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

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Abstract

Sellers of perishable goods increasingly use dynamic pricing strategies as technology makes it easier to change prices and track inventory. This paper tests how accurately theoretical models of dynamic pricing describe sellers' pricing behavior in secondary markets for event tickets, which are a classic example of a perishable good. It shows that some of the simplest dynamic pricing models describe seller behavior very accurately, and they explain why sellers cut prices dramatically, by 40% or more, as an event approaches. The estimates also imply that dynamic pricing is valuable, raising the average seller's expected payoff by around 16%.

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1 Introduction

Sellers of perishable goods, such as airlines, sports teams, concert organizers and retailers of fashion and seasonal items, have to sell inventory within a fixed time horizon. These firms increasingly use dynamic pricing (DP) strategies, where they change prices as a function of both inventory and the time remaining, as technology makes it cheaper to change prices, track inventory and model consumer behavior. Managers often identify these types of revenue management strategies as being very valuable. For example, Robert Crandall, the former CEO of American Airlines, has been widely quoted as describing them as "the single most important technical development in transportation management since we entered the era of airline deregulation in 1979".[1] The need to develop effective DP systems has also been identified as a major motivation for large corporate transactions such as the event promoter LiveNation's merger with Ticketmaster in 2010.[2]

The use of DP has led to a growing theoretical literature predicting how prices should be set. These predictions depend on assumptions about market structure (for example, monopoly or competition), how demand changes over time and the ability of consumers to act strategically. However, there is little work testing whether these models describe seller behavior or quantifying the value of DP, and the empirical evidence that does exist, using price data from airline markets, has led researchers to conclude that these models may not describe how firms actually price (McAfee and te Velde (2006)). In this paper I develop a new framework for testing DP models and I apply it using new price and quantity data from secondary markets (eBay and Stubhub) for Major League Baseball (MLB) tickets. In these markets fans and ticket brokers resell tickets in the weeks leading up to a game.

[FIGURE 1]

These markets provide a natural setting to examine DP for several reasons. First, there is a clear dynamic pattern in the data, with prices falling significantly as a game approaches, especially in the final month before a game. This can been seen in Figure 1, which shows the evolution of average list and transaction prices of tickets on eBay. These prices are raw averages, but, as shown below, the declines are very similar with rich controls for listing and game heterogeneity. Individual sellers cut prices even more dramatically, by around 90% of face value in the month before the game. The main

[1] Smith et al. (1992) estimate that yield management increased AA's annual revenues by $500 million. The San Francisco Giants implemented dynamic pricing for parts of their stadium in 2010 and estimated that it would increase their revenues by $5m per year and the Giants' ticketing manager described DP as "changing the ticket world" (taken from an article by Adam Satarino in Bloomberg Businessweek, May 20 2010, accessed July 19, 2011).

[2] Wall Street Journal, April 19, 2011, "Ticketmaster to Tie Prices to Demand" (accessed July 19, 2011).

contribution of the paper is to show that some of the simplest DP models explain these price cuts, both qualitatively and quantitatively. This is true even though sellers in this market are small and do not use the type of automated DP systems developed by airlines.[3]

Second, most sellers have a single set of tickets to sell for a particular game in a particular area of the stadium. As I will explain in a moment, this fact leads to a particularly simple test of DP, and it plays a role in explaining why prices fall so much. While this feature may be unusual, secondary ticket markets do share characteristics with other perishable goods markets, making it more likely that the results may also hold in other settings. For example, like many airline, hotel and retail markets, they lie somewhere between the polar extremes of monopoly and perfect competition that have been the focus of the theoretical literature, as product differentiation and search costs give each seller some degree of market power.

Third, a large amount of suitable data is available. The number of observations (over 178,000 fixed price listings on eBay and several million on Stubhub) allows me to get statistically precise estimates while flexibly controlling for differences in listing and game attributes. More importantly, I can use eBay's listing and transaction data to estimate time-varying demand, which is an essential part of my empirical strategy. Previous work using airline or hotel data has used listing data (Escobari and Gan (2007), Celen and Thomas (2009), Abrate et al. (2012)) or transaction data (Puller et al. (2009)) but not both.[4]

Section 2 sets out a general theoretical framework for DP where each seller has a single unit to sell. At any time t, the seller's optimal price should be equal to the opportunity of sale, which is just the expected value of holding the unit in the next period, $E_t(V_{it+1})$, plus a mark-up. The mark-up reflects the shape of the current demand curve and the effect that the seller's current price has on the opportunity cost, $\frac{\partial E_t(V_{it+1})}{\partial p_{it}}$. In all models in the existing theoretical literature $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \geq 0$, in which case I show that sellers' opportunity costs should decline over time. This provides a general testable prediction of DP behavior.

Specific DP models can be thought of as making different assumptions about $\frac{\partial E_t(V_{it+1})}{\partial p_{it}}$ and how demand changes over time, resulting in different predictions about price dynamics. For example,

[3] As part of an on-going project, I am working with a large ticket broker who sells tickets for major league sports events. This broker currently changes prices for individual tickets over time based on several informal 'rules of thumb' that are broadly consistent with dynamic pricing principles. By now, some brokers may have introduced more formal pricing structures, but they almost certainly did not use them in 2007, the year of my data.

[4] An exception is Lazarev (2011) who combines listing data that shows how the price of seats for individual flights changes as the date of departure approaches with aggregate transaction data which shows the distribution of prices paid on an individual route during a quarter without indicating when the tickets were purchased or on which flight the customer travelled.

in the classic DP models proposed by Gallego and van Ryzin (1994), Bitran and Mondschein (1997) and McAfee and te Velde (2008), which, for brevity, I will call "simple DP models" in what follows, a single seller has a fixed inventory to sell within a limited time horizon and stochastically arriving buyers, with valuations drawn from a time-invariant distribution, have to buy at once or exit the market forever.[5] These assumptions imply that each seller's demand is time-invariant, $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$ and that single-unit sellers should lower prices over time.[6] Alternatively, when consumers can delay purchasing, as assumed by recent theoretical papers such as Su (2007), Aviv and Pazgal (2008), Levin et al. (2009), Board and Skrzypacz (2010) and Horner and Samuelson (2011), it may be the case that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} > 0$, as the delay induced by a higher price increases future demand, and, in equilibrium, sellers may raise prices over time as demand becomes less elastic.[7] On the other hand, a model with a mass of competitive sellers and a mass of strategic buyers predicts that prices should evolve as a martingale (Deneckere and Peck (2011)), so that, in expectation, the 'law of one price' should hold.

The first part of the empirical analysis shows that the price declines illustrated above are robust features of the data. Of course, there may be alternative explanations for why prices fall. The second part of the empirical analysis therefore provides a more precise test of DP behavior, by looking at what happens to opportunity costs, and it seeks to identify which sort of DP model explains seller behavior. My qualitative findings are that demand is time-invariant, every percentile of the distribution of opportunity costs falls monotonically as a game approaches and that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \approx 0$ as a higher current price appears to have no effect on future demand or competition. The data are therefore consistent with simple DP models, but not other models in the literature. Assuming a plausible re-listing strategy, I also find that a DP model accurately predicts how much prices and opportunity costs decline as a game approaches, and that DP can be valuable, increasing the average seller's expected profit by 16%.

The ability of simple DP models to explain sellers' behavior is potentially puzzling because it is unlikely that buyers can only behave in the very simple way that these models assume. I show that an alternative demand model is also consistent with the data. In this model, buyers are strategic

[5] Gallego and van Ryzin (1994) and McAfee and te Velde (2008) present continuous time models with different functional forms for demand. Bitran and Mondschein (1997) present a model that is similar to Gallego and van Ryzin's formulation with a slightly different model of demand and periodic price reviews.

[6] When a seller has multiple units, the opportunity cost increases when a sale is made. Gallego and van Ryzin (1994) show that when demand is time-homogenous, the optimal policy involves a price which is close to being fixed as the time remaining and the number of units in the initial inventory are taken to infinity.

[7] Of course, many theoretical papers have extended simple DP models in other directions. Examples include Zhao and Zheng (2000) (time-varying demand), Gallego and Hu (2009) (competing sellers), Gershkov and Molodvanu (2009) (monopolist selling units of different qualities) and Dizdar et al. (2011) (monopolist selling to buyers who want different quantities).

but face search costs when they participate in the market, and there is heterogeneity in how willing consumers are to delay purchasing, possibly due to some of them having to make complementary investments to attend a game. These frictions can lead buyers to sort into when they participate in the market. The model generates the same equilibrium outcomes as a simple DP model, even though buyers make some form of strategic timing choice. Highlighting that these frictions can matter in theory and providing evidence that they may matter in practice are further contributions of the paper.

The finding that a particular type of DP model explain the interesting stylized facts in my data should be of general interest to a broad range of economists. In contrast to an existing literature that has studied declining prices in sequential auctions (Ashenfelter (1989), Ashenfelter and Genesove (1992), McAfee and Vincent (1993), Beggs and Graddy (1997), Ginsburgh (1998) and van den Berg et al. (2001)), my explanation for why the law of one price fails does not rely on either unobserved object heterogeneity or the particular ways that goods are sold. Instead, it reflects the fundamental profit-maximizing incentives of sellers and the role that search and waiting costs can play in limiting how strategically buyers behave, which are forces that should be at work in a broad range of markets. The findings should guide future theoretical work on DP models, by, for example, highlighting the limits of strategic buyer behavior and how this can lead to quite large and predictable trends in prices being observed in equilibrium. The results also stand in contrast to previous work that has found that, even in static settings, sellers fail to price or bid in the way that theoretical models predict (Genesove and Mayer (2001), Levitt (2006), Hortacsu and Puller (2008)). The results should also influence future work focused on secondary ticket markets. For example, existing theoretical and empirical work has examined the welfare effects of allowing ticket resale using one-shot models where the secondary market clears instantaneously (Courty (2000, 2003a, 2003b), Karp and Perloff (2005), Leslie and Sorensen (2010)). Recognizing that prices are set dynamically, with sellers cutting prices over time so that it is very likely that their tickets eventually sell, could potentially affect our understanding of how efficiently these markets work. It would also be relevant for trying to predict how effectively DP can be used in primary markets, where event organizers sell tickets to brokers and fans.

The paper is structured as follows. Section 2 presents the theoretical framework. Section 3 describes the data and the relevant institutional background. Section 4 shows that declining transaction and list prices are robust features of the data. Section 5 shows that simple DP models are consistent with the data, and investigates whether there is evidence of strategic consumer behavior. Section 6 concludes, and discusses implications of the results. An online Appendix provides additional details of the data and robustness checks on the main empirical results.

2 Theoretical Framework

This section outlines a general DP framework and presents a specific model to illustrate equilibrium price dynamics and the effects of strategic buyer behavior.

2.1 Dynamic Pricing and Opportunity Costs

Suppose that there is a finite sequence of discrete time periods $t = 1,..,T$ leading up to an event with no discounting.[8] In period t, N_t risk-neutral sellers, each with a single, differentiated listing to sell, simultaneously post prices. A seller leaves the market when his ticket is sold, and new sellers may enter the market each period. The probability that seller i's listing sells in period t is $q_{it}(p_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)$ where $\mathbf{p}_{-it}$ is the vector of other sellers' prices and $\mathbf{H}_t$ includes all state variables that can affect demand or entry by sellers. I assume that $q_{it}(p_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)$ is decreasing in p_{it} and that players use subgame perfect Nash equilibrium strategies where current prices are a function of $\mathbf{H}_t$ and expectations about how $\mathbf{H}_t$ will evolve. This set-up is more general than DP models in the literature which ignore the possibility of new entry.

A seller i using a DP strategy will choose a price in each period to maximize his value, which will be defined by the Bellman equation

$$V_{it}(\mathbf{H}_t) = \max_{p_{it}} p_{it} q_{it}(p_{it}, \mathbf{p}_{-it}, \mathbf{H}_t) + (1 - q_{it}(p_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)) E_t(V_{it+1}(\mathbf{H}_{t+1}) | p_{it}, \mathbf{p}_{-it}, \mathbf{H}_t) \tag{1}$$

where E_t denotes the expectation at time t. $E_t(V_{it+1}(\mathbf{H}_{t+1}) | p_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)$, which I will write as $E_t(V_{it+1})$ to reduce notation, is i's opportunity cost of a sale at time t, i.e., it is the expected future value foregone if the listing sells at t. $E_t(V_{iT+1})$ is the seller's expected value from an unsold ticket at the time of the event. Assuming free disposal, opportunity costs must be non-negative.

Under standard regularity conditions, i's optimal price in period t, determined by a first-order condition, will be equal to a mark-up plus the opportunity cost of sale

$$p^*_{it} = \frac{q_{it}(p^*_{it}, \mathbf{p}_{-it}, \mathbf{H}_t) + (1 - q_{it}(p^*_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)) \frac{\partial E_t(V_{it+1})}{\partial p_{it}}}{\left| \frac{\partial q_{it}(p^*_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)}{\partial p_{i,t}} \right|} + E_t(V_{it+1}) \tag{2}$$

[8] I use discrete time to simplify the presentation. Lin and Sibdari (2009) and Deneckere and Peck (2011) also use discrete time DP models.

In simple DP models, such as Gallego and van Ryzin (1994) and McAfee and te Velde (2008), $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$ so that the mark-up only depends on the shape of the current demand curve. These models also assume that demand is time-invariant, simplifying the calculation of prices. If optimal prices are determined by equation (2), the following proposition holds.

Proposition 1 *If* $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \geq 0$ *for* $\forall$ $\mathbf{H}_t, p_{it}, \mathbf{p}_{-it}$ *then, when a seller uses his optimal strategy, expected opportunity costs will fall over time.*

Proof. The assumption that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \geq 0$ implies a non-negative mark-up in equation (2), so that $p^*_{it} \geq E_t(V_{it+1})$ $\forall \mathbf{H}_t, t$. The Bellman equation then implies that $V_{it}(\mathbf{H}_t) \geq E_t(V_{it+1})$ $\forall \mathbf{H}_t, t$ and the inequality will be strict if $q_{it}(p^*_{it}, \mathbf{p}_{-it}, \mathbf{H}_t) > 0$. Application of the law of iterated expectations then implies that $E_t(V_{it+r}) \geq E_t(V_{it+r+s})$ for all $r \geq 1, s \geq 1$ so expected opportunity costs will fall. ■

Berman et al. (2010) also show that expected opportunity costs decline in a simple DP model where $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$. The condition that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \geq 0$ holds in all models of which I am aware in the current DP literature[9]: in simple DP models $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$; in models with strategic consumers $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \geq 0$ as an increase in the current price will increase how many potential buyers there are in the future[10]; and, in models with a fixed set of differentiated competitors $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \geq 0$ as a higher current price makes it more likely that competitors will sell, decreasing how many competitors the seller will face in the future or increasing the prices that they set (e.g., Lin and Sibdari (2009)).

A natural test of the empirical relevance of the existing DP literature as a whole therefore involves looking at whether the opportunity costs implied by observed prices do tend to decline over time. An alternative behavioral model might involve the seller setting a price which ignores his ability to re-list unsold tickets in the future, e.g., $p^*_{it} = E_t(V_{iT+1}) + \frac{q_{it}(p^*_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)}{\left|\frac{\partial q_{it}(p^*_{it}, \mathbf{p}_{-it}, \mathbf{H}_t)}{\partial p_{it}}\right|}$, where the implied opportunity cost should not systematically decline over time.

If $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$ the calculation of opportunity costs only requires knowledge of current prices and demand, and I proceed under this assumption in the first part of Section 5. I show that the changes in opportunity costs and prices are of approximately the correct size given an optimal DP strategy if this assumption holds, and I show that it cannot be rejected by the data by looking at how current prices

[9] One could construct a DP model where $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} < 0$ if a low current price deterred potential competitors from entering or caused current competitors to exit. However I am not aware of an example of this type of model in the existing literature.

