40 and more than 41 days prior to a game. The own price coefficients are allowed to vary across these time periods, I also include a complete set of days-to-go dummies so that the level of the single index can vary even more flexibly. The assumptions that residual demand only depends on the seller's current price and that the current price does not affect future residual demand, which will be implicit when I calculate opportunity costs, are consistent with the dynamic model. However, they imply that a seller's price does not shift his demand across periods, which it might do if consumers can time their purchases strategically. I show below that there is little evidence of this type of demand shifting in the data, which may well reflect the fact that each seller is small relative to the size of the market.

The included set of own listing characteristics are home team dummies, home team*face value interactions, the row variables, number of seat dummies, dummies for four levels of seller feedback, dummies for additional characteristics (such as highlighting and whether the seller operates an eBay store) and dummies for the exact mechanism used (e.g., a store fixed price). The level of interest in the game should affect the probability of sale, so I include the game's expected attendance at the time the listing is posted, calculated using the model described in Section 3, interacted with home team dummies. I also include the team form variables (e.g., how many games the team is back in its division) on the day of listing for both home and away teams.

[26]In contrast to much of the recent literature on differentiated products, I do not model demand by aggregating up from a model of individual consumers with different preferences. This reflects the fact that I only observe consumers when listings are purchased and have no information on their willingness-to-pay for other products. Hendricks and Porter (2007) discuss the problems of estimating individual preferences in markets such as eBay. Bacchus and Lewis (2009) provide a first attempt to solve these problems using bidding data in a framework which ignores factors such as search costs and the ability of consumers to buy products in other markets. These excluded factors are likely to be very important in my setting.

[27]I deduct shipping costs and commissions 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. For these listings the first assumption I try to make is that they 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. If no value is available I use the average shipping cost of all sellers during that time period. As shipping costs are relatively small (the eBay average is $4 per seat and it remains steady as a game approaches) this imputation should have little effect on the results and they remain very similar if shipping costs are ignored entirely.

Competition variables measure the number and prices of listings for the same game, with the same face value and for the same number of seats, that were available on the day the listing of interest was posted. It is these listings that should shape a seller's expectations about competition when he is choosing a price.[28] The specific variables are the mean and minimum relative prices of competing listings on eBay, a dummy for whether competing listings are available on eBay, the log of the number of competing listings (plus 1) 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 the day the listing is posted on Stubhub.

I estimate residual demand using single unit, pure fixed price listings for tickets with non-missing face value information posted in the last 90 days before the game. The price coefficients are sensitive to some outliers with extremely high prices relative to face value, so I use the 93.2% of listings with a posted price that is less than five times face value.

5.1.1 Unobserved Listing Characteristics and Price Endogeneity

While I can control for many observed ticket characteristics, sellers are likely to set higher prices for tickets with characteristics that are attractive to consumers but that I do not observe or do not control for. Standard intuition suggests that failing to address this issue will cause the estimated demand curve to be too inelastic. As the probit is a non-linear model, I address endogeneity by defining instruments and using a two-stage control function approach (e.g., Rivers and Vuong (1988), Wooldridge (2002), p. 472ff).[29]

This approach assumes that the probit's single index variable (Q_{it}^*, with a sale if $Q_{it}^* \geq 0$) can be defined as

$$Q_{it}^* = \widetilde{X_{it}}\theta_1 + p_{it}\theta_2 + u_{it} \tag{5}$$

where the $\widetilde{X_{it}}$s are exogenous observed characteristics and p_{it} is price, and that

$$p_{it} = \widetilde{X_{it}}\gamma_1 + Z_{it}\gamma_2 + v_{it} \tag{6}$$

[28] I have estimated specifications where the competition variables are defined either more narrowly (e.g., same game-section) or more broadly (e.g., same game). The variables based on face values gave the most consistently significant coefficients, which seems sensible as sections with the same face value are likely to be close substitutes.

[29] 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.

where the Zs are instruments, u and v are mean zero bivariate normals, and $var(u) = 1$. Prices are endogenous if u and v 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 stage OLS is used to estimate (6), and the estimated residuals ($\widehat{v_{it}}$) are included as additional variables in the second step estimation of the probit model. Standard errors are calculated using a block-bootstrap where games are resampled to account for the two-stage nature of the procedure.

Valid instruments will include factors which affect the seller's optimal price but which are not correlated with buyers' valuations of the tickets, conditional on the observed ticket and listing characteristics which are included in $\widetilde{X_{it}}$ such as the seller's feedback score and whether he operates an eBay store (these variables may affect how reliable a consumer expects the seller to be). As can be seen from the pricing equations (3) and (4) in the two period model, candidates for instruments will include factors which influence or reflect the seller's opportunity cost of sale (either his value to being left with tickets at game time or his cost of relisting unsold tickets) and do not reflect aspects of ticket or listing quality observed and valued by buyers. The following variables are used as instruments interacted with dummy variables for the four time periods prior to the game.[30]

- *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 brokers than season ticket holders. Brokers should have low costs of relisting tickets and so they should have high opportunity costs a long time before the game when they have the opportunity to relist tickets they do not sell. On the other hand, brokers should have low opportunity costs immediately prior to a game as they are unlikely to get utility from unsold tickets. Distant sellers are also likely to have low opportunity costs immediately prior to a game because they may be unable to sell them at the stadium. I therefore expect to observe distant sellers cutting prices particularly aggressively as a game approaches;

- *the proportion of the seller's unsold listings which are relisted on eBay* calculated based on listings for other games posted in the same time period close to the game.[31] The propensity to relist unsold tickets should reflect something about a seller's opportunity costs, although

[30] Two sets of instruments are based on listings of other tickets by the same seller. These variables are obviously not defined for sellers listing only one set of tickets. I therefore also include as an instrument a dummy 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 for sellers with 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.

[31] 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.

one can construct plausible stories where a high relisting rate should reflect either high or low opportunity costs. For example, sellers who do not have other ways to sell tickets should have low opportunity costs and tend to relist unsold tickets on eBay. On the other hand, sellers who find it cheap to relist tickets should have high opportunity costs and also be likely to relist;

- *the proportion of the seller's listings during the same time period (based on other tickets) that are in fixed price and hybrid BIN auction formats.* As suggested in Section 3.3, a seller's choice of mechanism is likely to be affected by their opportunity costs. For example, an auction is more likely to be optimal for a seller who is very keen to sell (low opportunity costs) because it allows the price paid by the buyer to vary in response to demand. On the other hand, fixed prices are likely to be optimal for a seller who is unwilling to sell below a relatively high price.

[TABLE 2 ABOUT HERE]

Table 2 reports the coefficients on the instruments when the posted price is regressed on the instruments and the exogenous variables. As expected, distant sellers set higher prices (relative to face value) a long time before the game and cut them aggressively as a game approaches. A higher propensity to relist unsold tickets is associated with lower prices, suggesting that it is sellers with limited ability to sell outside eBay who are the most likely to relist. Sellers who make a lot of use of fixed prices a long time before the game tend to set higher prices, as do sellers using hybrid BIN listings close to the game which is when this format, which incorporates a fixed price listing as an element, becomes popular. The instruments are jointly significant at standard significance levels.

5.2 Baseline Results

Table 3 shows the estimated coefficients from the baseline specification of the residual demand model. Column (1) shows the results when the possible endogeneity of prices is ignored and column (2) shows the second stage results using the control function. Consistent with endogeneity being successfully addressed, the estimates in column (2) imply more elastic demand (mean elasticities at observed prices are reported at the bottom of the table), and the coefficients on the first-stage residuals are also highly significant. I will therefore use the column (2) results as the baseline specification.

[TABLE 3 ABOUT HERE]

The first finding is that the residual demand curve is very similar across the four time periods, as can be seen in Figure 4(a) which plots the residual inverse demand curve for mean ticket characteristics assuming that the competition and form variables take on their average values in the period in question (I use the days-to-go coefficients for 45 to 47, 30 to 32, 15 to 17 and 6 to 8 days prior to the game for the first to final time periods respectively).[32] The fact that the residual demand curve is not moving suggests that sellers must be cutting prices because of dynamic considerations, rather than changes in demand or competition. Moreover, the fact that the residual demand curve is so similar across the time periods suggests that the standard dynamic model - which has a constant residual demand function - describes my setting almost exactly.

[FIGURE 4 ABOUT HERE]

Next, I calculate the opportunity cost of each listing by re-arranging the pricing first-order condition

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

where $\widehat{Q_{it}(p_{it})}$ is the estimated residual demand curve. Figure 5(a) shows how the distribution of implied opportunity costs evolves as a game approaches. Median opportunity costs fall monotonically as a game approaches, consistent with sellers becoming keener to sell as their future selling opportunities disappear, with a fall of almost 100% of face value ($40 per seat for the average fixed price listing) from the first to the final time period. These large changes in opportunity costs contrast with the small changes in residual demand, providing additional evidence that it is dynamic considerations that cause prices to fall.

One feature of the opportunity cost distributions that may seem problematic at first blush is that a significant proportion are negative, implying that some prices are below the level associated with static revenue maximization. However, this pattern may reflect the reluctance of a subset of sellers to price above the face value (or what they paid for the ticket) rather than model misspecification. In some states there are legal restrictions on the mark-ups that can be charged and while these laws are widely ignored, they, or other moral considerations, may constrain some sellers. Figure 5(b) therefore compares the distribution of prices (relative to face value) for tickets with positive and negative opportunity costs. A large number of tickets with negative opportunity costs have prices just below face value, which is how much a season ticket holder would have paid.[33]

[32] Without controlling for endogeneity, the residual demand curve becomes less elastic (for a given price) as a game approaches. This would imply that residual demand changes would lead, all else equal, to increasing prices, so that falling opportunity costs would be even more important in explaning why prices fall.

[33] Alternative specifications result in many fewer observations with negative implied opportunity costs. For example, if price variables are defined based on log prices then the sale probability becomes very sensitive to price when prices

[FIGURE 5 ABOUT HERE]

To provide a final illustration that prices are falling because of dynamic considerations rather than changes in the static environment, I use the estimated opportunity costs to calculate the price that each seller would set if, whenever he lists, he faced the residual demand curve implied by the coefficients for 11-14 days before the game and the average level of competition observed 11-20 days before the game, so that changes in competition are excluded as well.[34] Table 4 shows that counterfactual prices, which differ across periods only because of changing opportunity costs, decline by similar amounts to observed prices. This shows that sellers only cut prices because of dynamic pricing considerations.

[TABLE 4 ABOUT HERE]

So far, the results have emphasized that the evidence is qualitatively consistent with dynamic pricing behavior and the standard dynamic model. However, with some additional assumptions on sellers' ability to relist tickets, it is possible do some 'back of the envelope' calculations to check that the estimates are quantitatively sensible and to give an estimate of the benefits of using a dynamic pricing strategy. To do this, I assume that a seller starts with one set of tickets, with mean characteristics, that he wants to sell in the 45 days leading up to the game. I further assume that he can post a fixed price listing on eBay every 10 days (i.e., at 45, 35, 25, 15 and 5 days before the game) and that he expects to face the average level of competition actually observed on those dates. If the tickets remain unsold after the final eBay posting he receives 12.5% of their face value as utility reflecting his expected profit from trying to sell them at the stadium or giving them to a friend. 12.5% is the median opportunity cost observed in the data for the final time period.

Given these assumptions, it is straightforward to calculate both the seller's optimal price and opportunity cost each time he lists if the tickets have not been sold previously and he uses a dynamic pricing strategy.[35] Optimal prices fall from 203% of face value 45 days before the game, to 191%, 177%, 157% and 125% of face value as a game approaches, so that over the 40 day period prices fall by 62.4% relative to their level immediately before a game. This percentage decline is similar to the one observed for sellers relisting unsold tickets (Figure 2(c)). At the same time the seller's opportunity

are low, which can rationalize why very low prices are set. In this specification, the residual demand curves are also similar across time periods and counterfactual prices are close to observed prices (see Sweeting (2009)).

[34] The use of mean values results in counterfactual prices being slightly different to those observed even for listings posted 11-14 days before the game.

[35] In period t he chooses a price p_{it} to maximize $p_{it}Q_{it}(p_{it}) + (1 - Q_{it}(p_{it}))o_{it}$, where $o_{it} = p_{it+1}Q_{it+1}(p_{it+1}) + (1 - Q_{it+1}(p_{it+1}))o_{it+1}$. These formulae can be used to calculate prices working backwards from the final listing opportunity, when the opportunity cost of sale is assumed.

cost should fall from 139% of face value, to 123%, 101%, 69% and 12.5% (the assumed final level) as the game approaches. This decrease is slightly larger than the (cross-seller) decline observed in the data (Figure 5(a)). However, this difference is to be expected because of selection: sellers who have lower opportunity costs 45 days before the game will set lower prices and so will be more likely to sell and exit the sample. As a result, there will be more attrition from the lower part of the opportunity cost distribution in each period and average opportunity costs for observed sellers should fall less than they would for an individual seller who does not sell his listing.

Finally, one can also calculate how much the seller benefits from using a dynamic pricing strategy rather than using a static strategy that maximizes his static profits in each period and ignores his ability to relist, possibly at a different price, in the future. To make the comparison more reasonable I assume that the static maximization strategy always involves the seller pricing 'as if' he has a marginal cost of 12.5% of face value, the cost he is assumed to have in the final time period when he prices dynamically. Because residual demand is stable, the static payoff-maximizing price is always close to 125% of face value, which, relative to the optimal dynamic prices, raises the probability that the ticket is sold early on. Overall, static maximization gives the seller expected revenues equal to 121% of face value (the tickets are sold with probability 0.97), while dynamic maximization gives expected revenues equal to 150% of face value (sale probability 0.86), an increase of 24%.

5.2.1 Robustness Checks

I now consider various alternative demand specifications for the baseline model. While some of the coefficients do change across specifications the conclusions that residual demand is stable and that counterfactual prices are close to observed prices do not.

More Flexible Specification for Competition and Price Effects. The baseline specification assumes that the competition coefficients are the same across periods and does not allow for interactions between the competition variables and a listing's own price. Figure 4(b) plots the estimated residual demand curves from a richer specification where the competition variables are interacted with time period dummies and the own price variables are interacted with both time period dummies and the number of competing auction and fixed price listings. While some of the individual competition coefficients do differ significantly across time periods, these differences tend to cancel out so that the residual demand curves evaluated at mean ticket characteristics remain very similar as a game approaches.

Definition of the Dependent Variable. In the baseline specification the dependent variable is equal to 1 if the listing is sold within 7 days of posting. One concern with this specification is that the competition variables, which are based on competition at the time of posting, may do a poor job of measuring the level of competition which the seller expects one week later. Column (2) of Table 5 shows the estimated coefficients when I use a shorter 3 day window. This change only has a small effect on the estimated own price coefficients.

[TABLE 5 ABOUT HERE]

Endogeneity of Competitor Prices. The baseline specification takes the prices of competing listings to be exogenous, on the basis that these are chosen prior to the price of the listing in question. However, this assumption will be invalid if there are elements of aggregate demand which are observed by all sellers but which are not adequately controlled for in my specification. One can allow for endogeneity of the competitor price variables by using the same instruments as before, but now averaged across the relevant competing listings, in addition to the instruments used for the listing's own price. The coefficient estimates are reported in column (3) of Table 5. Allowing for competitor price endogeneity increases the magnitude of the cross-price effect with competing fixed price listings, and it makes the estimated demand curve 21-40 days and 1-10 days before the game more elastic. However, the differences in elasticities are small, so that counterfactual prices, reported at the bottom of the table, remain close to observed prices.

Varying the Instrument Set. The baseline analysis used three sets of instruments (distance, relisting propensity and mechanism choice). Although there is no obvious *a priori* reason to prefer one particular group of instruments, it is important to check that the qualitative results are robust to using different groups of instruments. Columns (4)-(6) show how the coefficients change when one set of instruments is excluded at a time. Excluding the distance instruments produces the most elastic estimates of the residual demand curve, and excluding the mechanism choice IVs produces the least elastic estimated curve. In each case however, I continue to find that the slope of the residual demand curve is similar across the four time periods.

Richer Controls for Seat Quality. The descriptive regressions in Section 4 included very detailed fixed effects to control for seat quality. The baseline specification did not include such rich fixed effects because consistent estimates of the coefficients on the fixed effect dummies would be required to estimate plausible opportunity costs.[36] Including a large number of dummies is also computationally burdensome in a non-linear model. Column (7) of Table 5 presents the coefficient estimates when I include game-face value fixed effects in a linear probability model (which may imply sale probabilities outside the unit interval). The coefficients cannot be directly compared with the probit specifications, but the slope of the residual demand curve is similar across the four time periods.

