Resale, Refunds, and Demand Uncertainty: Evidence from College Football Ticket Sales

Drew Vollmer*

This Version: May 24, 2021
Click for latest version

Abstract

This paper studies the optimal sales strategies used to reallocate perishable goods after purchase when demand is uncertain. Using data on primary and secondary college football ticket sales, I evaluate three strategies in a structural model: resale, partial refunds, and a menu of refund contracts. In the model, consumers anticipate shocks when making initial purchases. After shocks are realized, they participate in an endogenous resale market. The results matter for aftermarket design, showing that refunds are more efficient than resale. They also inform resale policy, showing that sellers benefit relative to not reallocating and that consumer welfare increases substantially.

*Department of Economics, Duke University. Contact: drew.vollmer@duke.edu
I am grateful for helpful conversations with Allan Collard-Wexler, James Roberts, Curtis Taylor, Bryan Bollinger, Jonathan Williams, Daniel Xu, and Juan Carlos Suàrez Serrato. I also benefited from seminar presentations in the Duke IO and theory groups. I would like to thank the university that provided its sales records for the project. All errors are mine.

1 Introduction

Consumers frequently have uncertain demand because they receive demand shocks after making purchases. They buy tickets for sports, concerts, and travel far in advance and then learn they have schedule conflicts; they buy clothes online and then learn they do not fit; and they buy electronics and then learn the devices do not work together. When initial purchases are suboptimal, reallocation is critical for efficiency—especially so for perishable goods like tickets and reservations. But sellers use several reallocation mechanisms and it is not clear which is best. For example, sellers of event tickets typically allow resale, but airlines prohibit resale and offer refund contracts instead. Which strategy maximizes profit and welfare?

The purpose of this paper is to evaluate the performance of common reallocation mechanisms in markets for perishable goods with uncertain demand. Specifically, I use data on college football tickets sales to study the performance of three widely used sales strategies that reallocate after shocks: allowing resale, offering a partial refund, and offering a menu of state-dependent refund contracts. Football tickets are an ideal setting because consumers often receive shocks after initial purchases:[1] in addition to schedule conflicts, they also receive shocks when they learn about the team's performance, similar to how learned quality matters in markets for clothing and other seasonal goods.

To assess the performance of the strategies, I estimate a structural model of the market for football tickets using primary and secondary market ticket sales data from a major university.[2] In the model, consumers make initial purchase decisions with rational expectations of future shocks. After shocks are realized, they learn their final values and participate in an endogenous resale market. I use the estimated model to compare resale to the refund strategies in counterfactual experiments.

In numerical examples, I show that each strategy can be optimal.

[1] Sweeting (2012) uses sports tickets to study perishable goods. Event tickets have also been used as a setting in Leslie and Sorensen (2014).

[2] The data sharing agreement does not allow me to name the university.

Resale can be better than partial refunds when price flexibility is valuable. For example, suppose the team's star player is injured, causing consumer values to fall. If the seller has rigid prices—as many ticket sellers do—and offers a refund, then its prices will be high relative to values and few consumers will buy the refunded tickets.[3] But if the seller allows resale, the resale price will fall, allowing more tickets to be reallocated. Which strategy is best depends on the size of demand shocks and the costs associated with resale, such as search frictions and fees paid to the resale market operator. The menu of refund contracts is best when different consumers want the tickets in different states of the world. For instance, the consumers who want tickets in a state where covid-19 disappears and a state where it is endemic may be different. The seller could target each group by offering a menu of refund contracts that depend on the status of covid-19.[4] The optimal strategy therefore depends on the primitives of the market, which must be recovered in estimation.

After estimating the model, I find in counterfactual experiments that the refund strategies outperform resale, but that resale is better for all parties than not reallocating. In counterfactuals with no uncertainty over states of the world, partial refunds raise profit by 2.1% and total welfare by 0.5% relative to resale. However, the seller and consumers benefit from resale when compared to not reallocating: profit increases by 2.8%, total welfare by 5.1%, and consumer welfare by 6.9%. The changes are substantial because only 8% of tickets are reallocated in the estimated model. In counterfactuals with uncertainty over whether there will be a covid-19 vaccine, the menu of state-dependent refund contracts also outperforms resale, raising profit by 3.5% and total welfare by 2.8%.

The analysis has broad implications for our understanding of aftermarkets and resale. Evidence on the performance of reallocation mechanisms, and of the factors that affect them, is valuable for deter-

[3]For sellers with flexible prices, like airlines, refunds are likely to be optimal.