[10] Deneckere and Peck (2011) assume perfect competition with homogenous products, a mass of sellers and a mass of strategic buyers. Because each seller is small, a higher price in the current period only affects the probability that the seller sells in the current period, not the probability that it sells at a given price in a future period.

affect future demand and competition. Together these results lead to the conclusion that simple DP models accurately describe both the pricing problem of sellers in these markets and their behavior.

2.2 Equilibrium Price Dynamics and Strategic Buyer Behavior

The evolution of prices will depend on what happens to the shape of the demand curve as well as opportunity costs. I illustrate how demand and prices may change over time in a simple differentiated products DP model. Initially I assume that consumers cannot time their purchases strategically, but I then extend the model to allow for strategic timing behavior.

I assume that there are two time periods ($t = 1, 2$), and that in period t, $N_t > 1$ symmetric sellers simultaneously post prices. A seller gets a payoff of V_3 if his listing is unsold at the end of period 2. As an initial assumption, one non-strategic buyer with unit demand arrives in the market with probability λ_t, and must buy at once or exit the market. Product differentiation is captured using a variant of Salop's (1979) circular city model. Specifically, the N_t listings are assumed to be equally spaced around a circle with circumference $\frac{N_t}{\alpha_0+\alpha_1 N_t}$.[11] A buyer's location is drawn at random from the circumference, and her utility if she buys product i is $u - \tau_t d_{it} - p_{it}$, where d_{it} is her distance from i, τ_t parameterizes her willingness to substitute between listings (a lower τ implies a higher price elasticity) and u is high enough so that all buyers purchase in equilibrium. To keep things simple, I will assume that τ_2, N_2 and V_3 are known in period 1, so that $\frac{\partial E_1(V_{i2})}{\partial p_{i1}} = 0$. I focus on the symmetric, pure strategy subgame perfect Nash equilibrium.

The probability that listing i is sold in period t is

$$\frac{\lambda_t}{N_t} + \frac{\lambda_t(\alpha_0 + \alpha_1 N_t)}{N_t * \tau_t}(p_{-it} - p_{it}) \tag{3}$$

as long as p_{it} is quite close to the price charged by other sellers, p_{-it}. This is seller's demand function, and if λ and τ change appropriately then demand might not change across periods even if $N_1 \neq N_2$ and $p_{-i1} \neq p_{-i2}$. This is useful to bear in mind when interpreting the empirical results, as I find that a seller's demand function changes very little over time even though there is observed variation in the number of competitors and the prices that they set, and it is also plausible that λ_t varies over time.

[11] In a a standard Salop model $\alpha_0 = 0, \alpha_1 = 1$ so that the circumference of the circle is fixed. My specification allows for the possibility that new products add additional variety, as happens in logit models that have used to study DP by Xu and Hopp (2006) and Lin and Sibdari (2009). Unfortunately, models with logit preferences have to be solved using computational methods.

Equilibrium prices will be equal to

$$p^*_{t=1} = \frac{\tau_1}{(\alpha_0 + \alpha_1 N_1)} + \frac{\tau_2}{(\alpha_0 + \alpha_1 N_2)} \frac{\lambda_2}{N_2} + V_3 \tag{4}$$

$$p^*_{t=2} = \frac{\tau_2}{(\alpha_0 + \alpha_1 N_2)} + V_3 \tag{5}$$

where the first term is the current period mark-up and the remaining terms are the opportunity cost of sale. Equilibrium prices will fall if $N_1 \leq N_2$ and $\tau_1 \geq \tau_2$ (residual demand is not less elastic in the second period). On the other hand, equilibrium prices will increase if $\tau_1 < \tau_2$ and $\frac{\lambda_2}{N_2}$ is sufficiently small, a parameterization that might describe an airline market where a few business travellers may be willing to pay very high prices close to departure. In a model with competitive sellers and endogenously evolving demand, Deneckere and Peck (2011) predict that there should be no systematic trend in prices.

Strategic Buyers. The recent theoretical literature has emphasized that buyers may delay purchasing if they expect prices to fall. To match the data, it is also useful to allow for two frictions which this literature has ignored: search costs, s, which buyers have to pay each time they search the market[12] and waiting costs, w, which some buyers may have to pay to buy in the second period. For example, some consumers may only want to make complementary investments, such as hotel, travel or baby-sitter reservations, when they buy tickets and this may become more expensive or harder to do at the last minute.

As a simple example of a model with strategic buyers, I assume that there are exactly two risk-neutral strategic buyers (A and B), with $\tau = 1$ for both of them, $N_1 = N_2 = 4$ (so I can focus on the effect of strategic consumer behavior on prices), and $\alpha_0 = 0$ and $\alpha_1 = 1$ (standard Salop preferences). For sellers, $V_3 = 0$. I assume that $w_A = 0$ and $s_A = s_B = s$ (common search costs). In each period a consumer gets a new draw of her position on the circle, which captures, in an ad-hoc way, the fact that the set of listings that a buyer finds when she searches may vary. The timing of the game is as follows. At the start of each time period, sellers simultaneously set prices and, at the same time, buyers simultaneously choose whether to be in the market. Entering buyers indicate their willingness to buy their first choice tickets. If both buyers are in the market and want to buy the same listing, I assume that it is allocated to the high waiting cost buyer B, and then A can choose whether to buy her second favorite listing. It is straightforward to see that an active consumer j will choose to buy a

[12] On eBay, searching for listings to a particular game can be quite costly as even quite specific searches often return listings for other events or memorabilia. Searching on Stubhub is easier, but the large number of listings can also make a detailed search quite time-consuming for new users.

ticket with characteristics (d_{j1}, p_1) in the first period if and only if $d_{j1} + p_1 \leq E_{t=1}(d_{j2} + p_2) + w_j + s$ where the expectation will also reflect knowledge or uncertainty about the choice of the other buyer.

It is interesting to consider two sets of parameters. In the first parameterization, all waiting and search costs are equal to zero, which maximizes the scope for strategic buyer behavior. In the unique pure strategy equilibrium, both buyers will enter the market in period 1. If one or both buyers are still in the market in period 2, equilibrium prices are 0.25 and 0.2857 respectively. In period 1, the equilibrium price is lower (0.1875), even though the opportunity cost of sale is higher in period 1 and $\frac{\partial E_1(V_{i2})}{\partial p_{i1}} > 0$, because the ability of consumers to wait makes period 1 demand more elastic.

In the second parameterization, $s = \frac{1}{16}$ and $w_B = \frac{1}{8}$ so that buyer B has a preference to buy in the first period. The unique pure strategy equilibrium involves only buyer B entering the market in the first period, buying from his preferred seller at a price of 0.3125, while A enters in the second period and buys at a price of 0.25.[13] A does not enter in the first period because he expects a lower price in the second period and the search cost makes it too expensive to check whether a better-matched ticket is available in the first period, while sellers set higher first period prices because B's preference for buying early means that she has relatively inelastic demand. These prices are exactly the same as they would be without any strategic buyer behavior (equations (4) and (5) with $\lambda_1 = \lambda_2 = 1$), even though buyers do make a strategic timing choice, albeit one that is slightly different from that considered in the recent theoretical literature. I show below that the data suggests that the type of sorting on waiting costs illustrated in this example may be quantitatively important.

3 Data[14]

The empirical analysis uses data for single-game tickets to regular season MLB games in 2007 from two online secondary markets, eBay and Stubhub. Teams sell tickets to fans and professional resellers (brokers) in the primary market, and some of these tickets are reallocated in the secondary market with brokers and fans who do not want to attend games acting as sellers.[15] In 2007 Stubhub and

[13] If A's equilibrium strategy involved entering in the first period, the first period equilibrium price would be lower (0.25). However, the possibility that A does not get its first choice ticket in the first period means that her prefered strategy is to search only in the second period.

[14] The online Appendix includes more details and complete summary statistics.

[15] Brokers could also act as buyers in the secondary market with the intention of re-selling tickets. The price declines that I describe can make this type of activity unprofitable, and on eBay most cases where tickets are bought and resold result in losses. Brokers may also sometimes sell tickets on behalf of fans without owning the tickets themselves, receiving a percentage of revenues in the event of sale. One might expect that large price declines would make it profitable to sell a promise to supply tickets early on, fulfilling the order later when prices are lower. The problem with this strategy is that it is hard for a seller to be certain about exactly what types of tickets will be available at a later date. My regressions indicate that listings with missing information (e.g., without a listed row within a named section) sell for 15-20% less

eBay were the two largest online markets for event tickets (Forrester Research (2008)) and most states had relaxed legal restrictions on secondary market transactions. MLB teams had also stopped trying to limit secondary market transactions, and Stubhub was adopted as MLB's "Official Fan-to-Fan Marketplace" in 2008. The sample includes the home games of all MLB teams except the Colorado Rockies who were the only team to practice (a very limited form) of DP in the primary market.[16] I describe the nature of the data from each market, before highlighting some important summary statistics.

On Stubhub, sellers list tickets at fixed prices, with potential buyers observing the section and row of each listing (e.g., Loge Box 512 row D at Yankee Stadium), the number of tickets available, and an indicator for whether fewer tickets can be purchased, and the price per seat.[17] They do not observe anything about the seller, which is possible because Stubhub provides a guarantee that anyone buying from its site will receive tickets at least as good as those listed. Stubhub collects 25% commissions on each transaction and also sets shipping costs.[18] My Stubhub data consists of daily listing (not transaction) information on the 'buy' page for each game from January 6, 2007 to September 30, 2007, collected using an automated script.[19] Each listing has an identification number which allows for some tracking of listings over time, although this is imperfect because many sellers change prices by posting a new listing.[20] For the analysis below, I drop listings with missing section information (0.3% of the initial sample), more than 6 seats (9%) and prices more than $1,000 per seat (0.1%).

Sellers on eBay list tickets in a variety of auction and fixed price formats (auction, hybrid buy-it-now auction and pure fixed prices that may or may not be offered through an eBay store). Sellers set shipping fees and pay small listing fees and commissions of between 1% and 7% depending on the transaction price and sale format. Buyers observe seller IDs and feedback scores, which can be important because eBay does not guarantee transactions. The eBay data was purchased from Advanced E-Commerce Research Systems (AERS) and it contains data on listings, bids and transactions from

than complete information listings. This discount may be large enough to make this type of strategy unprofitable.

[16] I exclude make-ups of rained out games, but include the original game as my focus is on dynamics in the weeks leading up to the game rather than on the day itself. I also exclude three Tampa Bay home games played in Orlando.

[17] In 2007, sellers could list tickets in an auction format which has now been discontinued. I drop the 0.5% of listings in this format. I also drop the 0.4% of listings in a format that automatically changed prices in a linear fashion every day as a game approached.

[18] FedEx shipping costs were $11.95 for transactions more than 14 days before the game and $16.95 for transactions thereafter. Tickets sold within three days of the game were picked up at an office close to each stadium for a $15 handling charge.

[19] As described in the Appendix the Stubhub data is unbalanced because of some problems collecting data on particular days. The eBay data is complete apart from missing listing data for May 18, 2007.

[20] As a result, when a listing ID exits the data the probability that a new listing ID appears for the same game, section and row on the following day is 0.66.

all event ticket listings from January 1 to September 30, 2007. For listings, the data contains the same information as the Stubhub data, together with information on the listing's format, its duration, reserve prices for auctions, indicators for whether the listing was highlighted or had pictures and seller identity numbers and feedback scores. The bid data contains information on the bidder's identity number, the level of the bid and an indicator for whether the bid was successful for all auction bids and all fixed price transactions. For all transactions, the data includes buyer and seller identity numbers, their feedback scores, shipping costs and the zipcodes of the buyer and seller.[21] For the analysis below, I drop listings with missing section information, more than 6 seats, prices more than $1,000 per seat and or shipping costs more than $40. These restrictions together drop 0.7% of the sample. Most of the analysis uses data on non-auction fixed price listings as theoretical DP models assume that fixed prices are used.

The single-game face value of each ticket was identified from team websites. 3.1% of eBay listings (3.6% on Stubhub) in season-ticket only sections could not be matched to face values, and these listings are excluded in what follows. The value of tickets in the secondary market should be a function of expected attendance and team performance. All of the specifications control for a number of variables measuring the performance of both teams which can change as a game approaches. The linear specifications also include game fixed effects to control for differences in demand, while the non-linear specifications include home team dummies and their interactions with a measure of the game's expected attendance. The Appendix describes how this variable is constructed using a censored regression model estimated using attendance, game characteristic and team performance data from 2000-2007. The model explains over 90% of the variation in realized attendances. The measure is also used to identify games which should have high or low demand.

3.1 Summary Statistics

Table 1(a) reports summary statistics on the availability, characteristics and prices of listings in both markets, and Table 1(b) shows how some these statistics vary with the time until the game. The lower section of Table 1(a) shows the number and prices of listings for the six teams in the National League Central division.

[TABLE 1a and 1b]

[21] I only use listings for tickets to regular season MLB games, but data for all other events allows me to impute bidder and seller zipcodes for many sellers who do not complete an MLB transaction.

Many more listings tend to be available on Stubhub than eBay, and there are some differences in how the number of listings tends to evolve over time.[22] On Stubhub, the number of available listings peaks about one month before a game, and drops dramatically in the last few days before a game, reflecting the fact that tickets can only be listed if hard copies are provided to Stubhub. On eBay the average number of fixed price listings remains fairly constant as a game approaches, but peaks about 10 days prior to the game. More tickets tend to be available for high demand games, so that sellouts in the primary market are not associated with scarcity in the secondary market, although prices are higher. This is reflected in the NL Central where the Cubs and the Cardinals have the most listings, and it can also be seen by comparing the number of tickets available for different games for a given team. For example, an average of 79 listings are available on eBay two days before a Boston Red Sox home game against the New York Yankees (arguably the highest profile game in baseball), compared with 31 for other Boston home games which also sold out. Ticket characteristics, measured by face value and whether the seats are in the front row, are similar across the sites and do not vary systematically over time, although more four seat listings are posted on Stubhub where it is easy to allow a buyer to purchase only two of them.

Average prices (deducting seller commissions) are very similar on eBay and Stubhub, consistent with them both being part of a broader online secondary market. Consistent withg Figure 1, both fixed prices and transaction prices (on eBay) decline significantly as a game approaches. Average transaction prices for non-fixed price listings on eBay also decline, and these prices are lower than the average prices of fixed price transactions. This difference in price levels may reflect the fact that buyers may only be willing to participate in auctions, which have an uncertain outcome, if they expect prices to be lower, but it may also reflect the fact that a seller who is very keen to sell may find using an auction more attractive because it increases the probability of sale by allowing the price to respond to the realization of demand.[23] This type of selection is also consistent with the number of auction listings increasing as a game approaches.

As discussed in Section 2, the assumption of single-unit sellers leads to the prediction that expected opportunity costs should fall over time. On eBay (where seller ids are available), 88% of sellers try to sell only a single set of tickets with a particular face value to a particular game[24], with the tickets posted

[22] The most informative comparison is in Table 1(b) which shows the average number of different listings that are available at start of the day (eBay) or when the data was downloaded (Stubhub).

[23] This difference is robust to including a large number of controls for listing characteristics. Malmendier and Lee (2011) find that transaction prices for non-perishable goods on eBay are often higher for auction listings than fixed price listings.

[24] A precise statement of this statistic is that 87.6% of game-seller-face value combinations list tickets for only a single section-row pair. 99% list less than 4 section-row pairs.