Controlling for Demand Shocks. The baseline specification controls for aggregate demand shocks for tickets to a particular game by including the level of latent demand predicted by the model of attendance described in Section 3 and a set of measures for the current performance of each team. One might be concerned that these variables may fail to adequately capture time variation in demand. I consider two ways to address this concern. First, I use only games in April and May for which demand shocks may be less important because it is unlikely that shocks will make games in either of these months pivotal to a team's season. Second, I can add a measure of demand based on what I observe happening to prices on Stubhub as a change in demand for tickets should affect prices on Stubhub as well as sale probabilities on eBay. The variable is the median price of tickets relative to face value on Stubhub based on all tickets to the game, on the day the fixed price listing is posted on eBay. I include this measure interacted with home team dummies and the coefficients are positive and significant for every team. However, for both of these alternative specifications (columns (8) and (9) in Table 5) the slope of the residual demand curve in each time period remains similar across time periods.

Intertemporal Spillovers/Demand Shifting. The specification of residual demand and the calculation of the seller's opportunity cost assume that a seller's demand is not a function of the previous prices he has set. This may be incorrect if buyers persist in the market and only consider a narrow range of tickets so they may wait in the market until a seller drops his price. As a simple test of whether there is any evidence for a significant demand-shifting effect, I add to the specification the price the seller previously set for an unsold listing for tickets to the same game with the same face value. As this lagged price may be endogenous, I also include the residual from the first stage regression for this prior listing as well as a dummy for if no such previous listing was made. The demand curve estimates are shown in column (10) of Table 5. The coefficient on the previous price is

[36] For example, random realizations might lead to only one listing in a large fixed effect group being sold. In this case, the coefficient on the group dummy would be low and exceptionally high opportunity costs would be be required to rationalize observed prices.

close to zero indicating that a high previous price has almost no effect on a listings's current demand.

Sellers with Listings on Multiple Sites or Multiple Listings on eBay. The analysis only uses data from eBay, but some sellers are likely to be posting tickets on other sites at the same time. While this should not affect the estimation of residual demand on eBay, it may complicate the interpretation of estimated opportunity costs. To understand the issue, suppose that a listing is posted on two symmetric sites with the same $Q_{it}(p_{it})$ functions. The new expression for the seller's opportunity cost (the cost of sale on *either* site) would be

$$o_{it} = p_{it} + \frac{Q_{it}(p_{it})\,(2 - Q_{it}(p_{it}))}{\frac{\partial Q_{it}}{\partial p_{it}}\,(2 - 2Q_{it}(p_{it}))} < p_{it} + \frac{Q_{it}(p_{it})}{\frac{\partial Q_{it}}{\partial p_{it}}} \tag{8}$$

so incorrectly assuming that a listing is available on only one site 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 sellers' opportunity costs of selling a listing on any of the sites they are using are falling, because it could just be that they are using different sites.

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 event 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. Therefore changes in the extent of cross-listing seem unlikely to explain why I find that opportunity costs are declining before the final time period.

I can also calculate opportunity costs and counterfactual prices using only the subset of 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, and they fall to 86%, 52% and 12% of face value as the game approaches. Table 4(b) shows that the counterfactual prices for these listings fall in the same way as observed prices.

The interpretation of opportunity costs is also affected by sellers with multiple similar listings posted at the same time on eBay. Here the opportunity cost of a sale will implicitly reflect how a sale affects the probability that one of the seller's other listings will be sold. Restricting attention to those listings where the seller only has one listing posted during the 7 day window produces counterfactual prices which are close to those observed in the data (Table 4(c)) and median opportunity costs in each time period that fall from 90% of face value to 74%, 46% and 6% as the game approaches.

Seller Learning. A maintained assumption is that sellers know their residual demand curve when they set prices. This is a completely standard assumption but it does rules out an alternative explanation for why prices fall which is based on sellers learning about demand 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 was in the market if a good is sold. In this model a fully informed seller would set the price equal to the reservation value in each period because lowering prices 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 than his price and set a lower price in the second period. 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 and is sufficiently patient, 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 being the principal cause of price declines comes from comparing how experienced and inexperienced sellers cut prices, under the reasonable assumption that experienced sellers know more about demand (i.e., have a tighter prior). In this case, a failure to sell should have less impact on their beliefs about demand and so they should tend to cut prices less aggressively than an inexperienced seller. Figure 6 compares the price paths for fixed price listings - controlling for ticket characteristics and game-section or seller-game-section-row fixed effects, for the quartile of listings posted by sellers with the most MLB listings in the data and the quartile posted by sellers with the least listings. In both cases, the price declines are *larger* for more experienced sellers. The same pattern holds for auction start prices (not reported). A theory based on changing opportunity costs can easily explain why professional (large) sellers are likely to cut prices dramatically: a long time before the game they should have high opportunity costs because it is cheap for them to relist but close to a game they should have low opportunity costs because they get no utility from being left with tickets.

[FIGURE 6 ABOUT HERE]

Auction Listings. The analysis so far has focused on fixed price listings. Appendix B presents an analysis of single-unit auction listings.[37] Since these listings can result in no sale, or a sale at a price which is at or above the auction start price I model the outcome of the listing using two equations: a probit which determines the probability of sale and a truncated normal regression model which determines expected revenues in the event of sale.

The estimated demand parameters are similar for the first three time periods (up until 10 days before the game), so that the model implies declining opportunity costs and counterfactual prices which are quite close to those that are observed. The results for these time periods are therefore consistent with dynamic pricing and the stable demand function of the standard dynamic model. A different result emerges in the final time period when opportunity costs increase. This pattern emerges not only because auction start prices are not declining (Figure 2(b)), which can be explained by changes in the type of seller using auctions, but also because of a significant decrease in the estimated elasticity of the revenue function with respect to the auction start price. This change in elasticity reduces the optimal price of a seller relative to earlier time periods, so that higher opportunity costs are needed to explain why prices are flat. It is not obvious what would cause this change in elasticity, given that both start prices and the probability of sale remain fairly constant in the final time period.

Looking across auction and fixed price models, one can compare how implied opportunity costs evolve over time for particular seller-seat combinations (i.e., a seller-game-section-row combination) that are posted multiple times. When I observe a seller posting two fixed price listings, the implied opportunity cost for these listings falls for 76% of observations. For two auction listings the implied cost falls for 57% of observations, the smaller percentage explained by the change in the final period revenue function. When a seller switches from using a fixed price to using an auction (the most common type of switch in the data) implied opportunity costs fall 64% of the time. This is consistent with opportunity costs falling and with the models used for different selling mechanisms providing broadly comparable estimates.[38]

[37] See an earlier working paper (Sweeting (2009)) for an analysis of hybrid BIN auction listings. These listing present additional problems because there can be more than two outcomes, and a control function approach is difficult to apply without *ad hoc* assumptions. However when I make these assumptions, I find that opportunity costs of sale decline for sellers using these listings and that counterfactual prices are similar to observed prices in each time period.

[38] When a seller using a fixed price uses an auction listing for his next posting, he tends to have lower opportunity costs than when he uses another fixed price listing for his next posting (conditional on the time until the game). This pattern is consistent with my earlier arguments concerning how opportunity costs may affect mechanism choice.

6 Buyer Sorting and Further Evidence in Favor of Stable Demand

The analysis so far has shown that sellers price dynamically. The results also show that the time-invariant residual demand feature of the standard dynamic model holds in this setting. This is a more surprising result because the assumptions that lead to time-invariant demand in the model - ex-ante identical consumers who arrive stochastically and must buy at once or exit - are strong. This prompts one to ask whether there is any evidence of consumer sorting in the data, and, if there is evidence of sorting, why does this not lead to changes in residual demand, because, if different types of consumers with different preferences choose to buy at different times, we might expect residual demand to change.

I investigate these questions using eBay data. I find that there is evidence of sorting based on the experience of buyers (people who buy more MLB tickets tend to buy earlier) and the distance that they have to travel to attend the game (more distant buyers buy earlier). This suggests that a very literal interpretation of the standard dynamic model - that consumers are really identical - is not true, and that at least some consumers choose when to buy. However, there is no evidence that people who buy at different times have different preferences for seats, so there is no reason why this type of sorting would cause a systematic change in the residual demand curve, which is what is key for sellers' behavior. As preferences are not observed directly, I look at the type of seat purchased, based on the logic that in any differentiated product market, consumers who are less price-sensitive will tend to buy higher quality products.[39] Based on this approach, I find that preferences are similar both across time and across the dimensions in which consumers do appear to be sorted.[40] After presenting the empirical evidence, I sketch a simple model that ties these findings together.

Table 6 reports two types of regressions, where an observation is a purchase of a ticket with non-missing face value information and non-missing zip code information.[41] The first set of regressions (columns (1)-(3)) examine which types of consumers tend to purchase early and which types of seats tend to be purchased early. The dependent variable is the number of days prior to a game that the transaction takes place and the regressors include ticket characteristics (face value, row variables), listing characteristics (number of seats), game characteristics (home team dummies, day and month of game dummies and expected attendance 90 days before the game) and buyer characteristics. Buyer

[39] As an example of the logic behind the analysis, consider airline tickets. We expect business travellers, who are likely to be less price-sensitive, to buy tickets for premium seats with fewer restrictions, as well as being willing to pay higher prices for a particular type of seat.

[40] An issue would obviously arise if the average face value of *available* tickets tends to change as a game approaches. Figure 1(d) indicates that this is not the case.

[41] The zip code criterion excludes listings purchased by people outside the U.S., including Canada.

characteristics include a set of dummies measuring how many MLB listings the buyer purchased on eBay during 2007 (which measures experience but should also proxy the buyer's interest in baseball) and variables measuring the distance of the buyer's zipcode from the stadium where the game is played.[42] To avoid confusing buyer experience/interest in baseball with the behavior of professional traders, I exclude observations for buyers who ever list more than one set of MLB tickets on eBay.[43]

[TABLE 6 ABOUT HERE]

In column (1) the effects are identified from cross-game (within team) and cross-buyer variation. Seats of different qualities are purchased at approximately the same time, even though the coefficients are statistically significant. For example, a $60 seat tends to be purchased 0.7 days *later* than a $40 seat, and front row seat 1.7 days *earlier* than a row 20 seat. Groups of six seats are purchased two weeks earlier than other listings, which is sensible because these listings are rare, so a consumer who wants six seats should probably buy a listing as soon as one becomes available. However, six seat listings make up less than 1% of purchases.

On the other hand, buyer characteristics have quite large effects on when tickets are purchased. For example, someone who has to travel the distance from New York to Boston tends to buy 6.7 days earlier than someone living next to the stadium. This is a large difference given that the median purchase date is ten days before a game. This pattern may be explained by people who have to travel having to make more complementary investments (hotel rooms, plane tickets, baby-sitters) to attend a game. If these investments are more expensive or more difficult to make at the last minute, then a distant consumer may prefer to make all of her arrangements some time before the game, even though ticket prices tend to fall. Experienced consumers also tend to purchase early. This may be explained by people who really like baseball tending to make plans earlier than more casual fans. Assuming that experienced buyers are more knowledgeable about how prices change, this pattern also suggests that early purchasing is not simply due to consumer ignorance. However, it would be interesting to investigate how many consumers are aware of how much prices change.

Column (2) shows that the coefficients are almost unchanged when I include game fixed effects to control, in a more complete way, for how differences in demand across games may affect when people

[42] I have also estimated specifications including the average household income in the zip code (taken from the 2000 Census), which should be a proxy for the buyer's income. The estimated income coefficients are statistically significant but very small, implying that a $20,000 average income increase delays purchase by one day and raises the face value of the purchased ticket by $0.78.

[43] Unfortunately, I cannot rule out the possibility that they sell tickets elsewhere or under different identities. For this reason, the results for consumers buying more than 21 sets of tickets should be interpreted with some caution.

purchase. Column (3) investigates the robustness of the distance effect by adding buyer-zipcode fixed effects.[44] The distance coefficients are now identified from the choices of people who buy tickets for games in multiple stadia, and they imply that someone living in Boston buys a ticket 5.3 days earlier for a game in New York than a game in Boston. This provides strong evidence that distance affects the timing of purchases.

These results show that certain types of consumers tend to buy tickets early, and that, controlling for consumer characteristics, the quality of seat purchased remains similar as a game approaches. I now show that different types of consumer also tend to have similar preferences. Columns (4)-(6) repeat columns (1)-(3), using the face value of a ticket as the dependent variable and excluding other observed ticket characteristics. The coefficients on buyer characteristics indicate that different types of buyer tend to purchase similar types of ticket, even though some differences are statistically significant. For example, a Boston-based consumer tends to buy a ticket with a $1.52 higher face value when she goes to a game in New York than when she goes to a game in Boston (column (6)). This difference is less than half the average price of a hotdog ($3.70) in an MLB stadium, and all of the differences are much less than one standard deviation of observed face values ($36.47).[45]

These results are consistent with the following simple model where consumers can choose when to buy. Suppose that there are two periods, 1 and 2, and that there is a distribution of consumers with different preferences for tickets. Independent of these preferences, some consumers have to pay an additional cost if they buy in period 2. This cost could reflect the additional expense of making complementary investments at the last minute. Now suppose that it is known that tickets will be available in both periods, but that prices will be lower in period 2.[46] If the cost of waiting is high enough, consumers will sort with high cost consumers active in the market in period 1, and no cost consumers active only in period 2. Critically, however sellers will face consumers with similar ticket preferences and willingness to pay for tickets in both periods. This pattern would be consistent with the estimates of demand (Section 5), as well as the fact that the observed price declines are similar for different types of seat (Appendix A).

[44] I include a buyer-shuipping zipcode fixed effect to control for sellers who move during the season.

[45] Average price for the 2009 season reported by Brown, Maury, "Average Ticket Price Up 5.4 Percent in MLB. Yankees/Mets" on www.bizofbaseball.com, April 2, 2009

[46] An earlier working paper contained a more formal version of this model with sellers choosing prices, which fall in equilibrium, as well as consumers choosing when to enter the market.

7 Conclusion

This paper has examined the pricing behavior of sellers in online resale markets for MLB tickets. A striking feature of the data is that sellers cut prices quite dramatically as a game approaches. I show that this pattern is explained by sellers using dynamic pricing strategies, and that their pricing problem is accurately described by standard dynamic pricing models for perishable goods that have been widely used in Revenue Management. However, the patterns that are observed are quite different from those in airline markets which, ironically, have been used to motivate much of the theoretical literature. At a more general level, the results support the assumption that even small sellers, who might be thought to be relatively unsophisticated, respond to dynamic economic incentives.

There are many directions which seem ripe for further analysis in this type of market. First, it would be interesting to understand why pricing patterns in other markets, such as airlines, do not follow those which I observe here. One explanation is simply that incentives to price discriminate across different types of consumers dominate the dynamic incentives that I have identified. However, there are other possibilities which are more intriguing. For example, airline markets are characterized by a high degree of concentration and consumers are likely to interact with the same firms repeatedly. In this case, firms may want to develop a reputation for not reducing prices to influence how consumers buy in the future.

Second, there are many aspects of sellers' choices that I have abstracted away from in the current paper. For example, sellers are choosing which resale markets to participate in and which types of sales mechanisms to use (fixed prices vs. auctions). Their choices likely reflect the preferences of buyers for the convenience of fixed price listings and their own desire to sell tickets quickly, which may favor auctions which provide a flexible price in response to realizations of how many consumers are interested in the listing. A nice feature of my setting is that perishability creates significant variation in the types of mechanism chosen by individual sellers over time, so the choice of mechanism cannot be attributed solely to exogenous heterogeneity in sellers' preferences.[47] Quantifying how these effects lead to equilibrium market structures would potentially have important implications for the design of markets in other settings.

Third, it would be interesting to investigate the importance of small sellers in generating the large equilibrium price declines which are observed, by comparing observed outcomes with counterfactual prices generated by a structural model where there are a small number of large sellers. This would

[47] For example, Zeithammer and Liu (2006) focus on differences across sellers when looking at listings for electronic goods on eBay.

also help to predict what would happen if dynamic pricing was introduced in the primary market. Finally, there are clearly open questions concerning the behavior of consumers. I have provided evidence that suggests that consumers who are active in the market at different times tend to have similar valuations for tickets, even though they may be sorted on other dimensions. However, this leaves open the question of how strategically buyers behave, whether most consumers are aware of how much prices decline and whether more strategic behavior by consumers would affect equilibrium outcomes.

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A Coefficient Estimates for Average Price Declines and Additional Robustness Checks

Table A1 reports the coefficients presented in Figures 2(a)-(d). Tables A2-A4 present additional robustness checks for Stubhub list prices (A2), eBay fixed prices (A3) and eBay transaction prices (A4) where fixed price and auction sales are pooled. In all cases I continue to find significant price declines, although there is some variation across the price measures in whether a particular robustness check makes the decline larger or smaller.

Alternative Price Measures. Column (1) presents the results where the dependent variable is the price divided by the face value of the ticket. For all measures, prices are declining by at least 40% of face value in the month prior to the game.