[4]A related source of uncertainty is if consumers have different probabilities of having a schedule conflict, studied in Lazarev (2013).

mining how to run aftermarkets. Yet there is little work on the matter, leaving the difference in efficiency and the theoretical advantages of resale unclear. This paper provides evidence on both. Moreover, comparing resale with not reallocating quantifies the net effects of resale. The effects of resale on both sellers and society have been hotly contested, with governments alternately restricting and protecting resale of event tickets[5] and some sellers prohibiting resale while others embrace it.[6] Some of the controversy is due to systematic underpricing, which is not present in this setting, but the net effect of resale on profit remains ambiguous in theory[7] and the benefits for consumers have rarely been measured. Additionally, the relevant class of perishable goods is large, covering items like reservation goods (e.g. live events, airlines, hotels, etc.) and seasonal goods (fashion). Online event ticket sales alone exceeded $56bn in 2019 (Statista (2020)).

The analysis relies on a structural model in which consumers purchase tickets over two periods. In the first period, consumers decide whether to buy season tickets based on rational expectations of shocks and future resale prices. In the second period, shocks are realized and consumers make final purchase decisions. Consumers who bought tickets in the first period choose whether to attend or resell; other consumers decide whether to acquire tickets in the primary or resale markets. The resale price clears the resale market and changes in response to shocks.

The essential task for the model is to capture the forces affecting the performance of the sales strategies. The most important forces are three demand shocks that are present in the model, common in other markets, and salient in the market for football tickets.

The first shock is purely idiosyncratic and can be interpreted as a schedule conflict, which is common in markets for event tickets and travel reservations. It causes some consumers who purchase early to

[5] Many states prohibit resale at prices above face value but have exempted internet sales (Squire Patton Boggs LLP (2017)). Others forbid sellers from using non-transferrable tickets, which are designed to prevent resale (Pender (2017)).

[6] Musicians like the band U2 have prohibited resale for their concerts (Pender (2017)), but many sports teams have sponsorship deals with platforms like StubHub and SeatGeek.

[7] The key determinant in this setting is whether resale displaces primary market sales. Resale is more profitable when capacity constraints are tighter.

have low final values, motivating reallocation. The second shock, a common value shock, shifts all consumers' values by the same amount and can be interpreted as learning the quality of a team or good, or of weather conditions in a vacation destination. It makes the optimal price after shocks unpredictable, boosting the returns to resale and its flexible prices. The third shock is a state of the world that has a potentially heterogeneous effect on consumer values. The most general example is the business cycle, where the recession state affects some consumers more than others. In the market for tickets, the states can be interpreted as the future status of covid-19, which could disappear or become endemic, and the estimation captures the associated uncertainty using survey data on a similar shock, whether there will be a covid-19 vaccine at the start of the season.[8] States of the world cause the efficient allocation to vary with the state, increasing the return to a menu of refund contracts conveying tickets in different states.[9]

I assemble a broad data set to learn about demand for tickets and the three demand shocks. The main data set consists of transaction-level primary and resale market sales records for one football season at a large U.S. university, covering 30,000 primary market transactions and 5,500 resale transactions on StubHub.[10] The ticket sales data, however, are not enough to learn about all demand shocks. A one-season snapshot cannot illustrate the effects of variation in team quality, and the data does not feature two covid-19 states. I introduce additional sources to learn about the remaining shocks. From SeatGeek, another online resale market, I gather average annual resale prices covering 76 college football teams from 2011–2019. Variation in annual prices for each team indicates the effect of quality variation on values. The final source of data is a survey that I conducted on demand with and without a covid-19 vaccine, asking 500 consumers (250 of whom were 50 or over) their

[8]The survey was distributed in August 2020, when it was unclear if or when there would be a vaccine.

[9]The NFL has offered a similar refund contract where fans only receive a Super Bowl ticket if their favorite team is in the game. More generally, the principle of contracting on observed states is the basis for financial derivatives.

[10]There is resale on other sites, but StubHub is the largest resale service (Satariano (2015))

willingness to pay for tickets in each state. Responses directly reveal values in each state.

