THE WELFARE EFFECTS OF TICKET RESALE*

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1 Introduction

Ticket reselling is a controversial activity. In many jurisdictions (indeed in many countries) it is regulated or banned, and even where it is legal it is often stigmatized. Whether labelled as brokers, scalpers, or touts, ticket resellers are commonly loathed by concert artists, sports teams, and consumers. Roth (2007) even includes ticket scalping as an example of a "repugnant transaction." This widespread hostility toward ticket resale seems at odds with the conventional view of economists, which is that voluntary trades made in resale markets result in more efficient allocations and increased social welfare.[1] Resale does not just affect final allocations, however. It also affects initial allocations, because buyers' choices in the primary market are influenced by the existence and characteristics of the resale market. Thus, even if resale markets do lead to net gains in social welfare, the *distribution* of gains is not clear—and the ambivalence of some market participants suggests there may be some who are made worse off.

Our purpose in this paper is to empirically analyze the welfare consequences of ticket resale. Do existing resale markets increase social surplus? By how much? How are welfare gains distributed across the various market participants (sellers, brokers, and consumers)? That is, who wins and who loses when resale markets are permitted to flourish?

There are various underlying sources of resale activity. One is general underpricing in the primary market. Concert artists or sports teams may underprice their tickets for many different reasons, but regardless of the reason, buyers may fully expect to resell any underpriced ticket at a profit. A related driver of resale activity stems from coarse pricing in the primary market. Producers tend to sell tickets at very few different price points, even for events with tens of thousands of seats. This can lead to a high degree of variation in seat quality among equally priced tickets, giving rise to profitable resale of high quality seats within any given price level. A third driver of resale is schedule conflicts: people buy tickets in the primary market and later realize they are unable to attend the event.

Whatever the motivation for reselling, buyers' decisions in the primary market depend on the purchase price and the *expected* resale price. Additionally, the availability of tickets in the resale market depends on the choices buyers make in the primary market. Hence, the primary and resale markets are clearly *interdependent*: outcomes in the primary market depend on expectations of what will happen in the resale market, and the equilibrium in the resale market depends on decisions in the primary market. Among other things, this implies that changes in primary market pricing will affect resale activity, and changes in the transaction costs associated

[1] See, Happel and Jennings (1995), Hassett (2008), McCloskey (1985), Mankiw (2007), and Williams (1994). In a 1999 Forbes magazine column, Dan Seligman asserted that anti-scalping laws are one of the ten dumbest ideas of the century (as referenced in Atkinson (2004)).

with resale will affect purchase choices in the primary market.

To capture this interdependence, we develop a two-period model with rational expectations. The primary market takes place in period one, and resale activity takes place in period two.[2] Buyers in period one have rational expectations of the period two equilibrium. That is, buyers make their primary market decisions based on expectations of what will happen in period two, and those primary market decisions lead to secondary market outcomes that are consistent (on average) with their expectations. Such an approach is essential for analyzing the welfare consequences of resale, because it explicitly allows the allocation of tickets going into the resale market to be endogenous to the degree of resale activity. Importantly, because our model incorporates the interplay between the two markets, it allows us to do more than simply say whether (and how much) aggregate welfare is increased by resale markets. Our primary focus is on describing how resale markets reallocate economic surplus among the various market players: sellers, brokers, and consumers.

The role of brokers is especially interesting, because they have a potentially important impact on the distribution of surplus. For the purposes of our analysis, we define a broker to be someone who buys tickets in the primary market with the sole intent of reselling them. In practice, there is a lot of negative sentiment towards brokers. Their participation in the market may increase total surplus by adding liquidity, but of course they also capture some of the surplus for themselves. They may also engage in costly efforts to obtain the highest-quality tickets in the primary market. The net effect of brokers on social surplus, and especially on the surplus to final consumers, is an empirical question.

Another interesting participant in these markets is the primary market seller or producer (e.g., the sports team or concert artist). In the past, producers have lobbied against resale activity or otherwise tried to prevent it. But the recent trend is for producers to accept or even endorse resale activity. This suggests some ambiguity as to the impact of resale markets on producers' profits.

For all the above reasons, ticket resale markets are an economically rich environment in which a variety of economic agents divide the surplus in ways that are unobvious. In this paper we attempt to pin down the welfare consequences of resale in the market for rock concerts. We estimate the structural parameters of our model using very detailed data on a sample of 103 concerts. This is the first study of ticket resale to utilize transaction data from both the primary market and the resale market. The primary market data come from Ticketmaster, the dominant ticketing agency in the industry, and the secondary market data come from eBay and StubHub,

[2] As we explain below, there is in fact little temporal overlap between the primary and resale markets, which supports this assumption.

the two leading online outlets for ticket resale. Even from a purely descriptive standpoint, our analysis of these data constitutes a significant contribution to the understanding of ticket resale markets.

The data reveal several interesting findings about resale markets for rock concert tickets. While brokers account for the majority of resale activity, 45% of the resale transactions in our data are sold by non-brokers. On average, ticket prices in the resale market are 39% above face value. However, it is relatively common to see prices below face value: brokers (non-brokers) appear to lose money on 24% (33%) of the tickets they sell. The overall rate of resale is relatively low, with only 4% of purchased tickets being resold on eBay or StubHub. Of course, for certain events this number is much higher. The event in our dataset with the most active resale market had 17% of its tickets resold on eBay or StubHub, and resale market revenue was equal to 37% of the primary market revenue. The likelihood of resale is strongly associated with seat quality: tickets for the best seats are nearly four times more likely to be resold than for the mid- to worst-quality seats.

Our structural model incorporates various frictions in the secondary market, including transaction costs and random participation in resale auctions. We also include various sources of buyer uncertainty. Buyers cannot perfectly forecast secondary market outcomes because they are uncertain about the allocation of tickets in the primary market (i.e., the order in which buyers arrived), about unanticipated schedule conflicts that may arise, and about the overall level of demand. Our estimates allow us to quantify the relative importance of these sources of uncertainty.

We find that current levels of resale activity have a relatively small impact on social welfare relative to a world without resale. We estimate that consumers have large transaction costs, preventing many exchanges that would otherwise be welfare-improving. Brokers' transaction costs are estimated to be much lower, and the results of our counterfactual analysis indicate that their participation in the market leads to a net welfare gain. In general, large reductions in transaction costs (for brokers and consumers) would lead to potentially large increases in social welfare. For example, we estimate that social welfare would increase by 16% if resale markets were frictionless. However, not everyone would be better off in such a world: primary market sellers' revenues would decline relative to their current levels, and much of the surplus would be captured by ticket resellers (at the expense of consumers who ultimately attend the events).

The welfare effects of new goods has a rich history in the industrial organization literature. For example, Petrin (2002) shows that the welfare gains from the introduction of the minivan accrue mainly to the buyers of minivans; and Goolsbee and Petrin (2004) show that the welfare gains from the introduction of satellite television accrue mainly to the consumers of cable television (because of the competitive effect). In this study we analyze the welfare effects of a different kind of innovation: namely, the flourishing of resale markets due to internet-driven reductions in transaction costs.[3] In this case, we find the welfare gains tend to accrue to resellers, to the detriment of people who consume the final product (i.e. those who attend the events).

The paper proceeds as follows. In Section 2 we briefly outline the relevant institutional details about the market for concert tickets. In Section 3 we discuss the expected welfare effects of ticket resale, and review the prior literature. In Section 4 we describe how we compiled the data, and provide summary statistics and descriptive analyses. Section 5 outlines the model. Section 6 explains details of the estimation, including identification, and reports some results. Section 7 discusses the results of various counterfactual simulations designed to assess the welfare consequences of resale, and Section 8 concludes.

2 Market overview

Live music and sporting events generated \$22 billion in primary market ticket sales in the U.S. in 2007. Reselling generated \$2.6 billion in revenue, and is expected to increase to \$4.5 billion over the next five years (Mulpuru and Hult, 2008). An important distinction from other ticketed products, such as airline travel, is that event tickets are usually transferable, which is necessary for legitimate resale activity. In this study we focus on music concerts, which allows us to avoid the complexity that season tickets, a major component of ticket sales for sports, would introduce to the analysis.[4]

Concerts are organized and financed by promoters, but the artists themselves are principally responsible for setting prices.[5] Typically the artist and/or artist's manager consults with the promoter and venue owner to determine the partitioning of the venue and the prices for each partition. Promoters employ ticketing agencies to handle the logistics of ticket selling. The dominant firm in this industry is Ticketmaster, which serves as the primary market vendor for over half of the major concerts in North America. Ticketmaster sells tickets primarily online or by phone. Tickets usually go on sale three months before the event, and sometimes sell out on the first day.

Choosing primary market ticket prices is a complex problem for producers. Venues often have over 10,000 seats, with significant quality variation, implying many potential price-quality menus

[3] Brynjolfsson et al (2003) also study welfare effects driven by the internet.

[4] There may be instances of event bundling in rock concerts, but they are rare and do not apply to any of the events in our dataset. See Chu, Leslie and Sorensen (2008) for an analysis of theater ticket bundling.

[5] See Connolly and Krueger (2005) for a detailed review of the music industry.

based on different partitions of the venue. Rosen and Rosenfield (1997) provide a theoretical analysis of how to divide a venue and what prices to set. TicketMaster has experimented with auctioning tickets in the primary market, but this is not yet common. The pricing problem may also be complicated by the possibility that artists have a preference for selling out the event, perhaps because artists obtain utility from playing to a full house, or because doing so enhances the experience for consumers.[6] These considerations may explain why artists seem to routinely under-price their concerts. It is also conceivable that concert tickets are complementary to recorded music sales and other merchandise, in which case the objective is not to simply maximize ticket revenues. Artists sometimes also cite a desire to be fair or assure access for all fans.[7] All of these are interesting issues, but in this study we do not seek to model or explain primary market pricing. In our empirical model we treat primary market prices as exogenous.

There is no federal regulation of ticket resale, but some states in the U.S. have laws forbidding or restricting ticket resale. For example, Arkansas, Kentucky, and Michigan prohibit reselling above face value. According to Fried (2004), as of 2004 there were 12 states with restrictions on resale, and 38 states without any restrictions (aside from limits on selling outside the venue). However, as best we can tell, these anti-scalping laws are rarely enforced by government authorities, perhaps because they are regarded as victimless crimes.[8] Ironically, while eBay makes ticket reselling easier in many ways, eBay also enforces anti-scalping laws, so that these laws are perhaps more pertinent today than in the past. Elfenbein (2005) finds that there are fewer (but not zero) eBay transactions for NFL tickets in states with stricter regulations. There are various ways to get around the laws, even on eBay, such as charging exorbitant shipping fees. In any event, there is a clear trend of deregulation: Connecticut, Pennsylvania, Minnesota, Missouri and New York repealed anti-scalping laws in 2007.

Regulatory attitudes also vary outside of the U.S. In the U.K., the Office of Fair Trading studied ticket reselling in 2004 and recommended against regulation.[9] Scalping is illegal in some states in Australia, and was illegal for the 2008 Olympics in Beijing. (The International Olympic Committee requires host countries to ban reselling.)

The internet has transformed the ticket resale industry. It is widely acknowledged by industry insiders and in the trade press that eBay is the dominant marketplace for ticket resale, followed by StubHub.[10] Two pieces of evidence support this belief. First, in a survey of concertgoers at a major rock concert in 2005, Alan Krueger found that eBay and StubHub accounted for

[6] See Becker (1991), Busch and Curry (2005), and DeSerpa and Faith (1996).
[7] See Kahneman, Knetsch and Thaler (1986).
[8] In a study of resale laws, Elfenbein (2005) also notes that he is yet to find an instance of online ticket resale being prosecuted by an authority.
[9] Office of Fair Trading (2005).
[10] In January 2007, StubHub was acquired by eBay. We study data from before the acquisition.

between a third and a half of all resold tickets (see Connolly and Krueger, 2005). Second, based on survey evidence from 2007, Mulpuru and Hult (2008) report that eBay and StubHub account for 55% of online ticket resales. Tickets are also resold on numerous other web sites (Razorgator, TicketsNow, TicketLiquidator, etc), as well as offline.