1.74 times on average (1.88 for fixed price listings). The eBay market is also very unconcentrated by standard measures, reflecting the fact that many sellers are season ticket holders who do not want to attend all 81 home games. For example, aggregating games, the Herfindahl-Hirschman Index (HHI) for Chicago Cubs tickets is 0.0013, whereas the 2010 Horizontal Merger Guidelines require an HHI of at least 0.15 for a market to be considered even moderately concentrated. The buyer side of the market is even less concentrated with 89% of eBay buyers purchasing no more than two listings during the entire 2007 regular season.

4 Declining Prices

This section shows that declining prices are robust features of the data.[25] As explained in Section 2, DP models predict that sellers should tend to lower prices over time as long as demand does not become much less elastic. However, in equilibrium, some models with strategic consumers can predict prices that are increasing or have no predictable trend.

I measure how prices change using a fixed effects regression model that controls for ticket quality, competition and observable factors, like team performance, that may affect demand

$$p_{it} = D_t \beta_t^D + F_{it}\beta^F + C_{it}\beta^C + Q_i \beta^Q + FE_i + \varepsilon_{it} \tag{6}$$

p_{it} is the price per seat of listing i on date t relative to face value and F are controls for the performance of each team. C includes 20 variables to control for the number of competing listings posted on either eBay or Stubhub.[26] Ticket quality is controlled for using game-face value or richer fixed effects FE_i, while Q_i includes 23 variables that measure listing characteristics (e.g., seller feedback, highlighting, type of listing e.g., eBay store) and seat characteristics (number of seats and row number) that are detailed in the Appendix. The path of prices is measured using the coefficients on a set of 22 dummies (D_t) that measure how many days prior to the game the listing or transaction is observed. Standard errors are robust to heteroskedasticity and clustered on the game.

[FIGURE 2]

[25] The Appendix contains a number of additional robustness checks with similar qualitative results.

[26] Separate variables measure competition from listings with the same and different numbers of seats, and from listings for tickets in the same section or different sections 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. The competition and form variables are both jointly significant in all of the specifications, but excluding them has little effect on the size of the estimated price declines.

Figure 2(a) and (b) show the price paths for posted fixed prices on both sites and transaction prices for all listings and fixed price only listings on eBay, when game-face value fixed effects are used. The plotted value is the value of the time dummy coefficient plus the average price of listings in the last 2 days prior to the game. The posted price regressions use all new listings on eBay (the dummies correspond to the date the listing was posted) and, reflecting the different structure of the data, all available listings for a 5% sample of game-sections on Stubhub. In each case, prices fall significantly and by similar amounts. For example, the four price measures all decline by between 46% and 50% of face value in the month before the game, or around $20 per seat given an average face value of $43.

DP models primarily make predictions about how individual sellers change prices, but these declines could reflect either individual sellers cutting prices or later sellers setting lower prices than earlier ones. The data clearly show that individuals do lower their prices, with 89% of price changes on Stubhub and 80% on eBay being price reductions.[27] The size of the within-seller declines are measured in Figure 2(c), based on regressions with seller-game-section-row fixed effects (eBay) or listing ID fixed effects (Stubhub). The within-seller declines are larger than those in Figure 2(a), with sellers cutting fixed prices by between 85% and 90% of face value in the month before the game, although more than 45 days before the game price cuts are larger on Stubhub than on eBay.

Variation Across Games, Seats and Sellers. While average prices clearly tend to decline, one might expect that patterns would be different for high and low demand games, or cheap and expensive seats. For example, if consumers in the market closer to the game are more price sensitive then one might expect that sellers of tickets with higher face values would cut prices more dramatically than the sellers of cheaper tickets. Table 2 shows selected coefficients on the days-to-go dummies and average prices 0-2 days before the game for the seller-game-section-row fixed effects regressions using fixed price listings on eBay for high demand games (defined as those where the expected attendance 90 days before the game is greater than 95% of capacity), low demand games (less than 70%), cheap seats (face value no more than $20) and expensive seats (face value no less than $45). The proportion of price changes that are price reductions are 79%, 83%, 80% and 81% respectively.

[TABLE 2]

The size of the price reductions for cheap and expensive seats are similar (86% of face value for cheap seats and 75% of face value for expensive seats in the month before the game), which suggests

[27] A price change on eBay is identified when a seller lists the same number of tickets for a game-section-row combination closer to the game at a different price per seat. A price change on Stubhub is identified by postings with the same listing ID number at different prices.

that price sensitivity of consumers may vary little over time, and there will be additional evidence for this conclusion below. As a percentage of face value, price reductions are larger for high demand games than low demand games, but this partly reflects the large difference in price levels: as a percentage of the final price, the declines are quite similar, equal to 63% (standard error 9%) and 55% (7%) respectively.

A comparison of price changes across different types of seller also provides evidence against an alternative explanation for why prices fall based on seller learning, in the spirit of Lazear's (1986) model of clearance sales. In Lazear's two period model, all consumers have a common reservation value for a good but the monopolist seller only knows the distribution from which this value is drawn. Assuming that consumers are not strategic, the seller should set a high first period price, and if no sales are made, set a lower price in the second period based on a more pessimistic updated belief about the valuation. If learning is important and experienced sellers have much tighter priors about the level of demand, then we would expect to see inexperienced sellers cutting prices more than experienced ones. Figure 2(d) shows the within–seller price paths for fixed price listings on eBay for experienced sellers, defined as those selling tickets to more than 100 games in 2007, and less experienced sellers, who list tickets to less than 20 games.[28] Both types of sellers cut prices by very similar amounts (between 90% and 100% of face value in the month before the game), suggesting that learning is not the main reason why prices fall, and the proportion of price changes that are price reductions are also similar in both cases (80% for experienced, 82% for inexperienced). It is also noticeable that experienced sellers, who are more likely to be professionals, set lower prices than inexperienced ones. This is consistent with these sellers having a lower value of being left with unsold tickets because they get no utility from going to games themselves or giving tickets away to friends.

5 Testing Dynamic Pricing Models

This section shows that for the average listing in the data demand is approximately time-invariant and that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$, consistent with the assumptions of simple DP models. It also shows that opportunity costs decline monotonically over time, and that a DP model accurately predicts how much sellers cut prices and how opportunity costs fall. All of the analysis in this section uses the eBay data as I need to observe transactions to estimate demand.

[28] Experienced and inexperienced sellers also cut auction start prices by similar amounts. The number of inexperienced sellers is much larger for auction listings.

5.1 Specification

I model the probability that a listing sells using a probit model where the linear index is a flexible function of the listing's own price and characteristics, the prices and characteristics of other listings and observable factors affecting expected demand, such as expected attendance and team performance. I allow for the endogeneity of the listing's own price by also specifying a linear pricing equation with a normally distributed residual, giving the following system of equations

$$Q_i = X_i\theta_1 + p_i\theta_2 + u_i \tag{7}$$
$$Q_i^* = 1 \text{ (sale) if and only if } Q_i \geq 0,\ Q_i^* = 0 \text{ otherwise}$$
$$p_i = X_i\gamma_1 + Z_i\gamma_2 + v_i$$
$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim N\left[\begin{matrix} 0 \\ 0 \end{matrix}, \begin{pmatrix} 1 & \rho\sigma_v \\ \rho\sigma_v & \sigma_v^2 \end{pmatrix}\right]$$

where p_i is the listing's own price (including shipping costs) relative to face value and this will be endogenous if u_i and v_i are correlated.[29] I estimate the system using Full Information Maximum Likelihood. The sample includes all fixed price listings on eBay posted in the last 90 days before a game, excluding 3.6% of listings with unusually high posted prices as these outliers have disproportionate effects on the estimated demand elasticities.[30] $Q_i^* = 1$ if a listing sells within seven days of posting. The standard errors are clustered on the game. The Appendix contains several alternative specifications, including ones where competitors' prices are also allowed to be endogenous.

Own listing characteristics (X_i) are home team dummies, home team*face value interactions, row controls, number of seat dummies, dummies for four levels of seller feedback and additional listing characteristics (e.g., highlighting) and dummies for the exact mechanism used (e.g., an eBay store listing). Game fixed effects are not included because of the non-linear specification but I control for game demand by including the team form variables and both expected attendance and the median

[29] Shipping costs and and commissions are deducted from the seller's revenue when opportunity costs are calculated. I do not observe shipping costs for listings which do not sell. For these listings, I impute shipping costs assuming that they have the average shipping costs of listings sold by the same seller in the same time period (as defined below) prior to a game. For sellers who never sell in a time period, I use the average shipping cost of all sellers during that time period. Shipping costs are typically fairly small (the eBay average is $4 per seat and it remains steady as a game approaches), and ignoring shipping costs altogether produces very similar results.

[30] 30% of fixed price listings are posted more than 90 days before the game. As noted by a referee, high demand games have higher relative prices so it is not appropriate to use the same cut-off for all games. I drop listings with relative prices greater than $5+6*\max(0, Att_{90}-0.8)$ where Att_{90} is the uncensored expected attendance 90 days before the game. This excludes a similar proportion of listings across games with different expected attendances. For the highest demand game this drops observations with relative prices above 8.33. The qualitative results are the same using a cut-off of 5 for all games.

relative price of concurrent listings on Stubhub for the same game interacted with home team dummies.

Controls for competition on eBay are measures of the number and prices of available eBay listings for the same game, with the same face value and for the same number of seats, that were available on the day listing i was posted. These listings are likely to determine the competition that the seller expects when he sets the price. The specific variables included 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 log of the count (plus 1) of the number of listings with the same face value on Stubhub.

I allow the demand curve to vary with the time until the game by including the complete set of 22 days-to-go dummies and estimating separate own price coefficients and covariance parameters for four "time periods" prior to a game, defined as 0-10, 11-20, 21-40 and more than 41 days to go. There are between 21,346 and 33,496 fixed price listings in each of these time periods.

Exclusion Restrictions. A seller's optimal price will be higher for listings that have higher demand because of factors that are not controlled for, creating an endogeneity problem. This is addressed by including the following set of instruments (Z_i) in the pricing equation that may be correlated with the seller's opportunity cost of sale, and hence his optimal price, but which are assumed to not directly affect demand:

- *the distance of the seller's zipcode from the home team's stadium* in the form of dummies for less than 25 miles, 25-125 miles (the excluded dummy) and more than 125 miles. Local sellers are more likely to be able to attend games themselves or sell their tickets at the stadium. Distance may also be correlated with the type of seller listing a ticket (e.g., season tickets holders are likely to be local) which may also affect opportunity costs;

- *the proportion of unsold listings that the seller relists on eBay* based on listings for other games posted in the same time period prior to the game. Sellers who have limited opportunities to sell outside eBay should have lower opportunity costs and be more likely to relist; and,

- *the proportion of the seller's listings in fixed price and hybrid BIN auction formats* based on listings for other games posted in the same time period prior to the game. As suggested in Section 3, sellers with different opportunity costs may tend to choose different types of listing.

[TABLE 3]

Table 3 reports the coefficients on the instruments when the seller's own price is regressed on the instruments and the exogenous variables in the demand specification. The F-statistic from a test of the joint significance of the instruments is greater than 10, indicating that weak instrument bias should not be significant (Stock and Watson (2007), p. 466). Distant sellers set higher initial prices but they cut them much more aggressively as a game approaches, consistent with being unable to attend games themselves. Sellers who tend to relist set lower prices, suggesting that they do have lower opportunity costs. Sellers who usually use fixed prices listings tend to set higher prices a long time before a game, as do sellers who use BIN listings close to the game, which is when this format is most commonly used.

5.2 Estimates of Demand and Opportunity Costs

The second column in Table 4 shows the price and competition coefficients from the full model while the first column provides estimates from a single-equation probit model where own price endogeneity is ignored as a comparison. Mean elasticities in each time period are shown at the bottom of the table. The positive correlation coefficients indicate that endogeneity is important, and when it is accounted for demand is much more elastic. Figure 3 shows the inverse demand curves for a listing with mean characteristics 3-5, 15-17, 30-32 and 51-55 days before the game based on the full model.[31] The curves are obviously very similar (each curve lies almost entirely within the confidence intervals (not shown) of the other curves), indicating that the simple DP model assumption of time-invariant demand cannot be rejected.

[TABLE 4]

[FIGURE 3 and 4]

The opportunity cost of sale implied by the price of each listing can be calculated using (2) where I assume that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$ (the second order conditions hold for all listings). Figure 4 shows how the distribution of these costs changes over time. The figure only shows 95% confidence intervals for the final time period to avoid clutter, but the distributions in earlier time periods are also estimated precisely. **Every** percentile of the distribution of opportunity costs falls monotonically as a game approaches, as DP models predict. Median opportunity costs in the final time period are 29% of face

[31] The demand curve is calculated using time-invariant listing characteristics and period-specific means for the time-varying variables such as the measures of competition, expected attendance and team form.

value (standard error 5%), while modal opportunity costs are just above zero, which is plausible if there are a group of sellers who cannot attend the game themselves and do not expect to be able to sell tickets offline.[32] One can also look at how opportunity costs change for individuals re-listing tickets: for 77.2% of tickets that are re-listed the later listing has a lower implied opportunity cost. A seller-game-section-row fixed effects regression of opportunity costs on the control variables in the demand specification and days-to-go dummies shows that they decline by 18% (2%), 19% (3%) and 68% (3%) of face value when a listing remains unsold from one time period to the next.[33]

While the qualitative changes are clearly consistent with DP behavior, one can also ask whether an optimal DP strategy predicts how much opportunity costs and prices fall. I perform an illustrative calculation for a listing with mean characteristics assuming that the seller will relist the tickets at most 4 times, starting 55 days before the game. If the ticket is unsold after 7 days, I assume that the seller would relist it with 32 days to go, then with 15 days to go and finally with 5 days to go, so that the relevant demand curves are exactly those shown in Figure 3. I assume that the seller values tickets that remain unsold at 40% of face value, which is between the mean (55%) and the median (29%) opportunity cost in the final time period.

With these simple assumptions, it is straightforward to calculate the seller's opportunity cost and his optimal price each time the ticket is listed. The optimal price should fall from 202% to 190%, 169% and 143% of face value as a game approaches (std. errors less than 3% in each case), and these declines of 12%, 21% and 26% are similar to the average within-seller declines of 13%, 18% and 40% observed in the data (Figure 2(c)). The associated opportunity cost should fall by 19%, 27% and 57% of face value, and these declines are also similar to the observed within-seller declines reported above. Therefore the observed average price-cutting behavior is also quantitatively consistent with the predictions of a DP model given the demand estimates.

This example can also be used to quantify the gains to DP. As an example of a non-DP strategy, suppose that the seller relists at the same times, but always sets a price based on opportunity cost of 40%, implicitly ignoring his ability to re-list prior to the game. Using this strategy, the price would be between 138% and 143% times face value in each period, the probability of sale would be 0.95, and

[32] Around 25% of opportunity costs in the final time period are significantly negative which is inconsistent with profit maximization and free disposal of tickets. Some of these observations are likely associated with sellers choosing to set prices that are close to face value (about 25% of these observations have prices within 10% of face value) for ethical reasons even when they could expect to achieve higher payoffs by setting as higher price. In a few states, the law still prevents sellers from charging a significant mark-up above face value. However, further analysis revealed that there was no significant correlation with 2007 state restrictions on ticket resale.

[33] These estimates come from regressing the opportunity costs on all of the control variables in the demand specification and seller-game-section-row fixed effects. The declines are measured by the coefficients on the dummies for 3 to 5, 15 to 17, 30 to 32 and 51 to 55 days to go.

the expected payoff 135% of face value (standard error 2%). Using the optimal DP strategy, initial prices are higher which reduces the sale probability to 0.85 but the expected payoff is 156% of face value (2%). DP therefore raises the seller's expected payoff by 21% of face value, or 16% of the payoff from using static pricing. For the average listing with 2 seats and a combined face value of $87.16, the gain would be just over $18.

