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

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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' behavior in secondary markets for event tickets, a classic example of a perishable good. It shows that the simplest dynamic pricing models describe very accurately both the pricing problem faced by sellers and how they behave, explaining why sellers cut prices dramatically, by 40 percent 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 percent.

I. 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 chief executive of-

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ficer 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 (*Wall Street Journal* 2011).

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 (e.g., monopoly or competition), how demand changes over time, and the ability of consumers to act strategically. However, there is little work testing which of these models describe the problem faced by sellers, whether they behave in the way predicted or quantifying the value of DP. 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.

These markets provide a natural setting to examine DP for several reasons. First, there is a clear dynamic pattern to prices 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, relative to face value, on eBay.[2] The figure shows raw average prices, but I show below that the declines are very similar controlling for listing and game heterogeneity. Individual sellers cut prices even more dramatically, by around 90 percent of face value in the month before the game. The main 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 so might have been assumed to be relatively unsophisticated, and do not use the type of automated DP systems developed by airlines.[3]

[1] Smith, Leimkuhler, and Darrow (1992) estimate that yield management increased American Airlines' 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 $5 million 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).

[2] Bhave and Budish (2012) also document large price declines in eBay secondary markets for concert tickets.

[3] As part of an ongoing 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

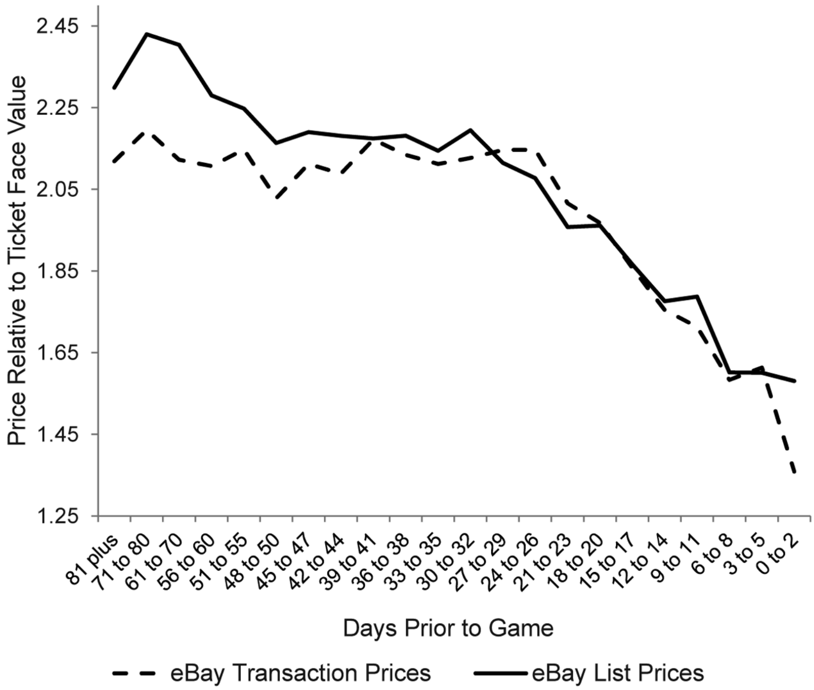

FIG. 1.—Average prices of tickets on eBay. Average list prices are calculated using 178,659 fixed-price only listings on eBay, and average transaction prices are calculated using 290,410 eBay transactions in any sales format.

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 result that theory accurately describes how sellers behave may also hold in other settings. For example, like many airline, hotel, and retail markets, these markets 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 mil-

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over time on the basis of several informal "rules of thumb" that are broadly consistent with DP 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.

lion 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 testing DP theories using airline or hotel data has used listing data (Escobari and Gan 2007; Celen and Thomas 2009; Abrate, Fraquelli, and Viglia 2012) or transaction data (Puller, Sengupta, and Wiggins 2009) but not both.[4]

Section II sets out a general theoretical framework for DP in which each seller has a single unit to sell. At any time t, the seller's optimal price should be equal to the opportunity cost of a sale, which is just the expected value of holding the unit in the next period, $E_t(V_{it+1})$, plus a markup. The markup reflects the shape of the current demand curve and the effect that the seller's current price has on his opportunity cost, $\partial E_t(V_{it+1})/\partial p_{it}$. Based on different assumptions about consumer demand and market structure, this structure leads to DP models giving a wide range of predictions about how prices should change. For example, 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 faces stochastically arriving buyers, with valuations drawn from a time-invariant distribution, who have to buy at once or exit the market forever.[5] These assumptions imply that each seller's demand is time invariant, $\partial E_t(V_{it+1})/\partial p_{it} = 0$, and that the sellers should lower prices over time, the robust pattern observed in the data.[6] On the other hand, if consumers can act strategically by delaying purchase when they expect prices to fall, as assumed by recent theoretical papers such as Su (2007), Aviv and Pazgal (2008), Levin, McGill, and Nediak (2009), Board and Skrzypacz (2010), and Horner and Samuelson (2011), then $\partial E_t(V_{it+1})/\partial p_{it} > 0$, as a higher price will increase future demand, but demand in earlier periods will tend to be more elastic so that the seller's optimal price may rise (a case illustrated by example in Sec. VI), or at least fall by less, in equilibrium. On the other hand, a model with a mass

[4] As an exception, Lazarev (2011) combines listing data that show how the price of seats for individual flights changes as the date of departure approaches with aggregate transaction data that show 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 traveled.

[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 homogeneous, the optimal policy involves a price that is close to being fixed as the time remaining and the number of units in the initial inventory are taken to infinity.

of competitive sellers and a mass of strategic buyers predicts that prices should evolve as a martingale (Deneckere and Peck 2012), so that, in expectation, the "law of one price" holds.

However, while DP theories do not make a general prediction about how prices should change, all existing models, which assume that $\partial E_t(V_{it+1})/\partial p_{it} \geq 0$, predict that the implied opportunity cost of sale, which can easily be calculated using observed prices, estimates of demand, and assumptions about $\partial E_t(V_{it+1})/\partial p_{it}$, should fall as a game approaches. In contrast, implied opportunity costs would not fall if, rather than pricing dynamically, sellers set prices ignoring their ability to relist unsold tickets in the future. Assuming that $\partial E_t(V_{it+1})/\partial p_{it} = 0$, I show that implied opportunity costs do fall, with every percentile of their distribution decreasing monotonically as a game approaches. I also show that the assumption that $\partial E_t(V_{it+1})/\partial p_{it} = 0$ is consistent with the data and that demand is approximately time invariant so that a simple DP model correctly characterizes a seller's pricing problem in this market. This model also predicts quite accurately how much sellers cut prices and how much their opportunity costs decline. Relative to a non-DP strategy, the estimates predict that DP increases the average seller's expected profit by 16 percent.

The fact that simple DP models work so well is potentially puzzling because demand is time invariant in these models partly because they assume that consumers cannot time their purchases strategically.[7] In contrast, in recent models, such as those cited above, that allow for strategic consumers, early demand tends to be more elastic as consumers will choose to wait if prices are too high. In Section VI, I present a simple alternative demand model that can generate time-invariant demand and falling prices in equilibrium. In this model, consumers are strategic but face search costs when they participate in the market, and there is heterogeneity in how willing they are to delay purchasing, possibly due to some of them having to make complementary investments to attend a game. These frictions lead to buyers sorting into when they participate in the market on the basis of their delay costs, and it can lead to the same equilibrium demand and pricing outcomes as a simple DP model. I also show that the data provide some evidence of this type of sorting, as consumers who live much further from the stadium, who might have to make more investments to attend games, tend to buy tickets much earlier before the game. Highlighting how search frictions and waiting costs can affect the predictions of DP models and providing evidence that they may matter in practice are further contributions of the paper.