Note that eBay and StubHub are marketplaces—unlike brokers, they do not own the tickets that are for sale. These web sites create value by lowering transaction costs. Features at some sites include interactive seating charts, personalizations, and parking and weather information. StubHub especially has a reputation for providing a well-designed and user-friendly interface. The web sites also extract value by charging fees on each transaction: eBay charges a transaction fee of about \$7 for a ticket that is resold for \$100, and StubHub charges \$25 for a ticket that is resold for \$100. To address fraud, eBay emphasizes their reputation mechanism, and StubHub provides a guarantee.

Brokers purchase tickets via the regular sales channels. Ticketmaster imposes a limit on how many tickets can be purchased in a single transaction, but some brokers have apparently been able to automate the online purchasing process, allowing them to complete many purchases in the time it takes a consumer to complete a single transaction. Other brokers employ "pullers" to purchase tickets on their behalf, while others may have relationships with the artist or promoter. Artists typically receive an allocation of tickets, which they can distribute or sell as they wish. Our understanding is that these tickets are often sold through Ticketmaster along with the other tickets. Recent press reports also reveal that artists sometimes arrange to sell their allocation of tickets via a broker directly into the secondary market. Tickets may also be resold by consumers who purchased tickets with the intention of using them, but subsequently learned they could not attend the event. Of course consumers may also resell their tickets to profit from high resale prices, in lieu of attending the event themselves.

Interestingly, there are professional sports organizations that now fully support ticket reselling. Major League Baseball (MLB) recently entered into a revenue sharing agreement with StubHub, and the National Football League (NFL) and National Hockey League (NHL) both entered into ticket resale agreements with TicketMaster (which also provides a resale marketplace called TicketExchange). There is evidence that music artists are starting to endorse reselling as well: in 2008 Madonna entered a reselling agreement with StubHub, for example. Historically, however, producers have tended to oppose reselling. One important difference is that the recent agreements allow the producer to share in the revenues generated in the resale market. Hence, we cannot conclude from these agreements that resale now has a positive impact on primary market revenues.

3 Prior research into the welfare effects of ticket resale

We are certainly not the first to point out that primary market outcomes depend on buyers' expectations about the resale market. Several papers address the question: does resale increase or decrease producers' profits? Using empirical methods, Williams (1994) was the first to analyze this question. He found that NFL primary market prices in 1992 were lower in states with anti-scalping laws, suggesting that resale is good for producer profits. However, Depken (2007) studies more recent evidence and finds that both MLB and NFL primary market prices are higher in states with anti-scalping laws.

Swofford (1999) provides the first theoretical analysis of this question. Swofford proposes that brokers have different risk attitudes, cost functions, or revenue functions than producers, which allows them to capture some consumer surplus without affecting producers' profits.[11] Producers may nonetheless lobby for anti-scalping laws, since reselling causes consumers to pay higher prices without creating higher profits for producers.

Subsequent theory by Courty (2003) suggests producer profit may be invariant to resale activity. Courty's model incorporates demand uncertainty at the individual consumer level (i.e. consumers don't know their own value for the event until just before attending). The producer has the option of selling tickets at different prices on different dates, and has the ability to commit in advance. Courty shows that the producer's profit from selling all tickets at the last minute to informed consumers (with no resale possibility) is equal to the profit from selling all tickets early and allowing brokers to buy and resell tickets. Karp and Perloff (2005) present a model with asymmetric information in which broker activity conveys information to consumers about the value of tickets, allowing producers to charge higher prices. Geng, Wu and Whinston (2004) also argue that resale may be beneficial to producer profits.

A few papers address the question: does resale benefit or harm consumers? On the one hand, in the absence of resale a common complaint of consumers is the difficulty of obtaining tickets for popular events. The ability to resell tickets also creates an option value for consumers who purchase in the primary market.[12] On the other hand, resale is generally driven by the ability of resellers to buy low and sell high: prices to final consumers are raised above primary market prices.

[11] Based on a similar characterization of brokers, Spindler (2003) argues that brokers may enhance producers' profits: if brokers are better at extracting consumer surplus than producers, this may allow the producer to charge higher prices than without brokers.

[12] The idea that reduced transaction costs and increased liquidity may enhance buyers willingness-to-pay has been analyzed in the context of financial markets: see Amihud, et al (1997).

In the first formal analysis of scalping, Thiel (1993) demonstrates that the presence of brokers may be good for some consumers and bad for others. Thiel assumes excess demand in the primary market (with exogenously low prices). The presence of brokers reduces the probability of a given consumer obtaining a ticket in the primary market, but provides a second chance for consumers to obtain a ticket in the secondary market. Hence, brokers may benefit consumers that would otherwise miss out on a ticket in the primary market, but harm consumers that otherwise would have purchased a ticket at a lower price in the primary market. The net effect on consumer surplus is unclear.

Busch and Curry (2005) argue that resale is harmful to consumers, based on a model with social externalities among consumers. They argue that lining-up is a screening mechanism that results in a selection of consumers which have more positive social externalities than may arise from using price to screen. In their approach, resale does not just reduce consumer surplus, it also reduces consumers' willingness-to-pay, and therefore lowers profitability for producers.

On the empirical side, Elfenbein (2005) estimates the effect of anti-scalping laws on resale prices for NFL tickets.[13] He finds that stricter regulations result in fewer tickets being resold, higher resale prices and markups. This suggests an increase in resale activity results in lower resale prices, which may be attributable to competition among resellers. The implications for consumer surplus are unclear. Some of these issues are also addressed in a recent study of resale price dynamics by Sweeting (2008).

In summary, the existing literature has focused on the role of brokers in affecting primary market prices, resale prices, producer profits and consumer surplus, providing a wide range of different answers. Taken together, the prior papers show that there are numerous dimensions to the welfare consequences of ticket resale, in what is a complex economic environment. Our goal is to develop a model which incorporates this richness, and to estimate the parameters of the model to resolve the ambiguities.

Our approach differs from the prior research in three important ways. First, unlike several of the prior studies mentioned above, we do not allow the producer to sell tickets in multiple periods. In the model we present below, the producer sells tickets in the primary market in period one, and resale activity takes place in period two. This is a simplifying assumption, motivated by the fact that there is minimal overlap in the timing of primary market activity and resale activity (as we show in the next section), and also by the fact that no producer in our dataset implements any form of dynamic pricing—primary market prices are equal over time for every event.[14] But our approach does preclude us from evaluating any counterfactual pricing

[13]See also Hassett (2008).

[14]Note, however, that our model includes uncertainty of the same kind emphasized in Courty (2003). Namely,

scheme in which producers vary primary market prices over time.

Second, we allow consumers (in addition to brokers) to resell tickets. This is important because it fundamentally affects how consumers value tickets in the primary market, and also because it allows consumers to capture some of the rents from reselling that only accrue to brokers in the prior research. Brokers may still be at an advantage over consumers in their role as resellers, because we allow for the possibility that brokers have lower transaction costs. Another benefit of our approach is that we can implement counterfactuals that preclude brokers from participating in the market while still allowing consumers to resell, or we can prohibit all resale activity. Perhaps even more importantly, our approach reflects reality—45% of the resold tickets in our dataset appear to have been sold by non-brokers (as reported in the data summary, below).

A third distinguishing feature of our approach is that we assess the welfare of consumers who attend the events separately from the welfare of consumers who engage in reselling (brokers are a separate group again). This is important because, as we show in our counterfactuals, resale activity can be harmful to the welfare of consumers who attend events, and beneficial to consumers who engage in resale. Moreover, the latter effect can outweigh the former—resale is good for consumer surplus, even though those who attend the events are made worse off. To the best of our knowledge, no prior paper has explicitly considered this distinction.

4 Data

Our data combine detailed information about primary and secondary market sales for a sample of rock concerts performed during the summer of 2004. Our sample is not intended to be representative of the thousands of concerts performed that summer. Rather, it focuses on large concerts by major artists, for which resale markets tended to be most active. For each concert, we observe details about tickets sold through the primary market vendor (Ticketmaster), as well as information about all tickets that were resold on eBay and StubHub.

Two unique features of the dataset are especially valuable for this research. First, by merging data from Ticketmaster, eBay, and StubHub, we observe primary and resale activity in parallel. We suspect that data from either market in isolation would still be interesting and informative. But by combining data on primary market sales and resales, we are able to study the *interaction* between the two markets, which we believe is crucial to understanding how these markets work.

consumers do not know whether they will be able to attend the event in period one (due to the possibility of a schedule conflict).

Second, as we explain below, we distinguish resale activity by brokers from resale activity by consumers. For the reasons explained in Section 3, this is important to evaluating the welfare effects of resale.

Figures 1 and 2 illustrate the data for four example concerts: two by Kenny Chesney and two by the Dave Matthews Band. In each of these figures, the vertical axis represents price, and the horizontal axis represents seat quality, ordered from worst to best (we explain the measure of seat quality in more detail below). Consider the first panel of figure 1, which shows the data for a Kenny Chesney concert performed in Tacoma, Washington. The dots along the horizontal lines represent tickets that were sold in the primary market, at three different price points. The other dots and squares represent resales by non-brokers (i.e. consumers) and brokers, respectively. Resale activity was concentrated among the highest-quality tickets, and the average premium paid for these tickets was substantial. The figure also illustrates that resale prices were highly variable, with some relatively high-quality seats even being sold below face value.

In the following subsections we explain how the data shown in Figures 1 and 2 were assembled. We describe the primary market and secondary market data sources in turn, and then explain how they were merged. We also report basic summary statistics, and describe some patterns in the data that motivate various aspects of our empirical model.

4.1 Primary market data

The primary market data were provided by Ticketmaster. For each concert, we obtain information from two sources: a "seat map" and a daily sales audit. The seat maps essentially list the available seats at a given event, indicating the order in which the seats were to be offered for sale, and the outcome (i.e., sold, comped, or open).[15] The daily audits contain ticket prices (including the various Ticketmaster fees), as well as how many tickets were sold in each price level on each day. Essentially, the daily audits allow us to assign prices and dates of sale to the seats listed in the seat maps.

We use the ordering of seats in the seat map data as our measure of relative seat quality. The main virtue of this approach is that it reflects the primary market vendor's assessment of quality: Ticketmaster uses this ordering to determine the current "best available" seat when a buyer makes an inquiry online or by phone. Also, it allows us to measure quality separately for each seat, as opposed to using a coarser measure (e.g., assigning qualities by section). The seat

[15] A "comped" or complementary seat is one that was given away. We discuss the issues arising from comped tickets below. An open seat is an available seat that went unsold. The seat maps also identify seats that were "held" or "killed." These seats were unavailable for sale, so naturally we ignore them in the analysis.

orderings are also fairly sophisticated: for example, seats in the middle of a row might be ranked above seats toward the outsides of rows further forward, and seats at the front of upper-level sections are sometimes ranked above seats at the back of lower-level sections.

Nevertheless, using this measure of seat quality has its drawbacks. Although the orderings appear to be carefully determined, we suspect they are not always perfect. More importantly, Ticketmaster's ordinal ranking of tickets does not tell us anything about absolute differences in quality between seats. We know that a given ticket is supposed to be better than all subsequent tickets in the ordering, but we do not know how *much* better. Because we think any information we could bring to bear on absolute quality differences would inevitably be arbitrary, in the analyses below we simply assume that quality differences are uniform—i.e., the difference in quality between seats j and $j+s$ is the same regardless of j. Specifically, we use $1-(j/J)$ as our measure of quality, where j is the seat's position in the "best available" order, and J is the total number of tickets available. The best seat ($j=0$) therefore has quality 1, and the worst seat has quality $1/J$.

Many of the events in our sample have large lawn sections, in which seats are first-come, first-served instead of pre-assigned. Tickets in these sections have identical quality *ex ante*: at the time of purchase, there is no reason that one lawn ticket is any better than another. We assign all lawn tickets the same relative quality for a given event, setting the quality based on the median lawn ticket. That is, if there are 2,000 lawn seats, and 4,000 seats that precede the lawn in the best available ordering, then the lawn seats are all assumed to be at position 5,000 in the ordering.