5.3 Effect of Current Prices on Future Supply

I now test the assumption that the current price does not affect the seller's value from relisting unsold tickets in the future. This assumption could be violated if buyers are strategic, as most of the recent theoretical literature assumes, or if a seller's current price affects the future entry or pricing decisions of competitors. On the other hand, these effects could be negligible in my setting because each seller is small relative to the online secondary market. As expectations of future values are not observed directly, I look instead at whether the price the last time that a ticket was listed has either a direct effect on a listing's demand or whether it affects the value of any of the competition variables that appear in the demand system. I first look at these competition effects, before examining the direct demand effect and considering more general evidence on whether buyers behave strategically.

[TABLE 5]

I test whether a seller's current price affects the competition variables that were included in the demand equation, by regressing the value of these variables the next time that a listing that does not sell is posted, on the listing's current price, the current value of the variables that affect demand and a set of days-to-go dummies to control for when the listing is relisted. Table 5 reports the results from three different linear specifications for each competition variable: an OLS specification, a 2SLS specification, using the same instruments for the current price as demand estimation, and a game-face value fixed effects specification. The reported coefficients are the coefficients on the seller's own price (relative to face value) in different specifications. The final row reports the total effect on the probability that the relisted tickets will sell when the current price is increased by an amount equal to face value, holding the relisting price fixed, combining all of the estimates in the column with the demand estimates from the full model.

In the OLS specification, the total effect and most of the individual coefficients are statistically significant but the effects are small. The total effect implies that increasing the current price by face value would raise the future listing's probability of sale by only 0.0025, or less than 1% from its mean of 0.2842. In contrast, the increase would reduce the current probability of sale by more than 0.2. The small positive effect could also be due to an unobserved factor raising the listing's current price and the future value of the competition variables. The fixed effect and 2SLS specifications provide alternative ways of addressing the endogeneity problem, and in neither of these specifications are the total effects significantly different from zero even though they are precisely estimated. The results are therefore consistent with the assumption that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}}$ is equal or very close to zero.[34]

5.4 Effect of Current Prices on Future Demand and Evidence of Buyer Sorting

A listing's current price could also affect its future demand if a high price causes some buyers to delay purchasing. I test whether this effect is significant by including the seller's lagged price in the demand function. As the demand specification controls for competition at the time of listing, the coefficient on the lagged price should capture any demand-shifting effect. The lagged price, as well as the current price, may be endogenous so I include the residual from the pricing equation for the previous listing as an additional covariate. This approach is in the spirit of Rivers and Vuong (1988) who suggest estimating probit models with an endogenous regressor by including the residuals from a first stage regression in the probit specification.

The estimates are reported in the third column of Table 4. The coefficient on lagged price is very small and statistically insignificant, and the coefficient on the lagged residual (not reported) is statistically insignificant as well. The other coefficients and demand elasticities are similar to the second column. This estimate indicates that a seller's current price has no significant effect on future demand, consistent with $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$.

The success of simple DP models at describing the pricing problem that sellers face and the lack of a significant demand-shifting effect may seem surprising, because, contrary to the model of demand assumed in simple DP models, it seems plausible that consumers can act strategically. However, it is important to remember that some of the additional assumptions made in the recent theoretical literature may also not hold in my setting.[35] For example, a high initial price may cause some buyers to wait, but, because the market is large, the probability that a buyer who delays will purchase

[34] A possible weakness of this test is that it is based on the selected sample of unsold listings that I observe being re-listed. I have also computed additional results based on the set of competing listings ten days after any listing is posted (all listings less than eleven days before the game are dropped in this case). These results are qualitatively similar, with the total effects statistically insignficant once I control for endogeneity.

[35] Of course, it may be that many buyers are simply not strategic. Osadchiy and Bendoly (2011) provide evidence that a population of MBA students fail to make optimal timing decisions about purchases even when they are well-informed about how prices change. In my setting, many consumers may not be aware of the aggregate price trends.

the same listing later on may be very small.[36] This issue is excluded in models with a single seller. Alternatively, as suggested at the end of Section 2, search costs and heterogeneity in buyers' willingness to buy at the last minute, may mean that strategic buyer behavior leads to a sorting of when buyers participate in the market, rather than causing a buyer to delay purchasing when she encounters a high price.

The information on buyers in the eBay transaction data provides evidence consistent with the second parameterization of the model with strategic buyers in Section 2. In that model, one buyer has to pay a cost if she delays purchasing and both buyers face search costs when they are active in the market and have the same ex-ante elasticity of demand (same τ). In equilibrium, the buyer with the delay cost chooses to be in the market in the first period, while the other buyer searches the market only in the second period when she expects prices to be lower. Equilibrium prices are the same as in a model where buyer arrivals are exogenous.

While we cannot observe exactly when buyers search the market, we can observe when they purchase tickets and how far a buyer lives from the stadium where the game is played. This distance is likely to be positively correlated with the complementary investments that the buyer has to make to attend a game and therefore with the cost of delay. The sorting model therefore predicts that distant buyers should tend to buy tickets earlier than other buyers, and this is what we see in the data. On the other hand, early and late purchasers buy similar types of ticket (e.g., face value and row characteristics). This is consistent with them having the same τs, whereas if people buying closer to the game tended to be more price sensitive one would expect them to buy lower quality tickets (recall that Table 1(b) showed that the set of available tickets remains similar) or for the prices of higher quality tickets to decline more rapidly in equilibrium (Table 2 showed that this is not the case).

[TABLE 6]

The distance that the buyer lives from the stadium is calculated using the center of the delivery zipcode (buyers outside the US are dropped), and the mean (median) distance is 184 (37) miles. Table 6 reports regressions using all eBay transactions (any mechanism) with non-missing face value and buyer zip code information, and the dependent variable is the number of days before the game that the transaction takes place. The regressors include a dummy variable for whether the centroid of the

[36] An interesting feature of the eBay auction data is that only 38% of unsuccesful bidders participate in another auction or buy a fixed price listing for the same game. This may reflect the fact that losing bidders substitute to other online markets like Stubhub, and a high degree of substitution would make the assumption that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} \simeq 0$ even more plausible.

buyer's zipcode is within 25 miles of the stadium in which the game is played, as well as distance and distance^2. The specification in the first column also includes controls for the sale mechanism and listing characteristics, such as face value and measures of the position of the row within a section, game fixed effects and controls for the experience of the buyer based on the number of MLB tickets the buyer purchased in 2007.[37]

The coefficients indicate that travel distances significantly affect the timing of purchases. For example, the estimates predict that someone living in New York City buys Boston Red Sox tickets 6.3 days (standard error 0.3) earlier than someone living in downtown Boston, which is a large difference given that the median purchase takes place ten days before a game.[38] In contrast, listing characteristics, that might appeal to consumers with different demand elasticities, have only small effects on when listings are purchased even though most of the coefficients are statistically significant because the sample size is large. For example, the model predicts that a \$60 seat would be purchased 0.6 (0.04) days later than a \$40 seat, and front row seats 1.4 (0.34) days earlier than seats in row 20. Six seat listings are purchased two weeks earlier than two seat purchases (the excluded group), which makes sense as six seat listings are rarely available on eBay (0.6% of listings) so that someone wanting to buy one probably searches in every period and will buy as soon as he finds one that is available.

As a robustness check, the specification in the second column includes buyer-delivery zipcode fixed effects, so that the distance coefficients are now identified from individuals who buy tickets for multiple teams. Differences in demand across games are controlled for using home team dummies and home team*expected attendance interactions rather than game fixed effects. The distance coefficients imply that someone living next to Yankee Stadium buys tickets 5.0 (1.3) days earlier for a Red Sox game than a Yankees game.[39] This provides further evidence that consumer sorting on distance, which are a proxy for waiting costs, are a significant feature of my data.

[37] Experience may proxy for a number of buyer attributes: for example, more dedicated fans might buy more tickets, but we may also expect some professional traders to be in the market trying to purchase tickets that are underpriced for re-sale. The estimated coefficients provide some evidence for this type of behavior, as, conditional on distance, more experienced buyers purchase tickets earlier and they also do so at significantly lower prices (when the transaction price is used as the dependent variable). I have also estimated specifications controlling for the income of the buyer's zipcode. The distance effects change very little, but people from higher income zipcodes are predicted to buy slightly closer to the game, but the effect is very small. These people are also predicted to buy tickets with slightly higher face values.

[38] An alternative approach involves regressing the log of the distance of the buyer's zipcode from the stadium on listing characteristics and days-to-go-dummies, in a similar fashion to the price regressions. The results indicate that the distance declines almost monotonically as the game approaches with buyers 12 to 14 (30 to 32, 81 to 90) days before the game living 47.5% (75.8%, 84.4%) further away than those buying in the last three days. These values are significantly different from each other at any conventional significance level.

[39] Regressions of the face value of the tickets purchased on distance and game or buyer-zipcode fixed effects indicate that, even though distant consumers buy earlier, they buy very similar tickets to close consumers. For example, someone living in New York is predicted to buy a ticket that is \$1.40 more expensive when they attend a game in Boston, which is much less than the cost of a hotdog at an MLB game.

6 Conclusion

This paper examines whether DP models, that are being widely explored in the theoretical literature, accurately describe pricing behavior in secondary markets for MLB tickets, which are a classic example of a perishable good. Consistent with all existing DP models, sellers price as if their opportunity costs of sale are falling over time. The data also support two additional features of some of the simplest DP models: sellers face demand curves that are almost time-invariant and their current prices have no significant effects on their value from trying to resell in the future. These features of the market make it optimal for sellers to cut prices substantially as a game approaches, and, on average, they cut prices by approximately the amount that a DP model with these features predicts.

These results are highly encouraging for the empirical relevance of DP models in general and simple DP models in particular, as these markets share characteristics with other markets where DP is used, such as being somewhere between the extremes of monopoly and perfect competition that have dominated the theoretical literature. My results stand in contrast to some of the negative conclusions about this literature that researchers have drawn when looking at airline prices (McAfee and te Velde (2006)), as well as more general evidence that sellers do not always price in the way that economic theory would predict (Genesove and Mayer (2001), Levitt (2006)).

There are several directions for future empirical research on DP models. Given appropriate data, one could use the framework developed here to assess how well DP models predict pricing behavior in other settings. An obvious example to look at would be airline markets (Lazarev (2011) considers monopoly airline markets), where revenue management techniques are widely applied, but prices tend to rise prior to departure. One possible explanation that can easily by captured by existing DP models is that demand becomes less elastic close to departure. An alternative explanation is that airlines choose increasing price paths partly to develop a reputation for not cutting prices so that consumers do not delay buying tickets on future flights.[40] These incentives would be missed by DP models that consider a single sales horizon. Reputational incentives are likely to be much more important for airlines, who interact with the same customers repeatedly, than for small sellers in markets like Stubhub where there are many sellers and transactions are anonymous. However, understanding reputational incentives might be very important for implementing DP in primary markets for event tickets.

[40] Airline pricing behavior may be better described by models where sellers choose (price,quantity) schedules that are not a function of time (e.g., Dana (1998 and 1999) and Gale and Holmes (1993)). The reputational incentive could then explain why they choose not to use time dependent prices, and to the extent that they do, why they use practices such as advance purchase discounts.

It would also be useful to understand more clearly why strategic buyer behavior does not seem to matter for pricing decisions in these markets. One explanation is that buyers fail to act strategically because of limited knowledge about how prices change, in which case we might expect to observe the type of behavior that is assumed in much of the recent theoretical literature in markets which are more transparent or buyers are more experienced. On the other hand, there is evidence consistent with a model where at least some buyers are strategic but have heterogenous costs of delay and must pay search costs when they participate in the market. These factors have been largely ignored in the theoretical literature, but if they are important in my setting, they are also likely to matter in other environments in which case outcomes may systematically diverge from those predicted by recent theory.

Finally, it would useful to move beyond pricing to look at sellers' other choices in perishable goods markets, such as the decision about when to use an auction and when to use a fixed price. The variation in incentives provided by the finite sales horizon could provide general insights into when these mechanisms are optimal, and understanding the extent of buyer and seller substitution between these mechanisms (Bauner (2011) and Hammond (2011) provide some estimates) would also guide the optimal design of markets where perishable goods are traded.

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Table 1(a): Summary Statistics

	Observations	Mean	Std. Dev.	Median	10th percentile	90th percentile
eBay Fixed Price Listings						
Posted Fixed Price (relative to face)	178,659	2.074	1.954	1.588	0.57	4.023
Face Value ($)	178,659	40.11	42.34	31	15	60
Number of Seats	178,659	2.263	0.761	2	2	4
Front Row Dummy	178,659	0.128	0.334	0	0	1
eBay Store Listing	178,659	0.255	0.436	0	0	1
Seller feedback > 1000	178,659	0.538	0.499	1	0	1
Listing highlighted or has pictures	178,659	0.267	0.442	0	0	1
Stubhub Fixed Price Listings						
Posted Fixed Price (relative to face)	66,236,993	1.99	1.46	1.629	0.85	3.48
Face Value ($)	66,236,993	38.97	26.87	35	15	60
Number of Seats	66,236,993	3.2	1.3	4	2	4
eBay Buyer Transaction Prices						
Fixed Price Listings (relative to face)	50,602	2.096	1.779	1.618	0.632	4.062
Non-Fixed Price Listings (relative to face)	239,808	1.696	1.606	1.237	0.4222	3.452

Selected Statistics for National League Central Teams

	Mean Attendance (Proportion of Capacity)	Stubhub Listings	eBay Listings	eBay Transactions	Average eBay Transaction Price	eBay Seller HHI
Chicago Cubs	0.96	485,003	52,508	25,755	2.30	0.0013
Cincinnatti Reds	0.59	32,426	16,882	7,968	1.85	0.0151
Houston Astros	0.85	100,240	10,225	5,650	1.70	0.0082
Milwaukee Brewers	0.78	27,650	14,743	8,845	1.42	0.0202
Pittsburgh Pirates	0.58	20,992	2,871	1,972	1.44	0.0286
St Louis Cardinals	0.95	260,886	42,521	19,418	1.51	0.0048

Note: Non-fixed price listings includes BIN auctions where the sale may take place at a fixed price. Attendances measured as a proportion of highest observed attendance. Posted fixed prices excludes the commission that the seller would pay in the event of sale. An observation on Stubhub is a listing-download, whereas an observation on eBay is a posting that may be available for several days.