I estimate the model in two stages. The key parameters estimated in the first stage govern the demand shocks and confirm that they are salient features of the market. The rate of idiosyncratic shocks is identified by the rate of resale in the ticket sales data: 6% of all seats were resold by consumers on StubHub. Common value shocks are identified by year-to-year resale price variation for each school in the SeatGeek data: average annual prices often differ by more than 25% from the long-term average. The distribution of value changes between the state with a covid-19 vaccine and the state without one is identified by the distribution of changes in reported willingness to pay in the covid-19 survey. The changes display significant heterogeneity: of consumers who would buy tickets with a vaccine, almost a third would pay the same amount without a vaccine while a fifth would pay nothing.

The second stage uses structural simulations to estimate demand and other remaining parameters. The simulations match observed to simulated resale prices and primary market quantities. The computational challenge is finding a rational expectations equilibrium where consumers correctly anticipate the distribution of resale prices.

The estimated model allows me to evaluate two core sets of counterfactuals. In the first, I consider a baseline model without states of the world and compare resale to partial refunds. I also consider benchmark cases with no reallocation (neither resale nor refunds) and flexible prices (refunds with price adjustments after shocks). In the second set of counterfactuals, the only uncertainty is over the state of the world[11] and I compare the performance of a menu of refunds to resale.

The remainder of the introduction discusses the relevant literature. Section 2 presents numerical examples demonstrating how the properties of demand uncertainty affect the seller's optimal sales strategy. Section 3 discusses the data sources used, and Section 4 presents de-

[11]The menu of refunds is not mutually exclusive from other sales strategies when the full refund depends on the state. Consumers who receive tickets in the realized state might still receive idiosyncratic shocks, which leaves room for resale and partial refunds. I do not consider idiosyncratic shocks to avoid testing combinations of the sales stratgies.

scriptive evidence. Section 5 develops a structural model of the market and Section 6 details how it is estimated. Section 7 presents the counterfactual experiments and their results. Section 8 concludes.

Related Literature. This paper contributes to several literatures, notably those on resale and demand uncertainty. For the resale literature, this paper provides estimates of how resale affects profit and welfare by modeling a primary market and an endogenous resale market. Leslie and Sorensen (2014) use a similar model combining primary and resale markets to study whether resale increases welfare in the market for concert tickets, but they do not consider profit because tickets are systematically underpriced in their sample. Tickets in my setting are not underpriced and so I study both profit and welfare. Sweeting (2012) also studies the resale of event tickets, focusing on the use of dynamic pricing in online resale markets. Lewis et al. (2019) investigate the effect of resale on demand for season tickets in professional baseball but do not model how resale of season tickets affects sales of other tickets. Waisman (2020) considers the ability to use auctions or posted prices when reselling sports tickets online. The net effects of resale on buyers and sellers are a traditional focus of the theory literature on resale, including studies such as Courty (2003) and Cui et al. (2014).

A separate literature considers resale of durable goods. With durable goods, sellers to compete against past vintages of their products, studied in Chen et al. (2013) and Ishihara and Ching (2019).

This paper also broadens the traditional focus on resale to consider alternative methods of reallocation. Two recent studies, Cui et al. (2014) and Cachon and Feldman (2018), have compared resale and refunds. Both use theory models and find that one strategy is always more profitable. This paper includes empirics and a model in which either can be more profitable.

The current analysis also relates to studies of demand uncertainty in which aggregate uncertainty affects firms' strategic choices, such as Kalouptsidi (2014), Jeon (2020), and Collard-Wexler (2013). This paper differs by focusing on strategies firms can use to cope with uncertainty. The emphasis is similar to studies of airline pricing with stochastic demand, such as Lazarev (2013) and Williams (2020), where stochastic consumer arrivals make dynamic pricing profitable. In contrast, this paper focuses on non-price strategies for reallocation, an emphasis shared by a theoretical branch of the management literature exemplified by Chen and Yano (2010) and Su (2010).

This paper also relates to the literature on price discrimination, particularly studies in which sellers use future value shocks as a screening device. Courty and Li (2000) show that refund contracts are an optimal mechanism when consumers make purchases before receiving shocks drawn from heterogeneous distributions. The setting is similar to the dependence on values on an unrealized state of the world, which lets this paper offer rare empirical evidence on the topic.[12]

The emphasis on reallocation also ties this paper to the literature on dynamic mechanism design, such as Pavan et al. (2014), Bergemann and Välimäki (2019), and Board and Skrzypacz (2016).

2 Examples

In this section, I present examples illustrating the connection between the sales strategies and the three shocks. The examples show that each strategy can maximize profit and welfare, with the result depending on the relative strength of the shocks.