Complementary tickets ("comps") represent a potential difficulty for our analysis. Although the Ticketmaster data identify exactly which tickets were given away as comps, we cannot typically tell if a resold ticket was originally a comp, because usually for resales we only know the section and row, not the exact seat number. This is problematic because we suspect resale is more likely for comps than for ordinary sales.[16] For some of the concerts in the original sample, a significant fraction of seats was given away, apparently in an effort to fill seats.[17] For most concerts, however, comps represent a small fraction of total tickets, and tend to be located toward the front—suggesting they are perhaps targeted toward friends of the artist and/or promoter. In order to minimize the potential difficulties associated with comps, we focus on 103 events for which comps account for less than 3% of total tickets. These 103 concerts were performed by 18 distinct artists: Aerosmith, Dave Matthews Band, Eric Clapton, Jimmy

[16] The reason is that people who purchase tickets value the tickets above the price paid, whereas recipients of comps may have valuations well below the face value. It is possible, however, that comps are successfully targeted at the artist's most devoted fans, in which case they may be *less* likely to be resold.

[17] For example, most of the concerts by Jessica Simpson had several thousand low-quality seats given away as comps.

Buffett, John Mayer, Josh Groban, Kenny Chesney, Kid Rock, Madonna, Phish, Prince, Rush, Sarah McLachlan, Shania Twain, Sting, Tim McGraw, Usher, and Van Halen. In total there were 1,739,315 tickets sold or comped in the dataset.

4.2 Secondary market data

To obtain information about resales, we captured and parsed eBay auction pages for all tickets to major concerts in the summer of 2004. From these pages we determined how many tickets were sold, on what date, at what price (including shipping), and the location of the seats. We only use auctions that ended with a sale (either via a bid that exceeded the seller's reserve, or via "Buy-it-now"). The auction pages also list information about the seller, including the seller's eBay username. We use this to distinguish between brokers and non-brokers: we categorize an eBay seller as a broker if we observe her selling 10 or more tickets in the data.

We also obtained data from StubHub, a leading online marketplace designed specifically for ticket resale. For every concert in our sample, we observe all tickets sold through StubHub, and for each transaction we observe the number of tickets sold, the seat location, the price (including shipping and fees), the date, and the seller identity and classification (broker vs. non-broker). This information was provided directly by StubHub, and includes some details that are not available at their web site.

Matching eBay auctions to specific concert events was straightforward, albeit tedious, because the auction pages contain standardized fields for the venue and event date. The process of assigning resales to specific seats was more complicated, because exact seat numbers were rarely reported in the eBay or StubHub auctions. We were able to determine the section and row for 75% of the resale transactions. For another 23% we could only determine the section. For the remaining 2%, our parser did not even detect the section, and we simply dropped these transactions from the analysis.[18] We are left with 68,828 resold tickets (the vast majority of them on eBay).

Beginning with transactions for which we observed both the section and row, we assigned resales to specific seats by spreading them evenly throughout the relevant section and row. So, for example, if in the Ticketmaster data we see that there were 20 seats in section 101, row 3, and we observe 3 tickets resold on eBay or StubHub in section 101, row 3, we assign them to seats 5, 10, and 15 within that row. Once the section-and-row transactions were assigned, we then assigned section-only transactions using the same principle. Suppose that after assigning

[18]Dropping these sales means that our data will slightly understate the total amount of resale on eBay and StubHub for these events.

all the section-and-row transactions, 200 seats in section 101 remain unassigned. Then if we observe 4 tickets resold in section 101, unknown row, we assign those 5 tickets to seats 40, 80, 120, and 160 (of the 200).[19]

For the empirical model we estimate below, it would be ideal to observe *all* resale activity for the sample concerts. We do not know exactly how much of total resale activity is accounted for by eBay and StubHub. As explained in Section 2, eBay is almost certainly the largest single outlet for ticket resales, with StubHub likely the second largest. Where necessary in our analysis below, we simply assume that the combined market share of eBay and StubHub is 50%, and later test the sensitivity of our findings to this assumption. Note that even if we knew eBay's and StubHub's exact market shares for rock concerts in the summer of 2004, we would have no way to verify if resales on these two sites are representative of resale activity more broadly. However, the fact that both brokers and non-brokers have a significant presence on eBay suggests that our data might be roughly representative of resale activity more broadly.

4.3 Summary statistics

As mentioned above, the dataset covers 1.7 million tickets sold in the primary market for 103 concerts by 18 different artists. Table 1 provides more detailed summary statistics. The capacity of each concert varies from 3,171 to 35,048 (the median is 15,313). The events tended to sell out: 36% of concerts sold 100% of their capacity, and 77% sold over 98% of their capacity.

The average ticket price in the primary market was $83.15 (including shipping and fees).[20] However, there is a good deal of price variation across events: the inter-quartile range of the distribution of average prices across events is from $53.87 to $90.87. There is also some within-event price variation, but not much. Most events tend to offer tickets at only two different price levels. The maximum number of price levels for a single event in our data is 5, and 7 concerts sold all tickets at a single price. Figure 2 depicts one of these events with a single price in the primary market (in this case, for all 24,873 seats). As we show in our analysis, the low number of price levels in the primary market, relative to capacity, is a key driver of resale activity.

We observe nearly 69,000 of the tickets purchased in the primary market being resold at eBay or StubHub (i.e. 3.95% of the number of tickets). As shown in Table 1, the maximum

[19] We also tried putting resales at the middle of their respective sections and rows, instead of spreading them evenly. That is, if there were 20 seats in the row, and three tickets resold, we assign the resales to seats 9,10, and 11 instead of 5, 10, and 15. We will check to make sure our empirical results are robust to this alternative approach.

[20] To be clear, $83.15 is the average across events of the average ticket price at each event. If all tickets are weighted equally, the average ticket price in the primary market is $76.40.

number of tickets resold for a given event is 3,130, or 17% of the tickets sold in the primary market. For most events the fraction of tickets resold is between 2% and 5%. On average, total revenue to resellers is equivalent to 6% of the primary market revenue, and the maximum for any single event is a striking 37%. It is important to remember that these numbers are based on reselling at eBay and StubHub alone, so they represent a lower bound for the total amount of resale activity.

Table 2 provides additional summary statistics of resale activity.[21] The average resale price is $111.66. Resellers make significant profits: the average markup is 39% over the face value, and 25% of resold tickets obtain markups above 65%. On the downside for resellers, 28% of tickets are sold below face value. Resold tickets are not a random sample of those purchased in the primary market, and in particular the resold tickets tend to have significantly higher face values than non-resold tickets: the average price in the primary market of the resold tickets is $89.82, while the average price of all purchased tickets in the primary market is $76.40.

One reason why resold tickets tend to have relatively high face values is that resold tickets tend to be for relatively better seats. The average seat quality of tickets purchased in the primary market is 0.51, but in Table 2 we report the average seat quality of resold tickets is 0.62 (median is 0.69). Figure 3 provides a more complete picture of the tendency for resold tickets to be higher quality than resold tickets. The figure shows the predicted probability of resale as a function of seat quality, obtained either from a parametric regression of a resale indicator (equal to one if the ticket was resold) on a cubic polynomial in the seat quality variable, or from a semiparametric regression.[22] It is clear that while tickets of all qualities are sometimes resold, higher-quality tickets are significantly more likely to be resold.

Of course seat quality is a key determinant of prices in both the primary and secondary markets. But there are a couple of important differences between these markets in terms of how price relates to seat quality. First, in the primary market prices are based on coarse partitions of each venue. Meanwhile, resale prices reflect small differences in seat quality—every seat may have a different price. Figure 4 depicts the general pattern of resale prices as a function of seat quality (showing both parametric and non-parametric functions). It is apparent that resale prices vary significantly according to seat quality. This is especially true for the highest-quality seats, where resale prices are a particularly steep function of seat quality. This figure also serves as a reality check on the data.

Another important difference in how seat quality is priced in the primary and secondary

[21] In Table 1 an observation is an event, while in Table 2 an observation is a resold ticket.

[22] In both cases, event fixed effects are included. The semiparametric regression is an adaptation of Yatchew's (1997) difference-based estimator for partial linear regression models.

markets relates to monotonicity. Primary market prices are weakly monotonically increasing in seat quality for a given event. In contrast, Figures 1 and 2 illustrate that resale prices are a rather noisy function of seat quality, and there are numerous instances of a low quality seat resold at a higher price than a higher quality seat (for a given event). This is basic evidence of inefficiency in the resale market. On the one hand, the resale market allows price to be a more flexible function of seat quality. On the other hand, some form of friction in the resale market causes significant variance in price conditional on seat quality. As we detail in the next section, our empirical model explains this fact as being a consequence of limited participation by potential buyers in resale market auctions.

The analysis in this study emphasizes the consequences of limited price flexibility in the primary market (i.e., utilizing only a few price levels) on resale activity. In Figure 5 we present basic evidence in support of this view. By definition, all seats in a given price level at a given event have the same face value. However, there can be thousands of seats in a given price level, and the difference in seat quality between the best and worst seats in the price level can be dramatic. At equal prices there will be higher demand for the good seats in a given price level than the bad seats. We therefore expect more resale activity for the relatively good seats in any given price level. Figure 5 shows exactly this pattern.

Figure 5 is evidence that unpriced seat quality is an important driver of resale activity. But notice also that the lowest quality seats in any given price level are also resold with positive probability (roughly 2%). This is consistent with other drivers of resale activity, such as general underpricing or schedule conflicts. From the figure it appears that unpriced seat quality may be the most important driver of resale activity.

In the primary market, tickets typically go on sale 3 months before the event date. In Table 1 we report that (averaged across events) 64% of tickets purchased in the primary market occur in the first week. In fact the concentration of sales in the first week is even more striking than this number suggests. In the top panel of Figure 6 we depict the complete time-pattern of sales in the primary market. It is clear that sales in the primary market are highly concentrated at the very beginning. The time-pattern of sales in the resale market is less concentrated than the primary market, as shown in the lower panel of the figure. In Table 2 we report that 50% of resale transactions occur within 24 days of the event, and 26% of resale transactions are within 7 days of the event. In the model presented in the next section we assume primary market transactions occur in period 1, and resale transactions occur in period 2. The above facts suggest this is a reasonable simplification.[23]

[23] The dynamics of resale prices are similar to those reported by Sweeting (2009) for Major League Baseball tickets, with one exception. Prices in the secondary market decline gradually as the event date approaches, but unlike for baseball tickets, prices for the events in our data tend to increase slightly in the two-week period just

As noted above, brokers are potentially important agents in resale markets. Based on seller identifiers, 11% of the sellers in the resale market are brokers, and they account for 55% of resold tickets (as reported in Table 2). One of the more important facts in our data is that 45% of resold tickets are sold by non-brokers (i.e. consumers). In the table we also report that 23% of the tickets resold by brokers were at prices below the purchase price in the primary market. By comparison, 33% of the tickets resold by consumers were sold below face value. One possible explanation for this difference is that unlike brokers (who never intend to attend the event), consumers sometimes resell tickets because of schedule conflicts. There are other possible explanations, but these numbers suggest 10% of the resale activity by non-brokers is an upper bound for the fraction of resales that are due to schedule conflicts.[24] In the structural analysis we obtain a specific estimate of the rate of schedule conflicts (taking into account other potential reasons for resale).

The total profit (i.e. aggregate markup) obtained from ticket resale in our data is slightly over \$1.5 million. This is equivalent to 1.14% of total revenue in the primary market for these events. As a measure of "money left on the table" this suggests a fairly modest amount of forgone profit by firms in the primary market. This may be misleading, however, because modified pricing policies that capture some of this value may also be more efficient at extracting consumer surplus. We address this issue in the counterfactual analyses in Section 7. And this number could be considered a lower bound, since we do not observe all resale activity (as mentioned above, we believe we observe about half of all resale activity).