Alternative Fixed Effects. The specifications in the text use game-section fixed effects to control for seat quality. This treatment may be seen as either too specific (because some listings are the only ones in their section for a particular game) or insufficiently specific (if row quality also matters in different ways across sections). Columns (2) and (3) therefore use game-face value fixed effects and game-section-row fixed effects respectively. For all of the price measures, prices decline in both cases by amounts which are broadly similar to the baseline case.

Different Face Values. 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 (4) and (5) report the results using only tickets with face values of less than \$20 and more than \$45 respectively. For listed prices the declines are similar for the two groups, while for transaction prices the declines are proportionally larger for cheaper seats, a pattern which would be reversed looking at the dollar value of the declines.

Level of Demand. Section 3 explains how I form an estimate of a game's expected attendance/demand based on several years of attendance data. Columns (6) to (9) show estimated price paths when I divide games into four groups, with roughly equal numbers of observations, based on the expected attendance 90 days before the game (i.e., based on how the teams were performing at that point). The results are qualitatively similar using realized attendances. For list prices there is a pattern that prices decline more in percentage terms for lower demand games. However, this pattern would be reversed look at dollar declines or the decline as a % of face value because secondary market prices are much higher for the highest demand games.

Team Success. A team's success is likely to affect the value of their tickets in the secondary market. In the baseline specifications, I control for how a team's performance may affect prices. However, more generally one might ask whether the price declines are driven by teams that have unsuccessful seasons. In Table A5 I look at how price declines compare for teams that have successful seasons (defined as making the playoffs), which should receive primarily good news shocks during the season, and those that do not. For several measures of price, the price declines are similar for the two groups of teams. One exception is that the flat pattern of auction start prices in the final two weeks before a game is only observed for unsuccessful teams. For successful teams, auction start prices decline right up to the game.

Table A6 reports the coefficients from the probability of sale regressions in Figure 3.

B Auction Listings

This Appendix presents an analysis of why sellers are cutting eBay auction start prices over time which parallels the analysis in Section 5 for fixed price listings. It only considers single unit auction listings with no BIN option. Hybrid BIN auctions listings create some additional issues because of the additional possible outcome (sale at a fixed price). The results of an analysis of BIN listings are contained in a working paper (Sweeting (2009)) and the results are consistent with those in Section 5: prices fall primarily because of declining opportunity costs.

B.1 Empirical Specification

Pure auction listings have the feature that revenues can exceed the start price set by the seller. The probability of sale is modeled using a probit, just as in the fixed price listing case, 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

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

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

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

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

where p_{it} is the start price and both $f()$ and the single index in the probit are linear functions of the same characteristics as the specification for fixed price listings except that dummies for the duration of the auction are added. Prices and revenues are defined 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. As with a fixed price, the chosen auction start price may be endogenous (i.e., correlated with unobserved ticket characteristics). The control function approach can be used for both the probit and the censored normal regression models, and I use the same instruments as in Section 5. The first stage results indicate that the instruments are jointly significant (F-test statistic is 48.0) although one difference from the fixed price case is that a higher relisting rate is associated with higher prices, suggesting that auction sellers with low relisting costs tend to be the ones who relist.

The estimation sample consists of single unit auction listings on eBay in the last 90 days before the game with non-missing face value information and no secret reserve price. To deal with the effect of outliers, I use the 96.9% of auction 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.

B.2 Empirical Results

Table A7 presents the second stage results. The probability of sale function (column (1)) becomes more elastic as we move from the first time period (41+ days before the game) to the second time period, but the slope remains similar across the later time periods. The revenue function has a similar slope with respect to the start price across the first three time periods (up until 10 days before the game) but revenues become less sensitive to price in the final time period.

The lower parts of the table show how these changes affect median implied opportunity costs and counterfactual prices. Opportunity costs fall across the first three time periods, although the change in the probability of sale function means that counterfactual prices fall by a little less than observed prices, i.e., a change in demand plays some role in causing prices to fall from the first to second time period. The change in the results in the final time period is more dramatic. The expected revenues are less sensitive to prices in this period, so low prices are rationalized by higher opportunity costs. As a result, the implied median opportunity cost rises in the final time period even though observed start prices are flat (Figure 2(b)). This change in opportunity costs could be rationalized by a change in the type of seller using auctions, but the change in the revenue function also causes the path of counterfactual prices to look different to what we see in the data.

In summary, the results for auction listings are broadly consistent with the assumptions of the dynamic model until the last ten days before the game. At that point, the estimates imply that there is a significant change in a feature of demand (the revenues a seller can expect for a given start price), which is inconsistent with the dynamic model. However, the fact that individual sellers continue to cut their start prices (Figure 2(c)) raises the question of whether this change in elasticity reflects some form of model misspecification.

C Summary Statistics

Table A8 presents summary statistics for the variables for four different groupings of tickets: the 5% sample of Stubhub listings used in the regressions in Figure 2(a), eBay fixed price listings (including personal offer listings with a fixed price option), eBay auction listings (including hybrid BIN auctions) and eBay transactions. The statistics are calculated using listings with non-missing face values. Note that the fixed price listings used in Section 5 exclude personal offer listings, listings made more than 90 days before a game and those with prices greater than 5 times face value.

Table 1(a) : Summary Statistics by Team

	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*10,000 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	face values 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. Face values unavailable for Colorado Rockies.

Table 1(b): Characteristics of Tickets Traded by Different Types of Buyer and Seller (eBay)

	Observations	Average Face Value ($)	Propn. of Season Ticket Only Sections (higher = better)	Average Row Number (lower = better)	Propn. of Tickets for NYY Home Games
Sellers	**Listings**				
List Tickets for Less than 5 Games	100,422	37.76	0.016	10.0	0.13
		(30.77)	(0.126)	(7.0)	(0.33)
List Tickets for 5-100 Games	357,612	37.11	0.008	9.9	0.19
		(34.40)	(0.089)	(7.2)	(0.39)
List Tickets for More than 100 Games	176,259	38.76	0.021	9.1	0.14
		(42.86)	(0.142)	(7.0)	(0.34)
Buyers	**Purchases**				
Less Than 10 Listings in Season	260,501	36.69	0.010	9.5	0.13
		(32.50)	(0.098)	(7.0)	(0.34)
10 or More Listings in Season	39,949	35.13	0.008	9.4	0.17
		(34.70)	(0.087)	(6.8)	(0.37)

Note: standard deviations in parentheses.

Table 2: Regressions of eBay Fixed Prices on Instruments

Distance Variables	
Seller Within 40 km	-0.029
	(0.024)
* 1-10 Days Prior to Game	0.049*
	(0.030)
* 11-20 Days Prior to Game	0.0286
	(0.028)
* 21-40 Days Prior to Game	-0.0209
	(0.028)
Seller More than 200 km	0.159***
	(0.023)
* 1-10 Days Prior to Game	-0.222***
	(0.030)
* 11-20 Days Prior to Game	-0.130***
	(0.026)
* 21-40 Days Prior to Game	-0.0628**
	(0.027)
Relisting Variables	
Proportion of Seller's Unsold Listings	0.034
During Time Period Relisted on eBay	(0.091)
* 1-10 Days Prior to Game	-0.0903*
	(0.051)
* 11-20 Days Prior to Game	-0.141**
	(0.062)
* 21-40 Days Prior to Game	-0.433***
	(0.050)
Mechanism Choice Variables	
Proportion of Seller's Other Listings	-0.0909
in Hybrid BIN Format	(0.057)
* 1-10 Days Prior to Game	0.150**
	(0.067)
* 11-20 Days Prior to Game	0.249***
	(0.072)
* 21-40 Days Prior to Game	0.085
	(0.071)
Proportion of Seller's Other Listings	0.144***
in Pure Fixed Price Formats	(0.040)
* 1-10 Days Prior to Game	-0.235***
	(0.047)
* 11-20 Days Prior to Game	0.0231
	(0.052)
* 21-40 Days Prior to Game	0.00853
	(0.054)
Observations	109,296
F-statistic on the instruments	15.67 (p-value 0.000)

Notes: Observations are pure fixed price listings on eBay posted within 90 days of the game with non-missing face values and prices less than 5 times face value. Specification includes 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.
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
Own Price Coefficients		
Relative Fixed Price	-0.199***	-1.120***
	(0.014)	(0.097)
1-10 Days Prior to Game*Relative Price	0.064***	-0.006
	(0.016)	(0.025)
11-20 Days Prior to Game*Relative Price	0.060***	0.000
	(0.016)	(0.027)
21-40 Days Prior to Game*Relative Price	0.032*	-0.031
	(0.018)	(0.025)
Competition Coefficients (EBay)		
Mean Relative Price for Fixed Price Listings	0.114***	0.344***
	(0.013)	(0.032)
Mean Relative Start Price for Auction Listings	0.029*	0.099***
	(0.015)	(0.025)
Minimum Relative Price for Fixed Price Listings	-0.035***	0.028
	(0.012)	(0.021)
Minimum Relative Price for Auction Listings	-0.042***	-0.098***
	(0.016)	(0.025)
Dummy Variable for No Competing	0.176***	0.717***
Fixed Price Listings	(0.029)	(0.069)
Dummy Variable for No Competing	-0.094***	-0.176**
Auction Listings	(0.025)	(0.069)
Number of Competing Fixed Price Listings	-0.151***	-0.207***
	(0.020)	(0.025)
Proportion of Competing Fixed Price Listings with	0.084*	0.158**
Seller Feedback Scores Above 100	(0.044)	(0.060)
Number of Competing Auction Listings	0.039***	0.052**
	(0.014)	(0.020)
Proportion of Competing Auction Listings with	-0.044*	-0.122***
Seller Feedback Scores Above 100	(0.023)	(0.028)
Competition Coefficients (Stubhub)		
Number of Stubhub Listings/100	-0.006	0.047***
	(0.010)	(0.016)
Days to Go Dummies (selection, 0 to 2 excluded)		
3 to 5	0.092***	0.098***
	(0.025)	(0.029)
11 to 14	-0.183***	-0.051
	(0.036)	(0.052)
30 to 32	-0.307***	-0.016
	(0.050)	(0.071)
41 to 44	-0.270***	-0.062
	(0.052)	(0.069)
51 to 55	-0.369***	-0.176***
	(0.044)	(0.063)
Mean Probability of Sale Elasticities at Observed Prices (absolute values)		
1-10 Days Prior to Game	0.199	1.656
11-20 Days Prior to Game	0.293	2.351
21-40 Days Prior to Game	0.467	3.244
More than 41 Days Prior to Game	0.747	4.253
Number of observations	109,296	109,296

Notes: see Table 2 for additional controls. Standard errors in parentheses clustered on the game (estimated using a block bootstrap with 200 repetitions).

Table 4: Comparison of Observed and Counterfactual Prices ($s) for Fixed Price Listings on eBay

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 for all listings.

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 $	71.67	67.60	62.01	53.71
	(2.15)	(2.27)	(2.27)	(1.89)
Median Price $	61.20	56.03	50.40	41.62
	(2.01)	(2.06)	(1.98)	(1.55)
Number of obs.	31,843	24,485	20,737	32,231

(b) 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)
Number of obs.	16,627	12,761	10,864	22,524

(c) 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 $	68.34	67.95	63.83	54.29
	(2.12)	(2.41)	(2.40)	(1.95)
Median Price $	56.53	56.03	52.00	42.55
	(1.77)	(2.08)	(2.10)	(1.63)
Number of obs.	18,003	14,016	12,164	21,055

Table 5: Fixed Price Listing Model : Robustness Checks

	(1) Baseline	(2) Dep Var = 1 if sold in 3 Days	(3) Instrument for Competing Prices	(4) Excluding Distance IVs	(5) Excluding Resale Rate IVs	(6) Excluding Mechanism Choice IVs	(7) Linear Probability Model with Game-Face Value Fixed Effects	(8) April and May Games Only	(9) Include Stubhub Demand Measure	(10) Include Lagged Price
Own Price Coefficients										
Relative Fixed Price	-1.120***	-1.133***	-1.106***	-1.628***	-1.126***	-0.806***	-0.309***	-0.898***	-1.158***	-1.057***
	(0.097)	(0.090)	(0.079)	(0.103)	(0.109)	(0.106)	(0.026)	(0.189)	(0.085)	(0.085)
1-10 Days Prior to Game*Relative Price	-0.006	0.019	-0.047*	0.006	-0.002	0.005	0.025	-0.058	-0.025	-0.011
	(0.025)	(0.025)	(0.027)	(0.022)	(0.026)	(0.025)	(0.016)	(0.044)	(0.028)	(0.027)
11-20 Days Prior to Game*Relative Price	0.000	0.002	-0.024	0.012	0.008	0.007	0.0259***	-0.033	0.005	-0.003
	(0.027)	(0.029)	(0.031)	(0.027)	(0.025)	(0.028)	(0.008)	(0.029)	(0.028)	(0.027)
21-40 Days Prior to Game*Relative Price	-0.031	-0.023	-0.074***	-0.016	-0.034	-0.033	0.008	-0.037	-0.006	-0.031
	(0.025)	(0.026)	(0.029)	(0.027)	(0.025)	(0.024)	(0.006)	(0.045)	(0.028)	(0.023)
Competition Coefficients (eBay)										
Mean Relative Price for Fixed Price Listings	0.344***	0.351***	0.705***	0.463***	0.345***	0.268***	0.095***	0.328***	0.229***	0.328***
	(0.032)	(0.029)	(0.114)	(0.035)	(0.037)	(0.034)	(0.035)	(0.060)	(0.021)	(0.032)
Mean Relative Start Price for Auction Listings	0.099***	0.090***	0.027***	0.136***	0.099***	0.076***	0.028	0.115***	0.014	0.096***
	(0.025)	(0.023)	(0.160)	(0.029)	(0.023)	(0.019)	(0.016)	(0.033)	(0.020)	(0.023)
Minimum Relative Price for Fixed Price Listings	0.028	0.039*	-0.030	0.061**	0.029	0.008	0.005	0.060*	0.010	0.027
	(0.021)	(0.022)	(0.108)	(0.027)	(0.020)	(0.016)	(0.011)	(0.034)	(0.015)	(0.021)
Minimum Relative Price for Auction Listings	-0.098***	-0.087***	-0.040*	-0.129***	-0.099***	-0.080***	-0.031***	-0.119***	-0.032***	-0.096***
	(0.025)	(0.029)	(0.216)	(0.029)	(0.025)	(0.017)	(0.011)	(0.030)	(0.021)	(0.027)
Dummy Variable for No Competing	0.717***	0.737***	1.373***	0.997***	0.719***	0.539***	0.189**	0.844***	0.460***	0.648***
Fixed Price Listings	(0.069)	(0.065)	(0.295)	(0.089)	(0.083)	(0.071)	(0.095)	(0.158)	(0.058)	(0.078)
Dummy Variable for No Competing	-0.176**	-0.168***	-0.171*	-0.225***	-0.177***	-0.148***	-0.056***	-0.146***	-0.158***	-0.171***
Auction Listings	(0.069)	(0.033)	(0.097)	(0.033)	(0.030)	(0.027)	(0.010)	(0.052)	(0.028)	(0.037)
Number of Competing Fixed Price Listings	-0.207***	-0.219***	-0.232	-0.233	-0.207	-0.188	-0.058	-0.119	-0.221	-0.150
	(0.025)	(0.029)	(0.060)	(0.031)	(0.024)	(0.024)	(0.010)	(0.042)	(0.022)	(0.028)
Proportion of Competing Fixed Price Listings with	0.158**	0.164***	0.259***	0.194**	0.162***	0.131**	0.040	0.130	0.274***	-0.036
Seller Feedback Scores Above 100	(0.060)	(0.058)	(0.079)	(0.074)	(0.056)	(0.059)	(0.036)	(0.080)	(0.054)	(0.067)
Number of Competing Auction Listings	0.052**	0.054**	0.019	0.054**	0.050**	0.048**	0.009	0.032	-0.001	0.032
	(0.020)	(0.022)	(0.094)	(0.025)	(0.021)	(0.018)	(0.015)	(0.027)	(0.020)	(0.023)
Proportion of Competing Auction Listings with	-0.122***	-0.143***	-0.059*	-0.160*	-0.122	-0.096***	-0.034***	-0.092**	-0.060**	-0.080**
Seller Feedback Scores Above 100	(0.028)	(0.029)	(0.035)	(0.034)	(0.027)	(0.028)	(0.012)	(0.043)	(0.025)	(0.035)
Competition Coefficients (Stubhub)										
Number of Stubhub Listings/100	0.047***	0.035**	0.019	0.075***	0.048**	0.030**	0.013	-0.038	0.105***	0.048***
	(0.016)	(0.017)	(0.015)	(0.019)	(0.015)	(0.013)	(0.015)	(0.024)	(0.014)	(0.015)
Listings's Own Lagged Price	-	-	-	-	-	-	-	-	-	-0.008
										(0.014)
Mean Counterfactual Prices										
1-10 Days Prior to Game (obs. mean $ 53.58)	53.71 (1.89)	50.53 (1.21)	55.26 (1.67)	54.91 (1.52)	53.78 (2.24)	52.14 (2.65)	53.04 (2.38)	52.55 (5.00)	53.36 (1.68)	71.93 (2.24)
11-20 Days Prior to Game (obs. mean $60.93)	62.01 (2.27)	61.86 (1.64)	63.45 (1.99)	61.95 (1.66)	62.01 (2.69)	62.17 (3.30)	61.08 (3.05)	61.48 (6.03)	61.75 (1.93)	62.05 (2.30)
21-40 Days Prior to Game (obs mean $65.81)	67.60 (2.27)	67.26 (1.74)	69.51 (2.03)	66.78 (1.60)	67.64 (2.84)	69.09 (3.77)	67.81 (3.68)	65.92 (6.18)	67.76 (1.96)	67.75 (2.30)
More than 41 Days Prior to Game (obs. mean $69.44	71.67 (2.15)	71.31 (1.61)	73.44 (1.82)	70.69 (1.50)	71.82 (2.61)	73.32 (3.42)	73.91 (4.22)	70.17 (5.90)	72.60 (1.89)	71.93 (2.24)
Number of observations	109,296	109,296	109,296	109,296	109,296	109,296	109,296	41,107	109,296	109,296

Notes: see Table 3 and text for details of each specification.