The structure of the examples closely resembles the empirical model. In each example, there are two periods and the seller has one ticket to sell to two consumers. The seller can set different prices for each period but, like the seller in the data, it must commit to its menu at the start of the first period. The consumers are forward-looking and one arrives in each period. Suppose that consumer i has value $\nu_i + V - b_i(\omega)$ and that the value is affected by three potential shocks realized at the start of the second period:

1. Idiosyncratic shocks. Each consumer i receives a shock with probability ψ. Draws are independent and consumers who receive a

[12] An exception is Lazarev (2013), who considers two types of airline passengers who receive schedule conflicts at different rates.

shock have zero value.

2. Common value shocks. The value of V, the common component to values, changes.
3. States of the world. Values depend on a realized state $\omega \in \{\omega^B, \omega^G\}$ through the $b_i(\omega)$ term.

Each shock has a natural interpretation in the market for college football tickets. Idiosyncratic shocks are like schedule conflicts that cause consumers to abandon their plans to attend. Common value shocks reflect changes in interest when the quality of the team deviates from expectations. States of the world have immediate relevance for the future status of covid-19, but could also capture aggregate states like the business cycle.

Illustrations and a more detailed explanation of each equilibrium can be found Appendix A.

Example 1: Idiosyncratic Shocks. The first example demonstrates that when there is no need for price flexibility or state-dependent contracts, partial refunds maximize profit and welfare. Suppose that there are only idiosyncratic shocks, $\psi = \frac{1}{5}$, but that $V = 0$ and $b_i(\omega) = 0$.

The first consumer, Alice, arrives in the market in the first period and prefers to buy early; she has value $\nu_A = 50$ in period one, but it falls to $\nu_A = 40$ if she waits to purchase until the second period. The second consumer, Bob, arrives in period two with $\nu_B = 40$ and never receives an idiosyncratic shock. The seller optimally offers a partial refund $r = 5$ and sets $p_1 = 41$, $p_2 = 40$.[13] Alice purchases the ticket in the first period despite the risk of a schedule conflict.

If Alice has a schedule conflict, she will return her ticket for a partial refund and the seller will sell the ticket on to Bob at $p_2 = 40$. Expected profit and total welfare equal 48, the highest possible value.

Profit would be lower with resale because of fees. Suppose that the reseller pays a fraction $\tau = \frac{1}{10}$ of the sale price to the resale market

[13] The choice of $r = 5$ is optimal but not unique. The seller could produce the same allocation and division of surplus by offering any refund r such that Alice returns her ticket if and only if she receives an idiosyncratic shock. For any such r, it can charge $p_1 = 40 + \psi r$ but will pay ψr in expected refunds.

operator, like the fees charged on platforms like StubHub. In the second period, Alice would resell to Bob at price 40[14], but only receive 36 after fees. The seller can only charge Alice 36 when she has a conflict—despite earning 40 in that case with a partial refund—leading to profit of $p_1 = 47.2$. Total welfare is unchanged with resale in this example, but it would be lower if resale incurred other frictions, like the search friction present in the empirical model.

It is worth noting, however, that the seller prefers resale to not reallocating: it could only charge Alice $p_1 = 40$ in the first period without resale or refunds. Resale is valuable because the seller has no additional tickets to sell to Bob; if the seller had two tickets it would prefer to ban resale to stop Alice from undercutting its price of $p_2 = 40$ when she has a conflict. More generally, the seller benefits from resale when resale does not displace primary market purchases, which is true when capacity is low relative to demand.[15]

Example 2: Idiosyncratic and Common Value Shocks. Resale can be superior when flexible prices are valuable, such as when there are common value shocks. Consider the same setting but suppose that $V = -20$ with probability $\frac{1}{4}$ and $V = 0$ otherwise.

If the seller offers a partial refund, it will set $r = 5$, $p_1 = 37$, and $p_2 = 40$.[16] As before, Alice is willing to purchase in the first period. The key difference is that Bob is unwilling to purchase at the seller's optimal price of $p_2 = 40$ when the common value is low. The seller's rigid prices thus make it possible that Alice will request a refund and Bob will not purchase, causing the ticket to go to waste. Expected profit and welfare are both 42.

But with resale, Alice could resell to Bob at both common values, earning 36 after fees when $V = 0$ and 18 when $V = -20$. The sale

[14]In the resale market, I assume that Alice makes a take-it-or-leave-it offer to Bob. The TILI assumption is not necessary in examples with many agents, but I use it here for simplicity. Moreover, the assumption is realistic because buyers cannot make counteroffers in online resale markets.