Lastly, we wondered if resale prices depend on the number of tickets grouped together. In particular, do pairs of tickets tend to sell for a higher price (per ticket) than single tickets? This would affect modeling assumptions in the next section. In an unreported regression, we regress $log(ResalePrice)$ on event dummies interacted with seat-quality deciles (i.e. flexible event and seat quality controls), and dummy variables for each of 1,...,5 tickets resold together. We found that the number of tickets has no significant effect on the resale price.

5 Model

We consider a two-period model describing equilibrium behavior in the primary and secondary markets. We assume that all primary market transactions take place exclusively in the first period, and resales take place exclusively in the second period—i.e., there is no overlap in the timing of the two markets. This greatly simplifies the analysis, and appears to be a reasonable

before the event.

[24]Another possible explanation is that brokers are better at identifying events with significant excess demand.

approximation of reality given the timing of sales described in Figure 6.

5.1 Basic setup

There are two types of agents in our model: brokers and consumers. The principal distinction between them is that brokers get no utility from consuming a ticket: if they purchase in the primary market, it is only with the intention of reselling at a profit. We assume there are M potential buyers in the market, a fraction β of which are brokers.

In the first period, consumers and brokers make their primary market purchase decisions. To capture the stochastic nature of ticket availability in the primary market (e.g., due to thousands of people calling or visiting the Ticketmaster website at exactly 10:00AM when the tickets go on sale), we assume that buyers make their decisions in a random sequence.[25] Let $g_z(z)$ be the probability of a given sequence z. In the present version of the model, we assume this probability is independent of buyer characteristics; later we will explore the consequences of letting arrival be correlated with willingness to pay and/or whether the buyer is a broker. Buyers are limited to choosing from the set of unsold tickets at their turn in the sequence, and each buyer is limited to buying one ticket.

Consumers vary in their willingness to pay for seat quality. Let $\nu_j \in (0, 1]$ denote the quality of ticket j, measured as described in Section 4.1.[26] Consumer i's gross utility from attending event k in seat j is

$$v^c(\omega_i, \nu_j) \equiv \mu_k(1 + \omega_i \nu_j^{\phi}) \ . \tag{1}$$

The term ω_i represents the consumer's willingness to pay for quality. The chosen functional form implies an intuitive interpretation of ω: the ratio of a consumer's willingness to pay for the best seat ($\nu_j = 1$) versus the worst seat ($\nu_j = 0$) is just $1+\omega$. We assume the ω_i's are drawn from an exponential distribution with mean λ. The curvature term, ϕ, captures the potential nonlinearity of premia for high quality seats (as evidenced in Figure 4). The idea is that even for a given consumer, willingness to pay is likely to be a nonlinear function of seat quality. Event-specific variation in willingness to pay is captured by μ_k.

In the second period, brokers and consumers holding tickets may sell those tickets via auction, where the buyers in the auction are consumers who chose not to purchase (or were rationed) in the primary market. Both brokers and consumers incur transaction costs if they choose to sell, denoted τ^b and τ^c, respectively. Of course, consumers also have the option of using the ticket

[25] Leslie (2004) implements a similar approach. See Mortimer and Conlon (2007) for an alternative approach to demand estimation with stock-outs.

[26] If j is the ticket's position in the "best available" order, and there are a total of J available, then $\nu_j \equiv 1-(j/J)$.

they purchased in the primary market. Thus, in the resale market the sellers' reservation prices depend on their transaction costs and (for consumers) on their consumption utilities.

5.2 Clearing the resale market

A natural way to clear the resale market would be to calculate every buyer's willingness to pay for every ticket (with the ticketholder's willingness to pay being equal to her reservation price), and then find a vector of prices such that there is no excess demand for any ticket. Although this approach is feasible in our model, it has one major drawback: it predicts resale prices that are monotonic in seat quality, which is clearly untrue in the data. Observed resale prices increase on average as a function of seat quality, but there is considerable variance in prices conditional on seat quality.

To accommodate this feature of the data, we clear the resale market using a sequence of private values, second-price auctions with limited bidder participation.[27] We begin with the highest quality ticket. From the pool of potential buyers (i.e., consumers who did not obtain a ticket in the primary market, and who did not have a schedule conflict), we randomly select L bidders. The owner of the ticket is offered a price equal to the second-highest willingness to pay among those L bidders. If the offer exceeds the owner's reservation price, then the ticket is transacted at that price: the bidder with the highest willingness to pay gets the ticket, and both seller and buyer exit the market.[28] If the offer is below the reservation price, the ticket remains with the seller. In this case, if the seller is a consumer, she uses the ticket herself and gets the utility defined in equation 1; and if the seller is a broker, she gets utility zero. Losing bidders remain in the pool of potential buyers. This process is then repeated for all tickets that were purchased in the primary market, in order of decreasing quality. In this mechanism every ticket purchased in the primary market is for sale in the resale market, regardless of whether it is owned by a broker or consumer.

5.3 Equilibrium

Consumers and brokers are assumed to be forward looking. Their decisions in the primary market depend on expectations about the resale market. There are four sources of uncertainty

[27] Assuming an auction mechanism in the resale market also corresponds with the actual functioning of this market.

[28] We allow only one transaction per period for any individual. So we do not allow consumers to buy in the primary market, sell in the resale market, and then buy another ticket in the resale market. We also rule out reselling any ticket twice. See Haile (2001) for an analysis of auctions followed by resale.

about outcomes in the resale market. The first is randomness in the arrival sequence, z, as mentioned above. Unless the resale market is entirely frictionless ($\tau^b = \tau^c = 0$), the equilibrium will depend on the allocation of tickets in the primary market, which in turn depends on the order in which buyers made their purchase decisions.

A second source of uncertainty that we introduce is the possibility of unanticipated schedule conflicts.[29] Formally, we assume there is a probability ψ that a given consumer will have zero utility from attending the event, with the uncertainty being resolved in between periods 1 and 2. Notice that if ψ is large, the ability to resell tickets in a secondary market may significantly increase willingness to pay in the primary market. Also, note that resale market outcomes depend on *which* consumers have schedule conflicts—i.e., the composition of schedule conflicts matters. For example, if by chance the individuals with conflicts are predominantly those with high willingness to pay, then their absence from the resale market will tend to make prices lower. We denote Ψ to be an $M \times 1$ vector of indicators identifying which of the M buyers have conflicts.[30]

Randomness in auction participation is the third source of uncertainty. As explained above, we clear the secondary market using a sequence of auctions, with a random subset of potential buyers participating in each auction. Obviously, realized outcomes in the resale market will depend on the particular subsets of buyers who bid for each ticket. We define H to be an $MJ \times 1$ vector containing a random ordering of the M buyers for each of the J tickets. This can be thought of as the order in which buyers "arrive" at each of the secondary market auctions, with only the first L arrivals being allowed to participate.

The fourth source of uncertainty is about the distribution of ω, consumers' willingness to pay for quality. Buyers know their own ω's (if they are consumers), and they know the distribution of ω's is exponential, but we assume they do not know λ—i.e., buyers are uncertain about the mean of the distribution of willingness to pay. Buyers believe that λ is drawn from some distribution with density g_λ (assumed to be log-normal). To keep things simple, we assume consumers do not use their own ω's as signals with which to update their beliefs about λ.

Incorporating this fourth kind of uncertainty is necessary if we want the model to fit the data. Specifically, for many events we observe both consumers and brokers reselling tickets below face value. For consumers, such transactions could be explained by unanticipated schedule conflicts. But for brokers, we would never observe resales below face value unless brokers sometimes overestimate the strength of demand. Essentially, uncertainty about λ allows us to explain why

[29]This source of uncertainty is equivalent to the uncertainty emphasized by Courty (2003) in his model of ticket resale.

[30]Technically, we keep track of the conflict indicator for brokers as well as non-brokers, but of course conflicts are ultimately irrelevant for brokers.

some events sell out in the primary market but then have very thin resale markets with very low prices, while other events do not sell out in the primary market but then have very high prices in the resale market.

The price of a ticket in the resale market is principally a function of its quality, but it will also depend on the realizations of the random variables described above. For notational convenience, we define the resale price function $R(\nu|z, \Psi, H, \lambda)$, which we will sometimes write simply as $R(\nu|\cdot)$.

The decision problem for a broker in the first period is straightforward. Her strategy is to purchase the ticket j that maximizes

$$E(u_j^b) = E(R(\nu_j|\cdot)) - p_j - \tau^b,$$

where p_j is the primary market price of ticket j, and $E(R(\nu_j|\cdot))$ is the expected price of ticket j in the resale market, where the expectation is with respect to the four sources of uncertainty described above. Of course, if the transaction cost τ^b exceeds the expected resale profits, a broker also has the option of not purchasing a ticket for a payoff of zero.

A consumer's decision problem is somewhat more complicated, as illustrated in Figure 7. If a consumer buys ticket j in the primary market, with probability ψ she will be forced to resell the ticket, obtaining some price $R(\nu_j|\cdot)$. While not illustrated explicitly in the figure, she also has the option of discarding the ticket if the transcation cost is higher than the resale profit, in which case her payoff is $-p_j$. If she has no schedule conflict, she will have the choice of reselling or using the ticket, with the latter option delivering a net utility of $\mu_k(1 + \omega_i\nu_j^\phi) - p_j$. The expected payoff from buying ticket j is therefore

$$\begin{aligned} E(u^c|\text{buy } j) &= -p_j + \psi E\left(max\{0, R(\nu_j|\cdot) - \tau^c\}\right) + \\ &\quad (1-\psi)E\left(max\{0,\ R(\nu_j|\cdot) - \tau^c, \mu_k(1 + \omega_i\nu_j^\phi)\}\right). \end{aligned}$$

Again, the expectations are with respect to z, Ψ, H, and λ.

If instead the consumer chooses not to buy a ticket in the primary market, but rather wait until the secondary market, her expected utility is given by

$$E(u^c|\text{wait}) = (1-\psi)E\left(max\{0, \mu_k(1 + \omega_i\tilde{\nu}^\phi) - R(\tilde{\nu}|\cdot)\}\right).$$

In this case, the consumer is not only uncertain about what prices will be in the resale market, she is also uncertain about which ticket (if any) she will be able to buy in the resale market. We use the notation $\tilde{\nu}$ to indicate that ticket quality is itself a random variable for a consumer who chooses to delay her purchase.

Given this payoff structure, a rational expectations equilibrium is one in which: (i) brokers and consumers make their first-period decisions optimally given their expectations about second-period outcomes; and (ii) those expectations are on average correct given optimal decision-making in the first period.[31] Given a primary market allocation and realizations of the model's random variables (z, Ψ, H, and λ), the resale market outcomes follow deterministically. The challenge is finding expectations that rationalize a set of primary market decisions that in turn lead to resale market outcomes consistent (on average) with those expectations. In other words, the trick is to find a fixed point in the mapping of expectations into average resale market outcomes.

The expectations described in the equations above cannot be calculated analytically, even for particular assumptions about the probability distributions of z, Ψ, H, and λ. Although realizations of these random variables lead deterministically to a set of resale market outcomes, the form of the function $R(\nu|z, \Psi, H, \lambda)$ is not known. Nor is it possible to determine the value of $\tilde{\nu}$ as a function of z, Ψ, H, and λ.

We therefore take a computational approach to solving this problem. We conjecture a parameterized approximation to the buyers' expected values, and then iterate on the parameters of that approximation until we converge to a fixed point. As explained above, a buyer's expected utility, as a function of the primary market choice, depends on: (i) whether the buyer is a broker or consumer; (ii) the quality (ν) of the ticket purchased, if any; and (iii) the buyer's ω if the buyer is a consumer. We therefore choose a parametric function $V(b, \nu, \omega|\alpha)$ to represent buyers' expectations, where b is an indicator for whether the buyer is a broker, and α are the parameters.

The algorithm for finding a fixed point is as follows:

1. Choose an initial set of parameters, α_0. Simulate primary and secondary market outcomes for S draws on the model's random variables (arrival sequences, schedule conflicts, etc.), where consumers make primary market choices to maximize $V(b, \nu, \omega|\alpha_0)$.

