Pricing Strategy under Reference-Dependent Preferences: Evidence from Sellers on StubHub*

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Abstract

This research uses listing prices on StubHub, a secondary market for sports tickets, to show that sellers have reference-dependent preferences, affected by two types of reference points: face values and previous lowest transaction prices within the same section of the stadium. First, I show evidence of the bunching of listing prices at the reference points, which is consistent with the prediction from the theoretical model. Then, I use a structural model to estimate the parameters of the gain-loss utility and simulate results for the case without reference-dependent preferences. Compared with the actual data, the counterfactual results indicate that the listing prices for game tickets will be lower by around 19.30% on the last day before the game if sellers have no reference-dependent preferences. Furthermore, the probability of a typical listing being sold increases from 0.43 to 0.48 during the last two weeks. In addition, I use the number of listings in a season to proxy for the size of sellers, and the results show that big sellers are less likely to be affected by the face value than small sellers, which is consistent with the previous literature's notion that market experience can eliminate the effect of reference points. However, sellers of different sizes are affected by the previous lowest transaction prices in a similar way, which suggests that market experience might only eliminate the effects of reference points such as the status quo, and not the effects of reference points such as recent outcomes.

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1 Introduction

Field evidence of reference-dependent preferences has been found in many studies (DellaVigna, 2009), but little has been shown in the online peer-to-peer markets. These markets, such as eBay and Airbnb, provide many innovative market design features to lower the entry costs for sellers, thereby attracting small suppliers to enter the markets. One of the important features of these markets is the pricing mechanism (Einav, Farronato and Levin, 2016). Nowadays, posted price mechanisms are widely used in the online market, and platforms attempt to provide useful information to both sellers and buyers to facilitate transactions. However, the information can play a different role, as reference points for individuals, and thus affect the market outcomes. This research uses the listing price data on StubHub to study how reference points affect sellers' pricing strategies over time.

StubHub is the most popular secondary market for sports tickets in the United States. For each venue and game, StubHub has a different web page with a detailed stadium map showing where the seating is in relation to the field. This allows sellers to list their tickets easily and lets consumers search for tickets with a clear understanding of where their seats will be. Because all sellers need to purchase the tickets from the primary market, the ticket information in that market, such as the face value, should be common information for both sellers and buyers. In order to attract sellers and ensure they can make a profit, StubHub also provides comprehensive transaction records so that the sellers can follow the information to set up initial listing prices and adjust those listing prices at any time before game day.

Reference-dependent preferences come from prospect theory, which was proposed by Kahneman and Tversky (1979). According to a reference point, a seller has an additional gain from gain-loss utility when the transaction price is higher than a given reference point, while the seller incurs a loss if the transaction price is lower than the reference point. The reference point could be backward-looking, such as the status quo or a recent outcome, or forward-looking, such as individuals' rational expectations (Kőszegi and Rabin, 2006, 2007). In this research, I focus on backward-looking reference points because they are easier to observe in the market.

To understand the effect of reference-dependent preferences, I first follow Sweeting (2012) to construct a theoretical dynamic pricing model, which predicts that listing prices will bunch at reference points if sellers have reference-dependent preferences. If a seller faces a loss in the last few days, the listing prices should be higher than those determined by sellers without reference-dependent preferences.

To verify the reference points, I focus on all the initial listing prices to see whether there is evidence of bunching at the potential reference points, based on the discontinuity test in McCrary (2008). Two reference points are found in this market: face values and previous lowest transaction prices (PLTPs) in the same section of the stadium. I also eliminate some alternative possible explanations, such as round numbers and original purchase prices in the primary market. The evidence of bunching is robust for these two reference points in most of the subgroups. Only for those sellers with over 150 listings in a season does the discontinuity test suggest that they are not affected by face values.

Furthermore, I use a two-stage estimation method from Bajari, Benkard and Levin (2007) to estimate the parameters of the gain-loss utility. In the first stage, I estimate the probability of a sale on each day before the game, the pricing strategies in each state, and the state transition matrix over time. In the second stage, a set of structural parameters are estimated by a simulated minimum distance method which rationalizes that the pricing strategies from the observed data are the optimal decisions.

To quantify the effect of the reference points, I use a counterfactual exercise to simulate the listing prices under scenarios without reference points. Compared with the actual data, the counterfactual results indicate that the listing prices will be lower by around 19.30% on the last day before the game if sellers have no reference-dependent preferences. Furthermore, the probability of a typical listing being sold increases from 0.43 to 0.48 during the last two weeks.

In order to determine the heterogeneity of the sellers, I also estimate the loss aversion parameter for sellers with different types of tickets. Those sellers who only hold single-game tickets are less likely to be affected by the face value than those holding package tickets or mixed types of tickets. However, all of the sellers have a similar loss aversion parameter for the PLTPs. When I use the number of listings in an entire season to proxy for the size of the sellers, the results show that the big sellers are less likely to be influenced by the face values, which is consistent with the previous literature's notion that market experience can eliminate the effect of reference points. However, I find no difference between sellers of different sizes when the PLTPs serve as the reference points. This implies that market experience might only eliminate the effect of reference points such as the status quo, and not those such as recent outcomes.

The first stream of literature related to this research relates to dynamic pricing[1], investigating how firms sell perishable goods in a limited time. The dynamic pricing models usually consider two types of consumers: myopic (Gallego and Van Ryzin, 1994; Bitran and Mondschein, 1997) and strategic (Su, 2007; Levin, McGill and Nediak, 2009; Deneckere and Peck, 2012; Board and Skrzypacz, 2016). Because Sweeting (2012) shows that consumers in the sports ticket secondary market are not strategic, I follow this assumption and further consider sellers with reference-dependent preferences. In addition, several previous studies combine dynamic pricing with reference points, and show how sellers impose dynamic pricing when consumers consider previous listing prices as reference points (Popescu and Wu, 2007; Bell and Lattin, 2000). Unlike the previous literature, however, this research focuses on how the reference-dependent preferences of sellers affect their dynamic pricing behavior.

This research is also linked to the literature on reference-dependent preferences (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991; Kőszegi and Rabin, 2006, 2009), both in the behavioral economics and the finance literature. In relation to behavioral economics, this research contributes to the field evidence of reference-dependent preferences, including that on the labor supply of taxi drivers (Camerer et al., 1997; Farber, 2008; Crawford and Meng, 2011; Thakral and Tô, 2019), the behavior of taxpayers in order

[1] Dynamic pricing is also called revenue management or yield management in the marketing literature.

to achieve a situation where no taxes are due (Rees-Jones, 2018; Engström et al., 2015), job search behavior under unemployment assistance (DellaVigna et al., 2017), marathon runners' efforts to achieve round-number goals (Allen et al., 2017), and housing prices (Genesove and Mayer, 2001). The intuition of this research is very close to Genesove and Mayer (2001), who find that sellers in the housing market tend to set higher asking prices to prevent losses, based on previous purchase prices as the reference points. In this research, I further provide evidence of the bunching of listing prices at reference points, and estimate the loss aversion parameters for sellers.

In relation to finance, the literature finds that investors are more likely to sell stocks trading at a gain relative to the purchase price than stocks trading at a loss, which is labeled the "disposition effect" (Shefrin and Statman, 1985; Odean, 1998; Heath, Huddart and Lang, 1999; Grinblatt and Keloharju, 2001). Barberis and Xiong (2009) use the initial wealth as the reference point to formalize this phenomenon, and show that the model predicts a disposition effect only if the diminishing sensitivity effect overcomes the loss aversion effect. Meng and Weng (2018) further extend the model to include forward-looking reference points. Although the intuition of the disposition effect is similar to this research, there is one big difference between this research and the previous behavioral finance literature: sellers in the sports ticket secondary market have a limited time in which to sell their tickets, leading the predicted price trend to be downward over time (Sweeting, 2012). This simplifies the seller's problem, such that they are only reluctant to sell tickets during the period close to the game day in the loss domain.

This paper makes three additions to the literature. First, to the best of my knowledge, my paper is the first to demonstrate evidence of the bunching of listing prices in the online peer-to-peer market. Second, the research also adds to the literature on structural behavior economics in estimating the loss aversion parameters for backward-looking reference points. Third, this article contributes to the literature related to market experience, with the evidence in this example showing that market experience might not eliminate all of the effects of reference points. When recent outcomes serve as reference points, the effects still exist for those sophisticated agents.

The remainder of this paper is organized as follows. Section 2 presents a theoretical model illustrating how reference-dependent preferences affect pricing. Section 3 summarizes the data used in this study and shows the descriptive evidence of reference points. Section 4 provides the details of the structural estimation. Section 5 shows the estimation and counterfactual results. Section 6 concludes this research.

2 Theoretical Framework

This section presents a dynamic pricing model, which follows from Sweeting (2012) to illustrate how reference-dependent preferences affect the behavior of sellers, and predictions from which are used for the empirical test in Section 3. Furthermore, in Section 4, I will extend this model and make more assumptions to estimate some important parameters.

For a given game, there are T periods, indexed by $t = \{1, 2, ...T\}$, in which the sellers can sell their tickets, with the game starting after period T. The sellers come into the market at different times, and during each period in which the number of sellers is large enough, the market power of each seller is relatively small. Because of the heterogeneity of tickets, each seller can decide on her own prices in each period so as to maximize expected profits. If a ticket is not sold in period t, the seller can change the price in period $t+1$. In the model, each seller is assumed to have only one ticket when entering the market, and there is no switching cost for sellers of adjusting their price every day.

The profit maximization problem for seller i at period t can be written as

$$V_{it} = \max_{p_{it}} u_i(p_{it})q_{it}(p_{it}) + [1 - q_{it}(p_{it})]E_t(V_{it+1}),\ \ t = 1, 2, ..., T, \qquad (1)$$

where $q_{it}(p_{it})$ is the probability of sale, for listing i at period t, given the listing price p_{it}. Because the quantity provided by each seller is relatively small in the market, the probability of sale, $q_{it}(.)$, is assumed to be exogenous for each seller, and can be estimated based on all the listings in the market. $E_t(V_{it+1})$ is the expected value of holding the ticket at period $t+1$, which can also be interpreted as the opportunity cost of a sale.

In the last period, T, the expected value, $E_T(V_{iT+1})$, can be interpreted as the expected value of holding the ticket after the game starts. For those sellers who can attend the game even if they cannot resell their tickets, the remaining value of their ticket should be positive. However, for those sellers who cannot attend the game, the remaining value may be zero. I assume that each seller has a different remaining value of their ticket, r_i, and that the expected value in the last period should be written as $u_i(r_i)$.

The first-order condition for the profit maximization problem is

$$u_i'(p_{it})q_{it}(p_{it}) + \frac{\partial q_{it}(p_{it})}{\partial p_{it}}(u_i(p_{it}) - E_t(V_{it+1})) = 0,\ t = 1, 2, ..., T. \quad (2)$$

Consider a risk-neutral seller without gain-loss utility, with utility defined as $u_i(p_{it}) = p_{it}$. Then, the first-order condition can be rewritten as

$$p_{it} = -\frac{q_{it}(p_{it})}{\frac{\partial q_{it}(p_{it})}{\partial p_{it}}} + E_t(V_{it+1}),\ t = 1, 2, ..., T. \quad (3)$$

The intuition behind equation (3) is that the optimal price in the current period is equal to the next period expected value plus the markup, which depends on the current period demand elasticity. This is the result of the traditional dynamic pricing model.

However, if the seller has gain-loss utility based on an exogenous reference point, RP_i, the utility can be specified as

$$u_i(p_{it}) = v_i(p_{it}) + \eta G(p_{it}|RP_i), \quad (4)$$

where $G(p_{it}|RP_i)$ is the gain-loss utility, and $\eta > 0$ is the parameter that indicates how the gain-loss utility relates to the consumption utility. Following Post et al. (2008), $G(p_{it}|RP_i)$ can be defined as

$$G(p_{it}|RP_i) = \begin{cases} (p_{it} - RP_i)^{\alpha} & \text{if } p_{it} \geq RP_i \\ (-\lambda)(RP_i - p_{it})^{\alpha} & \text{if } p_{it} < RP_i \end{cases}, \quad (5)$$

where $\lambda > 1$ is the loss aversion parameter, and $\alpha > 0$ represents the curvature of the gain-loss utility, reflecting the diminishing sensitivity effect.