Table 1(b): Market Dynamics

	0-5 Days	6-10 Days	11-20 Days	21-40 Days	41-90 Days
Average Number of Available Listings					
eBay Fixed Price - All	8.6	10.5	10.7	10.3	8.9
	(10.3)	(11.8)	(12.4)	(12.4)	(11.0)
High expected demand games	15.8	19.1	20.2	20.8	19.1
(expected attendance > 95% capacity)	(13.8)	(15.7)	(16.5)	(16.6)	(14.5)
Low expected demand games	4	5.0	4.8	4.0	3.2
(expected attendance < 70% capacity)	(5.2)	(11.9)	(5.6)	(4.9)	(4.1)
eBay Non-Fixed Price	25.1	34.3	22.4	9.4	3.5
	(33.9)	(39.5)	(29.1)	(15.2)	(7.1)
Stubhub	79.1	178.2	190.9	213.5	195.8
	(117.8)	(200.6)	(217.0)	(236.5)	(231.1)
Average Ticket Quality of eBay Fixed Price Listings					
Listing Face Value ($)	37.45	35.58	36.56	37.47	39.15
	(31.61)	(28.05)	(30.61)	(35.97)	(41.42)
Listing Proportion of Front Row Seats	0.14	0.12	0.12	0.12	0.12
	(0.34)	(0.32)	(0.33)	(0.33)	(0.32)
Transaction Face Value ($)	35.66	37.00	36.82	36.59	36.98
	(31.20)	(30.74)	(32.75)	(35.00)	(38.26)
Transaction Proportion of Front Row Seats	0.15	0.16	0.16	0.14	0.14
	(0.35)	(0.37)	(0.36)	(0.34)	(0.34)
Average Prices, proportion of face value					
eBay Listed Fixed Price - all games	1.59	1.66	1.86	2.10	2.32
	(1.57)	(1.55)	(1.70)	(1.87)	(2.14)
High expected demand games	2.08	2.31	2.52	2.77	3.02
(expected attendance > 95% capacity)	(1.90)	(1.90)	(2.10)	(2.29)	(2.57)
Low expected demand games	0.94	1.05	1.18	1.28	1.39
(expected attendance < 70% capacity)	(0.66)	(0.78)	(0.75)	(0.73)	(0.85)
eBay Transaction Price - fixed price listings	1.64	1.92	2.04	2.33	2.52
	(1.45)	(1.56)	(1.53)	(1.99)	(2.11)
eBay Transaction Price - non-fixed price listings	1.46	1.57	1.80	2.05	2.01
	(1.43)	(1.52)	(1.72)	(1.94)	(1.60)
Stubhub Posted Fixed Price	1.62	1.70	1.77	1.87	1.98
	(1.26)	(1.38)	(1.34)	(1.37)	(1.43)

Notes: Standard deviations in parentheses. Non-fixed price listings includes BIN auctions where the sale may take place at a fixed price. Posted fixed prices excludes the commission that the seller would pay in the event of sale. Expected attendance calculated 90 days before the game based on the censored regression model described in the Appendix.

Table 2: Within-Seller Price Changes for Particular Types of Ticket Using Fixed Price Listings on eBay

	High Demand	Low Demand	Cheap Seats (<=$20)	Expensive Seats (>=$45)
Average Price 0-2 Days Prior to Game	2.014	0.932	1.834	1.431
Selected Days <u>To Go Coefficients</u>				
3 to 5	0.341***	0.109**	0.184**	0.203***
	(0.097)	(0.052)	(0.088)	(0.077)
6 to 8	0.683***	0.184***	0.400***	0.381***
	(0.120)	(0.053)	(0.100)	(0.084)
9 to 11	0.799***	0.310***	0.470***	0.515***
	(0.120)	(0.048)	(0.092)	(0.073)
15 to 17	0.997***	0.430***	0.691***	0.620***
	(0.120)	(0.053)	(0.099)	(0.075)
21 to 23	1.175***	0.458***	0.822***	0.698***
	(0.150)	(0.054)	(0.130)	(0.081)
30 to 32	1.263***	0.509***	0.868***	0.745***
	(0.180)	(0.064)	(0.140)	(0.080)
39 to 41	1.304***	0.554***	0.868***	0.738***
	(0.160)	(0.066)	(0.120)	(0.086)
51 to 55	1.385***	0.577***	0.964***	0.791***
	(0.180)	(0.068)	(0.120)	(0.085)
81 plus	1.518***	0.679***	1.019***	0.821***
	(0.210)	(0.073)	(0.130)	(0.087)
Observations	84,413	28,158	56,769	49,051
Adj. R-squared	0.909	0.778	0.888	0.916

<u>Note:</u> coefficients from seller-game-section-row fixed effects regressions, standard errors clustered on the game. Regressions include controls for listing characteristics, competition and team performance described in the text. ***,**,* denote significance at 1, 5 and 10% levels.

Table 3: Regressions of eBay Fixed Prices on Instruments

Distance Variables	
Seller Within 25 Miles	-0.014
	(0.025)
* 1-10 Days Prior to Game	0.027*
	(0.030)
* 11-20 Days Prior to Game	0.004
	(0.028)
* 21-40 Days Prior to Game	-0.058**
	(0.028)
Seller More than 125 Miles	0.209***
	(0.023)
* 1-10 Days Prior to Game	-0.285***
	(0.030)
* 11-20 Days Prior to Game	-0.160***
	(0.026)
* 21-40 Days Prior to Game	-0.091***
	(0.026)
Relisting Variables	
Proportion of Seller's Unsold Listings	-0.137***
During Time Period Relisted on eBay	(0.034)
* 1-10 Days Prior to Game	-0.105**
	(0.051)
* 11-20 Days Prior to Game	-0.158**
	(0.064)
* 21-40 Days Prior to Game	-0.358***
	(0.054)
Mechanism Choice Variables	
Proportion of Seller's Other Listings	-0.0892
in Hybrid BIN Format	(0.064)
* 1-10 Days Prior to Game	0.148**
	(0.071)
* 11-20 Days Prior to Game	0.224***
	(0.078)
* 21-40 Days Prior to Game	0.097
	(0.075)
Proportion of Seller's Other Listings	0.173***
in Pure Fixed Price Formats	(0.047)
* 1-10 Days Prior to Game	-0.313***
	(0.053)
* 11-20 Days Prior to Game	-0.007
	(0.057)
* 21-40 Days Prior to Game	0.059
	(0.056)
Observations	113,186
F-statistic on the instruments	16.42 (p-value 0.000)

Notes: Specification includes competition variables, number of seat dummies, seller feedback score dummies, controls for ticket and listing characteristics, home team dummies, home team*face value, and home team*expected attendance interactions, form variables, game day of week dummies, days to go dummies and dummies for sellers with 1 and less than 10 listings in 2007.
Robust standard errors in parentheses clustered on the game. ***,** and * denote significance at 1%, 5% and 10% levels.

Table 4: Demand Estimates

	(1) Exogenous Own Price	(2) Full Model	(3) Full Model with Lagged Price
Own Relative Price Coefficients			
1-10 Days Before Game	-0.185***	-0.964***	-0.949***
	(0.010)	(0.026)	(0.027)
11-20 Days Before Game	-0.184***	-0.964***	-0.941***
	(0.010)	(0.026)	(0.028)
21-40 Days Before Game	-0.199***	-0.941***	-0.917***
	(0.012)	(0.027)	(0.028)
41+ Days Before Game	-0.214***	-0.925***	-0.905***
	(0.012)	(0.026)	(0.027)
Previous Price	-	-	-0.007
			(0.011)
Competition Coefficients (EBay)			
Mean Relative Price for Fixed Price Listings	0.072***	0.119***	0.116***
	(0.011)	(0.008)	(0.009)
Mean Relative Start Price for Auction Listings	-0.013***	-0.003	-0.003
	(0.012)	(0.011)	(0.011)
Minimum Relative Price for Fixed Price Listings	-0.045***	0.007	0.006
	(0.010)	(0.009)	(0.009)
Minimum Relative Price for Auction Listings	-0.005	-0.002	-0.004
	(0.014)	(0.012)	(0.012)
Dummy Variable for No Competing	0.086***	1.151***	1.055***
Fixed Price Listings	(0.028)	(0.028)	(0.028)
Dummy Variable for No Competing	-0.079***	-0.221***	-0.220***
Auction Listings	(0.026)	(0.023)	(0.023)
Number of Competing Fixed Price Listings (Log N+1)	-0.153***	-0.141***	-0.105***
	(0.018)	(0.016)	(0.016)
Proportion of Competing Fixed Price Listings with	0.138***	0.819***	0.357***
Seller Feedback Scores Above 100	(0.040)	(0.038)	(0.039)
Number of Competing Auction Listings (Log N+1)	0.015	-0.012	-0.025
	(0.015)	(0.014)	(0.014)
Proportion of Competing Auction Listings with	-0.017	-0.096***	-0.022
Seller Feedback Scores Above 100	(0.022)	(0.020)	(0.021)
Competition Coefficients (Stubhub)			
Log(Number of Stubhub Listings+1)	0.005	0.024**	0.026***
	(0.009)	(0.010)	(0.010)
Correlation Coefficients			
1-10 Days Before Game	-	0.713***	0.698***
		(0.024)	(0.025)
11-20 Days Before Game	-	0.712***	0.682***
		(0.025)	(0.026)
21-40 Days Before Game	-	0.675***	0.646
		(0.027)	(0.028)
41+ Days Before Game	-	0.680***	0.656
		(0.029)	(0.030)
Mean Elasticities			
1-10 Days Prior to Game	-0.288	-2.150	-2.079
	(0.020)	(0.148)	(0.147)
11-20 Days Prior to Game	-0.416	-3.100	-2.919
	(0.025)	(0.214)	(0.197)
21-40 Days Prior to Game	-0.601	-3.863	-3.658
	(0.045)	(0.0237)	(0.227)
More than 41 Days Prior to Game	-0.875	-5.212	-4.976
	(0.049)	(0.398)	(0.386)
Number of observations	113,186	113,186	113,186

Notes: Specification also include number of seat dummies, seller feedback score dummies, controls for ticket and listing characteristics, home team dummies, home team*face value, and home team*expected attendance interactions, form variables, game day of week dummies, days to go dummies. Robust standard errors in parentheses clustered on the game. ***,** and * denote significance at 1%, 5% and 10% levels.

Table 5: Effect of Current Price on Future Value of Competition Variables

Dependent Variable	OLS	Game-Face Fixed Effects	2SLS
Mean Price of Competing Fixed Price Listings	0.0244**	-0.0364***	0.1241***
	(0.0099)	(0.0112)	(0.0470)
Dummy for No Competing Fixed Price Listings	-0.0008	0.0001	-0.0326**
	(0.0019)	(0.0023)	(0.0136)
Number of Competing Fixed Price Listings	-0.0154***	-0.0307***	0.0842***
	(0.0045)	(0.0063)	(0.0288)
Minimum Price of Competing Fixed Price Listings	0.0427***	0.0100***	0.0984**
	(0.0094)	(0.0098)	(0.0446)
Proportion of Competing Fixed Price Listings with Feedback Scores >100	-0.0047***	-0.0031	0.0068
	(0.0018)	(0.0024)	(0.0117)
Mean Start Price of Competing Auction Listings	0.0289***	-0.0074	0.1337***
	(0.0074)	(0.0097)	(0.0386)
Dummy for No Competing Auction Listings	0.0003	0.0034	-0.0328*
	(0.0026)	(0.0033)	(0.0184)
Number of Competing Auction Listings	-0.0072	-0.0227	-0.0353
	(0.0047)	(0.0066)	(0.0288)
Minimum Price of Competing Auction Listings	0.0207**	0.0121	-0.0862**
	(0.0059)	(0.0083)	(0.0336)
Proportion of Competing Auction Listings with Feedback Scores >100	-0.0018	-0.0065*	-0.0085
	(0.0025)	(0.0034)	(0.0179)
Number of Stubhub Listings	-0.0001	-0.0031	0.0282*
	(0.0024)	(0.0027)	(0.0147)
Increase in the Probability that Relisted Tickets Sell When Current Price is Increased by Face Value	0.0025**	-0.0007	0.0024
	(0.0010)	(0.0011)	(0.0052)

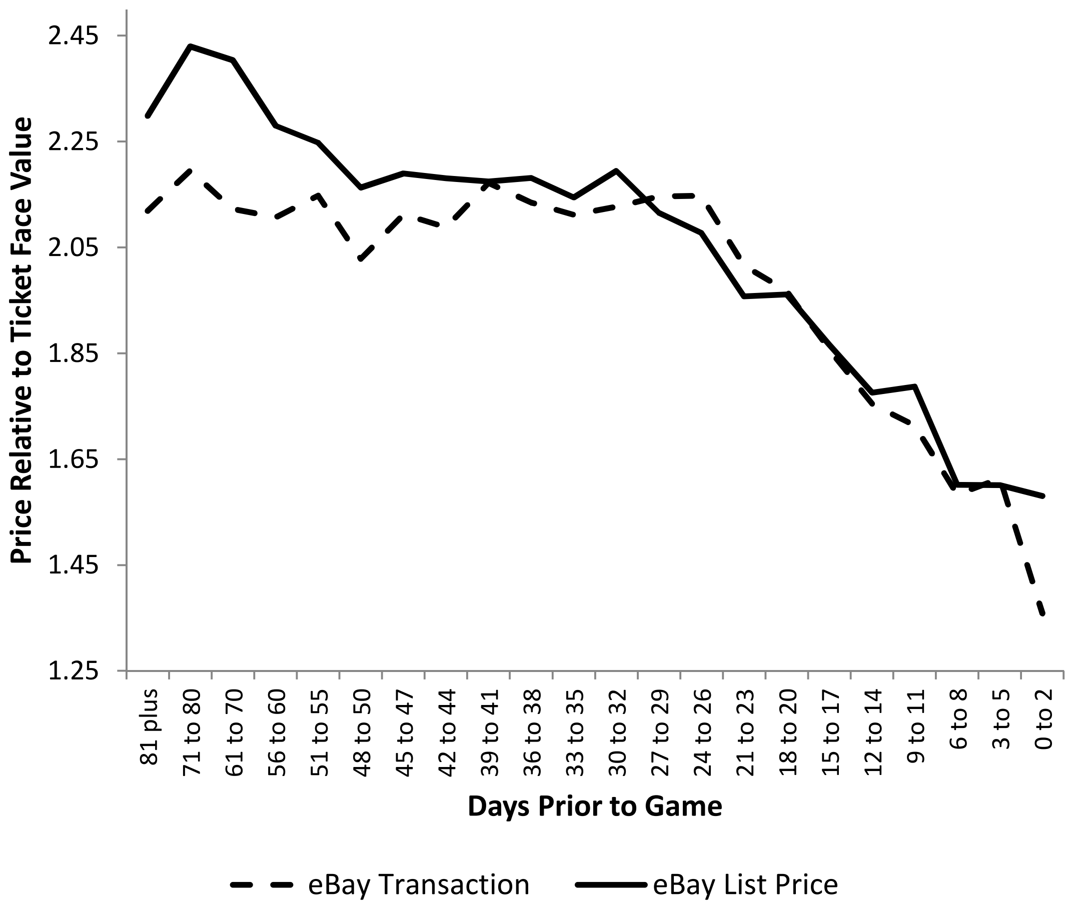
Notes: Robust standard errors in parentheses clustered on the game. ***,** and * denote significance at 1, 5 and 10% levels. Excluding final row, table shows coefficients on the current price in regressions which include the controls from the demand equation, plus days-to-go dummies for when the next listing takes place. The dependent variable is the value of the competition variable when the listing is next posted. Number of observations in each regression is 28,952. The coefficients in the final row reflect the combined effect of all of the changes in the competition variables, holding the price of the re-listing fixed, calculated using the full model results in column (2) of Table 4.

Table 6: Timing of Purchases

	(1)	(2)
Dep. Var	Days Prior to Game Purchase Made	Days Prior to Game Purchase Made
Distance of Buyer's Zipcode from Stadium		
Distance (miles)	0.0103***	0.0178***
	(0.0013)	(0.0044)
Distance^2/1000	-0.0020***	-0.0053***
	(0.0006)	(0.0018)
Distance Less than 25 miles	-4.3907	-1.8400***
	(0.3568)	(1.5554)
Number of Seats (Pair Excluded)		
One	-2.8527***	4.0946*
	0.8102	(2.4571)
Three	-4.8855***	1.1756
	0.3987	(1.8077)
Four	1.1387***	6.5024***
	0.2985	(1.6824)
Five	-6.1887***	
	0.6911	
Six	10.5381***	13.8976***
	1.3447	(3.4725)
Face Value		
Face Value ($)	-0.0307***	-0.0331***
	0.0027	(0.0079)
Row Variables		
First Row Dummy	2.2599***	1.0361
	0.3291	(0.6816)
Second Row Dummy	2.1605***	1.3149**
	0.3195	(0.6601)
Row Number	0.0432***	0.0199
	0.0157	(0.0338)
Game FEs	Y	N
Buyer Zipcode FEs	N	Y
Home Team, Home Team*Expected Attendance, Day of Game, Month of Game Controls	N	Y
Number of Observations	286,706	286,706
R-squared	0.17	0.79

Notes: Robust standard errors in parentheses clustered on the buyer. ***, ** and * denote significance at the 1, 5 and 10% levels. Sample includes auction listings and both specifications include controls for the sales format and the experience of the buyer.