2. Use the *realized* final utilities from the simulations in step 1 to re-estimate the function $V(b, \nu, \omega|\alpha)$. Essentially, we regress realized utilities on a function of b, ν, and ω to obtain a new set of parameters, α_1.

3. Use the new set of parameters from step 2 to simulate primary and secondary market outcomes as in step 1. Iterate on steps 1 and 2 until V converges—i.e., until $V(b, \nu, \omega|\alpha_t)$ is sufficiently close to $V(b, \nu, \omega|\alpha_{t-1})$.

[31] Forward looking consumer behavior with rational expectations of future market outcomes is also essential in the recent papers by Gowrisankaran and Rysman (2007), and Hartmann and Nair (2007). See also Chevalier and Goolsbee (2005).

In estimating the model below, we use a very simple parameterization of V. Letting h be an indicator for whether the buyer holds a ticket going into the second period, we let

$$
\begin{aligned}
V(b,\nu,\omega|\alpha) &= b\cdot h\cdot(\alpha_0+\alpha_1\nu)+(1-b)\cdot h\cdot(\alpha_2+\alpha_3\nu+\alpha_4\omega+\alpha_5\nu\omega) \\
&\quad +(1-b)\cdot(1-h)\cdot(\alpha_6+\alpha_7\omega). \qquad (2)
\end{aligned}
$$

This parameterization captures the essential elements of the expectations described above. For a broker, expected utility depends only on the quality of the ticket owned, ν. For a consumer without a ticket, expected utility depends only on the consumer's willingness to pay for quality, ω. For a consumer holding a ticket, expected utility depends on both ν and ω, since ultimately the ticket will either be consumed (yielding a payoff that depends on ν and ω) or resold (yielding a payoff that depends on ν).

Convergence of this algorithm means we have found a rational expectations equilibrium: a set of expectations V such that the primary market choices that follow from V lead to secondary market outcomes consistent with V. The convergence criterion we use is based on average differences in V. At each iteration of the algorithm, we essentially estimate the regression described in equation (2) using $M\times S$ "observations." We stop iterating when

$$\frac{1}{MS}\sum_{i=1}^{MS}\left(\frac{|V_i(\alpha_t)-V_i(\alpha_{t-1})|}{V_i(\alpha_{t-1})}\right)\le 0.005.$$

In other words, we stop when the fitted values of V differ from those of the previous iteration by less than half of one percent on average.

6 Estimation and results

There are 110 parameters to be estimated in the structural model: the curvature term in the utility function (ϕ), consumers' transaction cost (τ^c), brokers' transaction cost (τ^b), fraction of brokers (β), probability of schedule conflict (ψ), mean of distribution of λ ($\bar{\lambda}$), standard deviation of distribution of λ (σ_λ), and 103 event fixed-effects (μ_k).

Given prices and capacities by price level, for each event, the model described above allows us to predict both primary market sales and secondary market sales (including resale prices) as a function of the parameters. Heuristically, our estimation approach is simply to find a set of parameters that minimizes the differences between the outcomes we observe in the data and those predicted by the model.

Estimation is via simulated GMM. A wide range of moment conditions could potentially be incorporated in the estimation, subject to an important limitation. In the model, λ_k is unknown to all buyers in period 1. However, the realization of λ_k affects outcomes in period 2. Note that we do not estimate λ_k, but rather the parameters of its distribution. This implies that (given the true parameters) our model does not deliver unbiased predictions for resale market outcomes (e.g. fraction of tickets resold, average resale price, etc) *for any particular event.* Put differently, there is no reason to expect the model's predictions of resale outcomes to be correct event by event, since these outcomes depend on the unobserved realization of λ_k. The model's predictions about resale market outcomes can only be expected to be right on average (across events).

In contrast, our model does deliver predictions for primary market outcomes of particular events that should equal (in expectation) their empirical counterparts. For instance, our model is capable of predicting the fraction of tickets sold in the primary market for each event. This is because the realization of λ_k does not impact behavior in the primary market, since λ_k is also unknown to all participants in the market at that time.

Based on this reasoning, we estimate the model's parameters using the following moments: fraction of available tickets sold in the primary market for each event (103 moments), average fraction of tickets resold by consumers (1 moment), average fraction of tickets resold by brokers (1 moment), average resale price (1 moment), average quality of resold tickets (1 moment), 25th and 75th percentiles of resale price distribution (2 moments), and 25th and 75th percentiles of resale seat quality distribution (2 moments). Hence, there are a total of 111 moments to estimate 110 parameters.[32]

More formally, let $\tilde{s}_l$ and s_l denote the simulated and empirical values for each moment. We construct moment conditions of the form $m_l(\Theta) = \tilde{s}_l(\Theta) - s_l$, and select Θ to minimize $m'Wm$, where Θ is the set of all parameters, m is the stacked vector of moment conditions, and W is a weighting matrix.

The computational burden in estimating the model comes from simulating the primary and secondary market outcomes for a given set of parameters. This simulation needs to be done separately for each event, since events differ in their pricing structures, and, as described in section 5.3 above, in each case we must iterate until we converge to an equilibrium set of beliefs about secondary market outcomes (i.e. rational expectations).

In order to make this burden more manageable, instead of simulating outcomes for events with thousands of seats, we simulate events with 200 seats, and then scale up the predictions to match the size of the event in question. For example, for an event with 10,000 seats, with 4,000 and 6,000 seats in two respective price levels, we simulate primary and secondary market

[32]We could add any number of additional moments. The next draft will report results based on various alternative sets of moments.

outcomes for an event with 200 seats, with 80 and 120 seats in the two respective price levels. We then "scale up" by applying the predictions for seat 1 in the simulated event to seats 1-50 in the actual event, the predictions for seat 2 to seats 51-100, and so on.[33]

6.1 Identification

Two important variables in our model are neither known to us as data nor identified by the data as parameters. The first is the size of the market, M. In the estimates reported below, we fix M to be three times the capacity of the event. Later we can check whether our results are robust to alternative assumptions. The second is the fraction of total resales that our data account for. As explained above, we use the available information and assume that eBay and StubHub account for 50 percent of total resales. This factors into the estimation when we match predicted resale probabilities to observed resale outcomes: we simply divide in half the probabilities predicted by the model (i.e. we match the data to the probability of resale times the probability of observing that resale).

In this version of the paper we are also fixing the number of bidders in the resale auctions, L, to be 5. This is something we intend to relax in the future, since in principle there is variation in the data to identify L: namely, the variance in resale prices conditional on seat quality.

For the parameters we do estimate, we can provide intuition for how patterns in the data identify them. The event dummies μ_k are basically identified by differences across events in the fraction of tickets that get sold in the primary market, and the overall level of resale prices. The "curvature" parameter ϕ is identified by the shape of the relationship between resale prices and seat quality (e.g., as shown in Figure 4).

The shape of the price-quality relationship also influences $\bar{\lambda}$, the mean of the distribution of ω's. However, this parameter is driven primarily by the level of resale prices for the highest-quality tickets: as explained above, a consumer's ω determines the ratio of her willingness to pay for the best seat vs. the worst seat. If in the data we observe that resale prices for the best seats are typically 3 times more than for the worst seats, then $\bar{\lambda}$ needs to be such that the highest draws of ω are around 2.

The standard deviation of beliefs, σ_λ, is identified by the frequency with which tickets are resold at a loss. Essentially, the more often we observe instances where buyers (especially brokers) overestimated demand for an event, the larger will be our estimate of σ_λ.

[33]This obviously introduces additional noise into our estimator, but in principle we can eliminate as much of this noise as we want by increasing the size of the simulated event up to the size of the actual event.

The fraction of buyers who are brokers (β) is basically driven by the relative frequency of sales by brokers in the resale market. To be clear, however, the estimate will not simply equal the relative frequency of broker sales in the data. If consumers have higher transaction costs than brokers, as we expect, then brokers will be more likely than consumers to speculate in the primary market—so even a small β could be consistent with a large fraction of resales being done by brokers.

Identification of the transaction costs is driven by ticketholders' relative propensity to resell at high versus low expected markups. Loosely speaking, positive transaction costs allow the model to rationalize low rates of resale in the data even for tickets that would have fetched very high markups. Not so loosely speaking, the transaction costs estimates should depend on the slope of the relationship between the probability of resale and the expected markup, and specifically on where that slope becomes positive. For example, suppose that τ^c is equal to \$10. For tickets that would resell for less than \$10 above face value, the model will predict very low probabilities of resale by consumers. More importantly, the probability of resale will be independent of the expected markup if that markup is less than \$10. Only as the expected markup rises above \$10 will the probability of resale increase (i.e., at \$10 the slope would become positive).

Finally, the probability of schedule conflicts, ψ, is driven by the relative rate at which consumers versus brokers resell below face value. The model assumes that both types of buyer have the same information, so they should be equally likely to overestimate demand for an event. To the extent that consumers are more likely than brokers to sell at a loss, in the model this must be driven by schedule conflicts (which matter for consumers but are irrelevant for brokers).

6.2 Estimation Results

The estimates are reported in Table 3. Consumers' transaction costs are estimated to be about \$63, and brokers' transaction costs are estimated to be around \$12. The transaction cost for consumers may seem a little high. However, it seems plausible than many consumers have never used eBay before, and perceive there to be significant setup costs (learning and other fixed costs) to using eBay the first time. Another interpretation is that the transaction cost also captures an endowment effect (see Khaneman, Knetsch and Thaler, 1991): consumers' valuations of tickets increase after purchasing them. Indeed, Krueger (2001) has argued this is an important factor in ticket markets.

As expected (but not imposed), brokers are estimated to have significantly lower transaction cost than consumers. This implies total surplus will be higher if brokers are resellers rather than consumers. This issue is explored in the counterfactuals, below. The other main parameters of interest are the probability of schedule conflict and estimated fraction of buyers that are brokers. Both estimates seem implausibly low, meriting further investigation.

To help assess goodness of fit, in Table 4 we present actual and predicted values of the moment conditions, which are intuitive measures in themselves. Note that we report the average of the 103 primary market moments discussed above. The estimated model underpredicts primary market sales by about 5%, but does extremely well on the probability of resale by both brokers and consumers. Resale prices are low (by around 15% on average), and resale quality is low.

7 Counterfactual analyses

We now turn to our primary objective, which is to provide a quantitative assessment of how resale markets reallocate surplus among primary market sellers, brokers, and consumers. We do this by means of counterfactual analyses: i.e., given our estimates of the structural parameters, as reported in Table 3, we simulate market outcomes under various hypothetical changes to the market environment. We summarize the results from a preliminary set of counterfactuals in Table 5.

It is important to note that in this version of the analysis we do not re-optimize primary market prices under the various counterfactuals, although of course we do incorporate endogenous primary and secondary market decisions of consumers and brokers. We intend to include endogenous primary market pricing in a future version of the paper.

For purposes of comparison, the first two columns of Table 5 report various summary statistics about market outcomes as observed in the data (column 1) and for the baseline set of estimates (column 2). To construct the table, we simulate 100 outcomes for each event (i.e., outcomes for 100 separate draws of (z, Ψ, H, and λ), and average those outcomes to get the expected outcome for that event. The table then reports averages across the 103 events (in a way that is analogous to the summary statistics in Table 1).

We first consider the consequences of eliminating resale altogether. (Technically, we simulate this counterfactual by setting consumers' and brokers' transaction costs to arbitrarily high levels.) As can be seen in the third column of the table, this leads to slight increases in the number of tickets sold in the primary market and in primary market revenues. Overall, however, the results indicate that current levels of resale activity do not generate dramatic differences in producers' or consumers' surplus relative to a world without resale. We suspect this result reflects the high estimated transaction costs—especially for consumers—and consequent low levels of resale.