Before jumping into the simulation, I use a simple linear example, where $v_i(p_{it}) = p_{it}$, and $\alpha = 1$, to illustrate the effect of reference points. In this example, the optimal listing price p^*_{it} should satisfy one of the following three cases in each period t:

- **Case I.** When $p^*_{it} \geq RP_i$, the optimal price p^*_{it} should satisfy the first-order condition under the gain domain:

$$p^*_{it} = -\frac{\Phi_{it}(p^*_{it})}{\frac{\partial \Phi_{it}(p^*_{it})}{\partial p_{it}}} + \left(\frac{\eta}{1+\eta} RP_i + \frac{1}{1+\eta} E_t(V_{it+1}) \right). \tag{6}$$

- **Case II.** When $p^*_{it} < RP_i$, the optimal price p^*_{it} should satisfy the first-order condition under the loss domain:

$$p^*_{it} = -\frac{\Phi_{it}(p^*_{it})}{\frac{\partial \Phi_{it}(p^*_{it})}{\partial p_{it}}} + \left(\frac{\eta\lambda}{1+\eta\lambda} RP_i + \frac{1}{1+\eta\lambda} E_t(V_{it+1}) \right). \tag{7}$$

- **Case III.** If the previous two cases are not satisfied, the optimal price is binding at the reference point, that is $p^*_{it} = RP_i$.

The last two terms in equations (6) and (7) can be interpreted as the "adjusted" expected value of holding the ticket in the next period, which is a linear combination of the original expected value and the reference point. Compared with equation (3) in the case without reference-dependent preferences, equations (6) and (7) show that the optimal listing price is affected only through the adjusted expected values.

In Case I, the adjusted expected value could be influenced in an upward or downward direction, based on whether the expected value, $E_t(V_{it+1})$, is lower or higher than the reference point. As $E_t(V_{it+1}) > RP_i$, the adjusted expected value and the optimal price become lower, compared to the case without reference-dependent preferences. The seller with gain-loss utility tends to choose a lower price to ensure the sale of the ticket when she faces the gain domain. When $E_t(V_{it+1}) < RP_i$, the adjusted expected value and the optimal price become higher because the seller wants to avoid incurring a loss from selling the ticket. In Case II, the seller always faces the loss domain because $E_t(V_{it+1}) < RP_i$, so the adjusted expected value and optimal price are influenced upward. In addition, the seller has a high chance of falling into Case III, so the bunching of listing prices at the reference point should be expected from the model.

The simulation result is based on a time-invariant probability of sale, $q_{it}(p_{it}) = \Phi(-p_{it})$, where $\Phi(.)$ is the standard normal cumulative distribution function. For those sellers with the gain-loss utility, I assume that the consumption utility $v_i(p_{it}) = \log(p_{it})$, the gain-loss parameter $\eta = 1$, the loss aversion parameter $\lambda = 2.25$, and the curvature of the gain-loss utility $\alpha = 1$. To create heterogeneity of sellers, I assume that the remaining values of their tickets, r_i, follow a chi-squared distribution $\chi^2(0.5)$. The reference point is assumed to be 1. In Section A.1 of the appendix, I provide sensitivity tests of the important parameters. Figure 1 shows the simulated listing price distribution. For those sellers without reference-dependent preferences ($\eta = 0$), the listing prices (blue hollow ones) truly reflect the distribution shape of the remaining values. However, for those sellers with reference-dependent preferences, the listing prices (orange) clearly show evidence of bunching at the reference point. Instead of choosing a listing price lower than the reference point and thus suffering a loss, such sellers are more likely to set their listing prices at least higher than the reference point.

To further understand the listing price pattern over time, I simulate two sellers with the same remaining value, 0.01. Figure 2 shows the simulated price pattern over time. The blue solid line with circles shows the listing price pattern chosen by the seller who does not have reference-dependent preferences ($\eta = 0$), while the orange dashed line with asterisks indicates that chosen by the seller with reference point equal to one. Compared with the blue line, the listing prices on the orange line are higher in the last six days before the game, because that seller faces a loss domain over the last few days, and the listing prices are stuck at the reference point during the 7-9 days prior to the game.

To sum up, two predictions are generated by the theoretical model:

Prediction 1. *If sellers have reference-dependent preferences, the listing price distribution should show evidence of bunching at the sellers' reference points.*

Prediction 2. *Compared with the listing prices chosen by a seller without reference points, those chosen by a seller with reference-dependent preferences should be higher in the last few days, in the loss domain.*

In the next section, I will use the data to show that Prediction 1 holds for some potential reference points. However, it is not easy to show evidence of Prediction 2 because sellers without reference points may not exist in the market. Instead of showing that Prediction 2 holds, I will directly estimate the parameters in the gain-loss utility and use a counterfactual exercise to quantify the effect of reference points during the last few days prior to a game.

3 Data and Descriptive Evidence

This section describes the data used in this research, which I will use to show evidence of bunching at two types of reference points: the face value of each ticket, and the PLTPs within the same section of the stadium.

3.1 Data

The data in this study consist of three parts: the listing data on StubHub for one particular Major League Baseball franchise's home events in 2011, the transaction data for those home events on StubHub, and the purchasing information in the primary market[2]

The listing data were collected from the StubHub website daily during the period from March 25, 2011 to September 30, 2011, and included all the information shown for consumers on the website, such as the listing price, section number, row number, and seat number. Because each listing was obtained from the website daily, the initial listing price and each price adjustment can be observed from the data.

In the listing data, the disappearance of an available listing is not equivalent to a purchase, since sellers on StubHub can relist tickets with different listing identification numbers; therefore, the transaction data on StubHub are used to identify purchases within the listing data. Most of the purchased

[2]The last two sets of data were provided by an anonymous company.

listings in the sample can be matched to detailed transaction information, such as the transaction time, price, quantity, and seat information.

In addition, the listing data alone are not enough to identify sellers because StubHub hides such information. Therefore, the purchasing data in the primary market are used to identify the sellers, because all tickets are sold initially by the franchise[3]. Primary market transaction data include comprehensive purchase information, including type of ticket, purchase price, ticket characteristics, purchase date, and buyer identification number. Based on the buyers' IDs, the number of tickets bought over the entire season can be calculated. Besides the purchasing information, how many listings they have on StubHub can also be identified. However, not all listings contain detailed seat information, such as row and seat numbers, so for only around 71.9% of listings can I identify the seller. In the following analysis, I focus on those listings for which information on the seller is available.

Table 1 shows the summary statistics for the information from the listings on StubHub, including the listing price, starting date, original purchase price in the primary market, face value, sold status, and other ticket characteristics. I have excluded some of the listings with extremely high listing prices[4]. The remaining sample contains 103,245 listings for 81 home events, with around 1,300 listings for each game.

Sellers on StubHub can adjust the listing price easily at any time, so that the observed daily listing price might change over time for one listing. Table 1 reports summary statistics for the initial, maximum, minimum, and

[3] I assume that tickets are not resold or transferred in other secondary markets.

[4] Those listings with prices exceeding $999 or 9 times the face value are excluded.

average prices of each listing, relative to the face value. Because sellers tend to set higher prices in the beginning and lower the price as the event date approaches, the average initial listing prices is 1.68 times the face value[5]. The average maximum price (1.82) and average minimum price (1.31) are both greater than one. Regarding the timing of listing, most sellers tend to list their tickets well in advance of the event. Around 34.3% of listings are listed more than one month prior to the event, while 29.6% are listed two weeks ahead. The starting dates are strongly correlated with the initial listing prices, probably because different start times might be associated with sellers with different opportunity costs.

Because the prices for season tickets or group tickets are cheaper than the face value, the average original purchase price is 0.84 of the face value, lower than 1[6]. Table 1 also presents ticket characteristics related to quality, including the distance from the seat to the home plate[7], a front row dummy, and a row quality measure. Row quality is a normalized measure that quantifies the row number. A value of one represents the first row in a given section, while a value of zero represents the last row in that section. The listing period and number of price adjustments vary based on the observed periods for different events. The average listing period is about 38 days, and the sellers adjust their listing prices around twice for each listing. Since each

[5]Because I started to collect the listing data on March 25, 2011, I cannot observe the initial listing prices for those with starting dates before then. Around 80% of the initial listing prices can be observed.

[6]The maximum purchase price in the primary market is 1.29 of the face value, which is because around 1.8% of the listings in the data have original purchase prices greater than the face value, i.e. a relative value greater than 1. It seems that those prices might be adjusted a little bit in the primary market.

[7]This variable does not vary within the same section. I only calculate the distance from the seat to the home plate by section.

listing has many tickets (seats), a seller can sell them separately in many ways. On average, 39% of listings are sold out before the event, and around 40.6% of listings are sold partly during the period observed on StubHub.

Based on the primary transaction data, the total number of identified sellers is 9,664. Table 2 shows the summary statistics for all the identified sellers. In the primary market, two main types of tickets can be purchased: single-game tickets, and package tickets[8]. The prices for the single-game and package tickets in the primary market are different. People can purchase single-game tickets for any particular game, but package tickets are only designed for multiple games. People with different needs can purchase different types of tickets. 38.3% of sellers only purchase the single-game tickets in the primary market; 39.7% of sellers only buy the package tickets. The remaining 22% of sellers buy both types. Besides the types of tickets they buy, the sellers can also use different channels to buy their tickets. 44.2% of sellers purchase only through the website, and 41.9% only from the box office. Different purchase channels could represent different opportunity costs of sellers reselling their tickets.

In addition to the purchase information in the primary market, the listing and transaction data on StubHub indicate how many tickets the sellers tend to sell to in the secondary market. The average number of listings a seller makes in the entire season is 11.59, with around 34.89 tickets sold per seller. Some sellers will only make one listing in a year, but some will make many. To understand the behavior of heterogeneous sellers, I will use the types of

[8] In the data, a small proportion of other types of tickets were sold, such as group tickets. In the following analysis, I will only look at the two main types of tickets.

tickets they hold and the number of listings they make in a season to create subgroups for analysis.

3.2 Evidence of Bunching at Face Values

According to the lab experiment reported in Baucells, Weber and Welfens (2011), a combination of the first and the last price of a time series is the best estimate of a reference price for those data. However, in my data, I did not find evidence of bunching at the purchase price in the primary market. One reason could be that most of the sellers purchased multiple tickets at some kind of discount, such as package tickets, making the purchase price for one ticket somewhat irrelevant. Even focusing on those sellers who purchased single-game tickets in the primary market[9], the evidence of bunching is not very clear. Therefore, instead of the purchase price in the primary market, the face value could more naturally serve as the reference point for these sellers. This subsection presents the evidence of the bunching of listing prices at the face values of the tickets. I look only at the initial listing price for each listing in this subsection[10]

Figure 3 presents the frequency distribution for the initial listing prices relative to the face values, and clearly shows evidence of bunching at one. This implies that a seller tends to choose a listing price higher than the face

[9]Because the purchase price in the primary market is equal to the face value in this case, both could be the potential reference point if evidence of bunching existed.

[10]There are two reasons to focus on the initial listing, instead of each price adjustment during the listing period. First, the average number of price adjustments for one listing is around 1.8, so most sellers do not change their listing price too often. Second, the price adjustments could also reflect the switching cost for the sellers. To avoid mixing the effect of reference points with other effects, I use the initial listing prices for the following analysis. In fact, though, there exists evidence of bunching for all the price adjustments as well.

value, instead of a listing price lower than the face value. The bottom figure displays the results of the discontinuity test provided in McCrary (2008). The z-statistic of the test is 35.5, as shown in the last column of Table 3. The percentage of listings with a listing price in $[1, 1.1)$ is 8.45%, much larger than the percentage with listing prices in $[0.9, 1)$, of only 4.58%

To further understand the evidence of bunching across different subgroups, I use various pieces of the listing information, such as the number of tickets in a listing, the starting date, the month of the game, and the face value, to split the sample. The results are very robust across the subgroups. Besides the listing information, I also use information about the sellers, such as the types of tickets, number of listings, and purchase channel, to create subgroups. The results show that sellers who only purchase single-game tickets in the primary market tend to exhibit weaker (but still significant) evidence of bunching, which suggests that those sellers are less affected by the face value. This may be because they did not intend to resell their tickets when they purchased them in the primary market, making them quite different from other sellers in the secondary market. The other sellers, such as those holding package tickets or mixed ticket types, seem to be more affected by the face value.

In addition, I use the number of listings to proxy for the size of the seller. For sellers with more than 150 listings in a season, the discontinuity test is insignificant, which suggests that those big sellers are not affected by the face values of the tickets. This supports the previous literature, which has found that sophisticated sellers tend to be little affected by reference points (List, 2003). However, the evidence of bunching is very robust for the sellers with less than 150 listings in a season.

One possible explanation for the face values being the reference points could be the round number effect (Allen et al., 2017), because some of the face values end with a round number, such as 0 or 5. Indeed, I find that round numbers play an important role in listing prices, with many sellers choosing initial listing prices ending with 0 or 5. To further check whether the evidence of bunching is only due to the round number effect, I split the sample into two groups: one with face values ending in 0 or 5, and the other with face values ending in other numbers. Figure 4 shows that both groups exhibit clear evidence of bunching at one, which suggests that the listing prices are still affected by the face values even when the round number effect is eliminated. The bottom panel of Table 3 shows the z-statistics of the discontinuity test for these two groups.