Table 6: Timing of Purchases (eBay)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	Days Prior to Game Purchase Made	Days Prior to Game Purchase Made	Days Prior to Game Purchase Made	Ticket Face Value ($)	Ticket Face Value ($)	Ticket Face Value ($)
Distance of Buyer's Zipcode from Stadium						
Distance (km)	0.0069***	0.0068***	0.0105***	0.0013***	0.0010***	0.0014
	(0.0008)	(0.0008)	(0.0010)	(0.0003)	(0.0003)	(0.0019)
Distance^2/1000	-0.0008***	-0.0008***	-0.0018***	-0.0002***	-0.0001*	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0005)
Distance Less than 40 km.	-4.6432***	-4.5261***	-2.2545***	-1.0145***	-1.0191***	-1.1300
	(0.3035)	(0.3025)	(0.6748)	(0.1990)	(0.1983)	(1.4251)
Buyer Experience (Number of Listings Bought in 2007)						
2 to 10	2.9633***	3.2882***	-	-1.9314***	-1.9841***	-
	(0.2549)	(0.2566)		(0.1806)	(0.1817)	
11 to 20	8.3178***	8.8251***	-	-5.0846***	-4.9791***	-
	(1.1682)	(1.1631)		(0.5857)	(0.5865)	
21 or more	7.5111***	8.2459***	-	-1.3321	-1.4655	-
	(2.8742)	(2.9061)		(1.8916)	(1.8517)	
Number of Seats (One excluded)						
Two	0.4099	0.6584	-2.3007**	-0.6010	-1.2917**	-2.4573
	(0.8719)	(0.8743)	(1.0570)	(0.6642)	(0.6633)	(2.0742)
Three	-3.6664***	-2.9904***	-4.9802***	0.3197	-0.7032	-2.4557
	(0.9589)	(0.9596)	(1.3226)	(0.8748)	(0.8747)	(2.8126)
Four	1.4996	1.8091**	-0.6827	1.5292**	0.7062	-2.8195
	(0.9123)	(0.9129)	(1.1026)	(0.6947)	(0.6950)	(2.2266)
Five	-2.3935**	-1.4516	-3.7903*	-5.9251***	-7.0988***	-1.8758
	(1.1521)	(1.1426)	(2.0041)	(1.4839)	(1.4955)	(4.7619)
Six	13.3788***	13.5146***	8.1645***	-3.6406***	-4.3204***	-5.0150
	(1.4836)	(1.4647)	(1.6527)	(0.9938)	(0.9952)	(3.9963)
Face Value						
Face Value ($)	-0.0315***	-0.0279***	-0.0272***	-	-	-
	(0.0026)	(0.0026)	(0.0032)			
Row Variables						
First Row Dummy	2.6618***	2.8994***	1.4038***	-	-	-
	(0.3096)	(0.3073)	(0.3381)			
Second Row Dummy	2.3395***	2.4248***	1.0811***	-	-	-
	(0.3021)	(0.3018)	(0.3613)			
Number of Row	0.0805***	0.0626***	0.0394***	-	-	-
	(0.0148)	(0.0147)	(0.0182)			
Game Variables						
Expected Attendance 90 Days	0.2238***	-	0.1579***	-0.0547***	-	-0.0891***
Prior to Game (% of capacity)	(0.0111)		(0.0126)	(0.0074)		(0.0257)
Home Team Dummies	Y	N	Y	Y	N	Y
Day of Week of Game Dummies	Y	N	Y	Y	N	Y
Month of Game Dummies	Y	N	Y	Y	N	Y
Game FEs	N	Y	N	N	Y	N
Buyer Zipcode FEs	N	N	Y	N	N	Y
Number of Observations	245,829	245,829	245,829	245829	245829	245829
R-squared	0.07	0.10	0.83	0.10	0.11	0.76

Notes: Standard errors in parentheses clustered on the buyer. ***,** and * denote significance at the 1, 5 and 10% levels. Purchases with missing face value, buyer zipcode information or by buyers who are observed selling more than 1 MLB listing on eBay in 2007 are excluded.

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

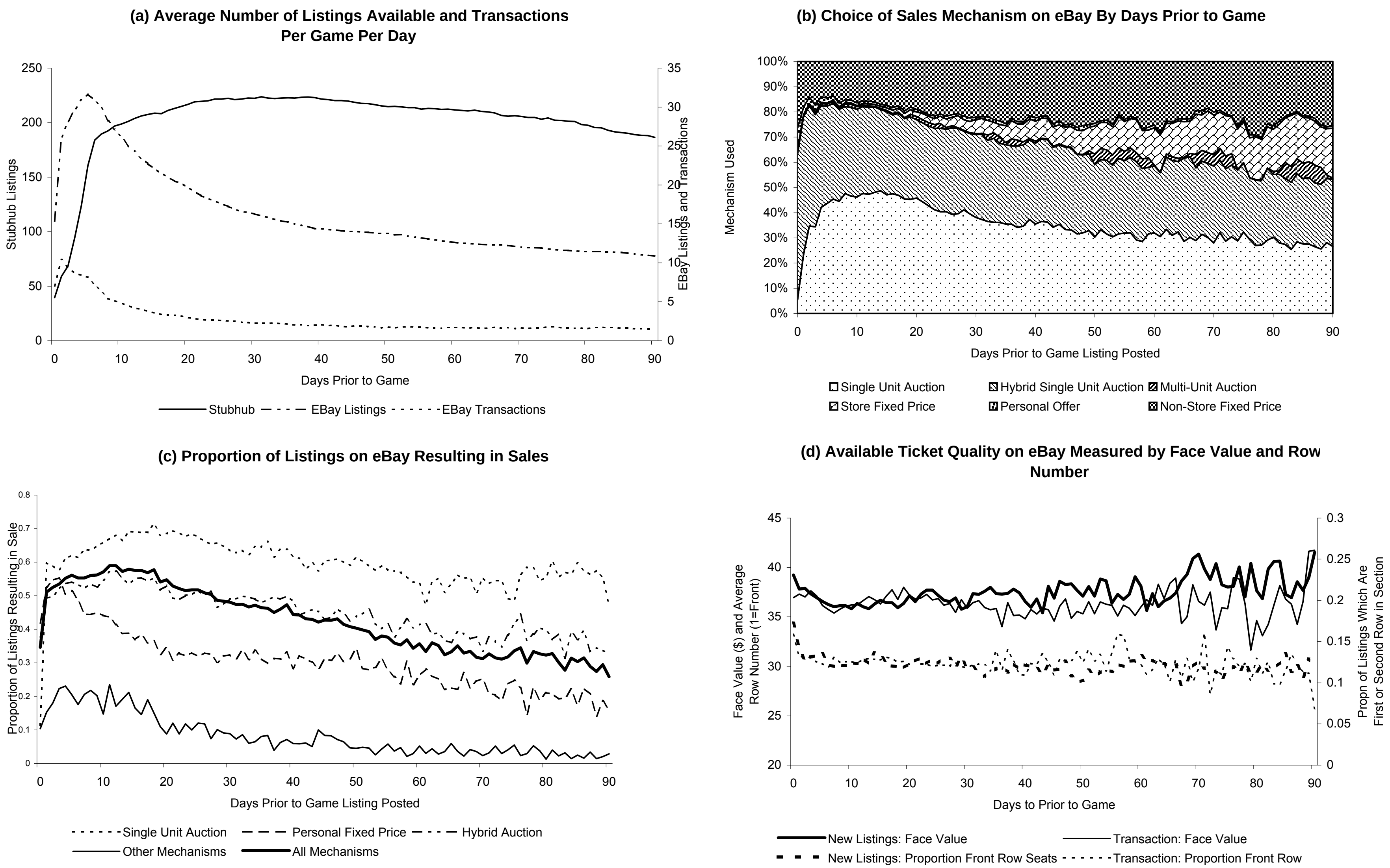


Figure 2: Estimated Price Paths

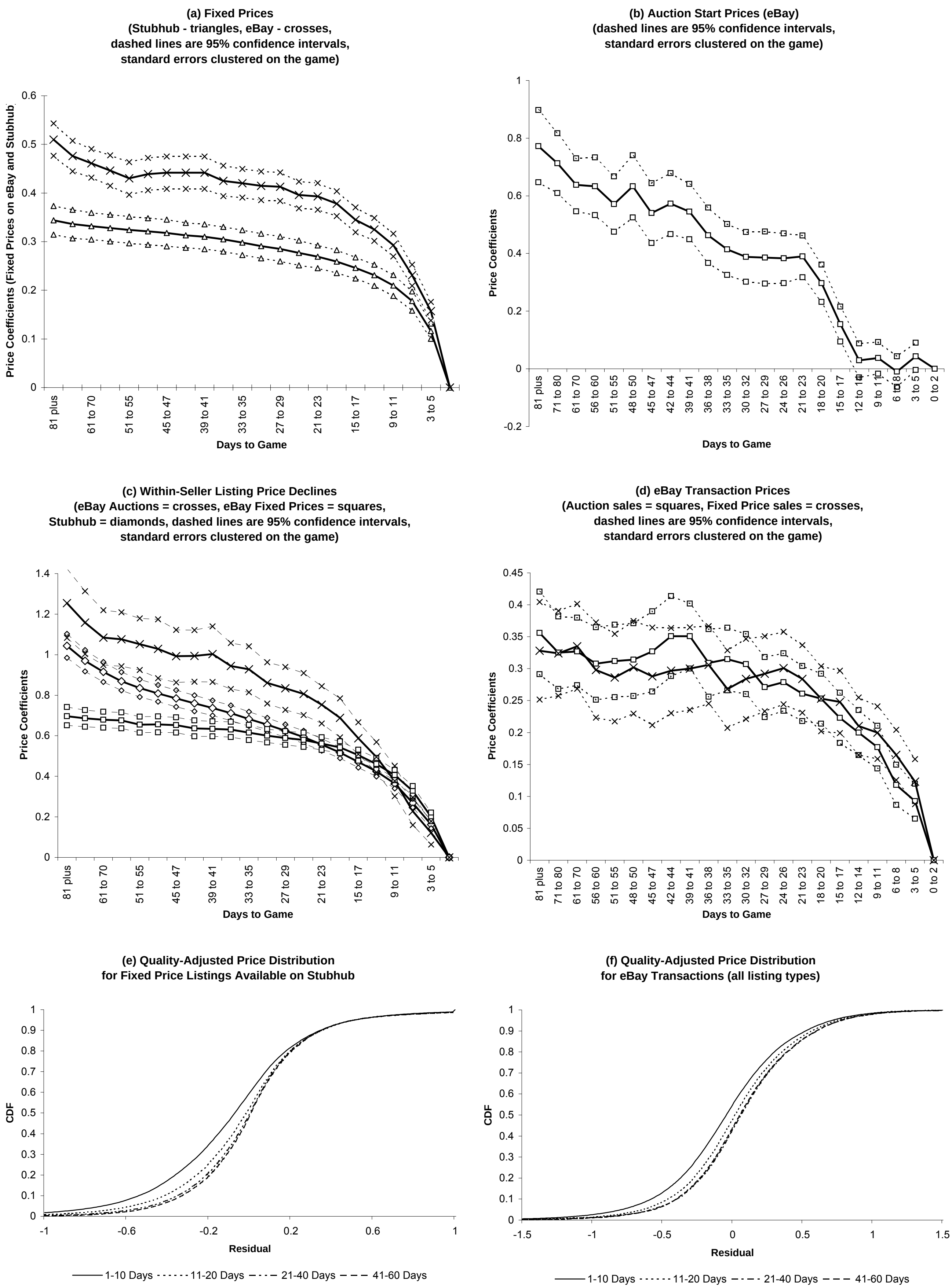


Figure 3: Probability of Sale

eBay Pure Fixed Price Listings - open triangles, eBay Hybrid Auction listings - crosses, eBay Auctions - squares, dashed lines are 95% confidence intervals, standard errors clustered on the game