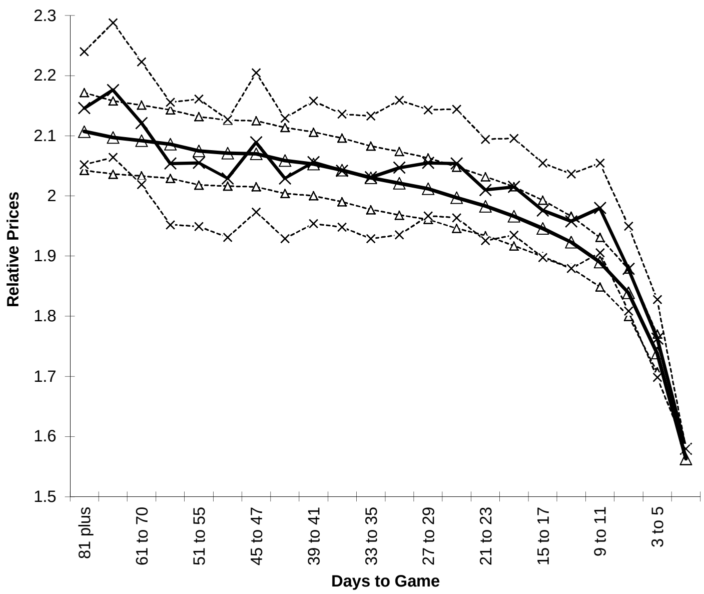
Figure 1: Average Prices on eBay and Stubhub



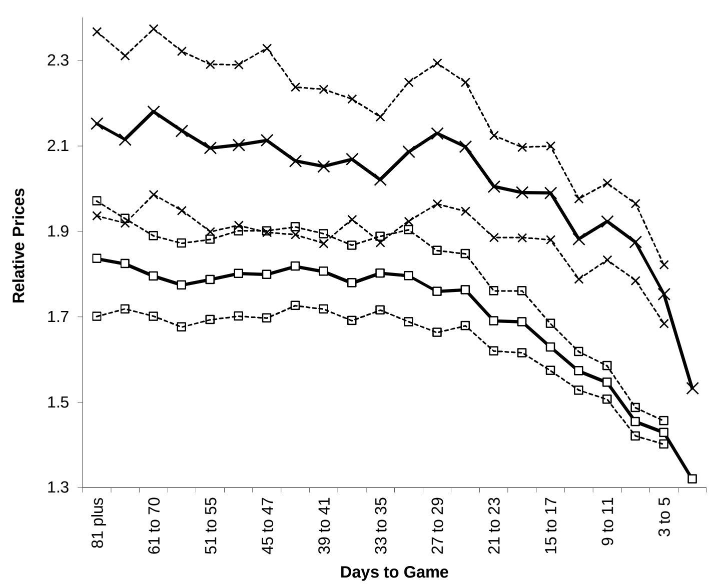
Notes: eBay list prices are the prices of 178,659 fixed price only listings on eBay, on. the day that the listing was posted. eBay transaction prices are for 290,410 transactions in any sales format.

Figure 2: Estimated Price Paths

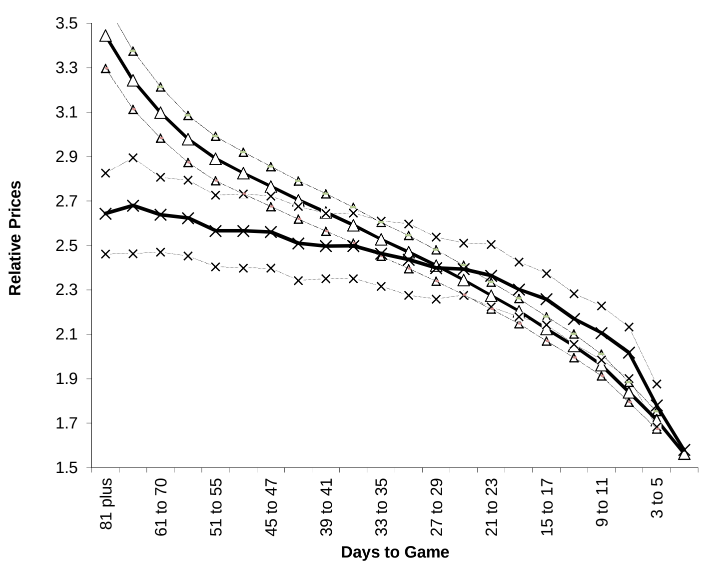
(a) Listed Fixed Prices
(Stubhub - triangles, eBay - crosses,
dashed lines are 95% confidence intervals,
standard errors clustered on the game)



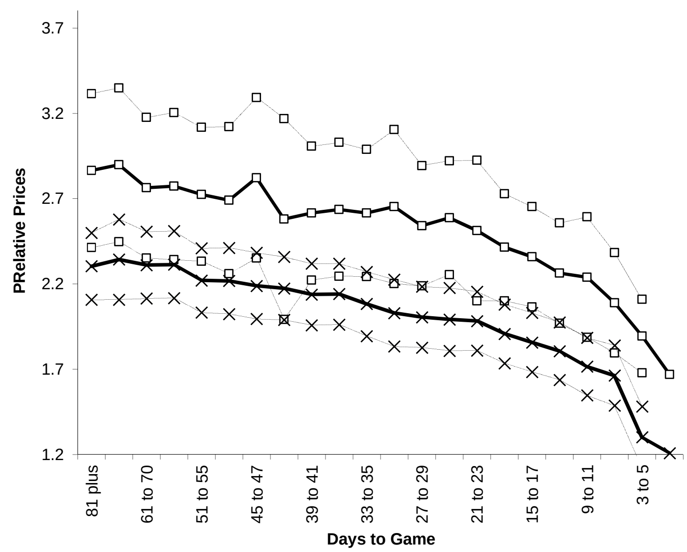
(b) eBay Transaction Prices
(All sales = squares, Fixed Price sales = crosses,
dashed lines are 95% confidence intervals,
standard errors clustered on the game)



(c) Within-Seller Listing Fixed Price Declines
(eBay Fixed Prices = crosses,
Stubhub = triangles, dashed lines are 95% confidence intervals,
standard errors clustered on the game)

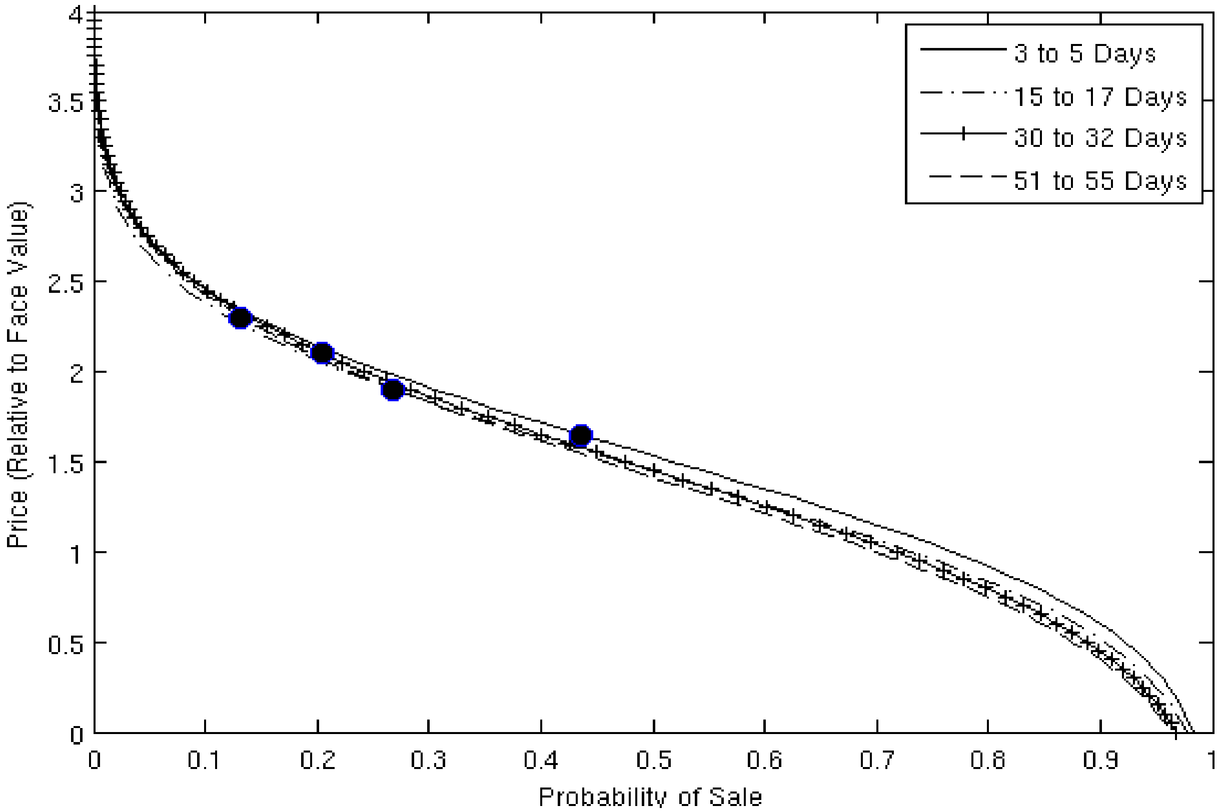


(d) Within-Seller EBay Listing Price Declines
(Experienced Sellers = crosses, Inexperienced Sellers = squares,
dashed lines are 95% confidence intervals,
standard errors clustered on the game)



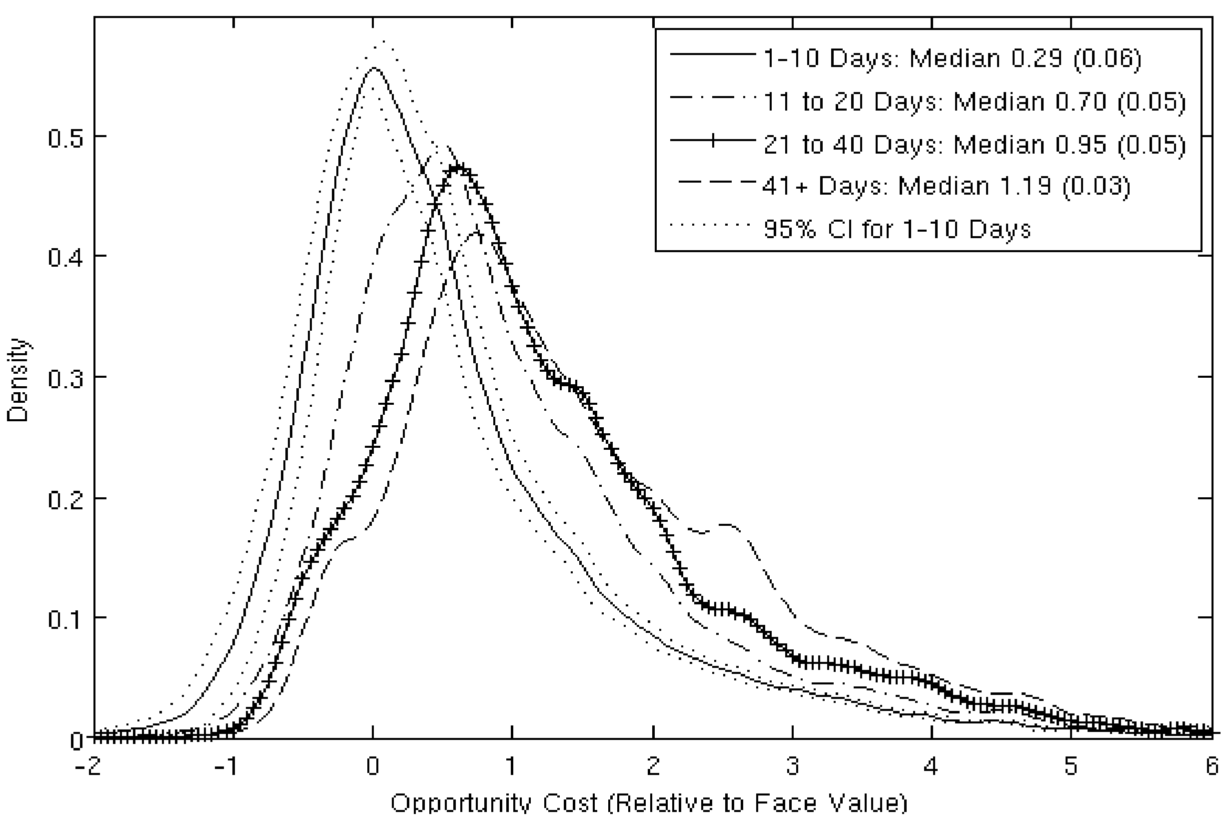
Note: point are the value of the coefficient for the number of days before the game from the pricing regression plus the mean price in 0 to 2 days before the game.

Figure 3: Estimated Inverse Demand Functions



Note: Dots indicate average prices in the four time periods

Figure 4: Distributions of Implied Opportunity Costs



Dynamic Pricing Behavior in Perishable Goods Markets
Not-For-Publication Appendix

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January 2012

1 Data and Summary Statistics

This section provides some additional details on the data, the variables used to control for team form and expected attendance, and a more complete set of summary statistics.

1.1 Stubhub Data

As mentioned in the paper, the list price data from Stubhub was collected using a script which downloaded data each day from the "buy" page for each game. Because of some problems with running the script caused by Stubhub sometimes changing web addresses, the dataset of available prices is not complete. Some data is available for all 2,346 games (excluding, just like the eBay sample, Colorado Rockies home games and 3 Tampa Devil Rays games played in Orlando), and 89% of potential game-day downloads were collected.

As most of the analysis uses eBay data, or uses Stubhub data to show that the patterns found on eBay are not unique to eBay, the incomplete nature of the Stubhub data should not present a problem. However, when estimating demand on eBay, I include the contemporaneous number of listings on Stubhub with the same face value and the median price (relative to face value) of listings on Stubhub as controls. For days when the Stubhub data is missing I use data from the previous day that data was available.

1.2 Team Form Control Variables

The performance of teams during the season is likely to affect demand for tickets to a particular game. In all of the specifications estimated I include 20 variables as controls for both the home and away teams. The following variables are included 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 the division (zero if leading), the number of games ahead in their division (zero if behind), the number of games back from leading their league's wild card race (zero if ahead) and the number of games ahead in the wild card race (zero if behind). These variables were constructed for each day of the season based on game results taken from the website retrosheet.org.

1.3 Expected Attendance Model

It is also useful to have a measure of the game's expected attendance, both as a summary measure of demand to include as a control and as a way of dividing the data into groups of games where demand conditions may be more homogenous. I form a measure by estimating a censored normal regression model of game attendance at 22 dates before a game, corresponding to the days-to-go dummies included in the main specifications in the text, using data from the 2000 to 2007 regular seasons. The dependent variable is the realized attendance of the game, reported by retrosheet.org, as a proportion of the highest attendance during the season. This normalization is used as the highest attendance is greater than nominal capacity for many team-seasons. As attendances vary even when games are sold out, I top-code this normalized attendance variable at 0.98 and use this value as the censoring point.