To further show that this bunching effect is not driven by the purchase price in the primary market, I again split the sample into two groups: one with face value equal to the purchase price in the primary market, and the other with face value not equal to the original purchase price. Figure 5 shows that the evidence of bunching is most driven by those listings with face value different from the purchase price in the primary market. This indicates that sellers are more likely to be affected by the face value than the purchase price in the primary market, which is different from the disposition effect whereby people usually use the purchase price to measure their gains and losses in the financial market.

3.3 Evidence of Bunching at the Previous Lowest Transaction Price

The previous literature also indicates that recent outcomes could be potential reference points, such as recent income being reference points for a job search in DellaVigna et al. (2017). Also, StubHub provides comprehensive transaction records that sellers can use to determine their listing prices, meaning that historical prices could also serve as reference points for sellers. Because transaction prices are on average decreasing in the secondary market over time, the PLTP could be the highest value a seller is like to obtain for a ticket in the future. Therefore, a seller could feel a sense of gain if she can sell the ticket at a price higher than the PLTP; otherwise, she might experience it as a loss. In this subsection, I will use the PLTPs within the same section of the stadium as the reference points and test for evidence of bunching.

Since the PLTPs differ quite widely for the listings, I divide the listing prices by the PLTPs to test for evidence of bunching. Figure 6 shows clear evidence of bunching in the listing prices at one. The bottom figure displays the results of the discontinuity test from McCrary (2008), and all the test statistics are shown in Table 4. As in the previous subsection, I check the evidence of bunching for different subgroups, based on the listing and sellers' information, and find the results to be robust across all the subgroups. Even for those sellers with more than 150 listings in a season, the clear evidence of bunching indicates that the big sellers are also affected by the PLTPs. One possible reason is that all sellers might observe the historical transaction prices before deciding on their listing prices, so that the PLTPs serve as significant reference points for them.

To further understand the effect of the PLTPs on sellers over time, I split the sample into two groups: one with PLTPs higher than the face value, and the other with PLTPs lower than the face value. The first case usually happens early in the period, and the second case in the last few days before the game. Figure 7 and the bottom panel of Table 4 show that both cases exhibit clear evidence of bunching, which suggests that the PLTPs have an effect throughout the entire period.

To sum up the results from these two subsections, the face values and the PLTPs might serve as important reference points that affect the pricing decision of the sellers. In the next section, I will add some assumptions to the previous theoretical model and develop a structural estimation method to estimate some important parameters, such as the loss aversion parameter.

4 Estimation

In this section, I will use the model from Section 2 and make some reasonable assumptions for the following estimation. First, I assume that each seller is relatively small, which means that sellers do not interact directly with other sellers. Therefore, the maximization problem over time for a seller can be treated as a single-agent finite period dynamic problem. Since the listing price is a continuous decision for the seller, I use the estimation method developed by Bajari, Benkard and Levin (2007) to estimate this structural model.

To simplify the estimation period, I only use the last two weeks before the game for the estimation. Each seller comes into the market 14 days before the game, and they know the remaining value of their tickets for themselves before determining the initial listing prices. The remaining values of the tickets, r_i, are assumed to follow a chi-squared distribution, $\chi^2(\nu)$. Based on the remaining value of a ticket, each seller can decide the optimal price to set for it in each period before the game. I assume that there is no switching cost, so sellers will adjust their listing prices every day.

The state variables $\mathbf{s}$ include three elements: the demand conditions, s_1, in the market, the number of days before the game, $s_2 = \{14, 13, ..., 1\}$, and the listing status, s_3. I will introduce s_1 later, in Subsection 4.2. The listing status, s_3, is binary and indicates whether the listing is still posted on StubHub, so $s_3 = 0$ when the listing has been purchased and has disappeared from the market.

The estimation method consists of two stages. In the first stage, I estimate the probability of sale $q_{it}(p_{it})$ for each state, the state transition matrix, and the pricing function conditional on each state for a specific group of the sellers. In the second stage, I use a minimum distance estimator to find a set of structural parameters which can rationalize that the observed listing prices are optimally chosen.

4.1 Probability of Sale

In order to estimate the probability of sale for each listing, I specify a probit model as follows:

$$y_{it}^* = \beta_0 - \beta_1 p_{it} + \mathbf{X}_{it}\boldsymbol{\gamma} + \epsilon_{1it}, \tag{8}$$

$$p_{it} = \mathbf{X}_{it}\boldsymbol{\Pi}_1 + \mathbf{Z}_{it}\boldsymbol{\Pi}_2 + \epsilon_{2it}, \tag{9}$$

where $y_{it} = 1\{y_{it}^* \geq 0\}$ represents the sale of a listing, and $\mathbf{X}_{it}$ includes the listing characteristics and competition variables used to control the demand equation. However, the prices set by sellers might be correlated with some unobserved demand shock, ϵ_{1it}, so equation (9) is needed to specify a cost-based shock to solve the endogeneity problem. The error terms ϵ_{1it} and ϵ_{2it} are jointly distributed according to a joint normal distribution:

$$\begin{pmatrix} \epsilon_{1it} \\ \epsilon_{2it} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma_v \\ \rho\sigma_v & \sigma_v^2 \end{pmatrix} \right), \tag{10}$$

where ρ is the parameter used to specify this endogeneity problem. If $\rho = 0$, there is no endogeneity problem and for the demand estimation I only need the traditional probit model. However, if $\rho \neq 0$, the endogeneity problem arises, I use the control function approach to first estimate equation (9), and then I include the residuals from the first stage in equation (8) to estimate the probit model.

Besides the endogenous listing price variable in equation (8), $\mathbf{X}_{it}$ include two sets of variables: quality-based characteristics of listings and competition variables for demand estimation. The quality-based characteristics include the distance from the seat to the home plate, the row quality, seat area dummies, the row quality×the seat area dummies, game dummies, the number of days until the game, and dummies for the number of tickets in one listing. The variables related to the quality of the tickets may not only affect how the sellers decide on their prices but also the consumers' demand.

The competition variables in $\mathbf{X}_{it}$ need to be controlled because they are correlated with the sellers' listing price decisions. I control the dummy to determine whether competing listings exist[11], the number of competing listings, the mean prices for competing listings, the proportion of listings with higher row quality, whether a listing has the lowest price, and the proportion of listings with lower prices.

To solve the endogeneity problem, the instrumental variables $\mathbf{Z}_{it}$ in equation (9) need to be correlated with the listing prices but not with the unobserved demand shock in u_{it}. I use three sets of instruments: the types of tickets the sellers have, the timing of the listings, and the purchase channel used in the primary market. Sellers with different types of tickets might have different considerations when reselling their tickets. Meanwhile, the timing of listings and the purchase channel used could reflect the seller's opportunity cost. These three factors could affect their pricing decisions, but should not be correlated with the unobserved demand shock.

Table 6 presents the regression on all the instruments. I also include all the characteristics $\mathbf{X}_{it}$ in this equation. The overall F-statistic for all the in-

[11] I define competing listings as those for the same event, in the same section, on the same date, and with the same number of tickets.

strumental variables is greater than 10, which indicates that there is no weak instrument problem in the first stage. Table 5 shows the estimates for the probability of sale. Column 1 presents the results for the traditional probit model with exogenous listing prices; Column 2 shows those for the instrumental variable probit model estimated using the control function approach. If the unobserved demand shock is ignored, the coefficients on the listing prices obtained from the probit model have positive bias. After obtaining the unbiased estimates $\{\hat{\beta}_0, \hat{\beta}_1, \hat{\boldsymbol{\gamma}}\}$, I can write the estimated probability of sale as $\Phi(\hat{\beta}_{it} - \hat{\beta}_1 p_{it})$, where $\Phi(.)$ is the standard normal cumulative distribution function, and $\hat{\beta}_{it}$ is defined as $\hat{\beta}_0 + \mathbf{X}_{it}\hat{\boldsymbol{\gamma}}$.

4.2 Discretizing the State Space and Estimating the State Transition Matrix

In fact, the demand condition s_1 should include a lot of information about the market, such as the game, section, and row information. To simplify the estimation procedure, I directly discretize $\hat{\beta}_{it}$ to represent the state variable s_1. The range of $\hat{\beta}_{it}$ is between -2 and 1, so the state variable is defined as $s_1 = \{-2, -1, 0, 1\}$.

The state transition matrix $\text{Prob}(\mathbf{s}'|\mathbf{s})$ is assumed to be

$$\text{Prob}(s_1'|s_1, s_2') \times \text{Prob}(s_2'|s_2) \times \text{Prob}(s_3'|s_3),$$

where $s_2' = s_2 - 1$ with certainty, and $\text{Prob}(s_3'|s_3)$ can be obtained using the estimated probability of sale in the previous subsection. $\text{Prob}(s_1'|s_1, s_2')$ can be directly estimated based on the discrete predicted data from $\hat{\beta}_{it}$.

4.3 Estimating Pricing Strategies by State

The optimal listing price $p^*_{it}(\mathbf{s}, r_i)$ is a function of the state variable and the remaining value of the ticket. Let $F_1(p_{it}|\mathbf{s})$ denote the probability that seller i chooses a listing price less than or equal to p_{it} in state $\mathbf{s}$. Based on the monotone choice assumption that the optimal pricing function $p^*_{it}(\mathbf{s}, r_i)$ is increasing in r_i, which is reasonable in this model, the pricing function can be written as

$$p^*_{it}(\mathbf{s}, r_i) = F_1^{-1}(F_2(r_i|\mathbf{s}; \nu)|\mathbf{s}),$$

where $F_2(.)$ is the chi-squared cumulative distribution function. $F_1(.)$ could be directly estimated nonparametrically from the data. For the baseline estimation, I use the whole sample to estimate the pricing strategies. In the subgroup analysis, a certain group of sellers are selected for the estimation.

4.4 Estimating the Parameters in Utility Function

In the second stage, I simulate N listings ($i = 1, 2, ..., N$) based on the estimated state transition matrix, estimated optimal pricing function, and the random draws for the remaining values. For each listing i, I simulate K times ($k = 1, 2, ..., K$). In equation (4), I assume that $\eta = 1$[12], and $v_i(p_{it}) = \log(p_{it})$. Also, I assume that the gain-loss utility is as in equation (5). Although ν is the unknown parameter in the distribution of remaining values, it might not be identifiable from the estimation[13]. Therefore, I assume

[12]Based on the previous literature, it is difficult to identify this parameter.
[13]I will explain this later, in Subsection 4.5.

$\nu = \{0.2, 0.4, 0.6, 0.8\}$ for the estimation, so that only two parameters, (α, λ), need to be estimated in the second-stage structural estimation.

Given the parameters (α, λ), the value function[14] for each period t in simulation k can be calculated by moving backwards from the last period:

$$\begin{aligned} V_{itk}(p^*_{it}(r_{ik}), \alpha, \lambda) = u(p^*_{it}(r_{ik}); \alpha, \lambda)\hat{q}_{it}(p^*_{it}(r_{ik})) \\ + [1 - \hat{q}_{it}(p^*_{it}(r_{ik}))]V_{it+1k}(p^*_{it}(r_{ik}), \alpha, \lambda), \end{aligned} \quad (11)$$

where $V_{iT+1k} = u(r_{ik})$, and $p^*_{it}(r_{ik})$ is the estimated optimal pricing function in each state, based on the remaining value r_{ik}. From K simulations, we have

$$\bar{V}_{it}(p^*_{it}, \alpha, \lambda) = \frac{1}{K}\sum_{k=1}^{K} V_{itk}(p^*_{it}(r_{ik}), \alpha, \lambda). \quad (12)$$

The values for any other alternative pricing function $\tilde{p}_{it}(s_{ik})$ should not be optimal, so we have

$$\bar{V}_{it}(p^*_{it}; \alpha, \lambda) \geq \bar{V}_{it}(\tilde{p}_{it}; \alpha, \lambda).$$

Define a function

$$g_{ith}(\psi) = \bar{V}_{it}(p^*_{it}; \alpha, \lambda) - \bar{V}_{it}(\tilde{p}_{it}(h); \alpha, \lambda) \geq 0,$$

where $\psi = (\alpha, \lambda)$, and $\tilde{p}_{it}$ are arbitrary price disturbances from the optimal pricing function. I take H alternative pricing function $(h = 1, 2, ..., H)$ for each listing in each period. Because the pricing function estimated from the

[14] I simplify the notation for the state variables.

data is treated as optimal, $g_{ith}(\psi)$ should be non-negative. Define another function

$$Q(\psi) = \frac{1}{HNT} \sum_{h=1}^{H} \sum_{i=1}^{N} \sum_{t=1}^{T} (\min \{g_{ith}(\psi), 0\})^2, \tag{13}$$

and then the estimator $\hat{\psi}$ is chosen to minimize the objective function $Q(\psi)$. In the baseline estimation, I choose $N = 100$, $T = 14$, $K = 50$, and $H = 50$.