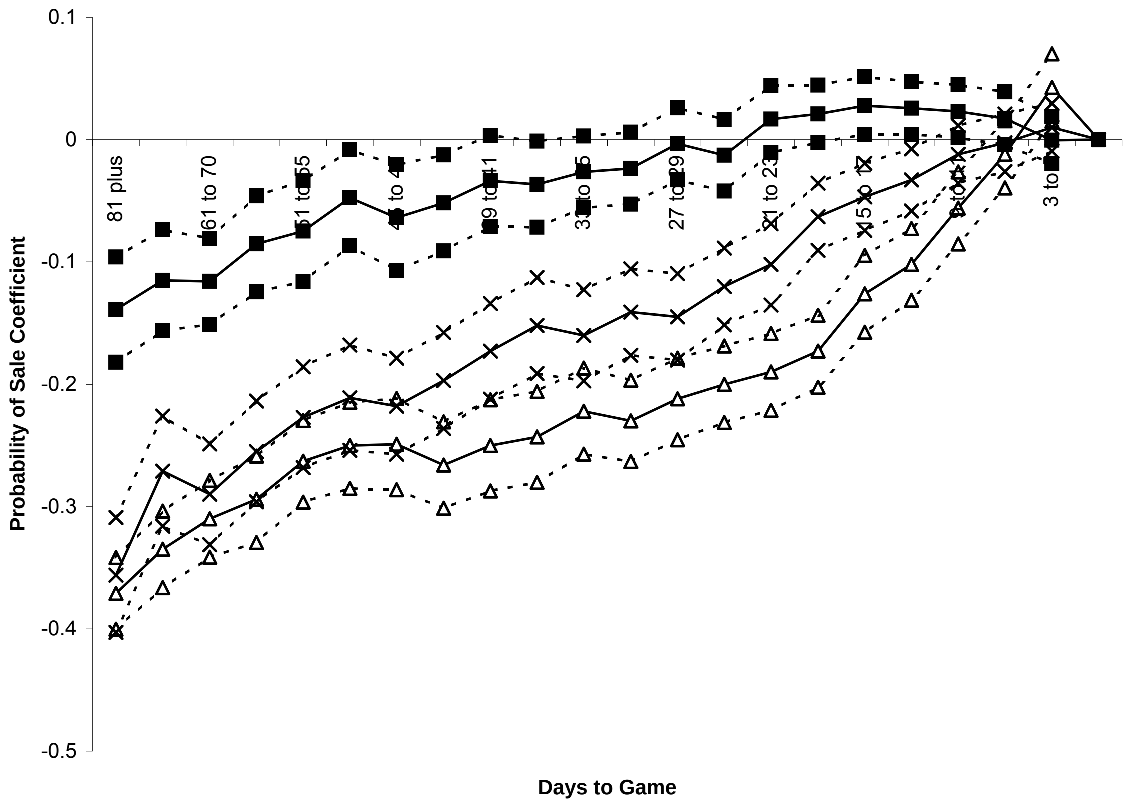
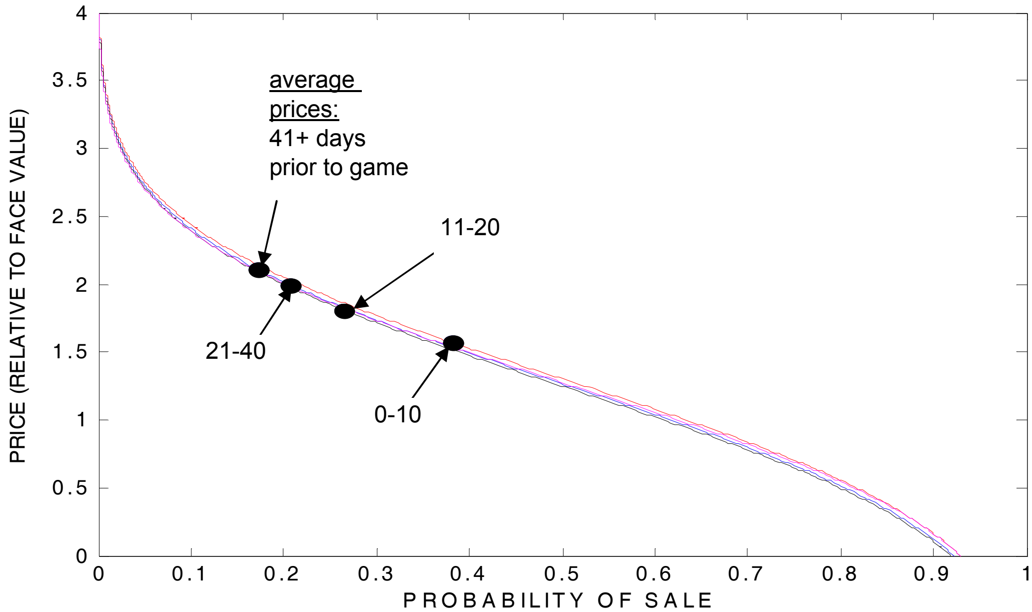
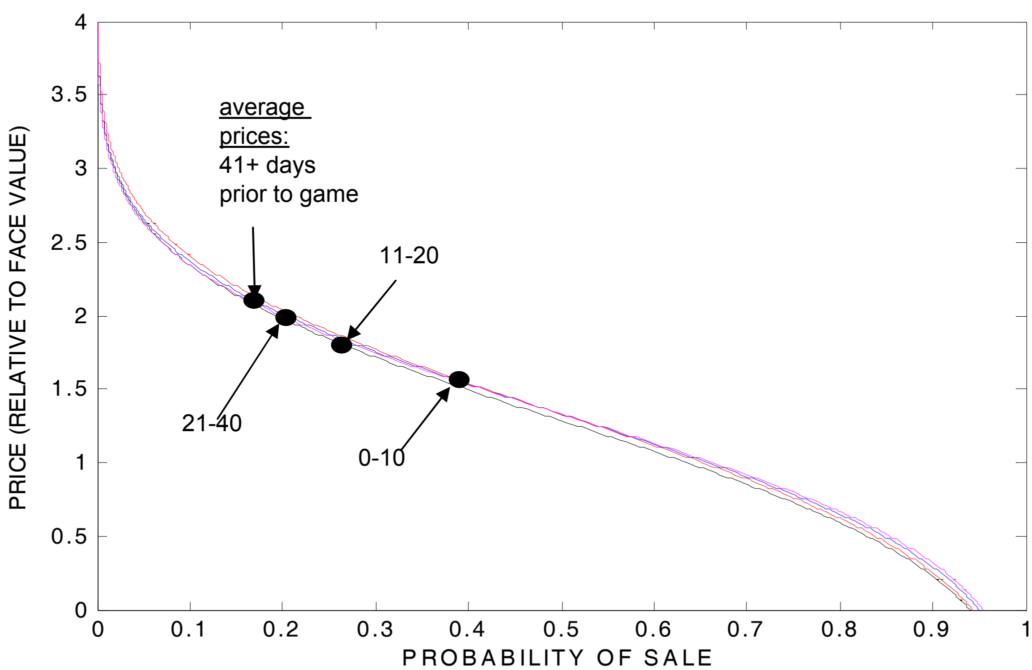


Figure 4 : Residual Inverse Demand Curves in the Four Time Periods Given Mean Ticket Characteristics and Mean Competition in the Time Period

(a) Baseline Specification



(b) Including Competition x Time Period and Competition x Time Period x x Own Price Interactions

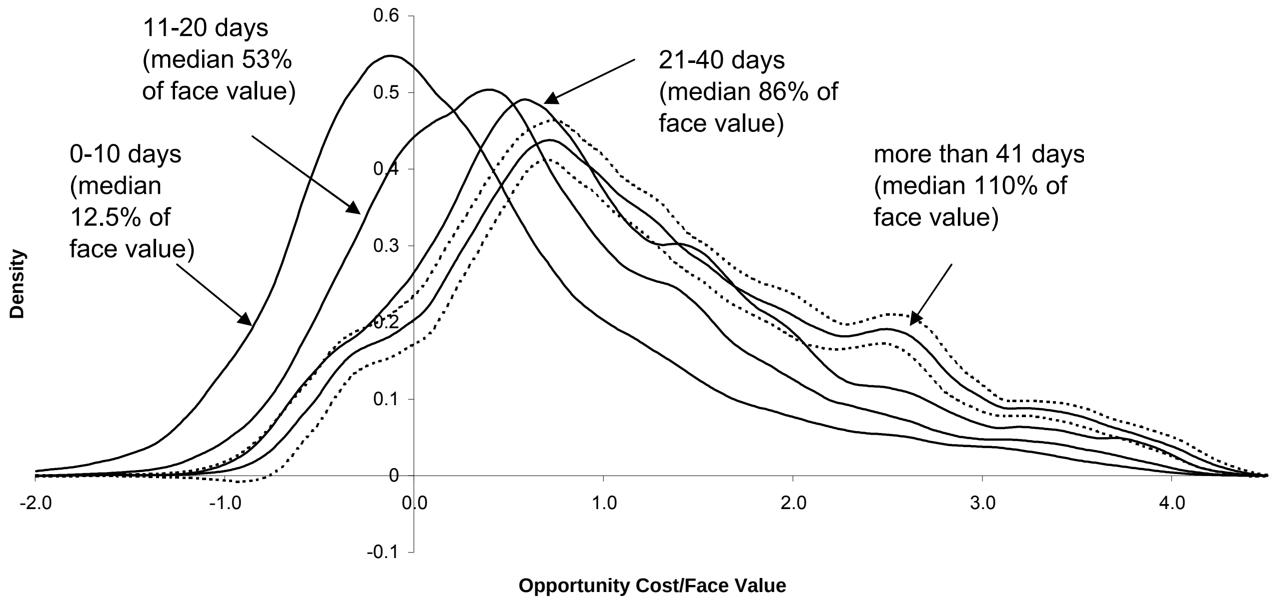


Note: Days-to-go dummies take on their values 6 to 8, 15 to 17, 30 to 32 and 45 to 47 days prior to game for the relevant time periods.

Figure 5(a): Opportunity Costs Implied by Baseline Fixed Price Listing Model

Dashed line shows 95% confidence intervals (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

(a) Baseline Relative Price Model



(b) : Distribution of Prices for Tickets with Positive and Negative Implied Opportunity Costs (Baseline Model)

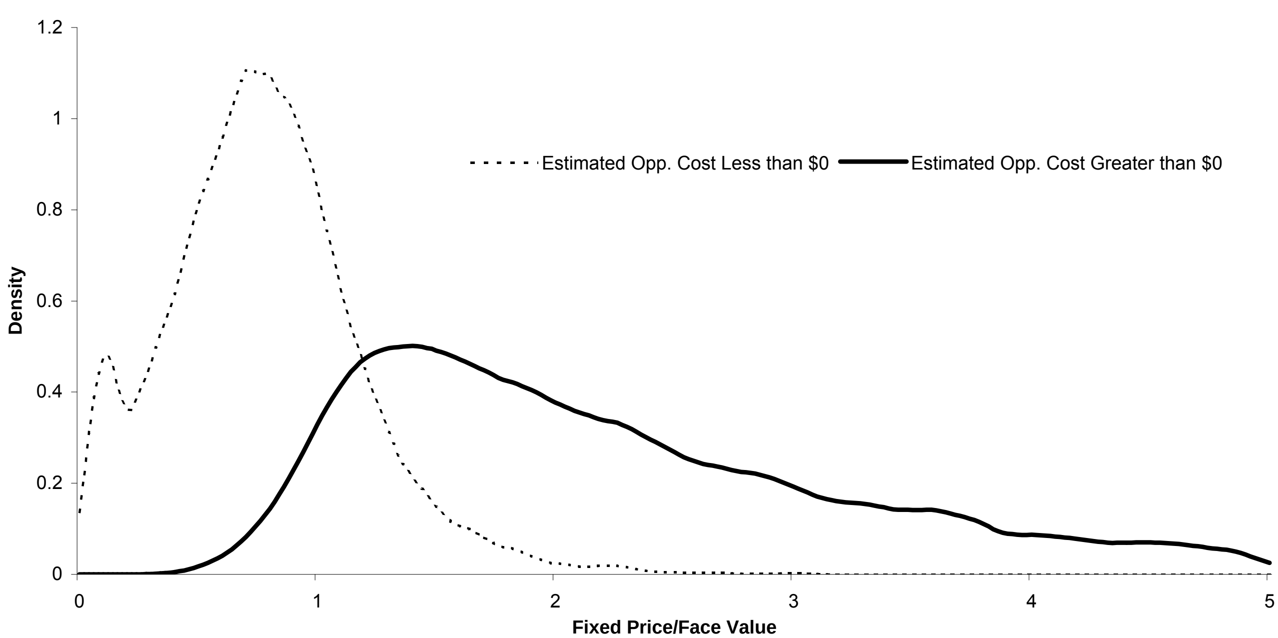


Figure 6: Comparison of Price Declines for Experienced and Inexperienced Sellers (eBay Fixed Prices)

(Quartile of listings by largest sellers = crosses, quartile of listings by least experienced sellers = squares)
dashed lines are 95% confidence intervals, standard errors clustered on the game

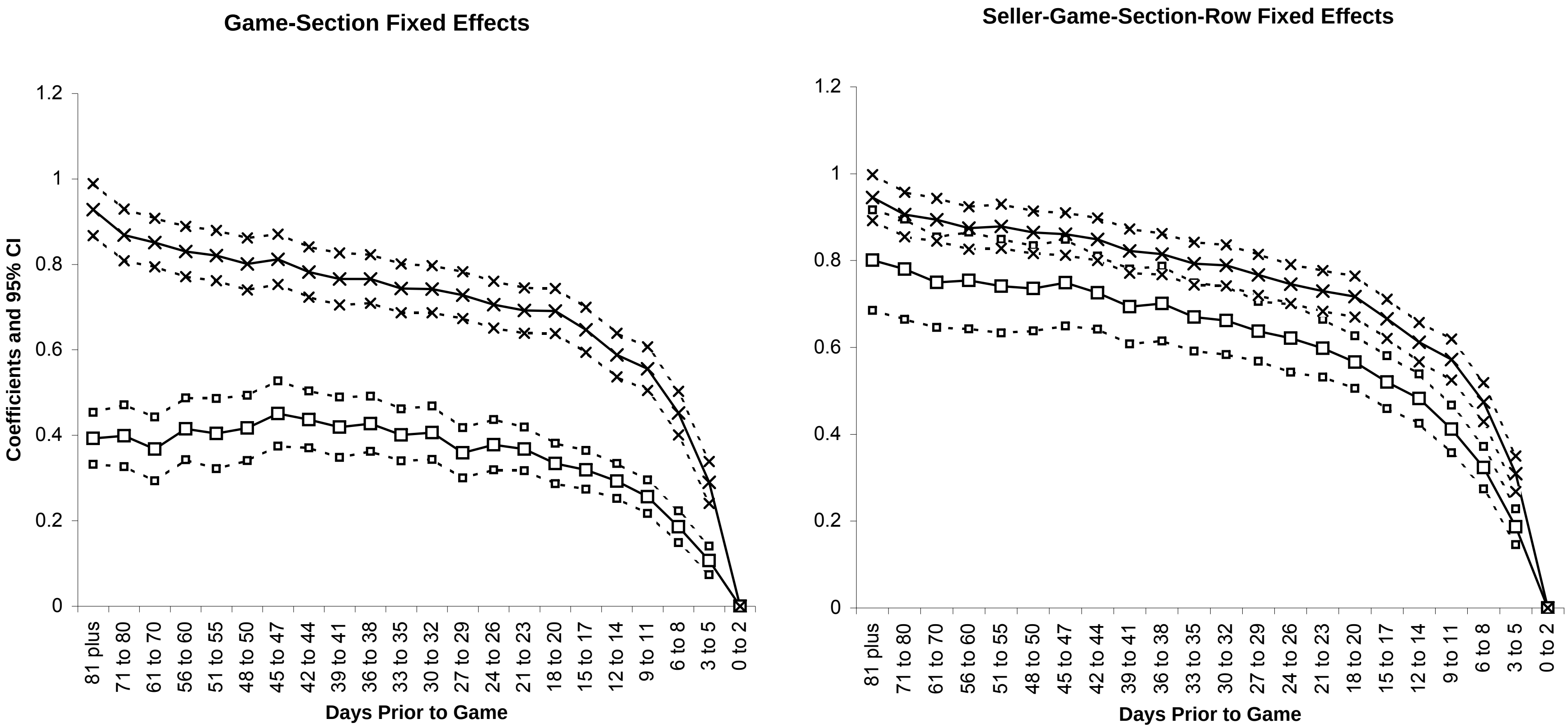


Table A1: Regression Coefficients for Results Shown in Figures 2(a)-(d)

	(1) Fig. 2(a)	(2) Fig. 2(a)	(3) Fig. 2(b)	(4) Fig. 2(c)	(5) Fig. 2(c)	(6) Fig. 2(c)	(7) Fig. 2(d)	(8) Fig. 2(d)
	Available Stubhub Listings	eBay Fixed Price Listings	eBay Auction Listings	Stubhub Listings	eBay Fixed Price Listings	EBay Auction Listings	eBay Auction Transaction	eBay Fixed Price Transactions
Definition of Time Dummies	Date Available	Listing Date	Auction End Date	Listing or Price Change	Listing Date	Auction End Date	Purchase Date	Purchase Date
Price Variable	Log(Seller Price)	Log(List Price)	Log(Auction Start)	Log(Seller Price)	Log(List Price)	Log(Auction Start)	Log(Buyer Price)	Log(Buyer Price)
Days to Go Dummies								
3 to 5	0.116***	0.157***	0.0435*	0.162***	0.200***	0.121***	0.0922***	0.123***
	(0.008)	(0.010)	(0.024)	(0.010)	(0.011)	(0.029)	(0.014)	(0.017)
6 to 8	0.178***	0.231***	-0.00984	0.268***	0.328***	0.228***	0.118***	0.166***
	(0.010)	(0.011)	(0.027)	(0.011)	(0.012)	(0.035)	(0.016)	(0.020)
9 to 11	0.210***	0.293***	0.0376	0.364***	0.406***	0.377***	0.177***	0.200***
	(0.011)	(0.012)	(0.028)	(0.012)	(0.013)	(0.038)	(0.017)	(0.021)
12 to 14	0.231***	0.325***	0.0291	0.425***	0.461***	0.495***	0.200***	0.210***
	(0.011)	(0.012)	(0.030)	(0.013)	(0.015)	(0.038)	(0.018)	(0.023)
15 to 17	0.246***	0.345***	0.155***	0.471***	0.504***	0.588***	0.223***	0.248***
	(0.011)	(0.013)	(0.031)	(0.014)	(0.014)	(0.040)	(0.020)	(0.025)
18 to 20	0.259***	0.378***	0.297***	0.517***	0.543***	0.688***	0.253***	0.253***
	(0.012)	(0.013)	(0.033)	(0.014)	(0.015)	(0.049)	(0.020)	(0.026)
21 to 23	0.269***	0.393***	0.390***	0.556***	0.561***	0.753***	0.261***	0.285***
	(0.012)	(0.014)	(0.037)	(0.015)	(0.016)	(0.047)	(0.022)	(0.027)
24 to 26	0.277***	0.396***	0.383***	0.594***	0.580***	0.806***	0.279***	0.301***
	(0.013)	(0.014)	(0.044)	(0.016)	(0.018)	(0.053)	(0.023)	(0.028)
27 to 29	0.285***	0.413***	0.386***	0.625***	0.589***	0.834***	0.271***	0.292***
	(0.013)	(0.015)	(0.046)	(0.016)	(0.017)	(0.054)	(0.024)	(0.030)
30 to 32	0.291***	0.415***	0.388***	0.655***	0.600***	0.861***	0.307***	0.284***
	(0.013)	(0.015)	(0.044)	(0.017)	(0.017)	(0.052)	(0.024)	(0.032)
33 to 35	0.298***	0.420***	0.414***	0.683***	0.616***	0.928***	0.315***	0.268***
	(0.013)	(0.015)	(0.045)	(0.018)	(0.019)	(0.058)	(0.025)	(0.031)
36 to 38	0.305***	0.425***	0.463***	0.712***	0.631***	0.944***	0.309***	0.306***
	(0.013)	(0.016)	(0.049)	(0.019)	(0.019)	(0.058)	(0.027)	(0.031)
39 to 41	0.310***	0.442***	0.545***	0.737***	0.634***	1.003***	0.351***	0.300***
	(0.013)	(0.017)	(0.049)	(0.019)	(0.019)	(0.070)	(0.026)	(0.033)
42 to 44	0.313***	0.442***	0.573***	0.760***	0.636***	0.994***	0.351***	0.297***
	(0.013)	(0.017)	(0.054)	(0.020)	(0.020)	(0.065)	(0.032)	(0.034)
45 to 47	0.318***	0.442***	0.540***	0.784***	0.653***	0.993***	0.327***	0.287***
	(0.014)	(0.017)	(0.053)	(0.021)	(0.019)	(0.066)	(0.032)	(0.039)
48 to 50	0.321***	0.439***	0.633***	0.809***	0.656***	1.029***	0.314***	0.302***
	(0.014)	(0.017)	(0.055)	(0.021)	(0.020)	(0.074)	(0.029)	(0.037)
51 to 55	0.324***	0.430***	0.571***	0.835***	0.655***	1.052***	0.312***	0.287***
	(0.014)	(0.017)	(0.049)	(0.022)	(0.020)	(0.065)	(0.029)	(0.035)
56 to 60	0.328***	0.446***	0.633***	0.869***	0.676***	1.076***	0.308***	0.298***
	(0.014)	(0.016)	(0.051)	(0.023)	(0.020)	(0.068)	(0.029)	(0.038)
61 to 70	0.332***	0.461***	0.638***	0.915***	0.679***	1.084***	0.327***	0.335***
	(0.014)	(0.015)	(0.047)	(0.025)	(0.020)	(0.069)	(0.027)	(0.034)
71 to 80	0.336***	0.476***	0.713***	0.970***	0.686***	1.158***	0.325***	0.324***
	(0.015)	(0.016)	(0.053)	(0.027)	(0.021)	(0.079)	(0.029)	(0.034)
81 plus	0.344***	0.510***	0.772***	1.044***	0.697***	1.254***	0.356***	0.328***
	(0.015)	(0.017)	(0.064)	(0.030)	(0.023)	(0.087)	(0.033)	(0.039)
Row Variables								
First Row	0.101***	0.157***	0.248***	-	-	-	0.167***	0.140***
	(0.010)	(0.009)	(0.023)				(0.012)	(0.017)
Second Row	0.0592***	-0.00529	0.0162	-	-	-	-0.00369	-0.0000174
	(0.008)	(0.008)	(0.024)				(0.013)	(0.016)
Number of Row	-0.0142***	-0.00370***	-0.00644***	-	-	-	-0.00867***	-0.00315***
(lower=better)	(0.001)	(0.000)	(0.001)				(0.001)	(0.001)
No Row Listed	-0.423***	-0.189***	-0.131***	-	-	-	-0.199***	-0.153***
	(0.018)	(0.013)	(0.037)				(0.014)	(0.024)
Fixed Effects	GS	GS	GS	Listing Id	SGSR	SGSR	GS	GS
Observations	3,294,733	376,530	432,736	2,182,725	376,530	432,736	190,105	100,305
R-squared	0.83	0.83	0.59	0.95	0.96	0.96	0.87	0.90