[15]For a general analysis, see Cui et al. (2014).

[16]As before, the choice of $r = 5$ is optimal but not unique. The division of surplus is again the same with other optimal selections of r.

increases both welfare and profit. Profit increases because the seller charges Alice for resale revenue earned when the ticket would go unused with a partial refund. Expected total welfare rises to 43 and profit rises to 42.3.

The choice between resale and a partial refund comes down to a tradeoff between common value shocks and resale fees. When primary market prices are rigid and there are common value shocks, resale is valuable because the seller's price might not be optimal. But fees reduce the profitability of using resale. In this case, the value of flexibility outweighs the profit lost to fees. But with higher fees, a partial refund could remain optimal. An empirical model is needed to determine which effect dominates.

Example 3: States of the World. A menu of state-dependent is best when the efficient allocation varies with states of the world. Suppose now that there are are no idiosyncratic or common value shocks, $\psi = 0$ and $V = 0$, but that there are two states, ω^G and ω^B, that each occur with probability $\frac{1}{2}$. The state is again realized at the start of the second period. Alice and Bob both arrive in the first period, and the seller only makes sales in the first period. Alice's value is $\nu_A = 40$ and does not respond to the shock—she has $b_A(\omega^B) = 0$. Bob has $\nu_B = 50$ but responds harshly to the shock, $b_B(\omega^B) = 40$.

If the seller offered a single price, it would set $p = 40$ and sell to Alice. But in state ω^G, Alice would have the ticket when Bob has a higher value. A single refund would not help because Alice would return her ticket in both states. With resale, Alice could resell to Bob in the good state, but doing so would incur frictions.

A menu of state-dependent contracts would avoid fees and maximize welfare and profit. The seller could offer a contract granting a full refund in state ω^B at price 50, which Bob would purchase, and another granting a full refund in state ω^G at price 40, which Alice would purchase. The menu is valuable because Alice and Bob have heterogeneous reactions to the realized state, making the consumer with the highest value different in each state. If there were no heterogeneity, then one consumer would have had the highest value in both states and the menu would add no value, as in the first two examples.

3 Data

The analysis relies on three data sets. The first consists of ticket sales for a single university, covering both the primary and resale markets. The sales records are informative about demand for tickets and the extent of resale. To learn about common value shocks and covid-19 states, I introduce two other sources. The second consists of annual resale prices for football tickets at many universities, which are informative about year-to-year demand swings that reflect common value shocks. The third is a survey containing consumer reports of willingness to pay in two states of the world, one with and one without a covid-19 vaccine.

Ticket Sales. The first source of data includes primary and secondary market ticket sales for a large U.S. university's football team. The primary market records include all ticket sales for two seasons. Each record indicates the price paid, date of purchase, and seating zone. Seating zones are groups of similar seats sharing one price, which I use as a measurement of quality. The primary market records also indicate whether the sale was part of a season ticket package or promotion.

Resale transaction records for the same university come from StubHub.[17] The main difference between the resale and primary market data is that the resale transactions do not include the transaction price.

To learn about the transaction price, I use daily records of all StubHub listings for the university's football games, which I gather using a web scraper. The listing data overlaps with the resale transaction data for the one full season studied in this paper. Each listing includes a listing ID, price, number of tickets for sale, and location in the stadium (section and row). For details on matching listings to transactions, see Appendix B.

[17] Resale is undercounted because consumers also resell on competing sites. However, StubHub is likely to account for most resale in this market for two reasons. First, the university has a partnership with StubHub and recommends that consumers resell on StubHub. Second, StubHub is one of the largest resale platforms, processing about half of all ticket resale in 2015 (Satariano (2015)).

The primary and resale market records are informative about demand for tickets, idiosyncratic shocks, and the choice between buying tickets in the primary or resale market. Resale is informative about idiosyncratic shocks because resale implies that a consumer changed her mind about whether to attend the game.

Average Annual Resale Prices. I gather average annual resale prices for 76 college football teams from SeatGeek, another online resale market. The annual prices end in 2019 and start as early as 2011, although records for some teams start later.

The SeatGeek data are informative about common value shocks. They show that the average price of a resold ticket varies meaningfully from one year to the next, reflecting changes in common values from factors like team performance.