4.5 Identification

It is plausible to identify both the mean remaining value ν and the loss aversion parameter λ in this model. Section A.1 shows that a seller with a larger λ tends to determine a higher listing price on the last day before the game; however, a higher remaining value for a seller can have the same effect on the listing price. In the structural estimation, I choose some reasonable values for ν, and estimate the loss aversion parameter λ directly. Since a reasonable value for the mean remaining value ν is between 0 and 1, I choose four values, 0.2, 0.4, 0.6, and 0.8, for the estimation. A higher remaining value is expected to produce a lower estimate of the loss aversion parameter.

Based on the sensitivity test, described in Section A.1, the loss aversion parameter λ and the diminishing sensitivity parameter α play different roles in the structural estimation. First, a seller with a larger loss aversion parameter λ is more likely to choose a higher listing price on the last day to prevent a loss, but the diminishing sensitivity parameter α does not have the same effect.

Second, these two parameters create bunching in different ways. The listing prices chosen by a seller with a larger λ stick to the reference point during more of the periods, which creates more significant bunching at the reference point. On the other hand, the diminishing sensitivity parameter α creates curvature in the gain-loss utility, so that a seller tends to adjust their listing price slowly when the listing price is close to and larger than the reference point. Also, based on the convexity of the utility function over the loss domain, a seller will be averse to choosing a listing price close to and lower than the reference point. Therefore, a higher α can produce more listing prices in the gain domain, instead of the loss domain. To sum up, both the loss aversion parameter λ and the diminishing sensitivity parameter α can be identified in this model.

In addition, DellaVigna et al. (2017) indicate that the estimates could be imprecise if the parameters η and λ are both estimated in the model. Since I face the same issue of estimating two parameters, I directly set $\eta = 1$ to avoid the problem. Therefore, in the structural estimation, I only estimate the loss aversion parameter λ and the diminishing sensitivity parameter α, based on different values of ν.

5 Estimation Results

In this section, I first present the results of the structural estimation, including the estimates of the loss aversion parameter and the diminishing sensitivity parameter. Then, I use a counterfactual exercise to show the effect of the reference points. In the last subsection, I focus on different groups of sellers to investigate how the reference points affect their listing behaviors in different ways.

5.1 Benchmark Estimates

Table 7 shows the results of the structural estimation across different means of the remaining values ν. In the top panel, sellers are assumed to treat the face values of the tickets as the reference points, while the PLTPs are assumed to be the reference points in the bottom panel. For a larger ν, the estimation results show a smaller loss aversion estimate and a larger diminishing sensitivity estimate, generating weaker bunching.

To further understand which values of ν might be the most reasonable to assume, I simulate predicted listing prices based on the estimates and compare them with the actual data. Figures 8(a) and 9(a) show how the models using different values of ν fit the actual data. In both cases, the listing prices are relatively higher when the mean of the remaining values is higher, because sellers have higher opportunity costs after the last day. In the case where the face values are the reference points, the predicted pattern under $\nu = 0.6$ gives a better fit than the others. However, in the case where the PLTPs are the reference points, the actual data lie between the patterns predicted under $\nu = 0.4$ and $\nu = 0.6$. If the estimates based on $\nu = 0.6$ are chosen, then the predicted listing prices are overestimated during the earlier periods, such as 8-14 days before the game. For convenience in the following analysis, I pick $\nu = 0.6$ as the benchmark, including in the subgroup analysis. Figures 8(b) and 9(b) show clear evidence of the bunching of listing prices at the reference points.

Based on a mean remaining value of $\nu = 0.6$, the loss aversion estimates $\hat{\lambda}$ under these two cases are 4.62 and 3.68, which are close to the estimates in the previous literature[15]. The magnitude of λ represents sellers' aversion to a loss when selling tickets. The diminishing effect estimates are 0.44 and 0.47, which shows the concavity and convexity of the utility function in the gain and loss domains, respectively.

5.2 Effects of Reference Points

If sellers do not have reference-dependent preferences, the listing price distribution will not show any evidence of bunching at any value. A seller will then be more likely to choose a listing price lower than the face value or the PLTP. Therefore, in the counterfactual exercise, lower listing prices will be expected in the market, which could result in more listings being sold. To quantify the effects of the reference points, I set the parameter η to zero and simulate the listing price pattern and distribution in the counterfactual exercise[16]. The results are shown in Figures 10 and 11.

Compared with the actual data (shown in orange), Figures 10(a) and 10(b) show that there is no evidence of bunching (in blue) at the face values or PLTPs. The blue line with the circles in Figure 11(a) shows the average listing prices simulated in the counterfactual exercise. On the last day, the average listing price in the scenario without reference points is around 0.92, lower than that in the actual data, of 1.14. The effect of the reference

[15] In the previous literature, it is suggested that the loss aversion parameter λ takes a value of 2.25 (Tversky and Kahneman, 1992). DellaVigna et al. (2017) obtain a loss aversion estimate of 4.54.

[16] When $\eta = 0$, both cases are identical because sellers no longer have reference-dependent preferences.

points on the last day's listing prices is around -19.30%, which is the biggest negative effect over the period.

Although the two types of reference points affect the listing prices through different mechanisms, both results show that the effect becomes larger as the game day approaches. When the face values of tickets serve as the reference points, the effect becomes larger due to the bigger loss that will be incurred in the last few days. Therefore, on the last day, the seller faces their biggest loss in the market, such that the gap between the actual listing prices and the simulated listing prices is the largest on that day.

However, when sellers treat the PLTPs as reference points, this effect can be further decomposed into two separate parts. The first comes directly from the reference points, the PLTPs. Because sellers are reluctant to sell tickets below the PLTPs, the listing prices are relatively higher. The second part is indirectly generated by the dynamic pattern. Because of the higher listing prices in the previous period, the PLTPs are also higher. In the counterfactual analysis, I can further distinguish these two effects. First, I simulate the listing prices in the scenarios without reference points, and then I further simulate the transaction prices based on the probability of sale in each period. Using the counterfactual PLTPs as the reference points, I can simulate the listing prices based on the estimates of the parameters, which provides the direct effect of the reference points. On the last day, the average simulated listing price generated only by the direct effect is around 0.98, which is around -14.28% lower than that in the actual data, showing that most of the effect stems from the direct mechanism.

Because of the lower listing prices, the probability of sale also increases for all the listings on each day, as shown in Figure 11(b). The effect of the reference points on the probability of sale becomes larger as the game day approaches, because more listings are affected on the last day. Considering the dynamic effect over time, the simulation result shows that a typical listing has a probability of 0.48 of being sold during the last 14 days, which is higher than the probability calculated from the real data, of around 0.43.

5.3 Heterogeneous Sellers

Since this structural estimation can be applied to a specific group of sellers[17], I split the sample into several subgroups based on the different features of the sellers, so as to investigate the heterogeneous behavior of sellers. In addition, the sellers are affected by the two types of reference points in different ways.

First, I consider the types of tickets the sellers have, which might represent different motivations for the sellers in the secondary market. Those sellers holding single-game tickets are probably reselling their tickets because they are unable to attend the game, as they would be unlikely to purchase single-game tickets in the primary market if their aim was to resell their tickets for a profit. Therefore, the motivation for those sellers holding single-game tickets will be quite different to that of the sellers holding package or mixed tickets, which would have had cheaper prices in the primary market. Table 8 shows that sellers who only hold single-game tickets are less likely to be affected by their face values than those holding package tickets or mixed ticket types. It is surprising that they are affected less even though most of them would have

[17]The number of listings needs to be large enough for the optimal pricing function to be estimated in each state in the first stage.

purchased their tickets at the face value in the primary market. Those sellers holding package tickets only are most affected by the face value. However, all sellers are affected similarly by the other type of reference point, the PLTPs.

In addition, I use the number of listings made in an entire season to proxy for the size of the seller. Big sellers post a lot of listings during a regular season, while small ones might only post one or two listings. I split the listing data into four groups, Q_1, Q_2, Q_3, and Q_4, based on the quartiles of the number of listings per seller. The first comprises small sellers with fewer than 8 listings in an entire season. The second and third groups contain sellers with between 8 and 24, and between 24 and 61 listings in a season, respectively. The fourth group contains the big sellers, with more than 61 listings in a season. The top panel in Table 9 shows that the big sellers, in the fourth group, have the smallest loss aversion parameter of $\hat{\lambda} = 2.97$, which suggests that sophisticated sellers might not be as affected by the face values of the tickets as inexperienced sellers are. This is consistent with the previous literature (List, 2003), which finds that market experience can eliminate the effect of reference points. According to the descriptive evidence provided in Subsection 3.2, I further focus on those big sellers with more than 150 listings in a season. The result, presented in the last column, shows that the loss aversion parameter is only 1.87, which is the smallest across all of the groups.

More interestingly, the bottom panel of Table 9 shows that there is no market experience effect when it comes to the other type of reference point, the PLTP. Because all the sellers can observe the previous transaction records from the StubHub website, this might explain why the effect of the PLTPs is similar across all sellers. This also implies that market experience might only eliminate the effects of reference points such as the status quo and not those such as recent outcomes.

6 Conclusion

In this research, I use the listing prices on StubHub to show that sellers of sports tickets are affected by two types of reference points: the face values of the tickets and the PLTPs within the same section of the stadium.

In the dynamic pricing problem for perishable goods, the theoretical model shows that the listing prices should demonstrate evidence of bunching at the reference points. The model also predicts that the listing prices set by sellers with reference-dependent preferences should be higher in the last few days of the selling period, than those set by sellers without reference-dependent preferences.

Then, I use the data to show evidence of the bunching of listing prices at these two types of reference points, and eliminate other possible sources of this evidence. In addition, I use the structural model to estimate the parameters of the gain-loss utility, including the loss aversion and diminishing sensitivity parameters. The loss aversion parameter in the benchmark model is around 3.68 to 4.62, which is close to the estimates in the previous literature.

To understand the effect of the reference points, I simulate the result for the case without reference-dependent preferences, which $\eta = 0$. Compared with the actual data, the counterfactual results show that the listing prices will be lower by around 19.30% on the last day before the game if the sellers do not have reference-dependent preferences. Furthermore, the probability of a typical listing being sold during the last two weeks increases from 0.43 to 0.48.

Based on the types of tickets sellers have, the results indicate that the sellers who only hold single-game tickets are less likely to be affected by their face values, compared to those holding package tickets or mixed types of tickets. However, there is no difference between these two groups regrading the effect of the PLTPs.

In addition, I use the number of listings in a season to proxy for the size of each seller, and the results show that the big sellers are less likely to be affected by the face values of their tickets than the small sellers, which is consistent with the previous literature, which has found that market experience can eliminate the effects of reference points. However, large and small sellers are affected by the PLTPs in similar ways, which suggests that market experience might only eliminate the effects of reference points such as the status quo, and not the effects of reference points such as recent outcomes.

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Figures and Tables

Figure 1: Simulation of Price Distribution

This figure shows the price distribution simulated using the theoretical model. The simulation result is based on a time-invariant probability of sale $q(p) = \Phi(-p)$, consumption utility $v(p) = \log(p)$, gain-loss parameter $\eta = 1$, loss aversion parameter $\lambda = 2.25$, and curvature of the gain-loss utility $\alpha = 1$, where $\Phi(.)$ is the standard normal cumulative distribution function. The reference point is assumed to be 1. For the case without a reference point, η is assumed to be 0. The remaining values follow a chi-squared distribution, $\chi^2(0.5)$.

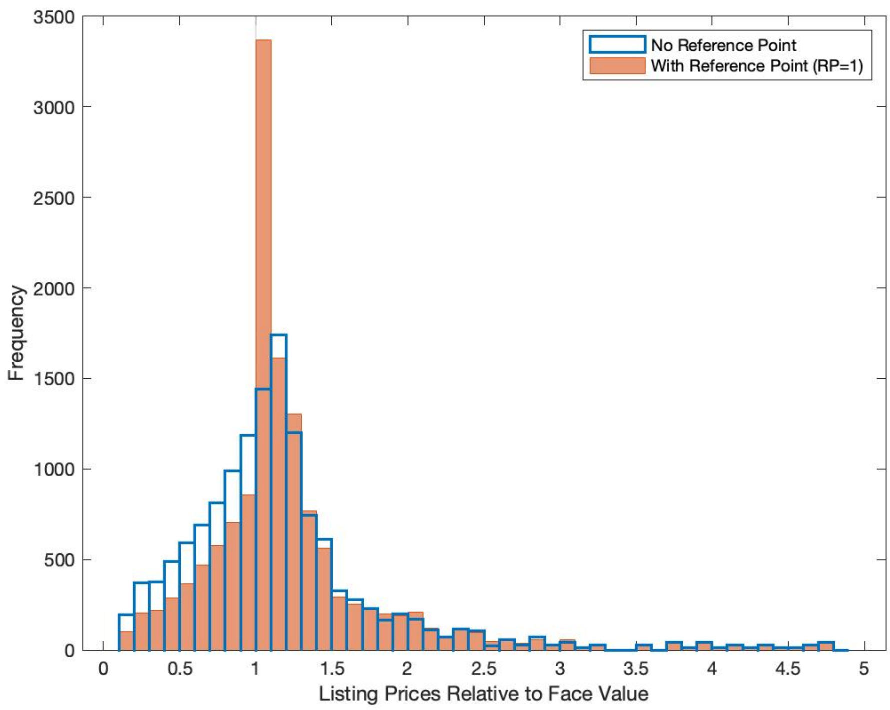


Figure 2: Simulation of Prices over Time

This figure shows the simulated pattern of prices over time. The simulation results are based on a time-invariant probability of sale $q(p) = \Phi(-p)$, consumption utility $v(p) = \log(p)$, gain-loss parameter $\eta = 1$, loss aversion parameter $\lambda = 2.25$, and curvature of the gain-loss utility $\alpha = 1$, where $\Phi(.)$ is the standard normal cumulative distribution function. The reference point is assumed to be 1. For the seller without a reference point, η is assumed to be 0. The remaining value is set to 0.01 for both sellers.