[7] The finding that $\partial E_t(V_{it+1})/\partial p_{it} \approx 0$, as a seller's price has very little effect on its own future demand or competition, can potentially be explained by the simple fact that each seller constitutes a small part of the market for most events.

The finding that a particular type of DP model explains 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; van den Berg, van Ours, and Pradhan 2001), my explanation for why the law of one price fails does not rely on either unobserved object heterogeneity or the particular ways in which goods are sold. Instead, it reflects the fundamental profit-maximizing incentives of sellers and the way in which search and waiting costs, that are likely to be present in a wide range of markets, may limit the effects of strategic consumer behavior. 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 in which 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 in which the secondary market clears instantaneously (Courty 2000, 2003*a*, 2003*b*; 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 II presents the theoretical framework. Section III describes the data and the relevant institutional background. Section IV shows that declining transaction and list prices are robust features of the data. Section V tests whether opportunity costs decline and shows that simple DP models characterize sellers' pricing problems and their behavior accurately. Section VI presents the model and evidence of consumer sorting as a form of strategic behavior that is consistent with my empirical results. Section VII presents conclusions. An online Appendix provides additional details of the data and robustness checks on the main empirical results.

II. Theoretical Framework

This section presents a general theoretical framework for DP models and outlines my empirical strategy. Section VI presents a specific model that is useful in thinking about the effects and limits of strategic buyer behavior.

Suppose that sellers, each with a single, differentiated listing (e.g., a pair of seats), play a finite-horizon, stochastic, discrete-time game with periods $t = 1, \ldots, T$ leading up to an event at $T + 1$.[8] There is no time discounting. In period t, the state of the market is described by the current level of demand for the event, the set of N_t sellers in the market, who are assumed to set prices each period, and their expected values of still holding their tickets at the time of the game. The game is stochastic as the state may vary exogenously (e.g., because of a positive demand or supply shock for the event) over time, as well as evolving endogenously because of sellers' pricing strategies. In order to simplify the exposition, I assume that sellers perfectly observe the state, although I briefly discuss the role that learning may play in causing prices to decline when I discuss the empirical results. Assuming that all sellers set prices optimally, only as a function of the current state, the equilibrium concept is Markov perfect Nash equilibrium.[9]

An optimizing risk-neutral seller i with a single listing to sell will choose a price p_{it} to maximize his value, defined by the Bellman equation

$$V_{it} = \max_{p_{it}} p_{it} q_{it}(p_{it}) + [1 - q_{it}(p_{it})] E_t(V_{it+1}), \tag{1}$$

where $q_{it}(p_{it})$ is the probability with which i will sell in period t given the current level of demand, his own price p_{it}, and the equilibrium prices set by competitors. I assume that $\partial q_{it}(p_{it})/\partial p_{it} < 0$. The opportunity cost of a sale at time t, $E_t(V_{it+1})$, is i's expected value of still having the listing at $t + 1$ given the current state and how it may evolve. To be general, it may depend on p_{it}. For example, a higher p_{it} may cause a buyer who is interested in listing i to wait, increasing future demand. The dependence of demand and expectations on the current state is suppressed to reduce notation. The term $E_t(V_{iT+1})$ is the expected value of still holding the listing at the time of the event, which might be equal to zero for some sellers. Assuming free disposal, opportunity costs must be nonnegative.

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

[8] I use discrete time to simplify the presentation. Lin and Sibdari (2009) and Deneckere and Peck (2012) also present discrete-time DP models. As my description focuses on the price-setting problem of a single seller, it would be straightforward, with some notational changes, to interpret the model as one in which only one seller gets to change his price in any period, and this seller's pricing strategy would be a function of competitors' prices that were set previously and the price changes that the seller expects before the next opportunity to change his price.

[9] As prices are set simultaneously, uniqueness of the equilibrium would depend on the particular form of demand that is assumed and the particular assumptions that are made about the entry and exit of sellers. My analysis is based on a seller's pricing first-order condition, the structure of which should be common across equilibria.

$$p_{it}^{*} = \frac{q_{it}(p_{it}^{*}) + [1 - q_{it}(p_{it}^{*})][\partial E_t(V_{it+1})/\partial p_{it}]}{|\partial q_{it}(p_{it}^{*})/\partial p_{it}|} + E_t(V_{it+1}). \quad (2)$$

Depending on how the shape of the demand curve changes, the markup may rise or fall over time, so that there is no general prediction about how prices change. For example, simple DP models with exogenous time-invariant demand predict that prices should fall, whereas a model with strategic consumers may predict that prices increase (see Sec. VI for an example) or evolve as a martingale (Deneckere and Peck 2012). However, the structure of equations (1) and (2) leads to a prediction about how opportunity costs should evolve.

Proposition 1. If $\partial E_t(V_{it+1})/\partial p_{it} \geq 0$ for all states and periods, then when a seller uses his optimal strategy, expected opportunity costs will fall over time.[10]

Proof. The assumption that $\partial E_t(V_{it+1})/\partial p_{it} \geq 0$ implies a nonnegative markup in equation (2), so that $p_{it}^{*} \geq E_t(V_{it+1})$ for all states and periods. Equation (1) then implies that $V_{it} \geq E_t(V_{it+1})$, and the inequality will be strict if $q_{it}(p_{it}^{*}) > 0$. 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. QED

The condition that $\partial E_t(V_{it+1})/\partial p_{it} \geq 0$ holds in all models of which I am aware in the current DP literature, so that declining opportunity costs are a quite general prediction.[11] For example, in simple DP models, $\partial E_t(V_{it+1})/\partial p_{it} = 0$ as there is a single seller and consumers arrive exogenously and cannot respond to a high price by delaying purchase. The ability of consumers to act strategically leads to $\partial E_t(V_{it+1})/\partial p_{it} \geq 0$ as an increase in the current price will increase how many potential buyers there are in the future;[12] and in models with a fixed set of differentiated competitors, such as Lin and Sibdari (2009), $\partial E_t(V_{it+1})/\partial p_{it} \geq 0$ as a higher current price makes it more likely that competitors make sales, decreasing how many competitors the seller will face in the future or increasing the prices that they set.

Looking at whether the opportunity costs implied by observed prices tend to fall over time therefore provides a general qualitative test of DP models. An alternative behavioral model would be one in which sellers

[10] Berman, Hu, and Pang (2010) also show that expected opportunity costs decline in a simple DP model in which $\partial E_t(V_{it+1})/\partial p_{it} = 0$.

[11] One could construct a DP model in which $\partial E_t(V_{it+1})/\partial p_{it} < 0$ 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.

[12] Deneckere and Peck (2012) assume perfect competition with homogeneous products, a mass of sellers, and a mass of strategic buyers. Because each seller is small, a higher price in the current period affects only the probability that the seller sells in the current period, not the probability that it sells at a given price in a future period.

ignored their ability to relist unsold tickets, possibly at different prices, in the future so that

$$p_{it}^{*} = E_t(V_{iT+1}) + \frac{q_{it}(p_{it}^{*})}{|\partial q_{it}(p_{it}^{*})/\partial p_{it}|} \tag{3}$$

in all time periods. In this case, the implied opportunity cost would always equal $E_t(V_{iT+1})$ and would not be expected to systematically decline over time.

Rather than trying to estimate a complete model of the market, I calculate opportunity costs using equation (2), observed prices, and estimates of per-period demand assuming that $\partial E_t(V_{it+1})/\partial p_{it} = 0$. The demand estimates indicate that demand is approximately time invariant, and I show that the other main assumption of simple DP models, that $\partial E_t(V_{it+1})/\partial p_{it} = 0$, is also consistent with the data by looking at how lagged prices affect a seller's own demand and its future competition. By making some additional plausible assumptions on how many times a seller expects to relist unsold tickets, I am also able to use equations (1) and (2) to predict how much prices and opportunity costs should fall over time and to confirm that these predicted declines are close to the average declines observed in the data.