The explanatory variables are home team dummies, away team dummies, interactions of the home team and away team dummies with the team performance measures on the day in question (e.g., 7 days before the game for the 6-8 day dummy), home team*year dummies, away team*year dummies, home team*month (of game) dummies, home team*day of week (of game) dummies and dummies for whether the game is an interleague game, a game between teams in the same division or an opening home game of the season. The correlation between the realized attendance and the predicted attendance immediately prior to the game is 0.912. The measure of expected attendance is the uncensored expected value of the latent attendance variable implied by the estimated model.

A point worth noting is that primary market prices are not included in the model, because these are not available for years prior to 2007. However, if teams set the same prices for all home games during the season, which used to be standard practice, a price coefficient would not be identified separately from the coefficients on the home team*year dummies.

1.4 Summary Statistics

Table A1 provides summary statistics for all of the variables included in the structural model in Section 5 of the paper, based on the eBay sample used in that part of the paper. The summary statistics are similar for the eBay data used in the price regressions in Section 4, although that sample is significantly larger because it includes listings posted more than 90 days before the game.

2 Robustness Checks on Declining Price Regressions

Table 2 in the paper shows that eBay sellers cut prices significantly for both high and low demand games, and for both cheap and expensive seats. Here I report several additional specifications. These are a small subset of the specifications that I have estimated.

Table A2 reports similar specifications to Table 2 for the Stubhub data, using listing ID fixed effects. Comparing these results with Table 2 reveals some interesting differences between the markets. First, and as was also suggested by the results in Figure 1(c) in the paper, sellers on Stubhub cut prices more than eBay sellers more than 45 days before the game. Second, Stubhub sellers cut prices more than eBay sellers for cheap seats. Unfortunately without Stubhub transaction data it is not possible to quantify how far these differences can be explained by differences in demand across the markets and across different types of ticket.

Table A3 looks in more detail at the eBay data by reporting the results of separate within-seller regressions (seller-game-section-row fixed effects) for each combination of high and low demand games and experienced and inexperienced sellers. Figure 1(d) in the paper showed that experienced and inexperienced sellers on eBay cut prices by roughly similar amounts, and these regressions act as a check on whether this result is misleading because different types of seller sell tickets for different types of games. As in the paper, high and low demand games are games with expected attendances 90 days before the game above 95% and below 70% of capacity respectively. Experienced and inexperienced sellers are those listing for more than 100 games and less than 20 games respectively during the entire dataset.

A noticeable feature of the data is that there are relatively few inexperienced sellers listing for low demand games, so that the number of observations is small and almost all of the coefficients are statistically insignificant. This pattern may seem surprising because one would have expected that brokers would be more active for more profitable high demand games. Set against this is the fact that for low demand games only the most attractive seats in a section tend to be traded on the secondary market and these may be the types of seat that brokers are more likely to have access to.

For high demand games, experienced and inexperienced sellers tend to cut prices by similar amounts, which is consistent with the results for all games in the paper. For low demand games, many of the point estimates are quite similar across the seller types, despite the small sample size for inexperienced sellers. The proportion of price changes that are price reductions are also similar.

3 High and Low Demand Games

Section 5 in the paper showed that on eBay (i) demand is approximately time invariant as a game approaches, (ii) opportunity costs implied by observed prices fall over time and (iii) the assumption that $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$ cannot be rejected in the data, in the sense that there is no evidence that higher prices change future demand or future competition. This section checks that these results hold when the model is estimated for high and low demand games separately. As noted by a referee, it is plausible that demand conditions or seller behavior would differ across these games, and, once again, it is important to know whether pooling these games generates misleading results. High and low demand games are defined in the same way as in the paper and in the previous section.

Columns (1) and (3) of Table A4 present the coefficients from the full model, with the estimated demand curves for the average listing in each case shown in Figure A1. Demand is clearly close to being time-invariant for both types of game, although listing demand is higher for high demand games. Median opportunity costs are lower for high demand games immediately before the game, even though prices are higher. This suggests that most of the people who try to sell tickets on eBay do not intend to go to games themselves or to try to sell them outside the stadium where, for a high demand game, they would probably be able to secure a price significantly above face value. The low demand results do come with a caveat: the F-statistic for the joint significance of the instruments in a first-stage regression is only 7.2 (10.6 for high demand games), suggesting that the instruments may lack power.

Columns (2) and (4) include lagged price in the demand specification, and in both cases the coefficient on the lagged price is small and statistically insignificant. Table A5 reports the OLS and fixed effect coefficients when I repeat the analysis of whether a higher price affects the future value of each of the competition variables, and the total effect of these competition changes on the probability that a re-posted listing sells. The IV results are similar, but as noted above the instruments lack power for low demand games. As with the results in the paper, the OLS total effects are statistically significant but very small (as a comparison, the probability that a relisting sells is 0.32 for high demand games and 0.25 for low demand games), while the total effects in the fixed effect specifications are even smaller and statistically insignificant. The results are therefore consistent with the condition $\frac{\partial E_t(V_{it+1})}{\partial p_{it}} = 0$ holding in the data.

4 Endogenous Competitor Prices

The estimated model in Section 5 of the paper treats the average and minimum prices of competitors' listings as exogenous. This is a useful assumption because, when only the seller's own price is endogenous, the model can be estimated efficiently using Full Information Maximum Likelihood. The method becomes infeasible as the number of parameters increases. However, it is possible to allow for the endogeneity of competitors' prices when the model is estimated using a two-step method, following Rivers and Vuong (1988). In this approach, first stage equations are estimated for each of the endogenous variables and the residuals from the first-stage equations are included in the second stage probit specification. This approach is less efficient than FIML, but it produces consistent estimates of scaled versions of the probit parameters. I calculate additional instruments by using the same instruments as before averaged across rival listings.

The demand and median opportunity cost estimates are included in columns (5) and (6) of Table A4, and the demand curves for average listings are shown in Figure A2. One change is that the coefficient on the mean price of rival fixed price listings becomes significantly larger, indicating stronger competition effects. However, demand remains close to time-invariant and implied opportunity costs fall significantly as a game approaches.

References

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

Table A1: Summary Statistics for eBay Fixed Price Listings
(sample and variables correspond to those in the structural model in Section 5)

Variable Name	Observations	Mean	Std. Dev	Min	Max
Sale Dummy	113,186	0.293	0.455	0	1
Relative Fixed Price (incl. shipping)	113,186	2.002	1.281	0.000	8.333
Relative Fixed Price (excl. shippning and commission)	113,186	1.773	1.201	0.000	8.057
Competition variables					
Average Price Competing Fixed Price Listings	113,186	1.947	1.653	0	36.251
Minimum Price Competing Fixed Price Listings	113,186	1.317	1.253	0	36.251
Average Start Price Competing Auction Listings	113,186	0.775	0.999	0	29.109
Minimum Start Price Competing Auction Listings	113,186	0.367	0.742	0	29.109
No Competing Fixed Price Listings	113,186	0.190	0.392	0	1
No Competing Auction Listings	113,186	0.349	0.477	0	1
Ln(Number of Competing Fixed Price Listings + 1)	113,186	1.371	0.967	0	4.585
Proportion of Fixed Price Listings with Feedback Scores > 100	113,186	0.464	0.296	0	0.977
Ln(Number of Competing Auction Listings + 1)	113,186	1.080	1.034	0	4.673
Proportion of Auction Listings with Feedback Scores > 100	113,186	0.383	0.379	0	1
Ln(Number of Stubhub Listings + 1)	113,186	3.689	1.344	0	7.062
Seat Characteristics					
2 Seats	113,186	0.847	0.360	0	1
3 Seats	113,186	0.029	0.169	0	1
4 Seats	113,186	0.099	0.299	0	1
5 Seats	113,186	0.010	0.100	0	1
6 Seats	113,186	0.010	0.099	0	1
Face Value, $	113,186	38.430	36.232	5	312
Parking Included	113,186	0.024	0.154	0	1
Front Row (of section)	113,186	0.128	0.334	0	1
Second Row	113,186	0.084	0.277	0	1
Row Number	113,186	9.174	7.600	0	26
General Admission	113,186	0.006	0.075	0	1
No Row Listed	113,186	0.083	0.276	0	1
Listing Characteristics					
Non eBay Store Listing	113,186	0.782	0.413	0	1
Seller ever uses eBay store	113,186	0.498	0.500	0	1
Seller Feedback 10-100	113,186	0.096	0.295	0	1
Seller Feedback 101-1000	113,186	0.421	0.494	0	1
Seller Feedback 1000+	113,186	0.462	0.499	0	1
Any Highlighting	113,186	0.035	0.185	0	1
Gallery	113,186	0.223	0.416	0	1
Picture	113,186	0.038	0.190	0	1

Table A1 cont.: Summary Statistics for eBay Fixed Price Listings
(sample and variables correspond to those in the structural model in Section 5)

Variable Name	Observations	Mean	Std. Dev	Min	Max
Game Demand Controls					
Monday	113,186	0.110	0.313	0	1
Tuesday	113,186	0.151	0.358	0	1
Wednesday	113,186	0.149	0.356	0	1
Thursday	113,186	0.095	0.293	0	1
Friday	113,186	0.162	0.368	0	1
Saturday	113,186	0.160	0.367	0	1
Expected Attendance	113,186	0.911	0.209	0.24	1.528
Median Relative Price on Stubhub	113,186	1.790	0.979	0	14.166
Home Team Record	113,186	0.512	0.107	0	1
Away Team Record	113,186	0.502	0.108	0	1
Home Games Ahead	113,186	0.803	2.114	0	11.5
Home Games Back	113,186	3.542	4.945	0	29
Away Game Ahead	113,186	0.676	1.996	0	11.5
Away Games Back	113,186	4.551	5.858	0	29
Home Wildcard Game Back	113,186	2.864	4.289	0	26.5
Home Wildcard Games Ahead	113,186	0.117	0.529	0	5.5
Away Wildcard Games Back	113,186	3.851	5.126	0	26.5
Away Wildcard Games Ahead	113,186	0.078	0.444	0	5.5
Days to Go Dummies (Listing date)					
3 to 5	113,186	0.089	0.285	0	1
6 to 8	113,186	0.081	0.273	0	1
9 to 11	113,186	0.047	0.212	0	1
12 to 14	113,186	0.084	0.278	0	1
15 to 17	113,186	0.055	0.229	0	1
18 to 20	113,186	0.049	0.216	0	1
21 to 23	113,186	0.045	0.207	0	1
24 to 26	113,186	0.039	0.193	0	1
27 to 29	113,186	0.035	0.183	0	1
30 to 32	113,186	0.033	0.178	0	1
33 to 35	113,186	0.030	0.170	0	1
36 to 38	113,186	0.027	0.163	0	1
39 to 41	113,186	0.016	0.126	0	1
42 to 44	113,186	0.031	0.173	0	1
45 to 47	113,186	0.023	0.149	0	1
48 to 50	113,186	0.022	0.147	0	1
51 to 55	113,186	0.034	0.180	0	1
56 to 60	113,186	0.032	0.175	0	1
61 to 70	113,186	0.055	0.227	0	1
71 to 80	113,186	0.051	0.220	0	1
81 plus	113,186	0.049	0.217	0	1
Instruments					
Seller Within 25 miles of Stadium	113,186	0.288	0.453	0	1
Seller More than 125 miles of Stadium	113,186	0.425	0.494	0	1
Proportion of Unsold Listings Relisted	113,186	0.262	0.234	0	1
Proportion of Other Listings in BIN Format	113,186	0.122	0.209	0	1
Proportion of Other Listings in Fixed Price Format	113,186	0.709	0.343	0	1
Seller with One Listing	113,186	0.012	0.107	0	1
Seller with Less than 10 Listings	113,186	0.070	0.255	0	1

Table A2: Within-Seller Price Changes for Particular Types of Ticket on Stubhub

	High Demand	Low Demand	Cheap Seats (<=$20)	Expensive Seats (>=$45)
Average Price 0-2 Days Prior to Game	1.94	0.83	1.53	1.45
Selected Days To Go Coefficients				
3 to 5	0.146***	0.0627	0.196***	0.0824***
	(0.033)	(0.043)	(0.039)	(0.020)
6 to 8	0.307***	0.142***	0.319***	0.198***
	(0.038)	(0.046)	(0.047)	(0.024)
9 to 11	0.457***	0.239***	0.494***	0.301***
	(0.042)	(0.048)	(0.051)	(0.026)
15 to 17	0.644***	0.428***	0.751***	0.428***
	(0.050)	(0.054)	(0.057)	(0.029)
21 to 23	0.808***	0.608***	1.025***	0.534***
	(0.055)	(0.062)	(0.067)	(0.031)
30 to 32	1.010***	0.821***	1.346***	0.662***
	(0.066)	(0.080)	(0.087)	(0.034)
39 to 41	1.176***	0.985***	1.626***	0.768***
	(0.078)	(0.080)	(0.095)	(0.038)
51 to 55	1.437***	1.197***	2.035***	0.899***
	(0.095)	(0.086)	(0.110)	(0.044)
81 plus	2.028***	1.681***	2.970***	1.146***
	(0.150)	(0.120)	(0.150)	(0.061)
Observations	964,047	315,477	542,559	741,566
% of Price Changes that are Price Declines	86.4%	90.2%	87.0%	88.5%
Adj. R-squared	0.931	0.737	0.787	0.908

Note: coefficients from listing ID fixed effect regressions, standard errors clustered on the game. Regressions include controls for listing characteristics, competition and team performance described in the text. Sample is based on a 5% sample of game-sections.
***,**,* denote significance at 1, 5 and 10% levels.

Table A3: Within-Seller Price Changes for High and Low Demand Games on eBay By Experience of Seller

	Experienced Sellers		Inexperienced Sellers	
	High Demand	Low Demand	High Demand	Low Demand
Average Price 0-2 Days Prior to Game	1.76	0.85	2.17	1.06
Selected Days To Go Coefficients				
3 to 5	0.298	0.204***	0.476	0.101
	(0.250)	(0.075)	(0.290)	(0.180)
6 to 8	0.951***	0.292***	0.713*	0.149
	(0.270)	(0.074)	(0.410)	(0.240)
9 to 11	0.988***	0.425***	0.789**	0.419
	(0.240)	(0.070)	(0.320)	(0.270)
15 to 17	1.143***	0.537***	1.098***	0.479
	(0.250)	(0.076)	(0.410)	(0.350)
21 to 23	1.413***	0.586***	1.410**	0.416**
	(0.260)	(0.073)	(0.650)	(0.190)
30 to 32	1.493***	0.653***	1.640**	0.406
	(0.290)	(0.086)	(0.700)	(0.290)
39 to 41	1.593***	0.660***	1.520***	0.625
	(0.260)	(0.086)	(0.570)	(0.410)
51 to 55	1.764***	0.718***	1.714***	0.749
	(0.290)	(0.089)	(0.550)	(0.500)
81 plus	1.962***	0.848***	1.802***	0.381
	(0.320)	(0.093)	(0.670)	(0.360)
Observations	28,544	16,278	14,613	2,657
% of Price Changes that are Price Declines	78.1%	84.6%	81.4%	85.2%
Adj. R-squared	0.93	0.85	0.97	0.97

Note: coefficients from seller-game-section-row fixed effects regressions, standard errors clustered on the game. Regressions include controls for listing characteristics, competition and team performance described in the text. ***,**,* denote significance at 1, 5 and 10% levels.