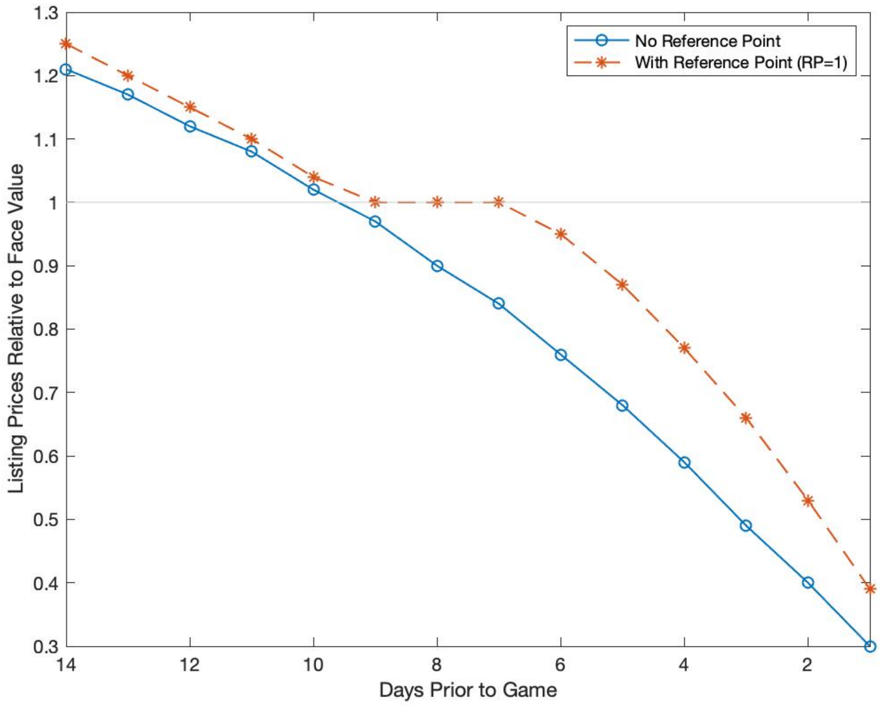


Figure 3: Evidence of Bunching at the Face Values of the Tickets

This histogram shows the evidence of bunching at the face values of the tickets. I use all the initial listing prices as the sample, and the total number of initial listing prices is 82,231. The x-axis shows the listing price divided by the face value. The bin width of the histogram is 0.1. The bottom figure shows the results of the discontinuity test from McCrary (2008).

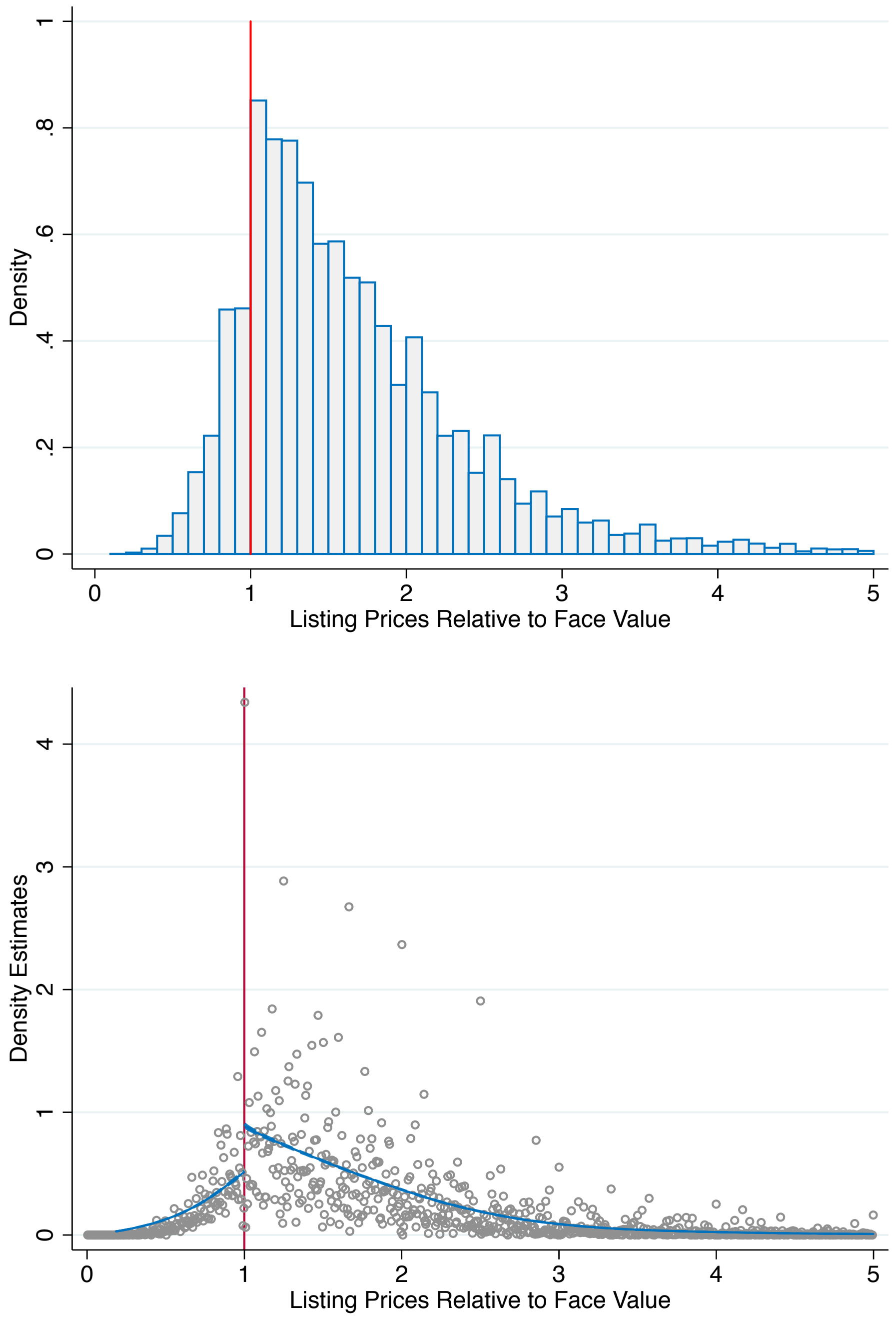
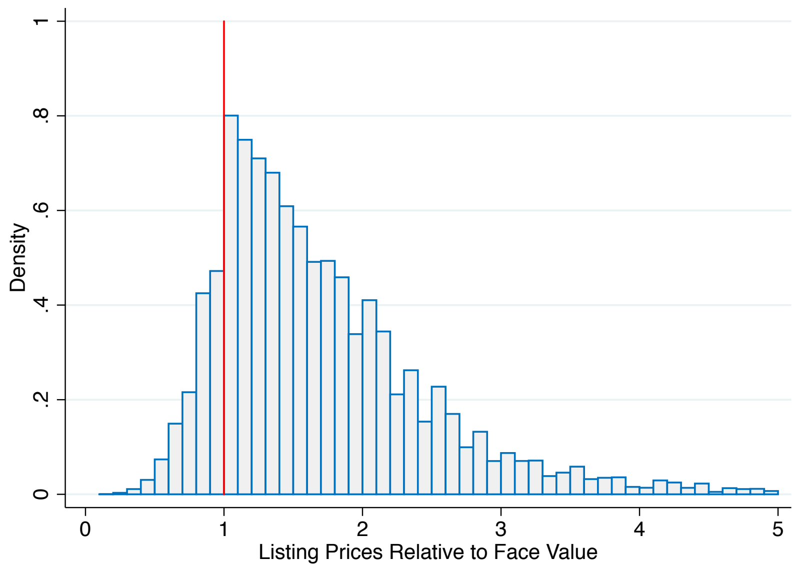


Figure 4: Robustness Test I of the Evidence of Bunching at the Face Value

This figure shows the evidence of bunching at the face value under two cases: face values ending with round numbers (0 or 5), and face values ending with other numbers. The discontinuity test results are shown in the bottom panel of Table 3.

(a) Ending with Other Numbers



(b) Ending with Round Numbers

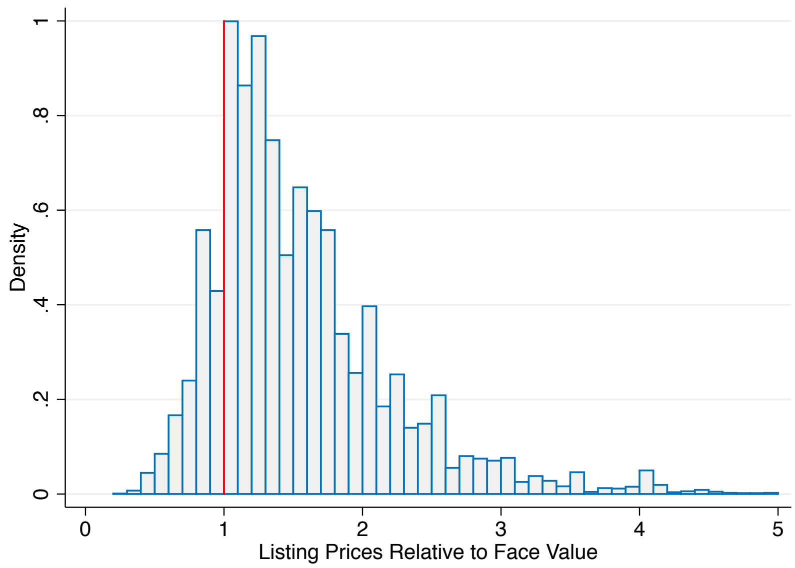
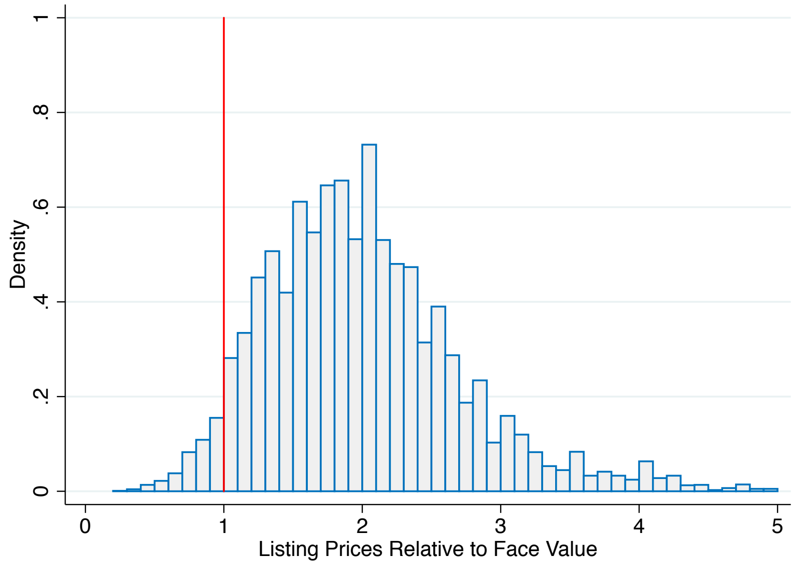


Figure 5: Robustness Test II of the Evidence of Bunching at the Face Value

This figure shows the evidence of bunching at the face value under two cases: face values equal to the purchase prices in the primary market, and those not equal to the purchase prices. The discontinuity test results are shown in the bottom panel of Table 3.