Notes: 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) and the exact sales mechanism used. Observations in columns (2) and (5) include fixed (BIN) prices in hybrid auctions. Observations in column (8) include BIN sales. Robust standard errors clustered on the game. ***,** and * denote significance at the 1, 5 and 10% levels.
Stubhub seller price excludes commissions. eBay buyer price includes shipping costs.
Fixed Effects: GS=Game-Section, SGSR=Seller-Game-Section-Row, Listing Id=Stubhub listing identification number

Table A2: Robustness Checks Using List Prices on Stubhub

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings	Available Stubhub Listings
Robustness Check	Price Rel to Face Value	GFV FEs	GSR FEs	Cheap ≤$20	Expensive ≥$45	Exp Att >95%	Exp Att ≤95%,>85%	Exp Att ≤85%, >75%	Exp Att ≤75%
Definition of Time Dummies	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available	Date Available
Price Variable	Seller 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	0.169***	0.116***	0.135***	0.114***	0.0953***	0.0739***	0.111***	0.119***	0.152***
	(0.016)	(0.008)	(0.008)	(0.019)	(0.008)	(0.016)	(0.013)	(0.021)	(0.013)
6 to 8	0.267***	0.178***	0.207***	0.171***	0.151***	0.117***	0.176***	0.188***	0.228***
	(0.020)	(0.010)	(0.009)	(0.022)	(0.010)	(0.020)	(0.017)	(0.026)	(0.016)
9 to 11	0.316***	0.211***	0.244***	0.203***	0.180***	0.137***	0.206***	0.215***	0.266***
	(0.021)	(0.011)	(0.010)	(0.023)	(0.010)	(0.020)	(0.018)	(0.028)	(0.017)
12 to 14	0.349***	0.232***	0.269***	0.226***	0.200***	0.156***	0.227***	0.228***	0.293***
	(0.022)	(0.011)	(0.010)	(0.025)	(0.011)	(0.022)	(0.018)	(0.030)	(0.017)
15 to 17	0.371***	0.247***	0.287***	0.242***	0.215***	0.163***	0.240***	0.233***	0.315***
	(0.023)	(0.012)	(0.011)	(0.026)	(0.011)	(0.022)	(0.018)	(0.032)	(0.017)
18 to 20	0.392***	0.259***	0.302***	0.253***	0.228***	0.174***	0.251***	0.242***	0.328***
	(0.024)	(0.012)	(0.011)	(0.028)	(0.011)	(0.022)	(0.019)	(0.034)	(0.017)
21 to 23	0.409***	0.270***	0.314***	0.258***	0.239***	0.179***	0.264***	0.247***	0.340***
	(0.025)	(0.012)	(0.012)	(0.029)	(0.012)	(0.022)	(0.020)	(0.036)	(0.017)
24 to 26	0.422***	0.278***	0.325***	0.264***	0.245***	0.182***	0.271***	0.251***	0.351***
	(0.026)	(0.013)	(0.012)	(0.031)	(0.012)	(0.023)	(0.021)	(0.037)	(0.017)
27 to 29	0.437***	0.287***	0.334***	0.276***	0.253***	0.190***	0.278***	0.258***	0.359***
	(0.026)	(0.013)	(0.012)	(0.031)	(0.012)	(0.023)	(0.021)	(0.038)	(0.018)
30 to 32	0.447***	0.293***	0.342***	0.281***	0.258***	0.196***	0.283***	0.261***	0.369***
	(0.026)	(0.013)	(0.012)	(0.032)	(0.012)	(0.023)	(0.021)	(0.038)	(0.018)
33 to 35	0.457***	0.299***	0.349***	0.288***	0.265***	0.198***	0.291***	0.268***	0.375***
	(0.027)	(0.013)	(0.012)	(0.032)	(0.012)	(0.023)	(0.021)	(0.039)	(0.018)
36 to 38	0.470***	0.307***	0.357***	0.294***	0.271***	0.201***	0.300***	0.275***	0.384***
	(0.027)	(0.013)	(0.012)	(0.033)	(0.012)	(0.024)	(0.021)	(0.039)	(0.018)
39 to 41	0.481***	0.311***	0.363***	0.299***	0.275***	0.204***	0.304***	0.279***	0.393***
	(0.027)	(0.013)	(0.013)	(0.033)	(0.013)	(0.024)	(0.021)	(0.039)	(0.018)
42 to 44	0.487***	0.314***	0.367***	0.302***	0.279***	0.208***	0.307***	0.282***	0.394***
	(0.027)	(0.014)	(0.013)	(0.033)	(0.013)	(0.024)	(0.022)	(0.040)	(0.019)
45 to 47	0.498***	0.320***	0.373***	0.310***	0.282***	0.214***	0.311***	0.288***	0.398***
	(0.028)	(0.014)	(0.013)	(0.034)	(0.013)	(0.025)	(0.022)	(0.040)	(0.019)
48 to 50	0.499***	0.322***	0.377***	0.314***	0.284***	0.213***	0.317***	0.291***	0.399***
	(0.028)	(0.014)	(0.013)	(0.034)	(0.013)	(0.025)	(0.022)	(0.040)	(0.019)
51 to 55	0.503***	0.325***	0.381***	0.320***	0.288***	0.219***	0.321***	0.292***	0.403***
	(0.028)	(0.014)	(0.013)	(0.034)	(0.013)	(0.026)	(0.023)	(0.041)	(0.019)
56 to 60	0.514***	0.329***	0.387***	0.326***	0.291***	0.224***	0.325***	0.293***	0.408***
	(0.029)	(0.014)	(0.013)	(0.035)	(0.013)	(0.026)	(0.023)	(0.042)	(0.019)
61 to 70	0.521***	0.333***	0.393***	0.325***	0.292***	0.228***	0.331***	0.294***	0.412***
	(0.030)	(0.014)	(0.013)	(0.035)	(0.014)	(0.026)	(0.023)	(0.043)	(0.019)
71 to 80	0.526***	0.336***	0.400***	0.331***	0.296***	0.227***	0.338***	0.295***	0.419***
	(0.030)	(0.015)	(0.014)	(0.036)	(0.014)	(0.027)	(0.024)	(0.043)	(0.020)
81 plus	0.538***	0.344***	0.413***	0.348***	0.302***	0.227***	0.357***	0.304***	0.426***
	(0.032)	(0.015)	(0.014)	(0.037)	(0.015)	(0.028)	(0.025)	(0.044)	(0.021)
Fixed Effects	GS	GFV	GSR	GS	GS	GS	GS	GS	GS
Observations	3,294,733	3,294,733	3,294,733	843,865	1,051,456	824,439	1,005,454	649,855	814,985
R-squared	0.56	0.81	0.92	0.6	0.82	0.88	0.81	0.78	0.83

<u>Notes:</u> see Table A1.

Table A3: Robustness Checks Using Fixed Prices on EBay

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	eBay Fixed Prices	eBay Fixed Prices	eBay Fixed Prices	eBay Fixed Prices	eBay Fixed Prices	eBay Fixed Prices	eBay Fixed Prices	eBay Fixed Prices	eBay Fixed Prices
Robustness Check	Price Rel to Face Value	GFV FEs	GSR FEs	Cheap ≤$20	Expensive ≥$45	Exp Att >95%	Exp Att ≤95%,>85%	Exp Att ≤85%, >75%	Exp Att ≤75%
Definition of Time Dummies	List Date	List Date	List Date	List Date	List Date	List Date	List Date	List Date	List Date
Price Variable	List Price /Face	Log(List Price)	Log(List Price)	Log(List Price)	Log(List Price)	Log(List Price)	Log(List Price)	Log(List Price)	Log(List Price)
Days to Go Dummies									
3 to 5	0.203***	0.160***	0.177***	0.128***	0.162***	0.150***	0.145***	0.173***	0.160***
	(0.023)	(0.008)	(0.011)	(0.016)	(0.016)	(0.017)	(0.018)	(0.026)	(0.018)
6 to 8	0.344***	0.226***	0.286***	0.183***	0.240***	0.238***	0.203***	0.227***	0.255***
	(0.029)	(0.009)	(0.012)	(0.018)	(0.018)	(0.020)	(0.021)	(0.028)	(0.020)
9 to 11	0.450***	0.283***	0.349***	0.267***	0.301***	0.286***	0.268***	0.309***	0.309***
	(0.035)	(0.010)	(0.013)	(0.019)	(0.019)	(0.021)	(0.024)	(0.031)	(0.021)
12 to 14	0.482***	0.304***	0.394***	0.289***	0.329***	0.305***	0.308***	0.330***	0.355***
	(0.033)	(0.010)	(0.014)	(0.020)	(0.020)	(0.021)	(0.025)	(0.029)	(0.021)
15 to 17	0.518***	0.321***	0.425***	0.304***	0.360***	0.341***	0.307***	0.347***	0.387***
	(0.037)	(0.011)	(0.015)	(0.021)	(0.021)	(0.023)	(0.026)	(0.035)	(0.021)
18 to 20	0.589***	0.359***	0.466***	0.345***	0.375***	0.349***	0.356***	0.377***	0.432***
	(0.041)	(0.012)	(0.015)	(0.022)	(0.021)	(0.024)	(0.026)	(0.034)	(0.022)
21 to 23	0.613***	0.366***	0.476***	0.367***	0.395***	0.368***	0.382***	0.394***	0.428***
	(0.041)	(0.011)	(0.015)	(0.022)	(0.022)	(0.024)	(0.028)	(0.033)	(0.022)
24 to 26	0.653***	0.374***	0.491***	0.355***	0.412***	0.371***	0.358***	0.407***	0.457***
	(0.052)	(0.012)	(0.017)	(0.022)	(0.024)	(0.023)	(0.028)	(0.036)	(0.026)
27 to 29	0.666***	0.393***	0.500***	0.397***	0.429***	0.382***	0.408***	0.428***	0.439***
	(0.048)	(0.013)	(0.017)	(0.023)	(0.023)	(0.025)	(0.031)	(0.039)	(0.023)
30 to 32	0.689***	0.397***	0.509***	0.392***	0.436***	0.381***	0.396***	0.421***	0.466***
	(0.061)	(0.014)	(0.017)	(0.024)	(0.024)	(0.025)	(0.031)	(0.035)	(0.027)
33 to 35	0.680***	0.386***	0.522***	0.391***	0.433***	0.376***	0.400***	0.442***	0.476***
	(0.050)	(0.013)	(0.018)	(0.025)	(0.026)	(0.026)	(0.034)	(0.039)	(0.025)
36 to 38	0.673***	0.386***	0.532***	0.372***	0.459***	0.395***	0.420***	0.421***	0.456***
	(0.050)	(0.013)	(0.019)	(0.026)	(0.025)	(0.027)	(0.033)	(0.039)	(0.028)
39 to 41	0.753***	0.402***	0.542***	0.394***	0.451***	0.414***	0.409***	0.481***	0.481***
	(0.062)	(0.014)	(0.018)	(0.026)	(0.028)	(0.029)	(0.033)	(0.047)	(0.027)
42 to 44	0.740***	0.399***	0.540***	0.403***	0.439***	0.419***	0.407***	0.476***	0.481***
	(0.057)	(0.014)	(0.020)	(0.027)	(0.030)	(0.029)	(0.035)	(0.040)	(0.028)
45 to 47	0.747***	0.395***	0.554***	0.383***	0.460***	0.392***	0.427***	0.454***	0.511***
	(0.067)	(0.015)	(0.019)	(0.028)	(0.025)	(0.028)	(0.039)	(0.044)	(0.028)
48 to 50	0.716***	0.389***	0.546***	0.384***	0.467***	0.402***	0.411***	0.474***	0.482***
	(0.053)	(0.015)	(0.020)	(0.029)	(0.028)	(0.027)	(0.037)	(0.052)	(0.030)
51 to 55	0.720***	0.393***	0.544***	0.389***	0.457***	0.385***	0.425***	0.437***	0.475***
	(0.059)	(0.015)	(0.019)	(0.025)	(0.025)	(0.025)	(0.036)	(0.043)	(0.029)
56 to 60	0.735***	0.404***	0.557***	0.389***	0.486***	0.398***	0.436***	0.475***	0.493***
	(0.054)	(0.014)	(0.019)	(0.027)	(0.025)	(0.029)	(0.034)	(0.042)	(0.027)
61 to 70	0.755***	0.409***	0.567***	0.419***	0.486***	0.404***	0.446***	0.489***	0.528***
	(0.051)	(0.013)	(0.019)	(0.025)	(0.025)	(0.026)	(0.032)	(0.041)	(0.025)
71 to 80	0.795***	0.430***	0.576***	0.441***	0.500***	0.428***	0.481***	0.524***	0.497***
	(0.060)	(0.013)	(0.020)	(0.025)	(0.026)	(0.026)	(0.034)	(0.040)	(0.027)
81 plus	0.839***	0.459***	0.591***	0.471***	0.535***	0.430***	0.526***	0.593***	0.546***
	(0.054)	(0.014)	(0.021)	(0.027)	(0.026)	(0.027)	(0.034)	(0.045)	(0.028)
Fixed Effects	GS	GFV	GSR	GS	GS	GS	GS	GS	GS
Observations	376,530	376,530	376,530	116,502	103,724	109,986	107,808	61,759	96,977
R-squared	0.71	0.68	0.94	0.76	0.84	0.82	0.8	0.8	0.83

Notes: see Table A1.