In the fifth column of the table we report results for the opposite extreme of nearly frictionless resale. We simulate outcomes with transaction costs set to zero for both consumers and brokers, and with 100 bidders in each resale auction. Not surprisingly, eliminating these frictions leads to dramatic increases in resale activity: on average, 71% of tickets purchased in the primary market would be resold, relative to only 2% in the base case. The average quality of resold tickets goes down. In the base case, only the very best tickets could fetch a premium large enough to cover the transaction cost; when the transaction cost is eliminated, it becomes economical to resell low-quality tickets too. Consumers' surplus goes up substantially, but this includes profits captured by consumers who resell their tickets. As we discuss below, frictionless resale *decreases* the surplus captured by consumers who actually attend the event.

Note that in our model, eliminating frictions from the resale market leads to fewer primary market sales and lower primary market revenues. Facilitating resale has two opposing effects on primary market sales. On the one hand, fluid resale markets increase the option value of holding a ticket, which should lead to more sales in the primary market. On the other hand, thicker resale markets make it more attractive to postpone purchases until the second period, especially for consumers with high willingness to pay who arrive late in the buyer sequence. In column two it is evident that the latter effect dominates. This result should be interpreted with caution, however, because it hinges on our assumption that consumers can only buy a ticket once. If instead consumers could buy a ticket in the primary market and then "trade up" in the secondary market (by reselling one ticket and buying another), there would be less of an incentive to postpone purchases. Also, recall that our results represent partial equilibrium effects; if our simulations allowed producers to re-optimize their prices in response to the change in resale activity, the results regarding primary market revenues could change significantly.

Since many legal restrictions on ticket resale seem to be motivated by hostility toward brokers, in column 4 we consider what would happen if brokers were eliminated altogether. (We simulate the model with β, the share of buyers who are brokers, set to zero.) The impact of this change is not large, but the results suggest that brokers' participation generates a net gain in consumer surplus. However, we note that our estimates imply brokers make losses on average in the base case. This is a puzzling result that requires further investigation; for now we are reluctant to draw any strong conclusions on this point.

We noted above that much of the observed resale activity in our data appears to be driven by unpriced seat quality. In particular, consumers evidently are willing to pay significant price premiums for the very best seats, but these seats are typically sold together with many inferior seats at the same coarsely-defined price point. In column 6 of the table, we consider what would happen to resale activity if the best seats were re-priced. Specifically, we take the top 10% of each event's seats, and assign them a new price point equal to the average observed resale price for those seats, and then simulate market outcomes using the parameter estimates from Table 3. (Unlike in the other counterfactuals, where we consider changes to the fundamental parameters, here we keep the same parameters but consider a change to the data.) The results suggest that primary market revenues would increase by nearly 6% (an average of $65,000 per event), which we take as a rough estimate of how much money producers are leaving on the table by not scaling the house more finely. It is also interesting that resale activity *increases* slightly in this scenario. One possible explanation for this is based on consumers' high transaction costs. In the base case, consumers with low willingness to pay who arrive early in the buyer sequence buy high-quality tickets and tend *not* to resell them (due to high transaction costs). When the price of the high-quality tickets is increased, these same consumers will begin to bypass the high-quality tickets in favor of lower-quality (and lower-price) tickets. This makes the tickets more accessible to brokers (who have lower transaction costs), and therefore increases the rate of resale.

The last column of the table shows what happens if we ignore the interplay between primary and secondary markets—i.e., if we assume buyers are not forward-looking when they make their primary market decisions. We eliminate brokers, and determine the primary market allocation by having consumers' first-period decisions depend only on their consumption utilities from attending the event. We then clear the resale market as in the baseline model. Ignoring the potential profits from resale obviously reduces the perceived value of the tickets, so our model predicts that primary market sales would decline if first-period decisions were made myopically. The magnitude of the decline gives a rough indication of how many primary market purchases are speculative in the baseline model—i.e., how many tickets are purchased only because the buyer expects to resell for a profit.

Table 6 provides a clear illustration of how the resale market reallocates surplus among the various market participants. The numbers in the table are for a single example event: Dave Matthews Band at the Home Depot Center in Carson, CA. (The data for this event are pictured in the top panel of Figure 2.) In the top row of the table we report the *gross* surplus of the consumers who attend the event. The principal consequence of resale markets is to reallocate products to consumers with higher willingness to pay, and changes in the gross surplus of attendees capture the efficiency gains from this reallocation. We normalize all numbers in the table so that gross surplus equals 100 in the no-resale case, which is depicted in the first column of the table. The second column shows that current levels of resale activity lead to a relatively small improvement in allocative efficiency: only 3.6% more surplus is generated as a consequence of resale. Moreover, the transactions costs incurred to broker the reallocation eat up two thirds of the efficiency gain.

The third column of the table describes outcomes if resale markets are nearly frictionless. (We set transactions costs to zero, and include 100 bidders in each resale auction.) The potential efficiency gains from resale are large: over 28% more surplus could be generated if tickets were more efficiently allocated to consumers with the highest values. This number probably understates the potential gains, because resale is not entirely frictionless in the simulations that generate this number (not all buyers participate in every resale auction), and because primary market sales decline in our model due to the restriction that buyers cannot "trade up" in the resale market.

Perhaps most importantly, the table illustrates that while resale markets can significantly increase total surplus, they also transfer surplus from the primary market seller and the event attendees to ticket resellers (brokers, and consumers acting as brokers). In the third column, resale generates a 28.5% gain in surplus, but this gain is captured entirely by resellers, and in fact resale markets result in lower primary market revenues and lower net surplus for final consumers. Put simply, in a world with frictionless resale, consumers get the "right" tickets, but they pay a much higher price for them.

Discussion and extensions

At present, our empirical model excludes three potentially important aspects of resale markets. The first, mentioned above, is that many consumers may sell *and* buy in the resale market—i.e., they may buy a ticket in the primary market expecting to "trade up" in the resale market. This leads our model to predict declines in primary market sales when frictions are removed from the resale market. We suspect this prediction is wrong, so we intend to expand the model to allow for multiple trades in the resale market.

A second critical restriction is that the arrival sequence is independent of buyers' willingness to pay. In reality, willingness to pay (captured by the parameter ω) may be correlated with arrival: consumers with high ω's may arrive earlier because they value the tickets more highly, or they may arrive later because they incur higher opportunity costs to call or log on to Ticketmaster at exactly the right time to obtain tickets. Moreover, brokers allegedly have better technologies for navigating Ticketmaster's system, so on average they may arrive earlier than consumers in the buyer sequence.

A third aspect currently excluded from our model is that buying tickets in the primary market may involve significant ancillary costs (beyond the price of the ticket). Both brokers and consumers may make costly investments to secure earlier positions in the arrival sequence, for example by waiting in line or by employing several confederates to place phone calls precisely when the tickets go on sale. Thus, not only might the arrival order be correlated with buyer characteristics, but it also might be endogenously determined by buyers' costly investments. This has important implications for the net welfare effects of resale, because if the costs incurred in the primary market are large enough, they could fully offset any gains in allocative efficiency.

Although we cannot directly observe any costs incurred in the primary market, some features of the data may allow us to indirectly identify the extent to which buyers "invest" in early arrival. For example, there is substantial variation across events in how compressed the sales are in time. For about 10% of concerts, more than 75% of the seats are sold in the very first day. But the median concert sells only 23% of capacity in the first day, and 66% in the first week. For the slowest 10% of concerts, less than 34% of capacity is sold at the end of the first week. This suggests that people make costly efforts to show up early when excess demand is expected to be high: if it were costless to show up early, we would not expect to see concerts with sales so spread out over time. Another potentially informative feature of the data is that early buyers sometimes purchase low-quality seats. Specifically, many first-day buyers purchase tickets outside the top price level, even when there are still seats available in the top price level. The frequency with which we observe this in the data may identify the correlation between arrival order and willingness to pay for quality (ω).

8 Conclusion

Our study has focused on the interdependence of primary and secondary markets, and is the first (to our knowledge) to analyze data from both markets in parallel. Our findings show that while the basic economics of resale markets are simple (buy low, sell high), the welfare consequences of resale—in particular, the *distribution* of gains and losses—are more subtle. In the market for rock concerts, we find that observed levels of resale activity do not generate dramatic welfare gains relative to a world without resale. However, large reductions in the transaction costs incurred by resellers would translate into substantial increases in social surplus. To the extent that online marketplaces like eBay, StubHub, craigslist, and others facilitate secondary market exchanges by lowering transaction costs, we can infer that their services increase the total surplus generated by the market for event tickets.

Not everyone benefits from resale, however. In particular, consumers who attend the event may be worse off when resale markets become more fluid. Seats are allocated more efficiently—high quality seats end up being occupied by consumers with the highest willingness to pay—but the additional surplus generated by the improved allocation is mostly captured by resellers. As a group, concert attendees would have preferred less efficiently allocated tickets obtained at lower prices. We find that frictionless resale markets would lower the surplus of concert attendees by over 40%. Thus, if the aim of public policy is to maximize *total* surplus (as arguably it should be), then our findings provide some support for the repeal of anti-scalping laws. From a consumer protection standpoint, however, the conclusion may be different: if the narrow goal is to maximize the surplus of those who ultimately attend the event, then restrictions on resale may be warranted. Also, our analysis currently ignores any costs that may be incurred by buyers trying to secure premium seats in the primary market, and such costs could arguably offset the gains in allocative efficiency resulting from resale.

Our results also imply that resale markets lead to slightly lower revenues for producers. This finding must be interpreted with caution, however, because producers' general equilibrium responses to changes in the resale market might offset the partial-equilibrium losses found here. More generally, our analysis highlights the degree to which resale activity is driven by pricing practices in the primary market. It follows that resale activity should be expected to decline as primary market sellers implement increasingly sophisticated pricing schemes. (Ticketmaster, for example, has actively encouraged artists to sell concert tickets using an auction mechanism.) Indeed, one interpretation of why scalping arises is that brokers are more efficient at implementing such schemes (see Swofford, 1999), and as primary market sellers develop these capabilities themselves the value of brokers will diminish.

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Table 1: Summary statistics: Events ($N = 103$)

			Percentiles				
	Mean	Std. Dev.	Min	.25	.50	.75	Max
Primary Market:							
Tickets sold	16678.74	6475.97	3169.00	13148.00	16012.00	19490.00	34844.00
Tickets comped	207.82	150.43	0.00	74.00	192.00	329.00	731.00
Revenue (000)	1292.64	561.05	230.76	900.74	1178.14	1748.51	2668.52
Venue capacity	16022.90	5176.39	3171.00	13772.00	15313.00	18164.00	35048.00
Capacity util.	1.05	0.22	0.58	0.99	1.00	1.00	1.65
Average price	83.15	39.79	39.91	53.87	68.16	90.87	187.24
Maximum price	130.05	99.63	45.00	66.60	85.60	138.90	315.75
# price levels	2.64	1.00	1.00	2.00	2.00	4.00	5.00
% first week	0.64	0.18	0.01	0.52	0.68	0.78	0.96
Secondary Market:							
Tickets resold	668.23	535.64	38.00	334.00	509.00	846.00	3130.00
Resale revenue	74.61	57.60	3.07	32.72	57.97	101.53	295.32
Percent resold	0.04	0.03	0.00	0.02	0.03	0.05	0.17
Percent revenue	0.06	0.05	0.00	0.03	0.05	0.07	0.37

Revenue numbers are in thousands of U.S. dollars. "# price levels" is the number of distinct price points for the event. "% first week" is the percentage of primary market sales that occurred within one week of the public onsale date. "Percent resold" is the number of resales observed in our data divided by the number of primary market sales, and "Percent revenue" is the resale revenue divided by primary market revenue.