(a) Equal to Purchase Prices



(b) Not Equal to Purchase Prices

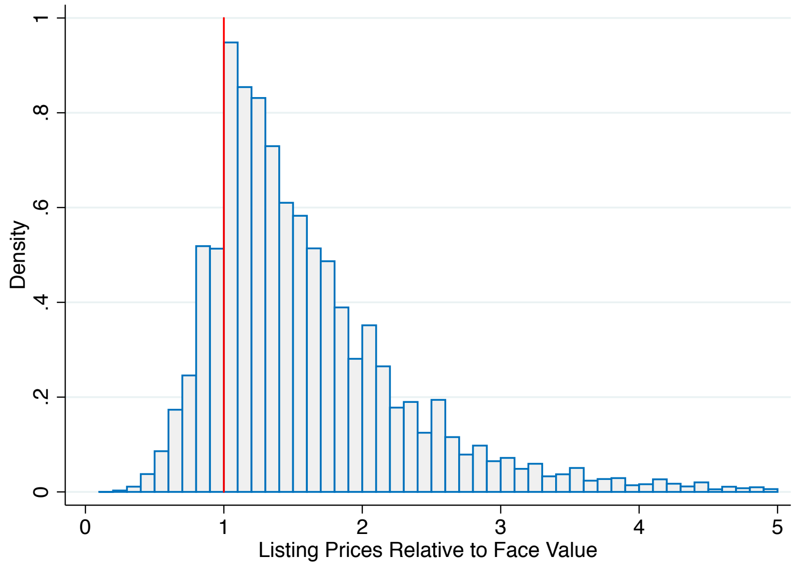


Figure 6: Evidence of Bunching at Previous Lowest Transaction Prices

This histogram shows the evidence of bunching at the previous lowest transaction prices. The sample consists of all the initial listing prices for which there is a previous lowest transaction price in the same section of the stadium, and the total number of listings is 64,279. The bin width of the histogram is 0.05. The bottom figure shows the results of the discontinuity test from McCrary (2008).

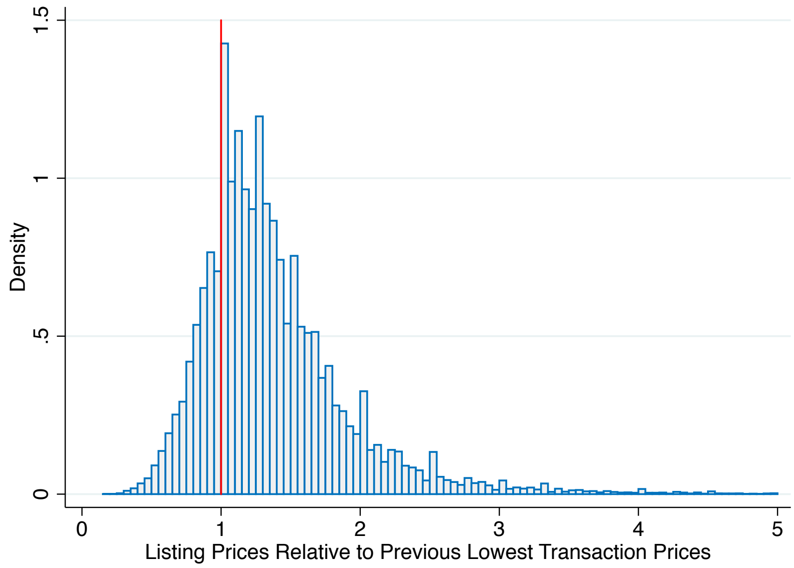


Figure 7: Robustness Test of Evidence of Bunching at Previous Lowest Transaction Prices

This figure shows the evidence of bunching at the previous lowest transaction prices under two cases: when the previous lowest transaction price is higher than the face value, and when it is lower than the face value. The discontinuity test results are shown in the bottom panel of Table 4.

(a) Higher Than Face Value

(b) Lower Than Face Value

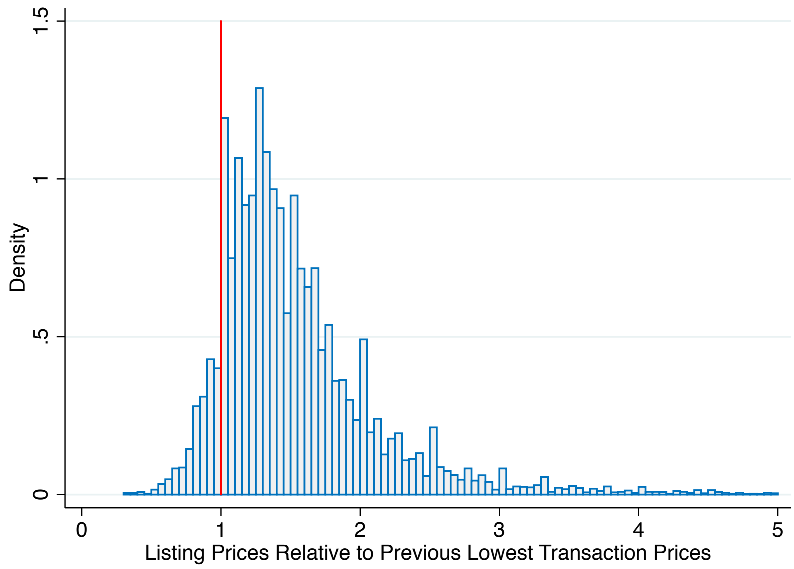
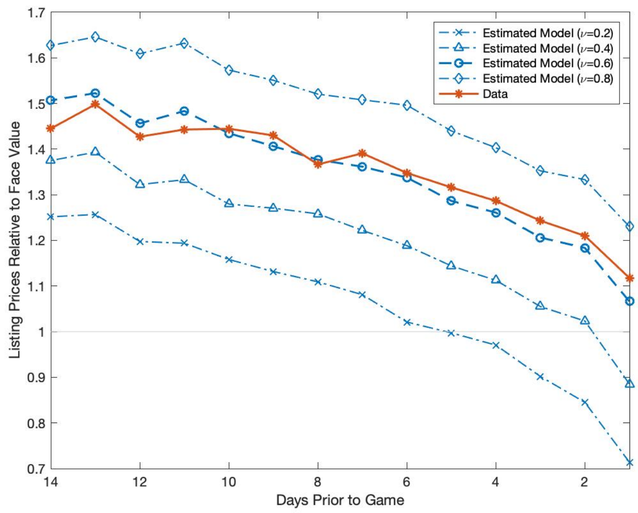


Figure 8: Estimated Models for the Face Values

Figure (a) shows how the different estimated models fit the data. The blue lines represent four different estimated results based on different values of ν, and the orange solid line with asterisks displays the actual data. The blue dashed line with circles shows the results when $\nu = 0.6$, and is closest to the true data. Figure (b) presents the listing price distributions from both the real data (orange) and as predicted by the model with $\nu = 0.6$ (blue).

(a) Listing Prices over Time from Different Estimated Models



(b) Listing Price Distribution When $\nu = 0.6$

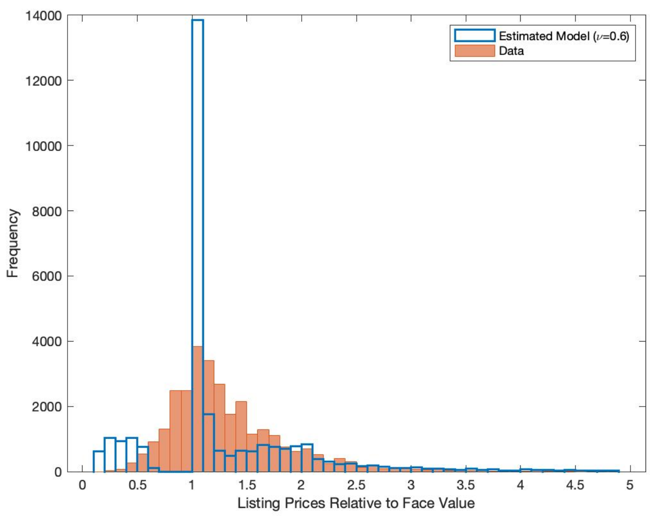
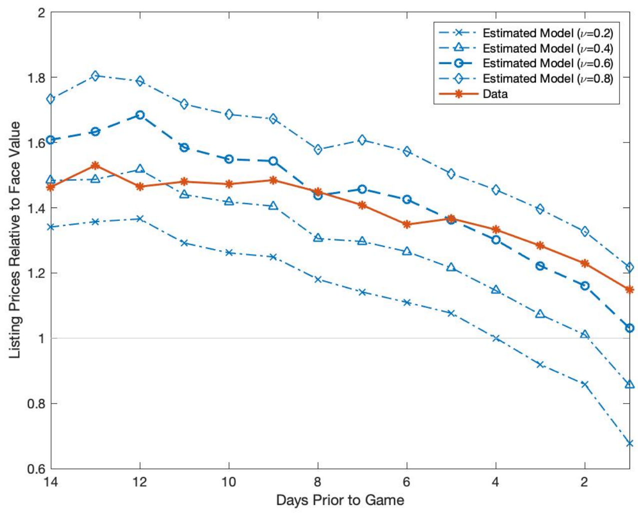


Figure 9: Estimated Models for the Previous Lowest Transaction Prices

Figure (a) shows how the different estimated models fit the data. The blue lines represent four different estimated results based on different values of ν, and the orange solid line with asterisks displays the actual data. The blue dashed line with circles shows the results when $\nu = 0.6$, and is closest to the true data. Figure (b) presents the listing price distributions from both the real data (orange) and as predicted by the model with $\nu = 0.6$ (blue).

(a) Listing Prices over Time from Different Estimated Models



(b) Listing Price Distribution When $\nu = 0.6$

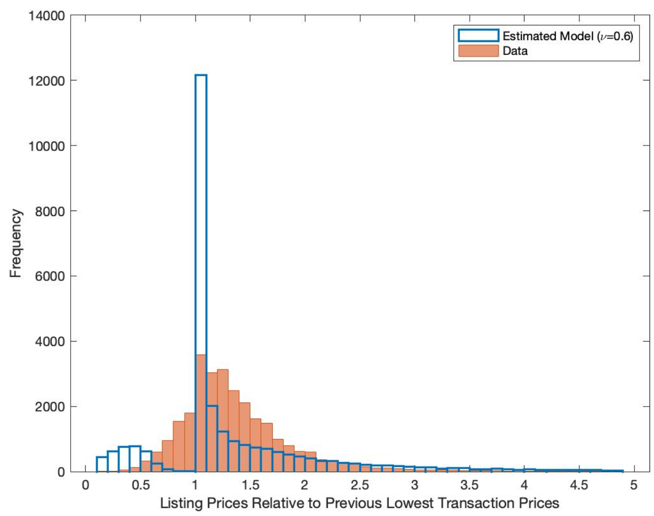
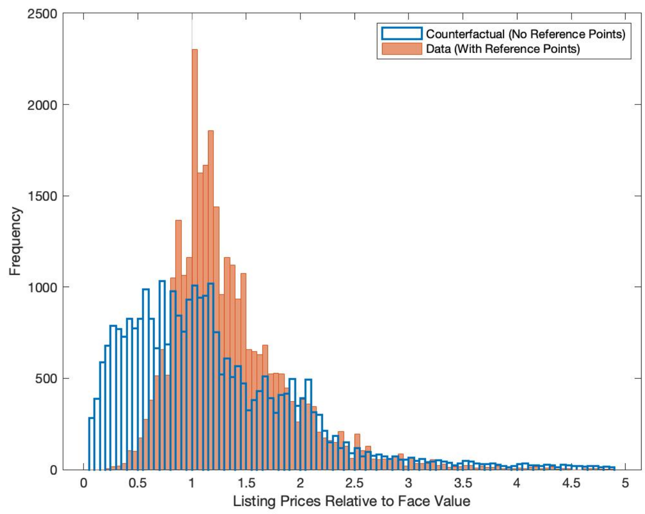


Figure 10: Counterfactual Results I

This figure shows the counterfactual results when the gain-loss utility function is removed ($\eta = 0$). Figure (a) shows the distribution of the listing prices relative to the face values of the tickets. Figure (b) shows the distribution of the listing prices relative to the previous lowest transaction prices for the tickets. The blue bars are from the counterfactual exercise, and the orange ones are from the real data.