Table A4: Robustness Checks Using Transaction Prices on EBay

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	eBay Trans Prices	eBay Trans Prices	eBay Trans Prices	eBay Trans Prices	eBay Trans Prices	eBay Trans Prices	eBay Trans Prices	eBay Trans Prices	eBay Trans Prices
Robustness Check	Price Rel to Face Value	GFV FEs	GSR FEs	Cheap ≤$20	Expensive ≥$45	Exp Att >95%	Exp Att ≤95%,>85%	Exp Att ≤85%, >75%	Exp Att ≤75%
Definition of Time Dummies	Sale Date	Sale Date	Sale Date	Sale Date	Sale Date	Sale Date	Sale Date	Sale Date	Sale Date
Price Variable	Buyer 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	0.118***	0.0908***	0.0798***	0.0724***	0.0606***	0.104***	0.0681***	0.0725**	0.120***
	(0.021)	(0.008)	(0.022)	(0.015)	(0.021)	(0.016)	(0.021)	(0.029)	(0.021)
6 to 8	0.162***	0.100***	0.115***	0.0792***	0.0925***	0.140***	0.0794***	0.0684*	0.130***
	(0.027)	(0.009)	(0.025)	(0.017)	(0.025)	(0.019)	(0.025)	(0.036)	(0.025)
9 to 11	0.279***	0.163***	0.176***	0.167***	0.157***	0.219***	0.163***	0.120***	0.170***
	(0.031)	(0.010)	(0.028)	(0.019)	(0.026)	(0.019)	(0.028)	(0.039)	(0.028)
12 to 14	0.295***	0.178***	0.197***	0.177***	0.156***	0.211***	0.187***	0.140***	0.221***
	(0.035)	(0.011)	(0.029)	(0.021)	(0.028)	(0.020)	(0.030)	(0.043)	(0.029)
15 to 17	0.365***	0.213***	0.225***	0.217***	0.162***	0.246***	0.239***	0.155***	0.240***
	(0.042)	(0.012)	(0.031)	(0.023)	(0.030)	(0.025)	(0.032)	(0.043)	(0.029)
18 to 20	0.426***	0.236***	0.260***	0.253***	0.165***	0.244***	0.240***	0.230***	0.287***
	(0.054)	(0.012)	(0.030)	(0.024)	(0.031)	(0.023)	(0.034)	(0.041)	(0.034)
21 to 23	0.434***	0.248***	0.283***	0.263***	0.204***	0.252***	0.272***	0.243***	0.277***
	(0.057)	(0.013)	(0.033)	(0.026)	(0.037)	(0.026)	(0.037)	(0.046)	(0.035)
24 to 26	0.536***	0.284***	0.277***	0.297***	0.229***	0.290***	0.295***	0.217***	0.331***
	(0.078)	(0.014)	(0.036)	(0.029)	(0.038)	(0.027)	(0.035)	(0.054)	(0.041)
27 to 29	0.524***	0.275***	0.280***	0.283***	0.247***	0.255***	0.321***	0.238***	0.307***
	(0.072)	(0.014)	(0.035)	(0.029)	(0.036)	(0.026)	(0.041)	(0.051)	(0.037)
30 to 32	0.524***	0.296***	0.295***	0.329***	0.223***	0.282***	0.335***	0.279***	0.315***
	(0.073)	(0.015)	(0.037)	(0.029)	(0.042)	(0.027)	(0.044)	(0.046)	(0.041)
33 to 35	0.544***	0.298***	0.313***	0.329***	0.256***	0.283***	0.336***	0.302***	0.329***
	(0.062)	(0.015)	(0.040)	(0.030)	(0.043)	(0.031)	(0.040)	(0.052)	(0.042)
36 to 38	0.520***	0.300***	0.306***	0.301***	0.253***	0.278***	0.368***	0.264***	0.311***
	(0.064)	(0.016)	(0.044)	(0.033)	(0.042)	(0.030)	(0.043)	(0.056)	(0.043)
39 to 41	0.560***	0.313***	0.330***	0.356***	0.280***	0.297***	0.387***	0.318***	0.358***
	(0.065)	(0.017)	(0.040)	(0.033)	(0.042)	(0.030)	(0.040)	(0.066)	(0.045)
42 to 44	0.556***	0.323***	0.338***	0.333***	0.247***	0.288***	0.379***	0.308***	0.359***
	(0.072)	(0.018)	(0.044)	(0.038)	(0.041)	(0.029)	(0.050)	(0.070)	(0.050)
45 to 47	0.562***	0.301***	0.322***	0.321***	0.271***	0.299***	0.384***	0.253***	0.301***
	(0.077)	(0.019)	(0.048)	(0.039)	(0.045)	(0.031)	(0.060)	(0.065)	(0.046)
48 to 50	0.582***	0.312***	0.298***	0.357***	0.232***	0.300***	0.360***	0.241***	0.353***
	(0.075)	(0.018)	(0.049)	(0.040)	(0.049)	(0.034)	(0.048)	(0.060)	(0.047)
51 to 55	0.573***	0.310***	0.312***	0.335***	0.244***	0.275***	0.376***	0.262***	0.358***
	(0.078)	(0.018)	(0.044)	(0.034)	(0.050)	(0.031)	(0.044)	(0.073)	(0.048)
56 to 60	0.554***	0.325***	0.328***	0.312***	0.320***	0.285***	0.393***	0.238***	0.359***
	(0.076)	(0.018)	(0.046)	(0.037)	(0.041)	(0.037)	(0.044)	(0.072)	(0.046)
61 to 70	0.583***	0.327***	0.318***	0.351***	0.303***	0.302***	0.406***	0.276***	0.341***
	(0.075)	(0.017)	(0.046)	(0.036)	(0.042)	(0.029)	(0.046)	(0.060)	(0.051)
71 to 80	0.584***	0.331***	0.331***	0.331***	0.355***	0.290***	0.437***	0.349***	0.299***
	(0.080)	(0.019)	(0.050)	(0.039)	(0.043)	(0.032)	(0.046)	(0.060)	(0.063)
81 plus	0.623***	0.349***	0.329***	0.393***	0.359***	0.293***	0.489***	0.327***	0.382***
	(0.098)	(0.021)	(0.056)	(0.043)	(0.046)	(0.034)	(0.052)	(0.074)	(0.076)
Fixed Effects	GS	GFV	GSR	GS	GS	GS	GS	GS	GS
Observations	290,410	290,410	290,410	89,317	71,611	90,219	83,667	46,449	70,075
R-squared	0.75	0.7	0.96	0.78	0.84	0.8	0.8	0.82	0.86

Notes: see Table A1.

Table A5: Successful and Unsuccessful Teams

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	eBay Fixed Price		eBay Auction Start		eBay Transaction		Stubhub Listing	
	Playoff Team	Non-Playoff Team	Playoff Team	Non-Playoff Team	Playoff Team	Non-Playoff Team	Playoff Team	Non-Playoff Team
Definition of Time Dummies	Listing Date		Auction End Date		Purchase Date		Date Available	
Price Variable	Log(List Price)		Log(Auction Start)		Log(Buyer Price)		Log(Seller Price)	
<u>Days to Go Dummies</u>								
3 to 5	0.150***	0.167***	0.102***	0.000	0.108***	0.077***	0.095***	0.140***
	(0.013)	(0.014)	(0.038)	(0.030)	(0.014)	(0.016)	(0.011)	(0.012)
6 to 8	0.229***	0.239***	0.104**	-0.0941***	0.137***	0.0790***	0.151***	0.207***
	(0.015)	(0.016)	(0.041)	(0.034)	(0.017)	(0.018)	(0.014)	(0.014)
9 to 11	0.287***	0.303***	0.159***	-0.052	0.216***	0.138***	0.183***	0.237***
	(0.016)	(0.017)	(0.045)	(0.037)	(0.017)	(0.020)	(0.015)	(0.015)
12 to 14	0.322***	0.330***	0.133***	-0.042	0.235***	0.152***	0.207***	0.256***
	(0.017)	(0.017)	(0.046)	(0.038)	(0.019)	(0.021)	(0.015)	(0.016)
15 to 17	0.346***	0.351***	0.250***	0.0974**	0.262***	0.190***	0.219***	0.271***
	(0.018)	(0.018)	(0.046)	(0.045)	(0.021)	(0.022)	(0.016)	(0.016)
18 to 20	0.373***	0.389***	0.370***	0.259***	0.268***	0.227***	0.229***	0.283***
	(0.019)	(0.018)	(0.050)	(0.045)	(0.022)	(0.023)	(0.016)	(0.017)
21 to 23	0.395***	0.396***	0.503***	0.316***	0.284***	0.236***	0.235***	0.295***
	(0.019)	(0.018)	(0.052)	(0.055)	(0.023)	(0.024)	(0.017)	(0.017)
24 to 26	0.384***	0.418***	0.473***	0.324***	0.320***	0.256***	0.239***	0.303***
	(0.018)	(0.020)	(0.056)	(0.074)	(0.024)	(0.027)	(0.017)	(0.018)
27 to 29	0.415***	0.419***	0.395***	0.404***	0.303***	0.259***	0.248***	0.310***
	(0.021)	(0.020)	(0.069)	(0.062)	(0.025)	(0.027)	(0.017)	(0.018)
30 to 32	0.395***	0.443***	0.398***	0.416***	0.317***	0.286***	0.253***	0.318***
	(0.021)	(0.020)	(0.067)	(0.059)	(0.027)	(0.027)	(0.017)	(0.018)
33 to 35	0.403***	0.443***	0.470***	0.399***	0.307***	0.309***	0.259***	0.324***
	(0.022)	(0.021)	(0.065)	(0.063)	(0.027)	(0.029)	(0.018)	(0.018)
36 to 38	0.406***	0.448***	0.583***	0.384***	0.305***	0.302***	0.264***	0.332***
	(0.022)	(0.022)	(0.073)	(0.062)	(0.029)	(0.029)	(0.018)	(0.018)
39 to 41	0.430***	0.459***	0.638***	0.492***	0.317***	0.352***	0.269***	0.338***
	(0.024)	(0.023)	(0.071)	(0.068)	(0.030)	(0.030)	(0.018)	(0.019)
42 to 44	0.426***	0.464***	0.688***	0.505***	0.328***	0.330***	0.273***	0.339***
	(0.024)	(0.022)	(0.083)	(0.068)	(0.034)	(0.033)	(0.018)	(0.019)
45 to 47	0.419***	0.470***	0.560***	0.568***	0.339***	0.285***	0.280***	0.343***
	(0.026)	(0.023)	(0.074)	(0.074)	(0.034)	(0.035)	(0.019)	(0.019)
48 to 50	0.424***	0.455***	0.700***	0.610***	0.328***	0.305***	0.282***	0.345***
	(0.024)	(0.025)	(0.077)	(0.080)	(0.033)	(0.031)	(0.019)	(0.019)
51 to 55	0.415***	0.449***	0.725***	0.451***	0.313***	0.311***	0.288***	0.347***
	(0.023)	(0.023)	(0.069)	(0.069)	(0.029)	(0.035)	(0.019)	(0.019)
56 to 60	0.424***	0.473***	0.647***	0.677***	0.319***	0.319***	0.293***	0.349***
	(0.024)	(0.022)	(0.070)	(0.075)	(0.032)	(0.034)	(0.019)	(0.020)
61 to 70	0.423***	0.505***	0.702***	0.618***	0.315***	0.350***	0.297***	0.353***
	(0.022)	(0.021)	(0.065)	(0.067)	(0.029)	(0.033)	(0.020)	(0.020)
71 to 80	0.449***	0.509***	0.756***	0.717***	0.319***	0.350***	0.300***	0.358***
	(0.022)	(0.023)	(0.075)	(0.074)	(0.031)	(0.036)	(0.020)	(0.021)
81 plus	0.455***	0.570***	0.696***	0.924***	0.324***	0.393***	0.306***	0.369***
	(0.024)	(0.023)	(0.090)	(0.079)	(0.035)	(0.039)	(0.020)	(0.022)
Fixed Effects	GS	GS	GS	GS	GS	GS	GS	GS
Observations	176,590	199,940	195,452	237,284	131,624	158,786	1,487,571	1,807,162
R-squared	0.83	0.82	0.57	0.62	0.83	0.83	0.85	0.81

<u>Notes:</u> see Table A1.

Table A6: Regression Coefficients for Results Shown in Figure 3 - Probability of Sale

	(1) Fig. 3	(2) Fig. 3	(3) Fig. 3
	eBay Fixed Price Listings (excl. Hybrids)	eBay Hybrid Auction Listings	eBay Auction Listings (excl. Hybrids)
Definition of Time Dummies	Listing Date	Listing Date	Auction End Date
Dep. Variable	Sale	Sale	Sale
Days to Go Dummies			
3 to 5	0.048***	0.010	-0.001
	(0.014)	(0.010)	(0.010)
6 to 8	-0.012	-0.003	0.017
	(0.014)	(0.012)	(0.011)
9 to 11	-0.056***	-0.012	0.023**
	(0.015)	(0.012)	(0.011)
12 to 14	-0.102***	-0.033***	0.026**
	(0.015)	(0.013)	(0.011)
15 to 17	-0.126***	-0.047***	0.028**
	(0.016)	(0.014)	(0.012)
18 to 20	-0.173***	-0.063***	0.021*
	(0.015)	(0.014)	(0.012)
21 to 23	-0.190***	-0.102***	0.017
	(0.016)	(0.017)	(0.014)
24 to 26	-0.200***	-0.120***	-0.013
	(0.016)	(0.016)	(0.015)
27 to 29	-0.212***	-0.145***	-0.003
	(0.017)	(0.018)	(0.015)
30 to 32	-0.230***	-0.141***	-0.023
	(0.017)	(0.018)	(0.015)
33 to 35	-0.222***	-0.160***	-0.026*
	(0.018)	(0.019)	(0.015)
36 to 38	-0.243***	-0.152***	-0.037**
	(0.019)	(0.020)	(0.018)
39 to 41	-0.250***	-0.173***	-0.034*
	(0.019)	(0.020)	(0.019)
42 to 44	-0.266***	-0.197***	-0.052**
	(0.018)	(0.020)	(0.020)
45 to 47	-0.249***	-0.218***	-0.064***
	(0.019)	(0.020)	(0.022)
48 to 50	-0.250***	-0.211***	-0.048**
	(0.018)	(0.022)	(0.020)
51 to 55	-0.263***	-0.227***	-0.075***
	(0.017)	(0.021)	(0.021)
56 to 60	-0.294***	-0.255***	-0.085***
	(0.018)	(0.021)	(0.020)
61 to 70	-0.310***	-0.290***	-0.116***
	(0.016)	(0.021)	(0.018)
71 to 80	-0.335***	-0.271***	-0.115***
	(0.016)	(0.023)	(0.021)
81 plus	-0.371***	-0.356***	-0.139***
	(0.015)	(0.024)	(0.022)
Fixed Effects	GS	GS	GS
Observations	178,659	197,871	234,865
R-squared	0.53	0.53	0.55

Notes: see Table A1.