III. Data

The empirical analysis uses data for single-game tickets to regular season MLB games in 2007 from two online secondary markets, eBay and StubHub.[13] 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.[14] In 2007 StubHub and 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 Market-

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

[14] Brokers could also act as buyers in the secondary market with the intention of reselling tickets. The price declines that I describe can make this type of activity unprofitable, and on eBay most cases in which 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 sales. 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 percent less than complete information listings. This discount may be large enough to make this type of strategy unprofitable.

place" in 2008. The sample includes the home games of all MLB teams except the Colorado Rockies, which was the only team to practice (a very limited form of) DP in the primary market.[15] 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.[16] 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 percent commissions on each transaction and also sets shipping costs.[17] My StubHub data consist 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.[18] Each listing has an identification number that allows for some tracking of listings over time, although this is imperfect because many sellers change prices by posting a new listing.[19] For the analysis below, I drop listings with missing section information (0.3 percent of the initial sample), more than six seats (9 percent), and prices more than $1,000 per seat (0.1 percent).

Sellers on eBay list tickets in a variety of auction and fixed-price formats (auction, hybrid buy-it-now [BIN] 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 percent and 7 percent 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 were purchased from Advanced E-Commerce Research Systems, and they contain data on listings, bids, and transactions from all event ticket listings from January 1 to September 30, 2007. For listings, the data contain the same information as the StubHub data, together with in-

[15] I exclude makeups 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.

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

[17] FedEx shipping costs were $11.95 for transactions more than 14 days before the game and $16.95 for transactions thereafter. Tickets sold within 3 days of the game were picked up at an office close to each stadium for a $15 handling charge.

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

[19] 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 .66.

formation on the listing's format, its duration, reserve prices for auctions, indicators for whether the listing was highlighted or had pictures, and seller ID numbers and feedback scores. The bid data contain information on the bidder's ID 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 include buyer and seller ID numbers, their feedback scores, shipping costs, and the zip codes of the buyer and seller.[20] For the analysis below, I drop listings with missing section information, more than six seats, prices more than $1,000 per seat, and shipping costs more than $40. These restrictions together drop 0.7 percent of the sample. Most of the analysis uses data on nonauction 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. On eBay, 3.1 percent of listings (3.6 percent 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 nonlinear specifications include home team dummies and their interactions with a measure of the game's expected attendance. The Appendix describes how the expected attendance 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 percent of the variation in realized attendances. The measure is also used to identify games that should have high or low demand.

Summary statistics.—Table 1 reports summary statistics on the availability, characteristics, and prices of listings in both markets, with table 2 showing the number and prices of listings for the six teams in the National League Central division. Table 3 shows how prices and availability vary with the time until the game.

Many more listings tend to be available on StubHub than on eBay, and there are some differences in how the number of listings tends to evolve over time.[21] On StubHub, the number of available listings peaks about 1 month before a game and drops dramatically in the last few days before

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

[21] The most informative comparison is in table 3, which shows the average number of different listings that are available at the start of the day (eBay) or when the data were downloaded (StubHub).

TABLE 1
Summary Statistics

	Observations	Mean	Standard Deviation	Median	10th Percentile	90th Percentile
eBay fixed-price listings:						
Posted fixed price (relative to face)	178,659	2.07	1.95	1.59	.57	4.02
Face value ($)	178,659	40.11	42.34	31	15	60
Number of seats	178,659	2.26	.76	2	2	4
Front row dummy	178,659	.13	.33	0	0	1
eBay store listing	178,659	.26	.44	0	0	1
Seller feedback > 1,000	178,659	.54	.50	1	0	1
Listing highlighted or has pictures	178,659	.27	.44	0	0	1
StubHub fixed-price listings:						
Posted fixed price (relative to face)	66,236,993	1.99	1.46	1.63	.85	3.48
Face value ($)	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	2.10	1.78	1.62	.63	4.06
Non-fixed-price listings (relative to face)	239,808	1.70	1.61	1.24	.42	3.45

Note.—Non-fixed-price listings include hybrid BIN auctions, where the sale may take place at a fixed price. Posted fixed prices exclude the commission that the seller would pay in the event of a 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 2
Selected Statistics for National League Central Teams

	Mean Attendance (Proportion of Capacity)	StubHub Listings	eBay Listings	eBay Transactions	Mean eBay Transaction Price (Relative to Face)	eBay Seller HHI
Chicago Cubs	.96	485,003	52,508	25,755	2.30	.0013
Cincinnati Reds	.59	32,426	16,882	7,968	1.85	.0151
Houston Astros	.85	100,240	10,225	5,650	1.70	.0082
Milwaukee Brewers	.78	27,650	14,743	8,845	1.42	.0202
Pittsburgh Pirates	.58	20,992	2,871	1,972	1.44	.0286
St. Louis Cardinals	.95	260,886	42,521	19,418	1.51	.0048

Note.—Capacity is measured by maximum observed attendance. eBay listings and transactions include all sales formats.

TABLE 3
MARKET DYNAMICS

	Days Prior to Game				
	0–5	6–10	11–20	21–40	41–90
	Average Number of Available Listings				
eBay fixed price—all games	8.6	10.5	10.7	10.3	8.9
	(10.3)	(11.8)	(12.4)	(12.4)	(11.0)
High expected demand games (expected attendance > 95% capacity)	15.8	19.1	20.2	20.8	19.1
	(13.8)	(15.7)	(16.5)	(16.6)	(14.5)
Low expected demand games (expected attendance < 70% capacity)	4	5.0	4.8	4.0	3.2
	(5.2)	(11.9)	(5.6)	(4.9)	(4.1)
eBay non-fixed-price listings	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 ($)	37.45	35.58	36.56	37.47	39.15
	(31.61)	(28.05)	(30.61)	(35.97)	(41.42)
Listing proportion of front row seats	.14	.12	.12	.12	.12
	(.34)	(.32)	(.33)	(.33)	(.32)
Transaction face value ($)	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	.15	.16	.16	.14	.14
	(.35)	(.37)	(.36)	(.34)	(.34)
	Average Prices Relative to 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 (expected attendance > 95% capacity)	2.08	2.31	2.52	2.77	3.02
	(1.90)	(1.90)	(2.10)	(2.29)	(2.57)
Low expected demand games (expected attendance < 70% capacity)	.94	1.05	1.18	1.28	1.39
	(.66)	(.78)	(.75)	(.73)	(.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)

NOTE.—Standard deviations are in parentheses. Non-fixed-price listings include hybrid BIN auctions, where a sale may take place at a fixed price. Reported list prices exclude the commission that the seller would pay in the event of a sale. Expected attendance is calculated using a regression model described in the Appendix.

a game, reflecting the fact that tickets can be listed only 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 National League 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 2 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 that 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 their both being part of a broader online secondary market. Consistent with 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 be willing to participate in auctions, which have an uncertain outcome, only 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.[22] This type of selection is also consistent with the number of auction listings increasing as a game approaches.

As discussed in Section II, 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 percent of sellers try to sell only a single set of tickets with a particular face value to a particular game,[23] with the tickets posted 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

[22] This difference is robust to including a large number of controls for listing characteristics. It contrasts with Malmendier and Lee's (2011) finding that transaction prices for nonperishable goods on eBay are often higher for auction listings than for fixed-price listings.

[23] A precise statement of this statistic is that 87.6 percent of game-seller–face value combinations list tickets for only a single section-row pair; 99 percent list fewer than four section-row pairs.

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 percent of eBay buyers purchasing no more than two listings during the entire 2007 regular season.