Table 2: Summary statistics: Resold tickets ($N = 68,828$)

			Percentiles				
	Mean	Std. Dev.	Min	.25	.50	.75	Max
Resale price	111.66	78.39	3.03	65.00	91.25	134.98	2000.00
Markup	21.83	66.35	-308.65	-3.28	18.90	43.89	1686.40
% Markup	0.39	0.75	-0.98	-0.04	0.29	0.65	14.86
Seat quality	0.62	0.27	0.00	0.38	0.69	0.87	1.00
Days to event	41.89	41.75	0.00	7.00	24.00	73.00	208.00
Sold by broker	0.55	0.50	0.00	0.00	1.00	1.00	1.00
Sold below face value:							
by broker	0.24	0.42	0.00	0.00	0.00	0.00	1.00
by non-broker	0.33	0.47	0.00	0.00	0.00	1.00	1.00

Resale prices include shipping fees. Markups are calculated relative to the ticket's face value, including shipping and facility fees. Seat quality is based on the "best available" ordering in which Ticketmaster sold the tickets, as explained in the text, and is normalized to be on a [0,1] scale (1 being the best seat in the house). Brokers are eBay sellers who sold 10 or more tickets in our sample, or StubHub sellers who were explicitly classified as brokers.

Table 3: Results

Parameter	Notation	Estimate	Standard Error
Consumers' transaction cost	τ^c	68.3776	0.353
Brokers' transaction cost	τ^b	11.6386	0.866
Curvature	ϕ	0.2818	0.060
Mean of log(λ)	$\bar{\lambda}$	0.5060	0.136
SD of log(λ)	σ_λ	0.0899	0.089
Prob(conflict)	ψ	0.0017	0.056
Prob(broker)	β	0.0065	0.015
Select event fixed effects:	μ_k		
Minimum		19.9984	
25th percentile		27.7693	
50th percentile		30.7877	
75th percentile		35.6734	
Maximum		65.6311	

There are 103 estimated event fixed effects, however, to save space we report only five, corresponding to various moments of the distribution of estimated fixed effects.

Table 4: Goodness of fit

	Observed value	Predicted value
Fraction of tickets sold in primary market	0.9583	0.9079
Fraction of tickets resold by brokers	0.0219	0.0193
Fraction of tickets resold by consumers	0.0175	0.0187
25th percentile of resale prices	73.8280	68.0422
Mean resale price	114.0643	97.8889
75th percentile of resale prices	136.8842	120.4072
25th percentile of resold seat quality	0.5246	0.3156
Mean quality of resold tickets	0.6809	0.5139
75th percentile of resold seat quality	0.8655	0.7002

Table 5: Counterfactuals

	(1) Observed in data	(2) Baseline estimates	(3) No resale	(4) No brokers	(5) 100 bidders zero τ	(6) Best 10% repriced	(7) No brokers Myopic consumers
Number of tickets sold	16678.74	16350.94	16394.91	16321.03	15123.10	16150.10	15438.45
Fraction of tickets resold	0.04	0.02	0.00	0.01	0.71	0.03	0.13
Average resale price	111.66	97.05	–	132.07	110.45	109.19	145.68
Average resale quality	0.62	0.53	–	0.52	0.50	0.52	0.64
Producer revenues	1292.64	1106.56	1109.22	1105.11	1053.64	1172.00	1061.01
Broker profit		-2.10	0.00	0.00	4.59	0.04	0.00
Consumer surplus		512.92	520.13	517.17	817.33	458.27	521.29

Each entry is the mean across all 103 events.

Table 6: Gains & losses from reallocation for an example event

	No resale	Base case	Frictionless
Gross surplus of attendees	100.0	103.6	128.5
Transactions costs incurred	0.0	2.4	0.0
Net surplus	100.0	101.2	128.5
Primary market revenues	60.3	60.3	54.0
Resellers' profits:			
Brokers	0.0	0.1	0.4
Non-brokers	0.0	1.3	53.4
Attendees' net surplus	39.7	39.5	20.7

Numbers represent averages across 100 model simulations for an example event (Dave Matthews Band at Home Depot Center in Carson, CA.) Numbers are normalized so that attendees' gross surplus equals 100 in the "no resale" case. The "no resale" column reflects outcomes when transactions costs are set arbitrarily high; the "base case" reflects outcomes at the estimated values of the parameters (i.e., current levels of resale activity); "frictionless" reflects outcomes when transactions costs are set to zero and the number of bidders in the secondary market auctions is set to 100.

Figure 1: Two sample events

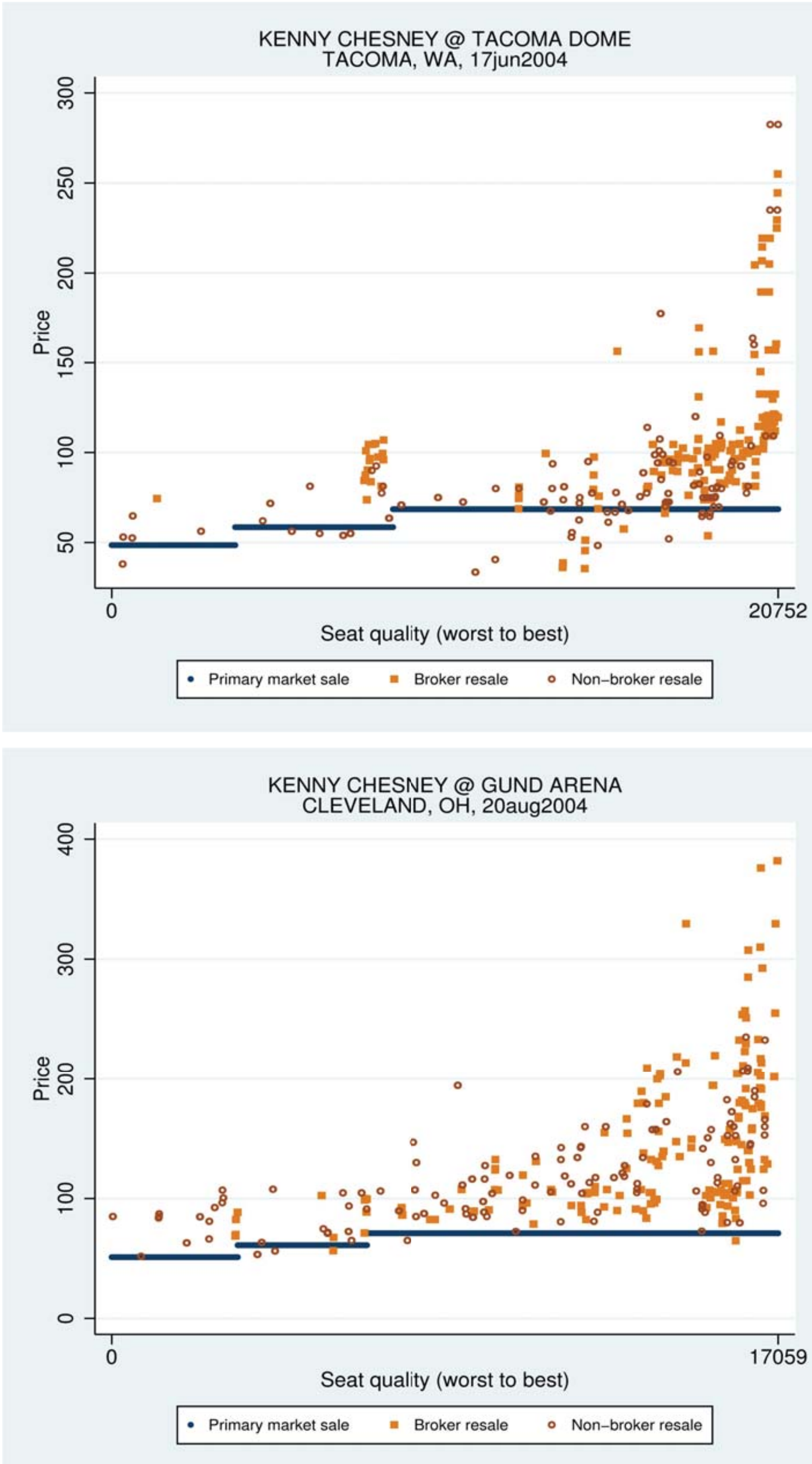
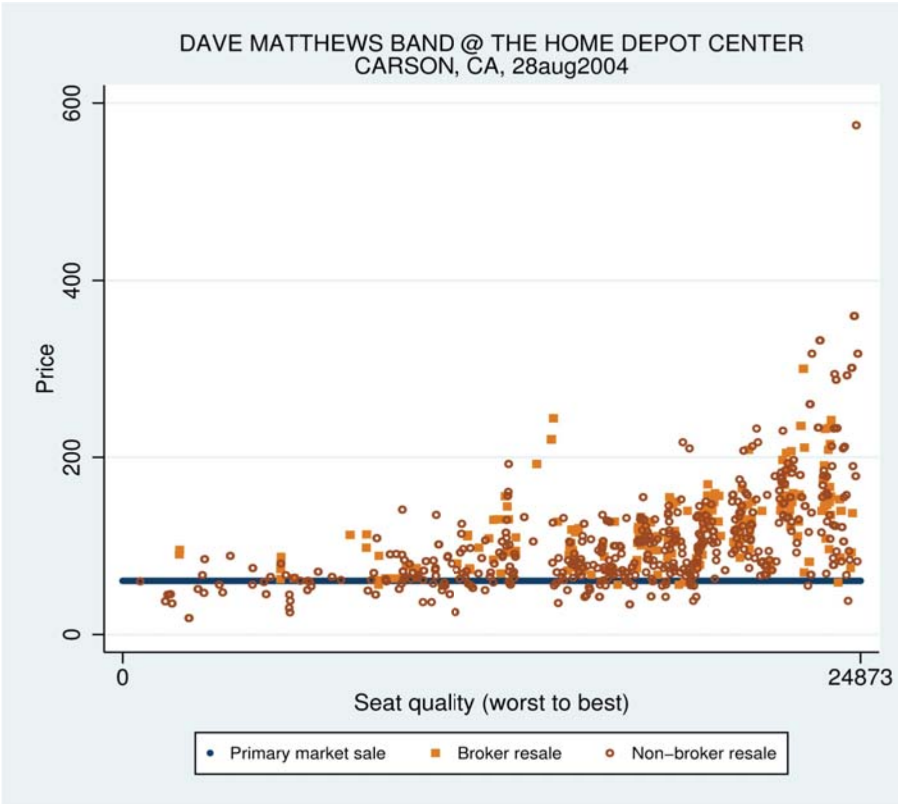