(a) Listing Prices Relative to the Face Values



(b) Listing Prices Relative to the Previous Lowest Transaction Prices

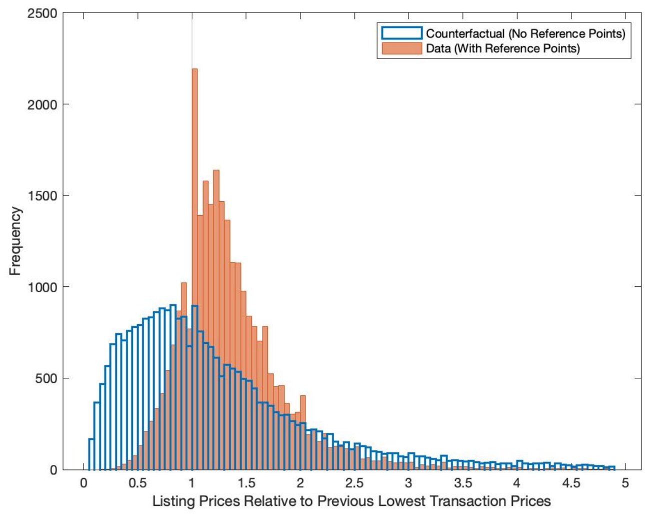
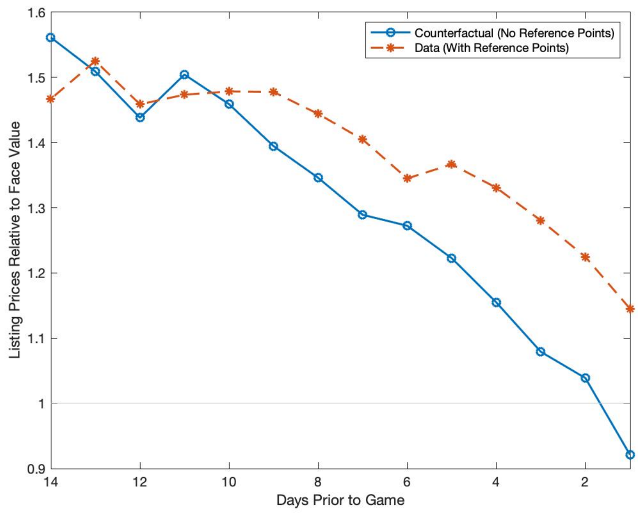


Figure 11: Counterfactual Results II

This figure shows the counterfactual results when the gain-loss utility function is removed ($\eta = 0$). Figure (a) shows the listing prices over time within the two weeks before the game. Figure (b) shows the probability of sale each day prior to the game. The blue line is obtained from the counterfactual exercise, and the orange one comes from the real data.

(a) Listing Prices Over Time



(b) Probability of Sale

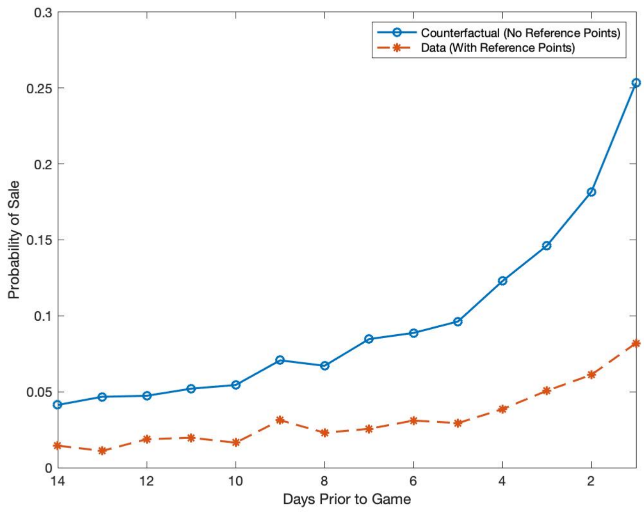


Table 1: Summary Statistics for Listings on StubHub

This table shows the summary statistics for each listing. The listing data were collected from March 25, 2011 to September 28, 2011. The data include the daily seat information given on the purchase page, such as the listing price, quantity, row number, and seat number. As some listings were not observed from the first day of listing, only around 79.65% of the listings have initial listing prices. Row quality is a measure in which the row number is normalized. A value of one represents the first row in that section of the stadium; a value of zero represents the last row in that section. Each listing might contain many tickets (seats), so some listings might only be partly sold.

	Obs.	Mean	Std. Dev	Min	Median	Max
Listing price relative to face value						
Initial price ($)	82,231	1.677	0.805	0.185	1.483	7.042
Maximum price ($)	103,245	1.820	0.885	0.185	1.618	7.059
Minimum price ($)	103,245	1.311	0.618	0.0286	1.184	7.059
Average price ($)	103,245	1.657	0.751	0.185	1.491	7.059
Starting date for listing						
(days prior to game)						
without information	103,245	0.204	0.403	0	0	1
>100	103,245	0.101	0.301	0	0	1
61 to 100	103,245	0.109	0.312	0	0	1
31 to 60	103,245	0.133	0.340	0	0	1
15 to 30	103,245	0.158	0.365	0	0	1
8 to 14	103,245	0.106	0.307	0	0	1
1 to 7	103,245	0.190	0.392	0	0	1
Purchase price						
in the primary market	103,245	0.844	0.123	0.333	0.853	1.294
Face value	103,245	42.62	21.89	12	36	108
Number of seats	103,245	2.737	1.076	1	2	6
Front row dummy	103,245	0.103	0.304	0	0	1
Row quality	103,245	0.559	0.307	0	0.595	1
Distance from seat						
to home plate (feet)	103,245	246.5	87.92	72.81	234.3	439.3
Listing periods (days)	103,245	37.72	43.43	1	18	187
Number of price adjustment						
for each listing	103,245	1.868	2.558	0	1	68
Sold out or not	103,245	0.390	0.488	0	0	1
Sold partly	103,245	0.406	0.491	0	0	1

Table 2: Summary Statistics for Sellers on StubHub

This table shows the summary statistics for each identified seller. The information can be separated into two parts: purchase information from the primary market and resale information on StubHub. Single-game tickets and package tickets are the two major ticket types in the primary market; those sellers who purchase both types of tickets or other types of tickets, are listed as others.

	Obs.	Mean	Std. Dev	Min	Median	Max
Primary Market Purchase Information						
Types of tickets they have						
single-game tickets only	9,664	0.383	0.486	0	0	1
package tickets only	9,664	0.397	0.489	0	0	1
others	9,664	0.220	0.414	0	0	1
Purchase channel						
from box office only	9,664	0.442	0.497	0	0	1
from internet only	9,664	0.419	0.493	0	0	1
from both channels	9,664	0.139	0.346	0	0	1
Renewed packages	9,664	0.590	0.492	0	1	1
Number of games purchased	9,664	31.78	31.71	1	20	81
Number of tickets purchased	9,664	139.8	317.0	1	53	9,720
Average number of tickets purchased in one game	9,664	5.527	25.28	1	3	1,201
StubHub Resale Information						
Number of tickets sold	9,664	16.17	78.51	0	2	4,029
Number of games listed	9,664	8.588	14.84	1	2	81
Number of tickets listed	9,664	34.89	137.5	1	7	6,377
Number of listings in an entire season	9,664	11.59	33.03	1	3	840
Average number of listings in one game	9,664	1.178	0.887	1	1	27
Average number of tickets listed in one game	9,664	3.501	5.555	1	2	142.5

Table 3: Evidence of Bunching at Face Value

Based on the listing and seller information, this table shows the evidence of bunching at the face value of the ticket in each subgroup. The last column shows the z-statistics for the discontinuity test from McCrary (2008). The bottom panel shows the robustness results related to Figures 4 and 5.

	Number of	Percentages of listings with prices relative to face values in						
	listings	$[0.7, 0.8)$	$[0.8, 0.9)$	$[0.9, 1.0)$	$[1.0, 1.1)$	$[1.1, 1.2)$	$[1.2, 1.3)$	z-statistic
All sample	82,231	2.20	4.55	4.58	8.45	7.73	7.70	35.50
Listing Information								
Number of tickets								
2	48,228	2.45	5.11	5.02	9.07	8.33	8.21	25.57
4	23,091	1.88	3.81	3.91	7.99	7.25	7.06	20.87
others	10,912	1.79	3.69	4.00	6.68	6.06	6.82	10.79
Starting date for listing								
(days prior to game)								
$\geq$ 100	10,622	0.26	0.99	1.10	3.06	3.80	4.50	10.52
30 to 99	25,609	0.93	2.16	2.69	5.31	5.37	6.77	20.04
15 to 29	15,527	2.38	4.30	4.70	8.60	8.39	8.81	15.49
8 to 14	10,903	2.45	5.56	5.86	11.16	10.29	8.80	14.25
1 to 7	19,570	4.64	9.26	8.11	13.85	10.99	9.17	16.83
Games in								
March/April	7,939	1.51	3.48	3.77	10.37	9.85	8.94	17.19
May	9,036	1.77	4.02	4.00	7.97	8.11	7.56	13.62
June	12,314	1.49	3.63	4.76	8.77	8.63	8.46	16.08
July	19,091	1.13	3.97	4.85	8.01	7.65	8.52	18.39
August	22,186	2.34	4.30	4.06	6.27	5.63	6.18	11.68
September/October	11,665	5.26	8.13	5.92	12.04	9.14	7.72	14.22
Face value in								
first quartile	22,407	1.04	1.87	2.00	5.22	4.01	5.20	19.89
second quartile	19,760	2.15	3.93	3.81	7.32	8.43	7.75	21.87
third quartile	20,959	2.30	4.64	4.35	9.96	8.37	9.76	24.35
fourth quartile	19,105	3.51	8.26	8.64	11.75	10.64	8.32	8.58
Seller Information								
With types of tickets								
package only	42,804	2.52	5.53	5.38	10.03	9.22	8.33	26.45
single-game only	9,529	1.37	1.84	2.15	3.43	3.75	4.87	4.81
both types	23,807	2.09	4.39	4.40	8.27	7.23	8.27	17.96
others	6,091	1.71	2.63	3.40	5.91	5.37	5.47	7.14
Number of listings								
in an entire season								
1-5	10,326	3.20	5.79	4.73	9.94	8.19	7.92	13.80
6-15	13,334	3.39	6.80	5.28	11.03	9.27	9.16	15.58
16-30	11,651	2.81	5.40	5.17	10.41	9.06	8.45	14.79
31-50	11,460	2.49	5.06	5.47	9.51	9.56	8.81	12.44
51-75	11,459	1.88	5.04	5.86	10.17	8.51	8.40	10.90
76-150	11,499	1.23	2.71	3.80	6.17	6.33	7.23	13.09
$\geq$ 150	12,502	0.48	1.13	1.87	2.18	3.33	4.05	0.97
Purchase channel								
from box office only	29,259	2.31	5.25	5.12	9.54	8.55	7.80	21.10
from internet only	28,666	2.43	4.66	4.24	8.22	7.63	7.48	21.14
both channels	24,306	1.80	3.59	4.32	7.41	6.85	7.84	18.47
Robustness check								
Face value								
no round numbers	61,343	2.14	4.21	4.68	7.93	7.42	7.03	27.83
round numbers	20,888	2.39	5.57	4.28	9.97	8.62	9.66	24.71
equal to								
purchase price	12,100	0.81	1.07	1.52	2.76	3.28	4.43	6.30
not equal to								
purchase price	70,131	2.44	5.16	5.10	9.43	8.49	8.26	32.70

Table 4: Evidence of Bunching at Previous Lowest Transaction Price

Based on the listing and seller information, this table shows the evidence of bunching at the previous lowest transaction prices (PLTPs) in each subgroup. The last column shows the z-statistics for the discontinuity test from McCrary (2008). The bottom panel shows the robustness results related to Figure 7.

	Number of	Percentages of listings with prices relative to PLTP in						
	listings	[0.7, 0.8)	[0.8, 0.9)	[0.9, 1.0)	[1.0, 1.1)	[1.1, 1.2)	[1.2, 1.3)	z-statistic
All sample	64,279	3.56	5.94	7.35	12.07	10.57	10.48	29.92
Listing Information								
Number of tickets								
2	38,484	3.79	6.21	7.68	12.88	11.18	10.82	24.21
4	17,467	2.94	5.34	6.61	10.64	10.00	10.37	13.77
others	8,328	3.77	5.96	7.40	11.36	8.91	9.19	8.89
Starting date for listing (days prior to game)								
$\geq$ 100	5,225	2.35	4.78	7.85	12.44	10.47	9.13	7.44
30 to 99	18,267	4.12	6.47	8.03	11.53	10.32	9.69	10.89
15 to 29	12,732	3.77	6.33	7.52	12.39	10.77	10.05	12.59
8 to 14	9,711	3.35	5.87	6.69	13.28	11.09	11.63	14.72
1 to 7	18,344	3.30	5.50	6.77	11.64	10.42	11.36	17.64
Games in								
March/April	6,545	3.07	4.95	7.18	13.00	11.83	11.55	10.54
May	7,628	3.89	6.35	8.09	12.91	10.87	11.23	9.52
June	10,511	4.66	7.53	8.65	12.99	11.45	9.41	10.19
July	15,605	3.30	5.47	7.04	12.02	11.03	11.07	15.22
August	17,879	2.82	5.18	6.82	11.39	9.31	10.55	14.68
September/October	6,111	4.57	7.15	6.74	10.59	9.79	8.54	7.89
Face value								
first quartile	16,248	3.17	4.54	5.58	9.26	8.06	9.38	15.64
second quartile	19,033	4.07	6.58	7.57	11.93	10.56	10.19	15.38
third quartile	14,887	2.33	5.13	6.93	12.80	11.51	11.14	15.52
fourth quartile	14,111	4.61	7.53	9.55	14.74	12.47	11.46	13.32
Seller Information								
With types of tickets								
only package	33,573	3.85	6.20	7.27	12.67	10.90	10.40	23.47
only single-game	7,155	3.51	4.84	7.02	10.03	9.88	9.95	7.65
both package and single-game	19,038	3.16	5.85	7.19	11.46	10.18	10.95	14.46
others	4,513	3.17	6.14	9.13	13.45	10.84	9.99	6.59
Number of listings in an entire season								
1-5	8,659	3.34	5.57	6.55	11.70	9.76	10.67	12.18
6-15	10,942	3.87	6.43	7.61	13.03	11.05	10.83	13.55
16-30	9,204	3.76	6.58	8.59	13.44	10.58	10.32	10.81
31-50	8,889	4.34	7.26	7.71	13.16	11.63	10.78	11.39
51-75	9,094	3.31	5.95	7.73	13.69	11.71	11.15	12.30
76-150	8,755	3.35	5.49	7.14	9.73	9.59	10.21	6.44
$\geq$ 150	8,736	2.85	4.10	5.96	9.35	9.44	9.32	8.68
Purchase channel								
only from box office	22,799	3.76	6.35	7.55	12.76	10.75	10.58	18.48
only from internet	22,621	3.55	5.88	7.12	12.08	10.77	10.59	18.09
both box office and internet	18,859	3.32	5.51	7.38	11.24	10.10	10.24	13.37
Robustness Check								
Previous Lowest Transaction Prices								
higher than face value	41,971	4.82	7.48	9.04	13.24	10.89	10.00	19.45
lower than face value	20,334	1.15	2.95	4.14	9.69	9.90	11.16	27.13