IV. Declining Prices

This section shows that declining prices are robust features of the data.[24] As explained in Section II, 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, such as team performance, that may affect demand:

$$p_{it} = D_t\beta_t^D + F_{it}\beta^F + C_{it}\beta^C + Q_i\beta^Q + FE_i + \varepsilon_{it}, \tag{4}$$

where 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. The term C includes 20 variables to control for the number of competing listings posted on either eBay or StubHub.[25] Ticket quality is controlled for using game face value or richer fixed effects FE_i, and 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), which are detailed in the online Appendix. The path of prices is measured using the coefficients on a set of 22 days-to-go dummies (D_t) that measure how many days prior to the game the listing or transaction is observed (0–2 days before the game as the excluded case). Standard errors are robust to heteroskedasticity and are clustered on the game.

Figure 2*a* and *b* shows the price paths for posted fixed prices on both sites and transaction prices for all listings and fixed-price only listings on

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

[25] 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.

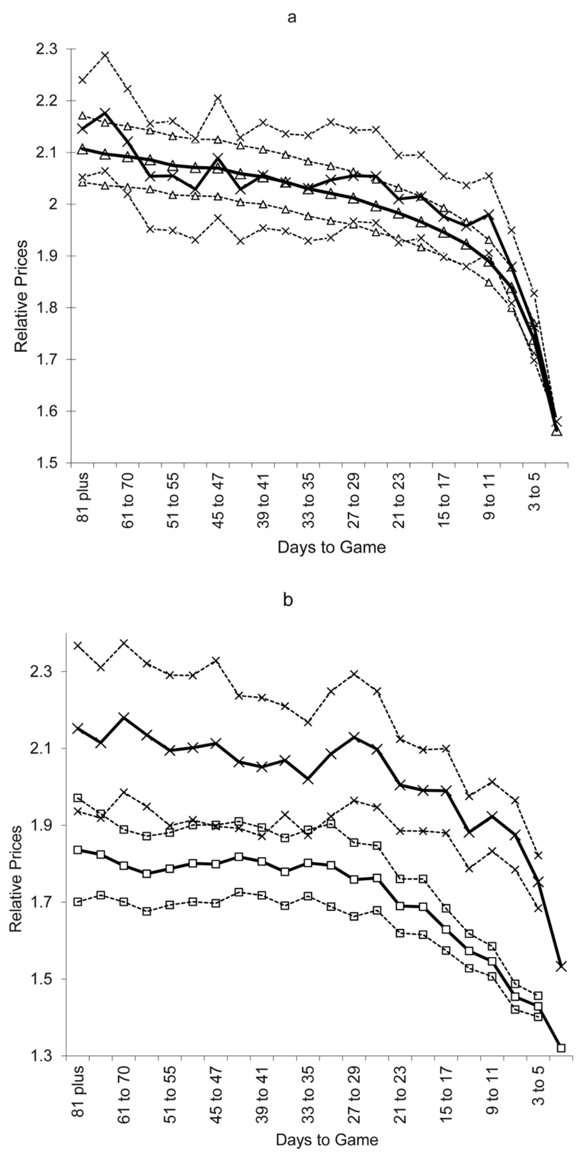
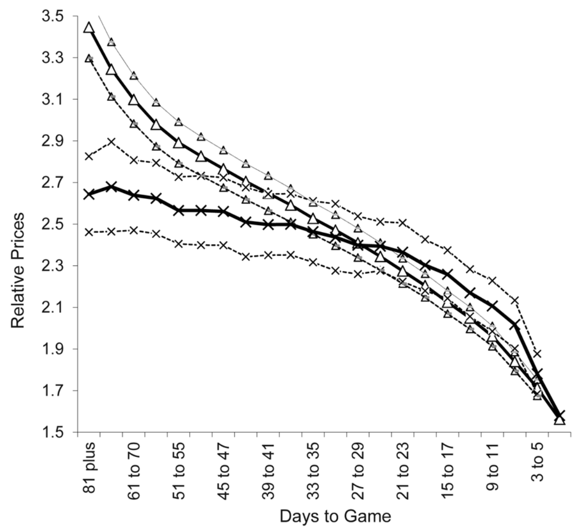


FIG. 2.—Estimated price paths: *a*, listed fixed prices (crosses: eBay; triangles: StubHub); *b*, eBay transaction prices (squares: all sales; crosses: fixed-price sales); *c*, within-seller listing fixed-price declines (crosses: eBay; triangles: StubHub); *d*, within-seller listing fixed-price declines by levels of experience (crosses: experience; squares: inexperience). Each point marks the value of the coefficient for the number of days before the game from a pricing regression plus the mean price 0–2 days before the game. Dashed lines represent 95 percent confidence intervals.

c



d

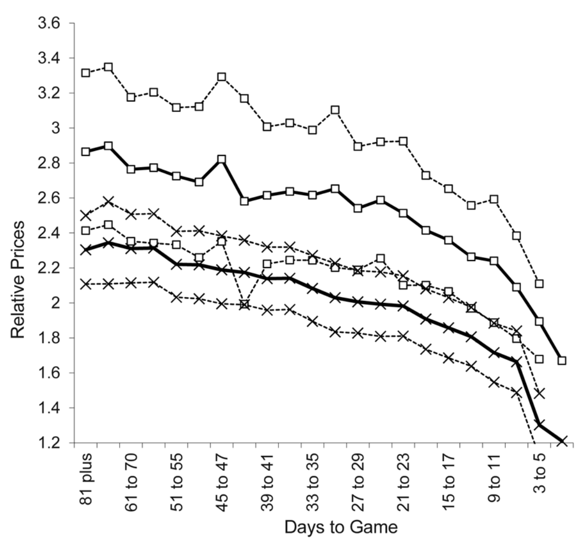


FIG. 2.—(*Continued*)

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 percent 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 percent and 50 percent 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 percent of price changes on StubHub and 80 percent on eBay being price reductions.[26] The sizes 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 percent and 90 percent 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 in equilibrium sellers of tickets with higher face values would have to cut prices more dramatically than the sellers of cheaper tickets. Table 4 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 in which the expected attendance 90 days before the game is greater than 95 percent of capacity), low-demand games (less than 70 percent), cheap seats (face value no more than $20), and expensive seats (face value no less than $45). The proportions of price changes that are price reductions are 79 percent, 83 percent, 80 percent, and 81 percent, respectively.

The sizes of the price reductions for cheap and expensive seats are similar (86 percent of face value for cheap seats and 75 percent of face

[26] 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.

TABLE 4
WITHIN-SELLER PRICE CHANGES FOR PARTICULAR TYPES OF TICKETS 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	.932	1.834	1.431
Selected days-to-go coefficients:				
3–5	.341***	.109**	.184**	.203***
	(.097)	(.052)	(.088)	(.077)
6–8	.683***	.184***	.400***	.381***
	(.120)	(.053)	(.100)	(.084)
9–11	.799***	.310***	.470***	.515***
	(.120)	(.048)	(.092)	(.073)
15–17	.997***	.430***	.691***	.620***
	(.120)	(.053)	(.099)	(.075)
21–23	1.175***	.458***	.822***	.698***
	(.150)	(.054)	(.130)	(.081)
30–32	1.263***	.509***	.868***	.745***
	(.180)	(.064)	(.140)	(.080)
39–41	1.304***	.554***	.868***	.738***
	(.160)	(.066)	(.120)	(.086)
51–55	1.385***	.577***	.964***	.791***
	(.180)	(.068)	(.120)	(.085)
81+	1.518***	.679***	1.019***	.821***
	(.210)	(.073)	(.130)	(.087)
Observations	84,413	28,158	56,769	49,051
Adjusted R^2	.909	.778	.888	.916

NOTE.—Specifications include seller-game-section-row fixed effects and controls for listing characteristics, competition, and team performance. Robust standard errors clustered on the game are in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

value for expensive seats in the month before the game), which suggests 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 for low-demand games, but this partly reflects the large differences in how expensive these tickets are in secondary markets: as a percentage of the price immediately before the game, the declines are quite similar, equal to 63 percent (standard error 9 percent) and 55 percent (7 percent), respectively.