Figure 2: Two more sample events



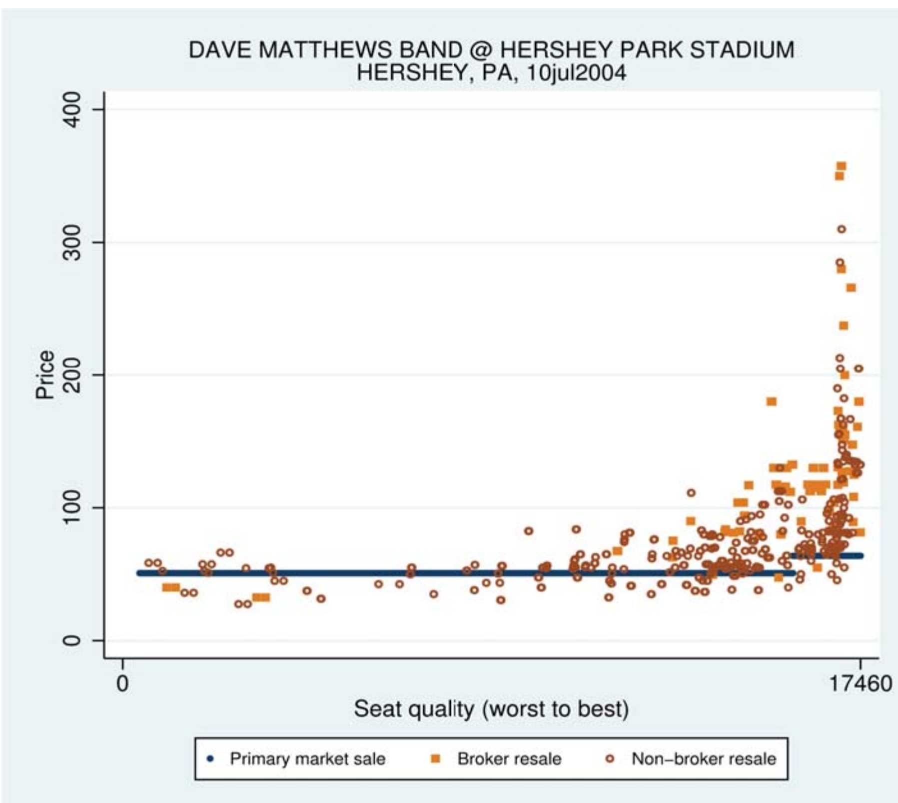


Figure 3: Probability of resale and relative seat quality

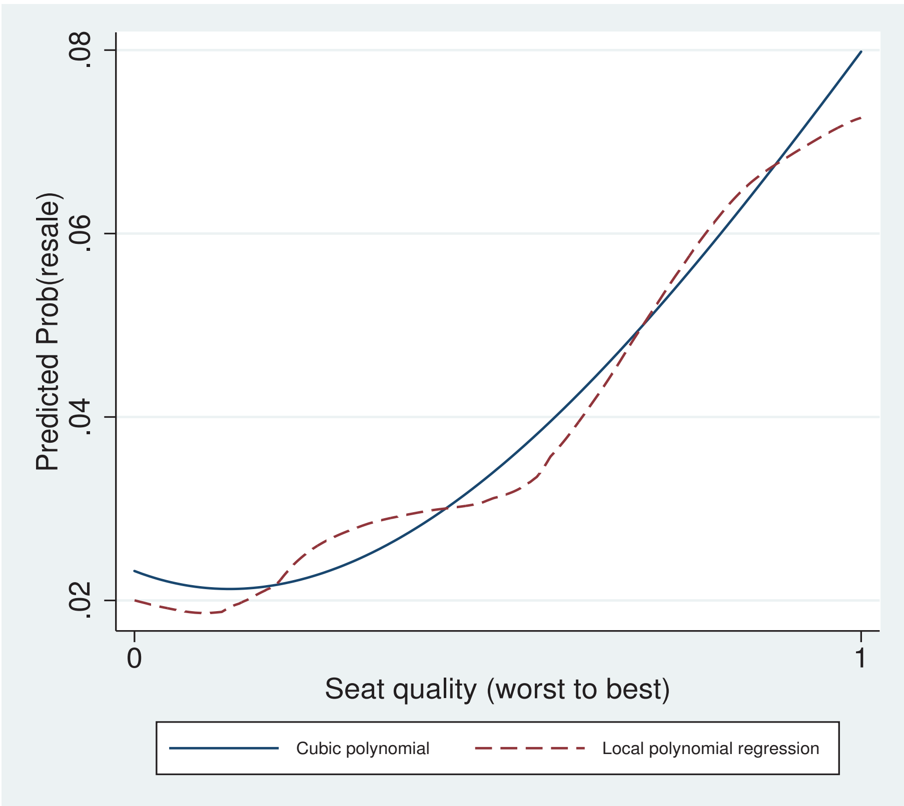


Figure 4: Resale prices and relative seat quality

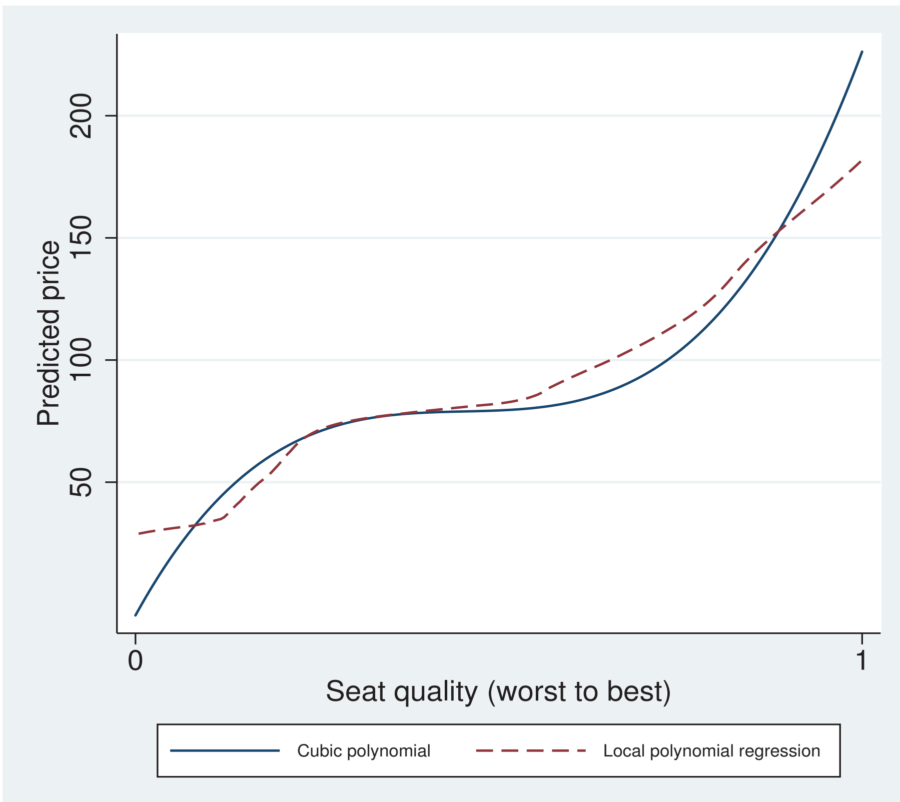
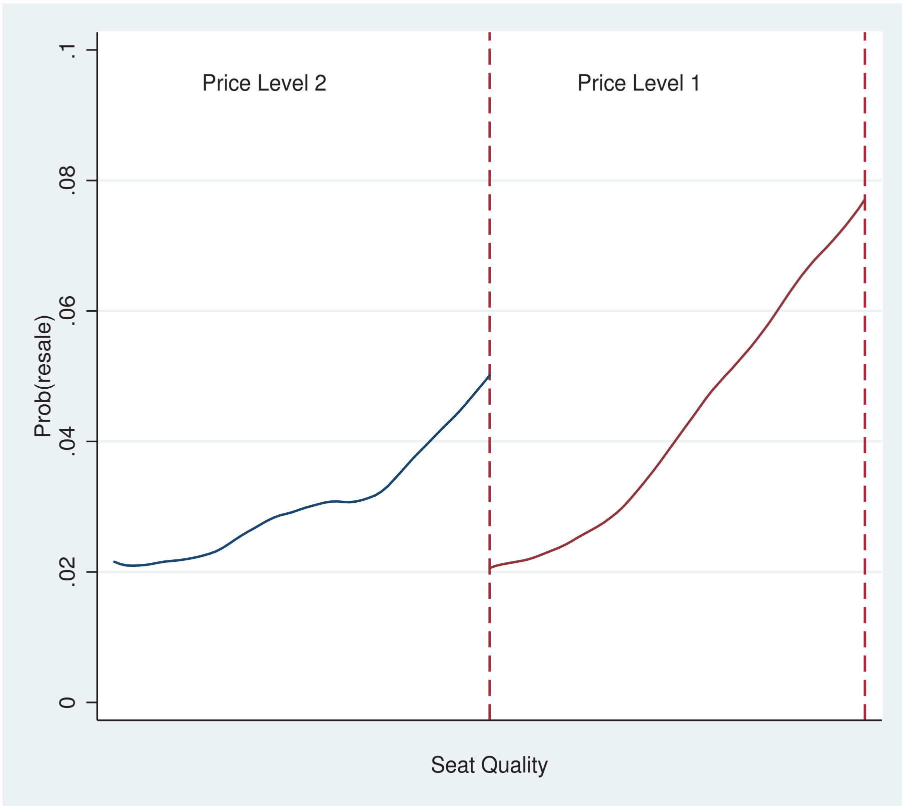
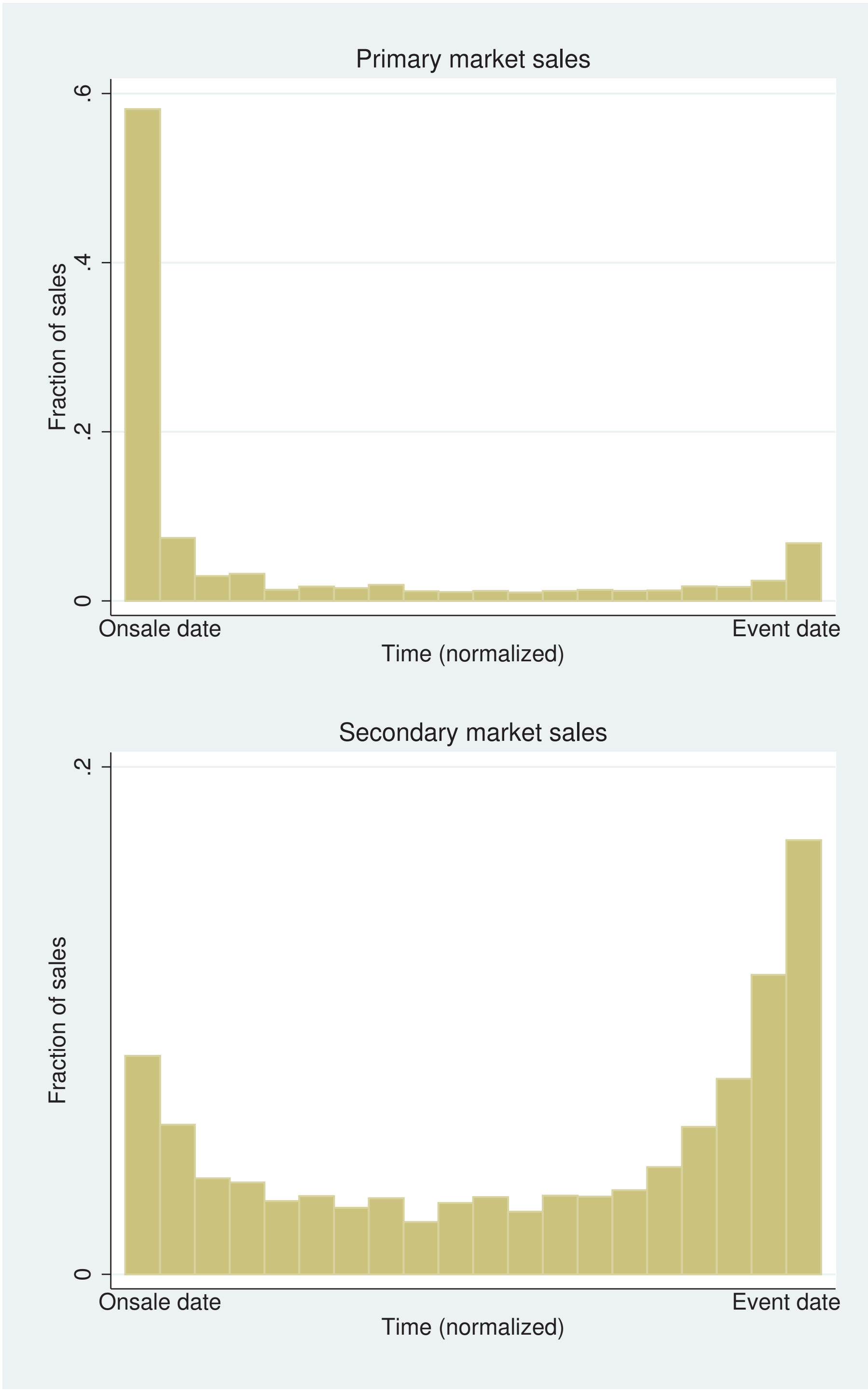


Figure 5: Probability of resale by price level



In generating this figure, only events with two or more price levels were used. Relative seat qualities are calculated *within* price level for this figure, and the probability of resale is estimated using kernel-weighted local polynomial regression. So, for example, the probability of resale is on average higher for the best seats in price level 2 than for the worst seats in price level 1.

Figure 6: Timing of sales in primary and secondary markets



Time is normalized to make it comparable across events; it is measured as (days since onsale)/(total days between onsale and event). The histogram in the top panel represents the 1,739,346 tickets sold by Ticketmaster; the bottom panel represents the 68,828 tickets resold on eBay or StubHub.

Figure 7: The consumer's decision problem