Table 5: Estimates for Probability of Sale

This table shows the estimates for the probability of sale. The first column displays the results of the probit model with exogenous listing prices, and the second column presents the results from equations (8) and (9). The first-stage results from equation (9) are shown in Table 6. Standard errors are given in brackets. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Probit	(2) IV Probit
Listing prices relative to face values	-0.8765***	-1.0530***
	[0.0072]	[0.0399]
Distance from seat to home plate (feet)	-0.0041***	-0.0046***
	[0.0001]	[0.0001]
Row quality	0.4092***	0.4583***
	[0.0092]	[0.0143]
Relative to number of seats = 2		
Number of seats = 1	-0.4409***	-0.4782***
	[0.0133]	[0.0157]
Number of seats = 3	0.0843***	0.1148***
	[0.0086]	[0.0109]
Number of seats = 4	0.0766***	0.0846***
	[0.0057]	[0.0060]
Number of seats = 5	0.2515***	0.3037***
	[0.0171]	[0.0207]
Number of seats = 6	0.0432**	0.0887***
	[0.0184]	[0.0208]
Competition coefficients:		
Dummy variable for competing listings	-0.0597***	-0.2492***
	[0.0127]	[0.0433]
Number of competing listings, log(N+1)	-0.0238***	-0.0574***
	[0.0059]	[0.0094]
Mean price for competing listings	0.0962***	0.1715***
	[0.0050]	[0.0173]
Proportion of higher row quality seats	-0.2165***	-0.2032***
	[0.0077]	[0.0082]
Whether the listing has the lowest price	0.2958***	0.3122***
	[0.0105]	[0.0111]
Proportion of listings with lower prices	-0.3723***	-0.0921
	[0.0223]	[0.0648]
Coefficients on residuals from the first stage		0.1824***
		[0.0398]
Constant	1.4231***	1.8819***
	[0.0354]	[0.1074]
Observations	3,858,510	3,858,510
Log-Likelihood	-334335.073	-332937.755
Game fixed effects	Yes	Yes
Day prior to the game dummies	Yes	Yes
Seat area fixed effects	Yes	Yes

Table 6: Regression on Instruments

This table shows the first-stage results from equation (9). The dependent variable is the listing price, and the regressors include all the exogenous variables in the main equation (8), and all the instruments. Robust standard errors given in brackets are clustered at the listing level. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Listing Prices
Purchase channel:	
relative to those from both channels,	
only from box office	-0.0371***
	(0.00546)
only from internet	-0.0325***
	(0.00586)
Starting date for listings (Days prior to game):	
relative to those without starting date information,	
$\geq$ 100	-0.0105
	(0.00645)
61 to 100	-0.0719***
	(0.00566)
31 to 60	-0.129***
	(0.00490)
15 to 30	-0.142***
	(0.00469)
8 to 14	-0.121***
	(0.00500)
1 to 7	-0.122***
	(0.00473)
Types of tickets:	
relative to those have mixed types,	
only have single-game tickets	0.0647***
	(0.00785)
only have package tickets	0.0520***
	(0.00523)
Constant	2.614***
	(0.0230)
Observations	3,858,510
R-squared	0.664
Game fixed effects	Yes
Day prior to the game dummies	Yes
Seat area fixed effects	Yes
Other control in the main equation	Yes
F-test	159.35

Table 7: Estimates for Parameters of the Game-Loss Utility

This table shows the results of the second-stage estimation, based on different levels of ν. In the top panel, I assume that sellers treat the face values of their tickets as their reference points. In the bottom panel, sellers are assumed to treat the previous lowest transaction prices for their tickets as their reference points. Standard errors given in brackets are from bootstrapping across listings. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Mean of the remaining value (ν)			
	0.2	0.4	0.6	0.8
Face values				
Curvature of the gain-loss utility (α)	0.2894*	0.3715***	0.4416***	0.5316***
	[0.1697]	[0.0150]	[0.0684]	[0.0139]
Loss aversion parameter (λ)	13.1125	6.7008***	4.6169***	3.4295***
	[22.8019]	[2.4380]	[1.2799]	[0.3757]
Previous lowest transaction prices				
Curvature of the gain-loss utility (α)	0.3185***	0.3946***	0.4788***	0.5023***
	[0.0116]	[0.0172]	[0.0437]	[0.0178]
Loss aversion parameter (λ)	12.0387***	5.9804***	3.6829***	3.1558***
	[3.1469]	[1.4499]	[0.7474]	[0.3381]

Table 8: Estimates by Type of Ticket

This table shows the results of the second-stage estimation, based on different samples. According to the types of tickets sellers have, I split the sample into three subsamples: sellers with single-game tickets only, sellers with package tickets only, and other sellers. I assume that the mean of the remaining value is equal to 0.6. In the top panel, I assume that sellers treat the face values of their tickets as their reference points. In the bottom panel, sellers are assumed to treat the previous lowest transaction prices for their tickets as their reference points. Standard errors given in brackets are from bootstrapping across listings. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		Type of Ticket		
	All sample	single-game	package	mixed or others
Face values				
Curvature of the gain-loss utility (α)	0.4416***	0.3790***	0.4645***	0.4937***
	[0.0684]	[0.0295]	[0.0635]	[0.0425]
Loss aversion parameter (λ)	4.6169***	2.7416***	4.9179***	4.6316***
	[1.2799]	[0.5584]	[1.7385]	[1.2938]
Previous lowest transaction prices				
Curvature of the gain-loss utility (α)	0.4788***	0.4225***	0.4871***	0.4516***
	[0.0437]	[0.0116]	[0.0568]	[0.0162]
Loss aversion parameter (λ)	3.6829***	3.3487***	3.3573***	3.8720***
	[0.7474]	[0.4984]	[0.9710]	[0.5932]

Table 9: Estimates by Size of Seller

This table shows the results of the second-stage estimation, based on different samples. I split the listing data into four groups, Q_1, Q_2, Q_3, and Q_4, based on the quartiles of the number of listings per seller. The first group (Q_1) contains sellers with fewer than 8 listings in a season. The second (Q_2) and third (Q_3) groups contain sellers with between 8 and 24, and between 24 and 61, listings respectively. The fourth group (Q_4) contains sellers with more than 61 listings in a season. To further focus on the big sellers, the last column shows the results for sellers with more than 150 listings in a season. I assume that the mean of the remaining value is equal to 0.6. In the top panel, I assume that sellers treat the face values of their tickets as their reference points. In the bottom panel, sellers are assumed to treat the previous lowest transaction prices for their tickets as reference points. Standard errors given in brackets are from bootstrapping across listings. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

		Number of Listings				Number of
	All sample	Q_1	Q_2	Q_3	Q_4	listings $\geq$ 150
Face values						
Curvature of the gain-loss utility (α)	0.4416***	0.4548***	0.4864***	0.5217***	0.4328***	0.4225***
	[0.0684]	[0.0743]	[0.0472]	[0.0521]	[0.0194]	[0.0127]
Loss aversion parameter (λ)	4.6169***	4.0585***	6.1258***	5.7602***	2.9701***	1.8672***
	[1.2799]	[1.2800]	[1.5709]	[1.7261]	[0.9018]	[0.4801]
Previous lowest transaction prices						
Curvature of the gain-loss utility (α)	0.4788***	0.4506***	0.4968***	0.5011***	0.3815***	
	[0.0437]	[0.0276]	[0.0388]	[0.0517]	[0.0196]	
Loss aversion parameter (λ)	3.6829***	3.8648***	3.5985***	3.7036***	3.5359***	
	[0.7474]	[0.8292]	[0.5223]	[0.9131]	[0.2972]	

A Appendices

A.1 Sensitivity Test for Theoretical Framework

This section presents the sensitivity tests of some important parameters of the theoretical model described in Section 2. To investigate how the important parameters affect the simulation result, I simulate the results based on different loss aversion parameters λ and diminishing sensitivity parameters α.

Figure A1 shows the results based on loss aversion parameters of $\lambda = 2.25$ and $\lambda = 4.25$. For a larger loss aversion parameter, the discontinuity in the distribution is larger, so that the evidence of bunching is more significant. For the listing prices over time, the blue line with circles sticks at the reference point during more periods. Also, on the last day before the game, based on the same remaining value, a seller with a larger loss aversion parameter is more likely to choose a higher listing price.

Besides the loss aversion parameter λ, the curvature of the gain-loss utility, α, also called the diminishing sensitivity parameter, also plays an important role in the behavior of the sellers. Figure A2 shows the results based on diminishing sensitivity parameters of $\alpha = 1$, $\alpha = 0.7$, and $\alpha = 0.4$. This parameter makes the function concave over gains and convex over losses; therefore, the seller is more reluctant to choose a price a little bit lower than the reference point. Also, it creates a smooth curvature of the price pattern in the gain domain, and a sharp decrease in the price in the loss domain. For a smaller α, the evidence of bunching in the distribution is sharper.

Appendix Figures

Figure A1: Sensitivity Test of λ

This figure shows the results of the sensitivity test of λ. The simulation result is based on a time-invariant probability of sale $q(p) = \Phi(-p)$, consumption utility $v(p) = \log(p)$, gain-loss parameter $\eta = 1$, and curvature of the gain-loss utility $\alpha = 1$, where $\Phi(.)$ is the standard normal cumulative distribution function. The loss aversion parameters are set to $\lambda = 2.25$ and $\lambda = 4.25$. The reference point is 1. For simulating the price distribution, the remaining values are assumed to follow a chi-squared distribution, $\chi^2(0.5)$. For simulating the price pattern over time, the remaining value is set to 0.01.

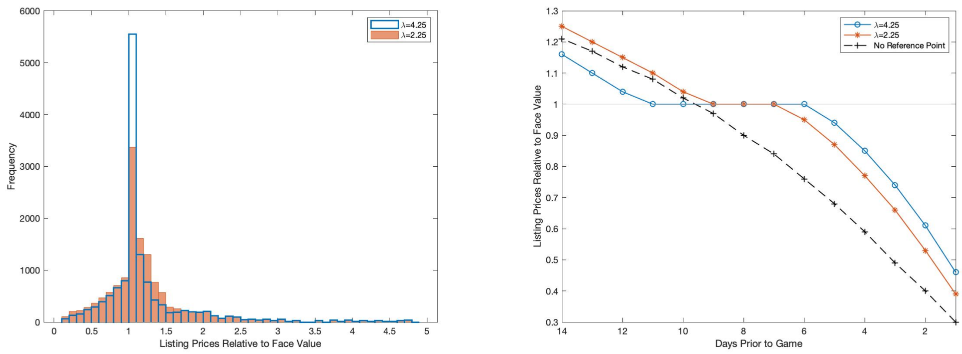


Figure A2: Sensitivity Test of α

This figure shows the results of the sensitivity test of α. The simulation result is based on a time-invariant probability of sale $q(p) = \Phi(-p)$, consumption utility $v(p) = \log(p)$, gain-loss parameter $\eta = 1$, and loss aversion parameter $\lambda = 2.25$, where $\Phi(.)$ is the standard normal cumulative distribution function. The curvature of the gain-loss utility is set to different values. The reference point is 1. For simulating the price distribution, the remaining values are assumed to follow a chi-squared distribution, $\chi^2(0.5)$. For simulating the price pattern over time, the remaining value is set to 0.01.