As noted in Section II, my theoretical framework assumes that sellers know the current state of demand and also understand how they expect demand and competitors' prices to evolve. An alternative model that could also predict declining prices might assume that at least some sellers do not know the level of demand but might learn about demand by setting prices and observing whether their listing sells or not, 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 knows only 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 demand. When demand is downward sloping, declining opportunity costs will also cause prices to fall, but introducing learning will generally lead them to set higher initial prices than if they know the level of demand or if they do not foresee updating their beliefs about demand from whether their listing sells or not.

If learning is a major factor causing prices to decline, then, assuming that experienced sellers have better information about demand, we would expect to observe inexperienced sellers cutting prices more than experienced ones.[27] 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 fewer than 20 games.[28] Both types of sellers cut prices by very similar amounts (between 90 percent and 100 percent 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 percent for experienced, 82 percent for inexperienced). It is also noticeable that inexperienced sellers set significantly higher prices than experienced ones. This provides some evidence against an alternative type of information story in which unsophisticated inexperienced sellers, who do not know demand or the value of secondary market tickets, simply copy how experienced sellers price their tickets.[29] On the other hand, the fact that inexperienced sellers set higher prices is consistent with a model of pricing based on expected future opportunity costs, as they are less likely to be brokers and so are more likely to get utility from unsold tickets by going to games themselves or giving them away to friends.

[27] The fact that a simple DP model with no learning predicts how much prices and opportunity costs fall quite accurately also provides some evidence against learning being the primary explanation for why prices fall.

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

[29] Of course, inexperienced sellers might just tend to set a fixed markup on top of the prices they see experienced sellers setting. However, my intuition is that if inexperienced sellers simply felt that they did not know how to price tickets, they would be more likely to set lower, rather than higher, prices than sellers that they might regard as having market expertise. Another piece of evidence against the argument that sellers copy the prices that they see in the market is that both experienced and inexperienced sellers are observed to cut prices more dramatically than the average price of tickets available in the market (compare figs. 2*a* and 2*c*).

V. Testing Dynamic Pricing Models

This section estimates listing demand in order to test whether opportunity costs decline over time. It looks at whether demand is time invariant and $\partial E_t(V_{it+1})/\partial p_{it} = 0$ to test whether simple DP models characterize the pricing problem faced by sellers, and it also asks whether this type of model predicts how much sellers cut prices as a game approaches. All of the analysis in this section uses the eBay data as I need to observe transactions to estimate demand.

A. *Specification*

I model the probability that a listing sells using a probit model in which 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:

$$Q_i = X_i\theta_1 + p_i\theta_2 + u_i, \tag{5}$$

$$Q_i^* = \begin{cases} 1 \text{ (sale)} & \text{if and only if } Q_i \geq 0 \\ 0 & \text{otherwise,} \end{cases}$$

$$p_i = X_i\gamma_1 + Z_i\gamma_2 + v_i,$$

$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim N\left[\begin{matrix} 0 \\ 0 \end{matrix}, \begin{pmatrix} 1 & \rho\sigma_v \\ \rho\sigma_v & \sigma_v^2 \end{pmatrix}\right],$$

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.[30] I estimate the system using full information maximum likelihood (FIML).

[30] Shipping costs and commissions are deducted from the seller's revenue when opportunity costs are calculated. I do not observe shipping costs for listings that 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.

The sample includes all fixed-price listings on eBay posted in the last 90 days before a game, excluding 3.6 percent of listings with unusually high posted prices as these outliers have disproportionate effects on the estimated demand elasticities.[31] The term $Q_i^* = 1$ if a listing sells within 7 days of posting. The standard errors are clustered on the game. The online Appendix contains several alternative specifications, including ones in which competitors' prices are also allowed to be endogenous.

Own listing characteristics (X_i) are home team dummies, home team $\times$ 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 nonlinear specification, but I control for game demand by including the team form variables and both expected attendance and the median 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

[31] Thirty percent 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 cutoff for all games. I drop listings with relative prices greater than $5 + 6 \times \max(0, \text{Att}_{90} - 0.8)$, 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 cutoff of five for all games.

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 are assumed to not directly affect demand:

- *The distance of the seller's zip code 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.
- *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 III, sellers with different opportunity costs may tend to choose different types of listings.

Table 5 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, 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-price 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.

B. Estimates of Demand and Opportunity Costs

Column 2 of table 6 shows the price and competition coefficients from the full model, and, as a comparison, column 1 provides estimates from a single-equation probit model in which own-price endogeneity is ignored. 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

TABLE 5
REGRESSION OF EBAY FIXED PRICES ON INSTRUMENTS

Variable	Estimate
Distance variables:	
Seller within 25 miles	−.014
	(.025)
× 1–10 days prior to game	.027*
	(.030)
× 11–20 days prior to game	.004
	(.028)
× 21–40 days prior to game	−.058**
	(.028)
Seller more than 125 miles	.209***
	(.023)
× 1–10 days prior to game	−.285***
	(.030)
× 11–20 days prior to game	−.160***
	(.026)
× 21–40 days prior to game	−.091***
	(.026)
Relisting variables:	
Proportion of seller's unsold listings during time period relisted on eBay	−.137***
	(.034)
× 1–10 days prior to game	−.105**
	(.051)
× 11–20 days prior to game	−.158**
	(.064)
× 21–40 days prior to game	−.358***
	(.054)
Mechanism choice variables:	
Proportion of seller's other listings in hybrid BIN format	−.089
	(.064)
× 1–10 days prior to game	.148**
	(.071)
× 11–20 days prior to game	.224***
	(.078)
× 21–40 days prior to game	.097
	(.075)
Proportion of seller's other listings in pure fixed-price formats	.173***
	(.047)
× 1–10 days prior to game	−.313***
	(.053)
× 11–20 days prior to game	−.007
	(.057)
× 21–40 days prior to game	.059
	(.056)
Observations	113,186
F-statistic on the instruments	16.42
	(p-value .000)

NOTE.—Specification includes controls for listing and seat characteristics, seller feedback scores, team form and competition, home team dummies, home team × face value and home team × expected attendance interactions, game day of week dummies, days-to-go dummies, and dummies for sellers with one and fewer than 10 listings in 2007. Robust standard errors clustered on the game are in parentheses.

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

the full model, with the solid circles indicating average prices in each time period.[32] 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 that a seller's demand is time invariant is at least approximately correct.[33]

The opportunity cost of sale implied by the price of each listing can be calculated using (2), where I assume that $\partial E_t(V_{it+1})/\partial p_{it} = 0$ (the second-order condition holds for all listings). Figure 4 shows how the distribution of these costs changes over time. The figure shows 95 percent confidence intervals only 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 percent of face value (standard error 5 percent), whereas 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.[34] One can also look at how opportunity costs change for individuals relisting tickets: for 77.2 percent of tickets that are relisted 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 percent (2 percent), 19 percent (3 percent), and 68 percent (3 percent) of face value when a listing remains unsold from one time period to the next.[35]

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 four 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

[32] The demand curve is calculated using time-invariant average listing characteristics and period-specific means for the time-varying variables such as the measures of the numbers and prices of competing listings, expected attendance, and team form.

[33] The fact that the curves are similar across periods reflects some offsetting effects. The increase in the number of competing listings and their declining prices tends to reduce demand, which is offset by increasing coefficients on the time dummies.