Table A7: 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	-1.211***	0.310***
	(0.084)	(0.060)
1-10 Days Prior to Game*Relative Price	-0.266***	-0.131***
	(0.057)	(0.047)
11-20 Days Prior to Game*Relative Price	-0.263***	0.024
	(0.058)	(0.043)
21-40 Days Prior to Game*Relative Price	-0.296***	-0.006
	(0.051)	(0.036)
Competition Coefficients (eBay)		
Mean Relative Price for Fixed Price Listings	0.241***	0.216***
	(0.016)	(0.022)
Mean Relative Start Price for Auction Listings	0.171***	0.199***
	(0.018)	(0.018)
Minimum Relative Price for Fixed Price Listings	0.042	0.120***
	(0.017)	(0.023)
Minimum Relative Price for Auction Listings	-0.136***	-0.177***
	(0.019)	(0.016)
Dummy Variable for No Competing Fixed Price Listings	0.472***	0.725***
	(0.034)	(0.048)
Dummy Variable for No Competing Auction Listings	0.023	-0.020
	(0.018)	(0.017)
Number of Competing Fixed Price Listings	-0.779***	-0.787***
	(0.138)	(0.217)
Proportion of Competing Fixed Price Listings with Seller Feedback Scores Above 100	-0.019	-0.010
	(0.174)	(0.016)
Number of Competing Auction Listings	-0.209	0.471***
	(0.174)	(0.168)
Proportion of Competing Auction Listings with Seller Feedback Scores Above 100	-0.026	-0.138***
	(0.027)	(0.035)
Competition Coefficients (Stubhub)		
Number of Stubhub Listings/100	-0.003	-0.019
	(0.034)	(0.015)
Number of observations	187,801	122,823

Median Implied Opportunity Costs (Relative to Face Value)	
More than 41 Days Prior to Game	0.54 (0.09)
21-40 Days Prior to Game	0.38 (0.09)
11-20 Days Prior to Game	0.09 (0.09)
1-10 Days Prior to Game	0.41 (0.08)

Counterfactual	Observed Prices $s		Counterfactual Prices $s	
	Mean	Median	Mean	Median
More than 41 Days Prior to Game	31.14	23.29	28.72	20.71
			(0.94)	(0.94)
21-40 Days Prior to Game	25.91	14.87	25.73	14.22
			(0.70)	(0.75)
11-20 Days Prior to Game	21.59	11.95	21.38	11.34
			(0.15)	(0.25)
1-10 Days Prior to Game	20.95	11.50	23.92	14.96
			(1.12)	(1.24)

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

Table A8: Summary Statistics

(a) Stubhub Price Listings (based on the 5% sample used in estimation of regression in Table A1 col (1))

Variable	Obs.	Mean	Std Dev.	Min	Max
Seller price (excl. shipping, commissions) per seat	3,294,733	73.537	64.192	0.833	765
Face value	3,294,733	38.591	26.272	5	312
Days-to-go Dummies					
3 to 5	3,294,733	0.012	0.111	0	1
6 to 8	3,294,733	0.018	0.134	0	1
9 to 11	3,294,733	0.019	0.136	0	1
12 to 14	3,294,733	0.020	0.138	0	1
15 to 17	3,294,733	0.020	0.140	0	1
18 to 20	3,294,733	0.020	0.142	0	1
21 to 23	3,294,733	0.021	0.144	0	1
24 to 26	3,294,733	0.022	0.146	0	1
27 to 29	3,294,733	0.023	0.149	0	1
30 to 32	3,294,733	0.023	0.150	0	1
33 to 35	3,294,733	0.023	0.150	0	1
36 to 38	3,294,733	0.023	0.150	0	1
39 to 41	3,294,733	0.023	0.149	0	1
42 to 44	3,294,733	0.023	0.149	0	1
45 to 47	3,294,733	0.022	0.148	0	1
48 to 50	3,294,733	0.022	0.147	0	1
51 to 55	3,294,733	0.036	0.187	0	1
56 to 60	3,294,733	0.036	0.186	0	1
61 to 70	3,294,733	0.069	0.253	0	1
71 to 80	3,294,733	0.065	0.246	0	1
81 plus	3,294,733	0.457	0.498	0	1
Number of seat dummies					
2 seats	3,294,733	0.440	0.496	0	1
3 seats	3,294,733	0.048	0.213	0	1
4 seats	3,294,733	0.406	0.491	0	1
5 seats	3,294,733	0.019	0.138	0	1
6 seats	3,294,733	0.076	0.265	0	1
Allows purchase of less than all seats	3,294,733	0.479	0.500	0	1
Row Variables					
First row dummy	3,294,733	0.163	0.370	0	1
Second row dummy	3,294,733	0.126	0.332	0	1
Number of row	3,294,733	8.797	6.945	0	26
No row listed	3,294,733	0.057	0.232	0	1
Row not applicable	3,294,733	0.004	0.061	0	1
Listing mentions 'piggy back' seats	3,294,733	0.000	0.006	0	1
Team Form (note specifications include with interactions with games remaining in season)					
Home record (win proportion)	3,294,733	0.502	0.110	0	1
Away record	3,294,733	62.593	24.593	0	161
Home games ahead	3,294,733	0.540	1.727	0	11.5
Home games back	3,294,733	3.021	4.341	0	29
Away games ahead	3,294,733	0.408	1.559	0	11.5
Away games back	3,294,733	3.612	5.056	0	29
Home wildcard games back	3,294,733	2.418	3.653	0	26
Home wildcard games ahead	3,294,733	0.061	0.375	0	5.5
Away wildcard games back	3,294,733	2.988	4.344	0	26
Away wildcard games ahead	3,294,733	0.055	0.351	0	5.5
Competition Variables (note specifications also include dummies for existence of competing listings and quadratic terms)					
Number of eBay listings same section, same # of seats	3,294,733	0.137	0.466	0	39
Number of eBay listings same section	3,294,733	0.309	0.852	0	44
Number of eBay listings same face value, same # of seats	3,294,733	2.505	5.948	0	170
Number of eBay listings same face value	3,294,733	5.958	9.798	0	221
Number of Stubhub listings same section, same # of seats	3,294,733	1.165	1.015	1	32
Number of Stubhub listings same section	3,294,733	1.457	2.849	1	75
Number of Stubhub listings same face value, same # of seats	3,294,733	31.744	36.603	1	547
Number of Stubhub listings, same face value	3,294,733	80.751	85.731	1	1168

(b) eBay Pure Fixed Price Listings (note includes listings made prior to 90 days before game and personal offer listings which are excluded from structural analysis is Section 5)

Variable	Obs.	Mean	Std Dev.	Min	Max
Listed fixed price per seat	178,659	68.953	68.914	0.005	1000
Face value	178,659	40.109	42.337	5	312
Days-to-go Dummies					
3 to 5	178,659	0.063	0.242	0	1
6 to 8	178,659	0.056	0.230	0	1
9 to 11	178,659	0.048	0.214	0	1
12 to 14	178,659	0.043	0.203	0	1
15 to 17	178,659	0.038	0.191	0	1
18 to 20	178,659	0.034	0.180	0	1
21 to 23	178,659	0.031	0.174	0	1
24 to 26	178,659	0.027	0.164	0	1
27 to 29	178,659	0.024	0.154	0	1
30 to 32	178,659	0.023	0.151	0	1
33 to 35	178,659	0.021	0.143	0	1
36 to 38	178,659	0.019	0.136	0	1
39 to 41	178,659	0.016	0.127	0	1
42 to 44	178,659	0.016	0.126	0	1
45 to 47	178,659	0.016	0.124	0	1
48 to 50	178,659	0.015	0.122	0	1
51 to 55	178,659	0.024	0.152	0	1
56 to 60	178,659	0.022	0.147	0	1
61 to 70	178,659	0.038	0.192	0	1
71 to 80	178,659	0.036	0.187	0	1
81 plus	178,659	0.337	0.473	0	1
Listing Type	178,659	0.000	0.000	0	0
Store fixed price	178,659	0.255	0.436	0	1
Personal offer with fixed price option	178,659	0.043	0.202	0	1
Non-store fixed price	178,659	0.702	0.457	0	1
Number of Seat Dummies					
2 seats	178,659	0.847	0.360	0	1
3 seats	178,659	0.024	0.154	0	1
4 seats	178,659	0.096	0.294	0	1
5 seats	178,659	0.008	0.092	0	1
6 seats	178,659	0.009	0.096	0	1
Row Variables					
First row dummy	178,659	0.128	0.334	0	1
Second row dummy	178,659	0.079	0.270	0	1
Number of row	178,659	9.306	7.673	0	26
No row listed	178,659	0.082	0.274	0	1
Row not applicable (e.g., open seating)	178,659	0.006	0.075	0	1
Seat Characteristics					
Piggy back	178,659	0.000	0.017	0	1
Aisle	178,659	0.058	0.233	0	1
Parking	178,659	0.019	0.137	0	1
Listing Characteristics					
Seller feedback 10-100	178,659	0.081	0.273	0	1
Seller feedback 101-1000	178,659	0.365	0.482	0	1
Seller feedback 1000+	178,659	0.537	0.499	0	1
Seller ever uses store format	178,659	0.598	0.490	0	1
Listing highlighted	178,659	0.027	0.163	0	1
Listing has pictures	178,659	0.251	0.434	0	1
Missing seller feedback score (cannot impute)	178,659	0.007	0.085	0	1
Form variables					
Home record	178,659	0.511	0.114	0	1
Away record	178,659	0.499	0.114	0	1
Home games ahead	178,659	0.756	2.074	0	11.5
Home games back	178,659	3.172	4.790	0	29
Away game ahead	178,659	0.588	1.856	0	11.5
Away game back	178,659	4.091	5.641	0	29
Home wildcard game back	178,659	2.585	4.176	0	26.5
Home wildcard games ahead	178,659	0.105	0.502	0	5.5
Away wildcard games back	178,659	3.466	4.953	0	26.5
Away wild card games ahead	178,659	0.067	0.413	0	5.5
Competition Variables					
Number of eBay listings same section, same # of seats	178,659	1.558	1.403	1	43
Number of eBay listings same section	178,659	1.680	1.713	1	47
Number of eBay listings same face value, same # of seats	178,659	9.251	12.679	1	174
Number of eBay listings same face value	178,659	12.785	17.331	1	221
Number of Stubhub listings same section, same # of seats	178,659	0.613	0.865	0	44
Number of Stubhub listings same section	178,659	1.002	2.765	0	104
Number of Stubhub listings same face value, same # of seats	178,659	25.705	40.653	0	547
Number of Stubhub listings, same face value	178,659	64.478	98.811	0	1168

(c) eBay Auction Listings (note includes hybrid BIN auction listings and listings made prior to 90 days before game which are excluded from structural analysis in Appendix B)

Variable	Obs.	Mean	Std Dev.	Min	Max
Auction start price per seat	432,736	33.792	48.333	0.0016667	1000
Secret reserve dummy	432,736	0.045	0.208	0	1
Listed fixed price (BIN)	432,736	36.665	33.695	5	312
Face value	432,736	36.665	33.695	5	312
Days-to-go dummies					
3 to 5	432,736	0.119	0.324	0	1
6 to 8	432,736	0.112	0.316	0	1
9 to 11	432,736	0.094	0.291	0	1
12 to 14	432,736	0.080	0.272	0	1
15 to 17	432,736	0.062	0.241	0	1
18 to 20	432,736	0.050	0.218	0	1
21 to 23	432,736	0.040	0.196	0	1
24 to 26	432,736	0.033	0.179	0	1
27 to 29	432,736	0.026	0.160	0	1
30 to 32	432,736	0.023	0.151	0	1
33 to 35	432,736	0.020	0.139	0	1
36 to 38	432,736	0.017	0.129	0	1
39 to 41	432,736	0.015	0.121	0	1
42 to 44	432,736	0.014	0.116	0	1
45 to 47	432,736	0.012	0.109	0	1
48 to 50	432,736	0.011	0.104	0	1
51 to 55	432,736	0.018	0.132	0	1
56 to 60	432,736	0.015	0.122	0	1
61 to 70	432,736	0.026	0.158	0	1
71 to 80	432,736	0.021	0.143	0	1
81 plus	432,736	0.113	0.317	0	1
Listing Type					
Multiple unit auction	432,736	0.018	0.134	0	1
Hybrid BIN auction	432,736	0.457	0.498	0	1
Number of Seat Dummies					
2 seats	432,736	0.884	0.320	0	1
3 seats	432,736	0.015	0.120	0	1
4 seats	432,736	0.087	0.282	0	1
5 seats	432,736	0.004	0.059	0	1
6 seats	432,736	0.005	0.071	0	1
Row Variables					
First row dummy	432,736	0.122	0.328	0	1
Second row dummy	432,736	0.087	0.282	0	1
Number of row	432,736	8.647	7.256	0	26
No row listed	432,736	0.086	0.280	0	1
Row not applicable (e.g., open seating)	432,736	0.013	0.114	0	1
Seat Characteristics					
Piggy back	432,736	0.000	0.016	0	1
Aisle	432,736	0.050	0.218	0	1
Parking	432,736	0.036	0.185	0	1
Listing Characteristics					
Seller feedback 10-100	432,736	0.220	0.414	0	1
Seller feedback 101-1000	432,736	0.451	0.498	0	1
Seller feedback 1000+	432,736	0.254	0.435	0	1
Seller ever uses store format	432,736	0.195	0.396	0	1
Listing highlighted	432,736	0.081	0.272	0	1
Listing has pictures	432,736	0.283	0.451	0	1
Missing seller feedback score (cannot impute)	432,736	0.031	0.172	0	1
Form variables					
Home record	432,736	0.510	0.114	0	1
Away record	432,736	0.501	0.116	0	1
Home games ahead	432,736	0.822	2.116	0	11.5
Home games back	432,736	3.698	4.933	0	29
Away game ahead	432,736	0.706	1.989	0	11.5
Away game back	432,736	4.532	5.699	0	29
Home wildcard game back	432,736	3.131	4.399	0	26.5
Home wildcard games ahead	432,736	0.103	0.504	0	5.5
Away wildcard games back	432,736	3.860	5.045	0	27
Away wild card games ahead	432,736	0.081	0.454	0	5.5
Competition Variables					
Number of eBay listings same section, same # of seats	432,736	1.473	1.358	1	43
Number of eBay listings same section	432,736	1.531	1.544	1	47
Number of eBay listings same face value, same # of seats	432,736	12.180	15.284	1	174
Number of eBay listings same face value	432,736	15.501	19.243	1	221
Number of Stubhub listings same section, same # of seats	432,736	0.697	1.181	0	55
Number of Stubhub listings same section	432,736	1.202	3.971	0	109
Number of Stubhub listings same face value, same # of seats	432,736	27.377	38.669	0	486
Number of Stubhub listings, same face value	432,736	61.789	85.501	0	1168

(d) eBay Transactions

Variable	Obs.	Mean	Std Dev.	Min	Max
Price paid by buyer (incl. shipping) per seat	290,410	54.450	52.890	0.0025	959.5
Shipping missing dummy	290,410	0.004	0.067	0	1
Face value	290,410	36.482	32.804	5	312
Days-to-go dummies					
3 to 5	290,410	0.169	0.374	0	1
6 to 8	290,410	0.120	0.325	0	1
9 to 11	290,410	0.080	0.272	0	1
12 to 14	290,410	0.060	0.237	0	1
15 to 17	290,410	0.045	0.208	0	1
18 to 20	290,410	0.037	0.189	0	1
21 to 23	290,410	0.030	0.169	0	1
24 to 26	290,410	0.025	0.157	0	1
27 to 29	290,410	0.021	0.144	0	1
30 to 32	290,410	0.019	0.135	0	1
33 to 35	290,410	0.017	0.128	0	1
36 to 38	290,410	0.014	0.117	0	1
39 to 41	290,410	0.013	0.112	0	1
42 to 44	290,410	0.012	0.108	0	1
45 to 47	290,410	0.011	0.105	0	1
48 to 50	290,410	0.010	0.097	0	1
51 to 55	290,410	0.014	0.117	0	1
56 to 60	290,410	0.012	0.109	0	1
61 to 70	290,410	0.020	0.141	0	1
71 to 80	290,410	0.018	0.131	0	1
81 plus	290,410	0.082	0.274	0	1
Sale Type					
Fixed Price	290,410	0.345	0.475	0	1
Number of Seat Dummies					
2 seats	290,410	0.866	0.340	0	1
3 seats	290,410	0.017	0.128	0	1
4 seats	290,410	0.098	0.297	0	1
5 seats	290,410	0.004	0.065	0	1
6 seats	290,410	0.007	0.081	0	1
Row Variables					
First row dummy	290,410	0.127	0.332	0	1
Second row dummy	290,410	0.086	0.280	0	1
Number of row	290,410	8.556	7.217	0	26
No row listed	290,410	0.088	0.283	0	1
Row not applicable (e.g., open seating)	290,410	0.014	0.117	0	1
Seat Characteristics					
Piggy back	290,410	0.000	0.017	0	1
Aisle	290,410	0.055	0.228	0	1
Parking	290,410	0.037	0.188	0	1
Listing Characteristics					
Seller feedback 10-100	290,410	0.221	0.415	0	1
Seller feedback 101-1000	290,410	0.452	0.498	0	1
Seller feedback 1000+	290,410	0.289	0.453	0	1
Seller ever uses store format	290,410	0.210	0.407	0	1
Listing highlighted	290,410	0.087	0.281	0	1
Listing has pictures	290,410	0.308	0.462	0	1
Missing seller feedback score (cannot impute)	290,410	0.000	0.005	0	1
Form variables					
Home record	290,410	0.516	0.115	0	1
Away record	290,410	0.503	0.115	0	1
Home games ahead	290,410	0.965	2.311	0	11.5
Home games back	290,410	3.444	4.880	0	29
Away game ahead	290,410	0.721	2.006	0	11.5
Away game back	290,410	4.616	5.786	0	29
Home wildcard game back	290,410	2.905	4.371	0	26.5
Home wildcard games ahead	290,410	0.114	0.531	0	5.5
Away wildcard games back	290,410	3.928	5.143	0	27
Away wild card games ahead	290,410	0.087	0.480	0	5.5
Competition Variables					
Number of eBay listings same section, same # of seats	290,410	1.335	1.258	0	43
Number of eBay listings same section	290,410	1.402	1.465	0	47
Number of eBay listings same face value, same # of seats	290,410	11.552	14.571	0	174
Number of eBay listings same face value	290,410	14.968	18.247	0	221
Number of Stubhub listings same section, same # of seats	290,410	0.637	1.159	0	55
Number of Stubhub listings same section	290,410	1.113	3.825	0	108
Number of Stubhub listings same face value, same # of seats	290,410	23.474	35.603	0	547
Number of Stubhub listings, same face value	290,410	53.088	78.973	0	1168