Table A4: Alternative Demand Specifications

	(1) High Demand Games	(2) High Demand Games with Lagged Price	(3) Low Demand Games	(4) Low Demand Games with Lagged Price	(5) Endogenous Competitor Prices	(6) Endogenous Competitor Prices with Lagged Price
Estimation Method	FIML	FIML	FIML	FIML	Two-Step	Two-Step
Own Relative Price Coefficients						
1-10 Days Before Game	-0.754***	-0.730***	-1.434***	-1.430***	-1.096***	-1.050***
	(0.037)	(0.038)	(0.052)	(0.052)	(0.095)	(0.072)
11-20 Days Before Game	-0.776***	-0.745***	-1.417***	-1.394***	-1.103***	-1.037***
	(0.034)	(0.036)	(0.055)	(0.056)	(0.096)	(0.079)
21-40 Days Before Game	-0.750***	-0.721***	-1.356***	-1.345***	-1.112***	-1.053***
	(0.035)	(0.037)	(0.066)	(0.066)	(0.094)	(0.073)
41+ Days Before Game	-0.745***	-0.718***	-1.318***	-1.314***	-1.068***	-1.019***
	(0.034)	(0.036)	(0.065)	(0.063)	(0.089)	(0.073)
Previous Price	-	-0.014	-	0.000		0.009
		(0.014)		(0.035)		(0.010)
Competition Coefficients (EBay)						
Mean Relative Price for Fixed Price Listings	0.159***	0.154***	0.183***	0.181***	0.687***	0.607***
	(0.012)	(0.012)	(0.025)	(0.025)	(0.121)	(0.116)
Mean Relative Start Price for Auction Listings	-0.015	-0.013	0.0503	0.049	0.193	0.165
	(0.013)	(0.013)	(0.032)	(0.032)	(0.158)	(0.155)
Minimum Relative Price for Fixed Price Listings	0.005	0.003	-0.015	-0.016	-0.114	-0.042
	(0.011)	(0.011)	(0.026)	(0.026)	(0.121)	(0.091)
Minimum Relative Price for Auction Listings	-0.006	-0.010	-0.001	-0.003	-0.276	-0.253
	(0.015)	(0.015)	(0.037)	(0.037)	(0.208)	(0.216)
Dummy Variable for No Competing	0.515***	0.465***	0.171***	0.141***	1.231***	1.200***
Fixed Price Listings	(0.045)	(0.046)	(0.052)	(0.053)	(0.354)	(0.288)
Dummy Variable for No Competing	-0.069*	-0.068*	-0.099**	-0.095*	-0.283***	-0.288***
Auction Listings	(0.034)	(0.034)	(0.051)	(0.051)	(0.100)	(0.102)
Number of Competing Fixed Price Listings (Log N+1	-0.111***	-0.079***	-0.236***	-0.194***	-0.257***	-0.164***
	(0.024)	(0.024)	(0.033)	(0.032)	(0.066)	(0.054)
Proportion of Competing Fixed Price Listings with	0.238***	0.092	0.190***	0.049	0.291***	0.110
Seller Feedback Scores Above 100	(0.059)	(0.061)	(0.073)	(0.072)	(0.073)	(0.077)
Number of Competing Auction Listings (Log N+1)	0.003	-0.014	0.043	0.034	-0.112	-0.118
	(0.021)	(0.022)	(0.029)	(0.029)	(0.091)	(0.100)
Proportion of Competing Auction Listings with	-0.030	0.003	-0.100**	-0.076*	-0.045	-0.014
Seller Feedback Scores Above 100	(0.032)	(0.033)	(0.041)	(0.041)	(0.029)	(0.034)
Competition Coefficients (Stubhub)						
Log(Number of Stubhub Listings+1)	0.008	0.013	0.051***	0.053***	-0.004	-0.001
	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.013)
Correlation Coefficients						
1-10 Days Before Game	0.635***	0.605***	0.773***	0.772***	-	
	(0.038)	(0.039)	(0.041)	(0.040)		
11-20 Days Before Game	0.664***	0.621***	0.749***	0.728***	-	
	(0.038)	(0.041)	(0.041)	(0.043)		
21-40 Days Before Game	0.588***	0.549***	0.717***	0.709***	-	
	(0.041)	(0.043)	(0.048)	(0.047)		
41+ Days Before Game	0.589***	0.553***	0.708***	0.707***	-	
	(0.042)	(0.044)	(0.054)	(0.052)		
Median Opportunity Costs						
1-10 Days Prior to Game	0.200	0.119	0.470	0.464	0.127	0.078
	(0.117)	(0.106)	(0.061)	(0.052)	(0.103)	(0.086)
11-20 Days Prior to Game	0.889	0.794	0.752	0.730	0.539	0.502
	(0.094)	(0.101)	(0.041)	(0.040)	(0.090)	(0.075)
21-40 Days Prior to Game	1.177	1.109	0.933	0.920	0.880	0.848
	(0.088)	(0.077)	(0.043)	(0.040)	(0.070)	(0.060)
More than 41 Days Prior to Game	1.574	1.522	1.055	1.050	1.137	1.116
	(0.072)	(0.067)	(0.038)	(0.031)	(0.057)	(0.056)
Number of observations	50,830	50,830	25,478	25,478	113,186	113,186

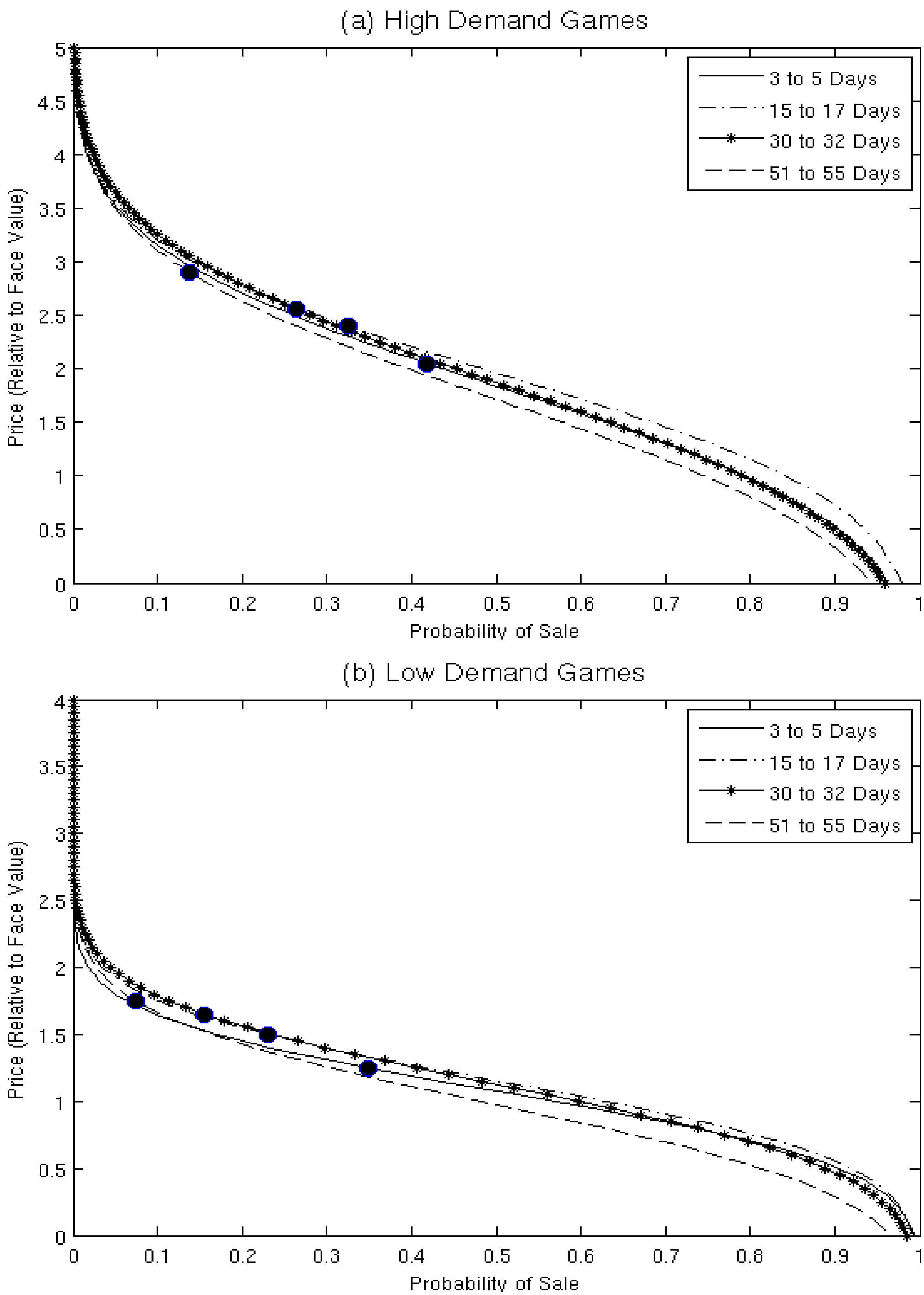
Notes: Specification also include number of seat dummies, seller feedback score dummies, controls for ticket and listing characteristics, home team dummies, home team*face value, and home team*expected attendance interactions, form variables, game day of week dummies, days to go dummies. Robust standard errors in parentheses clustered on the game. ***,** and * denote significance at 1%, 5% and 10% levels.

Table A5: Effect of Current Price on Future Value of Competition Variables

	High Demand Games		Low Demand Games	
Dependent Variable	OLS	Game-Face Fixed Effects	OLS	Game-Face Fixed Effects
Mean Price of Competing Fixed Price Listings	0.0063 (0.0134)	-0.0271* (0.0141)	0.0662 (0.0215)	-0.0419 (0.0328)
Dummy for No Competing Fixed Price Listings	-0.0028 (0.0021)	-0.0025 (0.0024)	-0.0075 (0.0079)	0.0120 (0.0111)
Number of Competing Fixed Price Listings	-0.0107 (0.0053)	-0.0203 (0.0069)	-0.0339** (0.0135)	-0.0512** (0.0228)
Minimum Price of Competing Fixed Price Listings	0.0295 (0.0130)	0.0185 (0.0122)	0.0725*** (0.0202)	-0.0162 (0.0239)
Proportion of Competing Fixed Price Listings with Feedback Scores >100	-0.0021 (0.0021)	-0.0011 (0.0026)	-0.0094* (0.0052)	-0.0117 (0.0089)
Mean Start Price of Competing Auction Listings	0.0030*** (0.0105)	0.0002 (0.0127)	0.0358 (0.0130)	0.0047 (0.0190)
Dummy for No Competing Auction Listings	-0.0014 (0.0031)	-0.0005 (0.0037)	0.0099 (0.0078)	0.0006 (0.0122)
Number of Competing Auction Listings	-0.0104* (0.0059)	-0.0196*** (0.0074)	-0.0228 (0.0133)	-0.0205 (0.0210)
Minimum Price of Competing Auction Listings	0.0268*** (0.0084)	0.0218** (0.0109)	0.0213* (0.0131)	0.0069 (0.0185)
Proportion of Competing Auction Listings with Feedback Scores >100	-0.0019 (0.0030)	-0.0063* (0.0035)	-0.0071 (0.0079)	0.0074 (0.0126)
Number of Stubhub Listings (Log N+1)	0.0004 (0.0029)	0.0016 (0.0028)	0.0002 (0.0076)	-0.0182* (0.0104)
Increase in the Probability that Relisted Tickets Sell When Current Price is Increased by Face Value	0.0062*** (0.0023)	-0.0017 (0.0033)	0.0090*** (0.0024)	-0.0009 (0.0033)

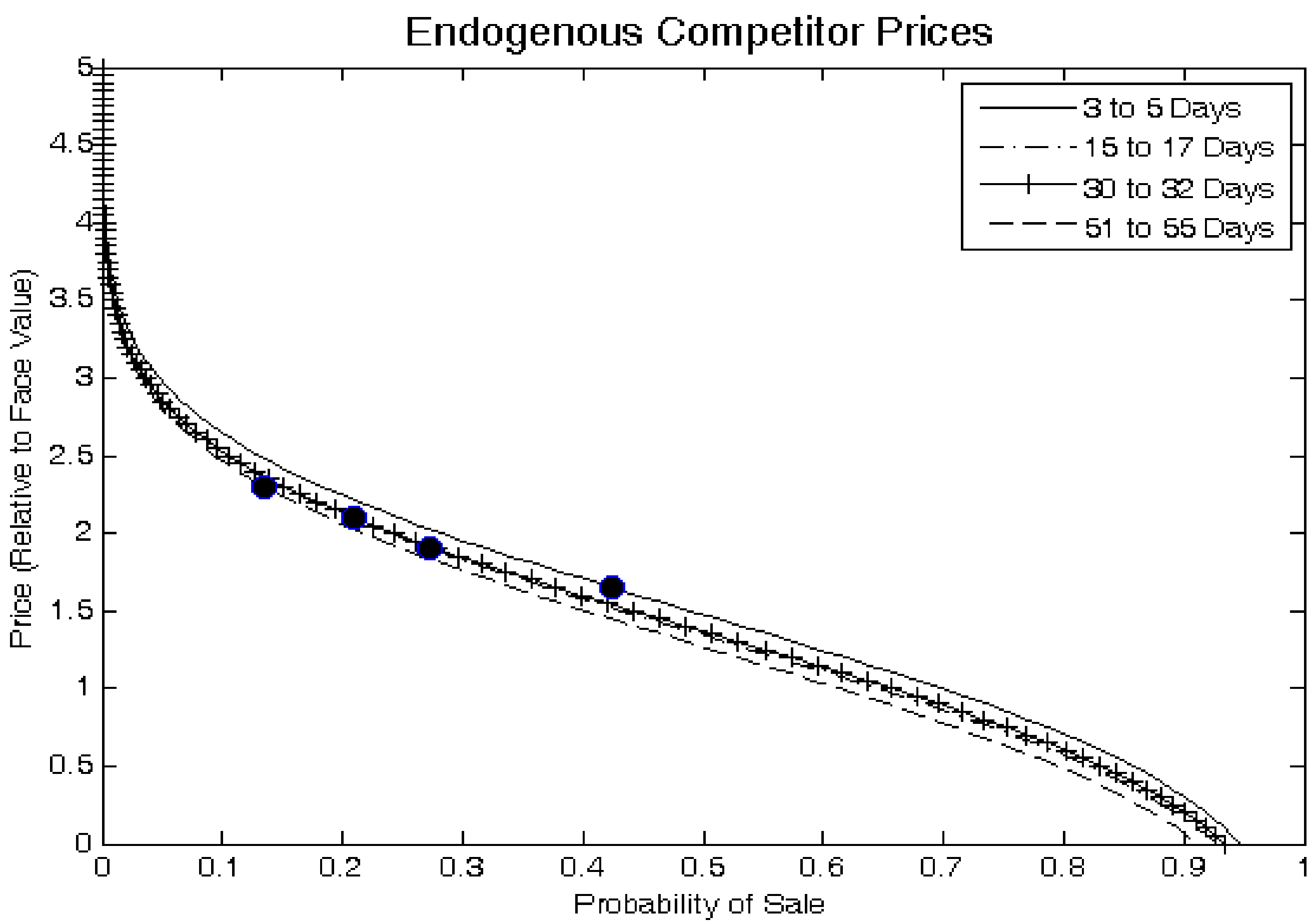
Notes: Robust standard errors in parentheses clustered on the game. ***,** and * denote significance at 1, 5 and 10% levels. Excluding final row, table shows coefficients on the current price in regressions which include the controls from the demand equation, plus days-to-go dummies for when the next listing takes place. The dependent variable is the value of the competition variable when the listing is next posted. Number of observations for high (low) demand games is 13,155 (7,117). The coefficients in the final row reflect the combined effect of all of the changes in the competition variables, holding the price of the re-listing fixed, calculated using the full model results in column (2) of Table 4.

Figure A1: Inverse Demand Curves



Note: Dots indicate average prices in the four time periods

Figure A2: Inverse Demand Curves



Note: Dots indicate average prices in the four time periods