[34] Around 25 percent 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 percent of these observations have prices within 10 percent of face value) for ethical reasons even when they could expect to achieve higher payoffs by setting a higher price. In a few states, the law still prevents sellers from charging a significant markup above face value. However, further analysis revealed that there was no significant correlation with 2007 state restrictions on ticket resale.

[35] The declines are measured by the coefficients on the dummies for 3–5, 15–17, 30–32, and 51–55 days to go. For example, the 18 percent decline is the change from 51–55 to 30–32 days to go.

TABLE 6
Demand Estimates

	Exogenous Own Price (1)	Full Model (2)	Full Model with Lagged Price (3)
Own relative price coefficients:			
1–10 days before game	−.185***	−.964***	−.949***
	(.010)	(.026)	(.027)
11–20 days before game	−.184***	−.964***	−.941***
	(.010)	(.026)	(.028)
21–40 days before game	−.199***	−.941***	−.917***
	(.012)	(.027)	(.028)
41+ days before game	−.214***	−.925***	−.905***
	(.012)	(.026)	(.027)
Previous price	. . .	. . .	−.007
Competition coefficients (eBay):			
Mean relative price for fixed-price listings	.072***	.119***	.116***
	(.011)	(.008)	(.009)
Mean relative start price for auction listings	−.013***	−.003	−.003
	(.012)	(.011)	(.011)
Minimum relative price for fixed-price listings	−.045***	.007	.006
	(.010)	(.009)	(.009)
Minimum relative price for auction listings	−.005	−.002	−.004
	(.014)	(.012)	(.012)
Dummy variable for no competing fixed-price listings	.086***	1.151***	1.055***
	(.028)	(.028)	(.028)
Dummy variable for no competing auction listings	−.079***	−.221***	−.220***
	(.026)	(.023)	(.023)
Number of competing fixed-price listings (log N + 1)	−.153***	−.141***	−.105***
	(.018)	(.016)	(.016)
Proportion of competing fixed-price listings with seller feedback scores above 100	.138***	.819***	.357***
	(.040)	(.038)	(.039)
Number of competing auction listings (log N + 1)	.015	−.012	−.025
	(.015)	(.014)	(.014)
Proportion of competing auction listings with seller feedback scores above 100	−.017	−.096***	−.022
	(.022)	(.020)	(.021)
Competition coefficients (StubHub):			
Log(number of StubHub listings + 1)	.005	.024**	.026***
	(.009)	(.010)	(.010)
Correlation coefficients:			
1–10 days before game	. . .	.713***	.698***
		(.024)	(.025)
11–20 days before game	. . .	.712***	.682***
		(.025)	(.026)
21–40 days before game	. . .	.675***	.646
		(.027)	(.028)
41+ days before game	. . .	.680***	.656
		(.029)	(.030)

TABLE 6 (*Continued*)

	Exogenous Own Price (1)	Full Model (2)	Full Model with Lagged Price (3)
Mean elasticities (all significant at 1% level):			
1–10 days prior to game	−.288	−2.150	−2.079
	(.020)	(.148)	(.147)
11–20 days prior to game	−.416	−3.100	−2.919
	(.025)	(.214)	(.197)
21–40 days prior to game	−.601	−3.863	−3.658
	(.045)	(.0237)	(.227)
More than 41 days prior to game	−.875	−5.212	−4.976
	(.049)	(.398)	(.386)
Observations	113,186	113,186	113,186

NOTE.—Specification includes controls for listing and seat characteristics, seller feedback scores, team form and competition, home team dummies, home team × face value and home team × expected attendance interactions, game day of week dummies, days-to-go dummies, and dummies for sellers with one and fewer than 10 listings in 2007. Robust standard errors clustered on the game are in parentheses.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

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 percent of face value, which is between the mean (55 percent) and the median (29 percent) 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 percent to 190 percent, 169 percent, and 143 percent of face value as a game approaches (standard errors less than 3 percent in each case), and these declines of 12 percent, 21 percent, and 26 percent are similar to the average within-seller declines of 13 percent, 18 percent, and 40 percent observed in the data (fig. 2*c*). The associated opportunity cost should fall by 19 percent, 27 percent, and 57 percent 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 an opportunity cost of 40 percent, implicitly ignoring his ability to relist prior to the game. When this strategy is used, the price would be between 138 percent and 143 percent of face value in each period, the probability that the ticket sells before the game would be .95, and the expected payoff would be 135 percent of

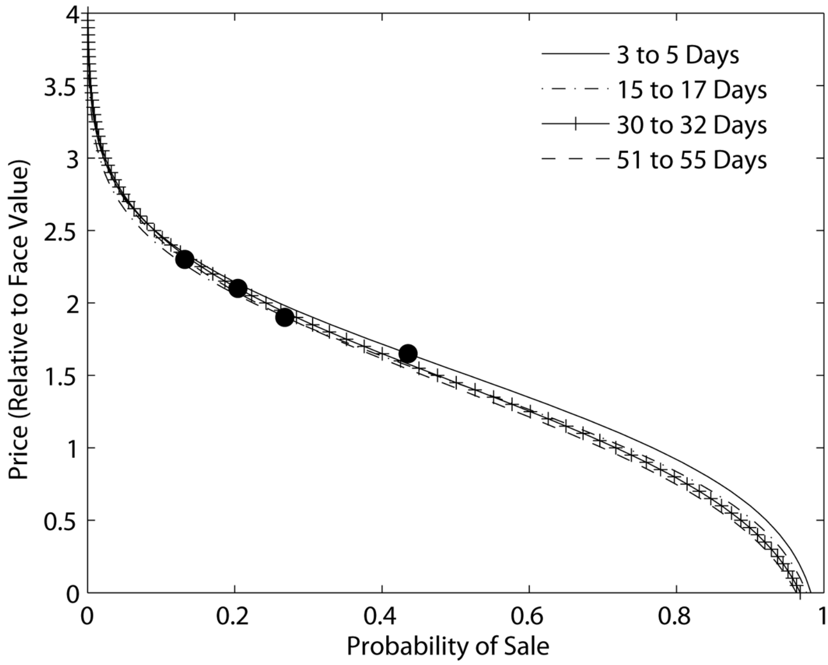


FIG. 3.—Estimated inverse demand functions. The dots mark the level of average prices in each of the four time periods on the associated inverse demand curve.

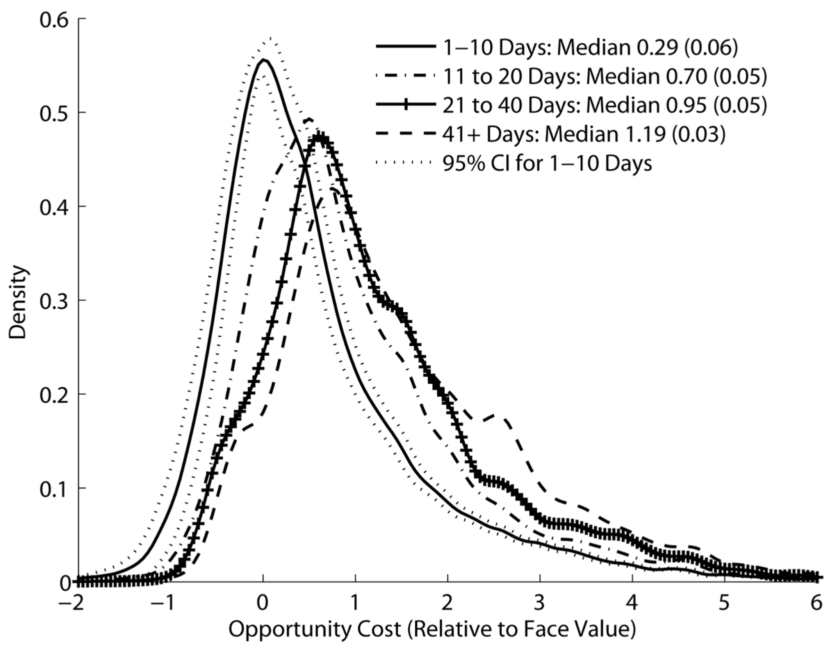


FIG. 4.—Distributions of implied opportunity costs by time period

face value (standard error 2 percent). When the optimal DP strategy is used, initial prices are higher, which reduces the sale probability to .85, but the expected payoff is 156 percent of face value (standard error 2 percent). DP therefore raises the seller's expected payoff by 21 percent of face value, or 16 percent of the payoff from using the alternative static pricing strategy. For the average listing with two seats and a combined face value of $87.16, the gain would be just over $18.

C. *Effect of Current Prices on Future Competition and Demand*

Opportunity costs were calculated assuming that $\partial E_t(V_{it+1})/\partial p_{it} = 0$, and I now provide evidence that this assumption is consistent with the data, looking at whether a seller's price affects its future competition or its future demand. The results validate my calculations and provide further evidence that simple DP models, which also make this assumption, accurately describe the pricing problem faced by sellers.

I test whether a seller's current price affects the future values of 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 7 reports the results from three different linear specifications for each competition variable: an ordinary least squares (OLS) specification, a two-stage least squares (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 the 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 .0025, or less than 1 percent from its mean of .2842. In contrast, this price increase would reduce the current probability of sale by more than .2. The small positive effect on future competition could also be due to an unobserved factor raising the listing's optimal 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 still quite precisely estimated. The results are

TABLE 7
Effect of Current Price on Future Values of the Competition Variables

Dependent Variable	OLS (1)	Game-Face Fixed Effects (2)	2SLS (3)
Mean price of competing fixed-price listings	.0244**	−.0364***	.1241***
	(.0099)	(.0112)	(.0470)
Dummy for no competing fixed-price listings	−.0008	.0001	−.0326**
	(.0019)	(.0023)	(.0136)
Number of competing fixed-price listings	−.0154***	−.0307***	.0842***
	(.0045)	(.0063)	(.0288)
Minimum price of competing fixed-price listings	.0427***	.0100***	.0984**
	(.0094)	(.0098)	(.0446)
Proportion of competing fixed-price listings with feedback scores > 100	−.0047***	−.0031	.0068
	(.0018)	(.0024)	(.0117)
Mean start price of competing auction listings	.0289***	−.0074	.1337***
	(.0074)	(.0097)	(.0386)
Dummy for no competing auction listings	.0003	.0034	−.0328*
	(.0026)	(.0033)	(.0184)
Number of competing auction listings	−.0072	−.0227	−.0353
	(.0047)	(.0066)	(.0288)
Minimum price of competing auction listings	.0207**	.0121	−.0862**
	(.0059)	(.0083)	(.0336)
Proportion of competing auction listings with feedback scores > 100	−.0018	−.0065*	−.0085
	(.0025)	(.0034)	(.0179)
Number of StubHub listings	−.0001	−.0031	.0282*
	(.0024)	(.0027)	(.0147)
Increase in the probability that relisted tickets sell when current price is increased by face value	.0025**	−.0007	.0024
	(.0010)	(.0011)	(.0052)

Note.—Excluding the final row, the table shows coefficients on the current price in regressions that include all of the controls from the demand regression, plus days-to-go dummies for when the listing is next posted. The dependent variable in each case is the value of the relevant competition variable when the listing is next posted. There are 28,952 observations in each regression. The final row reflects the combined effect of all of the changes in the competition variables on the probability that the listing is sold when it is next posted, holding the relisting price fixed, based on the demand estimates in col. 2 of table 6. Robust standard errors clustered on the game are in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

therefore consistent with the assumption that $\partial E_t(V_{it+1})/\partial p_{it}$ is equal or very close to zero.[36]

A listing's current price could also affect its future demand, separately from any effects on competition, if a high price causes buyers to delay purchasing. I test whether this effect is significant by including the sell-

[36] A possible weakness of this test is that it is based on the selected sample of unsold listings that I observe being relisted. I have also computed additional results based on the set of competing listings 10 days after any listing is posted (all listings less than 11 days before the game are dropped in this case). These results are qualitatively similar, with the total effects statistically insignificant once I control for endogeneity.

er'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 column 3 of table 6. 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 those in column 2. This estimate indicates that a seller's current price has no significant effect on future demand, consistent with $\partial E_t(V_{it+1})/\partial p_{it} = 0$.

These results may seem surprising given that when future competitors set prices they are likely to be influenced by prices they already see listed, and it seems plausible that high prices could cause some consumers to delay purchasing. However, one explanation is that because each seller is a small part of the market and buyers may be unlikely to find exactly the same listing if they return at a later date,[37] the effect of p_{it} on i's own future value, via either demand or supply, is likely to be small.[38] This fact is obviously missing from theoretical DP models that assume only one or two sellers.

VI. Strategic Buyer Behavior

As explained in the introduction, the recent DP literature has emphasized how strategic buyer behavior can affect pricing strategies. In particular, when there is still some time before the event, consumers may choose to delay purchasing if they expect prices to fall, which will have the effect of making early demand more elastic, lowering optimal prices. This could give rise to flat or increasing prices in equilibrium, which is clearly not what is observed in the data. Given that it seems plausible that many consumers should act strategically in resale ticket markets,[39] the

[37] An interesting feature of the eBay auction data is that only 38 percent of unsuccessful 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 such as StubHub, and a high degree of substitution across markets would make the assumption that $\partial E_t(V_{it+1})/\partial p_{it} \simeq 0$ even more plausible.

[38] This is the reason why $\partial E_t(V_{it+1})/\partial p_{it} = 0$ in the model of Deneckere and Peck (2012), where there is a mass of sellers and a mass of strategic buyers.

[39] Of course, some buyers may not be strategic because either they are unaware of how much prices decline or they do not think strategically. Osadchiy and Bendoly (2011) provide experimental evidence that a population of master of business administration students fail to make optimal timing decisions about purchases even when they are well informed about how prices change.

findings that demand is approximately time invariant and that prices decline so much potentially present a puzzle. In this section I describe a simple alternative model of demand that is helpful in understanding the possible effects of strategic buyer behavior on equilibrium prices and that can rationalize what is observed in the data while allowing consumers to be potentially strategic. The key idea is that the existence of search costs may lead to consumers with different waiting costs participating in the market at different times, and I present some empirical evidence consistent with this type of sorting story.

A. Model

As a very simple example of a model with strategic buyers, suppose that there are two time periods ($t = 1, 2$) and that in each period four symmetric sellers, who have no value of holding a listing after period 2, simultaneously post prices.[40] Product differentiation is captured using Salop's (1979) circular city model. Specifically, the sellers are modeled as being evenly spaced around a circle with unit circumference. There are two risk-neutral buyers (A and B) with unit demands who are strategic in the sense that they are able to visit the market when they choose and to delay purchasing if they want to. To visit the market in any period, a buyer has to pay a search cost s that reveals the consumer's position on the circle. This position is assumed to be redrawn each period to capture the real-world fact that a consumer who searches on eBay or StubHub may find different listings each time she searches. The utility of consumer j from buying listing i is $u - d_{ijt} - p_{it}$, where d_{ijt} is her distance from i, p_{it} is the price, and u is high enough so that, in equilibrium, all buyers purchase at some point. Consumer A is indifferent between buying in period 1 and period 2, while B incurs a cost w_B if she buys in period 2.

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 discover their locations and 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. I focus on the pure strategy subgame-perfect Nash equilibrium, where, in a given time period, all sellers set the same price. The equilibrium price in the second period will depend on what happens in the first period. It

[40] This assumes that if a listing is sold, another seller enters the market to replace it. One can also allow for stochastic entry, but this complicates the model without providing any additional intuition.

is straightforward to see that an active consumer j will choose to buy a ticket with characteristics (d_{ij1}, p_1^*) in the first period if and only if $d_{ij1} + p_1^* \leq E_{t=1}(d_2 + p_2^*) + w_j + s$, where the first-period expectation of second-period prices and travel costs will reflect knowledge or uncertainty about the choice of the other buyer.[41]

It is interesting to consider two sets of parameters. In the first parameterization, $w_B = s = 0$ (no waiting or search costs), which maximizes the scope for strategic buyer behavior. In the unique pure strategy equilibrium, both buyers will enter the market in period 1 and enter again in period 2 if they do not buy. As increasing the period 1 price raises second-period demand, $\partial E_1(V_{i2})/\partial p_{i1} \geq 0$, the opportunity cost of a sale declines but equilibrium prices tend to rise: $p_1^* = 0.1875$ and $p_2^* = 0.25$ if one buyer remains in period 2 or $p_2^* = 0.286$ if both buyers remain. This reflects the fact that the ability of consumers to wait makes first-period demand much more elastic.

In the second parameterization, $s = 1/16$ and $w_B = 1/8$ 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 $p_1^* = 0.3125$. Buyer B's preference for buying early means that first-period demand is relatively inelastic. Buyer A does not enter in the first period because of the search cost but buys in the second period at $p_2^* = 0.25$.[42] These prices are exactly the same as they would have been if one buyer exogenously arrived in each period and had to buy at once or exit the market, even though buyers do make a strategic timing choice and one customer chooses to wait for prices to fall. However, because this buyer (rationally) chooses not to search the market at all in period 1, this strategic behavior does not make first-period demand more elastic, which results in a different equilibrium pricing pattern than the existing theoretical literature with strategic buyers.

B. *Empirical Evidence*

The available data do not let us see when buyers search resale markets, but they do provide evidence that the timing of purchases is plausibly correlated with consumers' cost of delay. In particular, people who have to travel a long way to attend a game may tend to have higher costs of de-

[41] For example, if A is considering buying her second-choice ticket in the first period, then the reason is that B purchased the first-choice ticket, so A knows that B will not be in the market in the second period. On the other hand, A has to indicate her willingness to buy her first-choice ticket without knowing B's location or what B will choose.

[42] 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 her first-choice ticket in the first period means that her preferred strategy is to search only in the second period.

lay because they have to make more complementary investments to attend (purchasing airline tickets or hotel reservations, organizing longer periods of child care), and these investments may be more costly or difficult to make at the last minute.[43] Consistent with the model and this story, consumers who buy early tend to live further from the stadium than those who buy close to the stadium. On the other hand, both groups tend to buy tickets with similar face value and row characteristics, indicating that, as in the model, their underlying demand for seats is similar.[44]

The distance that the buyer lives from the stadium is calculated using the center of the delivery zip code (buyers outside the United States are dropped), and the mean (median) distance is 184 (37) miles. Table 8 reports regressions using all eBay transactions (any mechanism) with nonmissing face value and buyer zip code information, and the dependent variable is the number of days before the game in which the transaction takes place. The regressors include a dummy variable for whether the centroid of the buyer's zip code is within 25 miles of the stadium in which the game is played, as well as distance and distance^2. The specification in column 1 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.[45]

The coefficients indicate that travel distance affects 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 10 days before a game.[46]

[43] For example, airline tickets are more expensive when purchased within 7 or 14 days of departure (Escobari and Gan 2007; Puller et al. 2009).

[44] For example, if people buying close to the game were more price sensitive, we would expect either that they would buy cheaper, lower-quality tickets (recall that table 3 showed that the set of available tickets remains similar) or that the prices of higher-quality tickets would decline more rapidly in equilibrium (table 4 showed that this is not the case).

[45] Experience may proxy for a number of buyer attributes: e.g., 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 resale. 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 zip code. The distance effects change very little, but people from higher-income zip codes are predicted to buy slightly closer to the game; the effect is very small. These people are also predicted to buy tickets with slightly higher face values.

[46] An alternative approach involves regressing the log of the distance of the buyer's zip code 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 12–14 (30–32, 81–90) days before the game living 47.5 percent (75.8 percent, 84.4 percent) further away than those buying in the last 3 days. These values are significantly different from each other at any conventional significance level.

TABLE 8
TIMING OF PURCHASES

	Dependent Variable: Days Prior to Game Purchase Made	
	(1)	(2)
Distance of buyer's zip code from stadium:		
Distance (miles)	.0103***	.0178***
	(.0013)	(.0044)
$\text{Distance}^2/1{,}000$	−.0020***	−.0053***
	(.0006)	(.0018)
Distance less than 25 miles	−4.3907	−1.8400***
	(.3568)	(1.5554)
Number of seats (pair excluded):		
1	−2.8527***	4.0946*
	(.8102)	(2.4571)
3	−4.8855***	1.1756
	(.3987)	(1.8077)
4	1.1387***	6.5024***
	(.2985)	(1.6824)
5	−6.1887***	. . .
	(.6911)	
6	10.5381***	13.8976***
	(1.3447)	(3.4725)
Face value ($)	−.0307***	−.0331***
	(.0027)	(.0079)
Row variables:		
First row dummy	2.2599***	1.0361
	(.3291)	(.6816)
Second row dummy	2.1605***	1.3149**
	(.3195)	(.6601)
Row number	.0432***	.0199
	(.0157)	(.0338)
Game fixed effects	Yes	No
Buyer zip code fixed effects	No	Yes
Home team, home team × expected attendance, day of game, month of game controls	No	Yes
Observations	286,706	286,706
R^2	.17	.79

NOTE.—Sample includes transactions in all sales formats, and the specification includes controls for the sales format and the experience of the buyer. The five-seat dummy is not included in specification 2 because no buyers make multiple purchases with five seats in only a subset of these purchases. Robust standard errors clustered on the game are in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

As a robustness check, the specification in column 2 includes buyer-delivery–zip code 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 an effect similar to that in column 1, with someone living in downtown Boston buying tickets 5.0 (1.3) days earlier for a Yankees game than for a Red Sox game. These results are consistent with sorting on waiting costs. In contrast, ticket characteristics have only limited effects on when listings are bought, which would not be the case if consumers buying at different times had different price sensitivities. For example, the model predicts that a $60 seat would be purchased 0.6 (0.04) day later than a $40 seat and front row seats 1.4 (0.34) days earlier than seats in row 20.[47] These results are consistent with demand curves looking fairly similar as a game approaches. The one exception to the pattern is that six-seat listings are purchased 2 weeks earlier than two-seat purchases (the excluded group). This makes sense as six-seat listings are rarely available on eBay (0.6 percent of listings) so that someone wanting to buy six seats probably has to search in every period, even if he has no other cost of delay, and should buy a listing as soon as one becomes available.

VII. Conclusion

This paper examines whether DP models, which 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 amounts that a simple 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 in which 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

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

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 be 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.[48] These incentives would be missed by existing DP models that consider a single sales horizon. Reputational incentives are likely to be much more important for airlines, which interact with the same customers repeatedly, than for small sellers in markets such as 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.

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 that are more transparent or buyers are more experienced. On the other hand, there is evidence consistent with a model in which at least some buyers are strategic but have heterogeneous 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 be 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

[48] Airline pricing behavior may be better described by models in which sellers choose (price, quantity) schedules that are not a function of time (e.g., Gale and Holmes 1993; Dana 1998, 1999). 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.

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 in which perishable goods are traded.

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