Covid-19 Survey. I conducted a survey on consumer demand with and without a covid-19 vaccine. Respondents report the maximum they are willing and able to pay for one ticket to a college football game in several scenarios related to covid-19.[18] Although there are several scenarios, including the possibility of social distancing at the game, responses mainly depend on whether a vaccine was available.[19] Respondents also report their demographic information and the percent chance of each scenario in January 2021, September 2021, and January 2022. I distributed the survey to 500 users of Prolific.co, an online distribution platform, in August 2020. Half of respondents were aged 50 or over. The full survey and details can be found in Appendix D.

The survey is informative about how consumer values change across aggregate states, which is used to evaluate screening strategies in the empirical model. Even though vaccines are now available, the results are indicative of responses to potential future shocks, like the emergence of new strains or a failure to reach herd immunity.

[18]Eliciting willingness to pay by asking directly is used in other surveys, such as the one analyzed in Fuster and Zafar (2021). Eliciting assessments of probabilities in the same way is commonly used in Federal Reserve Bank of New York surveys: see Potter et al. (2017).

[19]When the survey was distributed, public concern focused on whether a vaccine would exist rather than how quickly it could be manufactured and distributed.

4 Descriptive Evidence

In this section, I provide evidence that advance sales are common and that each of the three demand shocks is significant.

Market Background. The university is a monopolist seller of its tickets.[20] In the season used in the analysis, it sells tickets to five home games.[21]

The stadium has about 50,000 seats, but only 30,000 are available to the public. Seats unavailable to the public include premium seats for athletics boosters, student seats, and seats reserved for visiting team fans.

Tickets are sold in two main phases. The first consists of season ticket sales and takes place months before the season—80% of season tickets are bought at least four months before the season starts. The second phase consists of single-game ticket sales and resale and occurs much later. Single-game tickets do not go on sale until the first game is about a month away. 70% of resale and full-price single-game transactions occur within a month of the game and 50% within two weeks. The gap between the two phases makes it plausible that consumers learn new information between them. The empirical model reflects the timing of the market, with a first period in which season tickets are available and a second in which single-game tickets and resale tickets are available.

Figure 1 shows the average number of tickets sold to each game by type of sale and quality. Most tickets are sold as season tickets, amounting to 75% of tickets sold to the public (the "other" category consists of tickets that are not available to the public, like student tickets). Most of the rest are sold as single tickets or unsold. A minuscule number are sold in mini-plans, bundles of tickets to a subset of games that I exclude from the analysis. The single ticket purchases in Figure 1 include group sales and promotions. I only consider full-price single ticket sales in the analysis because promotions and group sales are not optimally priced

[20] Local allegiances mean that nearby schools are not close substitutes.

[21] An additional home game was scheduled but cancelled. The cancelled game is excluded from the data provided by the university, so I exclude it from the analysis. I assume that consumers would have made the same season ticket purchases if that game had not been scheduled, and I use prorated season ticket prices in the estimation.

and may only be available to targeted groups, like veterans.[22]

The stadium is divided into five seating zones, which I use to measure the quality of each seat. Higher zones (e.g. zone 5) contain worse seats. Zone 1 seats are close to the field and near the 50-yard line, but zone 5 seats are at the extreme edges of the upper deck.

The menu of primary market prices is shown in Table 1.[23] Primary market prices vary mainly by seat quality. Tickets in zone 1 cost \$60–\$70 depending on the game, but zone 5 tickets always sell for \$30. Season tickets are \$25–\$35 cheaper than buying primary market tickets to each game. Prices vary slightly across games, but never by more than \$10.

Table 1: Primary market prices for each game, their sum, and season ticket prices. Table excludes the cancelled game. Season ticket prices are prorated to reflect the cancellation.

Game	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
1	70	60	50	40	30
2	70	60	55	45	30
3	70	60	50	40	30
4	70	60	55	45	30
5	60	55	40	35	30
Season Tickets	315	270	216	179	125
Face Value Sum	340	295	250	205	150

Resale Markets. Resale is a notable feature of the market, with 5.98% of all tickets sold to consumers resold on StubHub.[24] The true resale rate is higher because some tickets are resold on other resale markets. The number of tickets resold is consistent with the idea that consumers who purchase tickets early receive shocks and decide to resell. The difference

[22] Nearly 40% of promotional tickets in the season were given away for free, and 98% were sold for half-price or less. Group tickets are discounted by over 40% on average. Promotions are not used to cope with demand uncertainty because they are too steeply discounted and too targeted.

[23] The cancelld game is excluded and season ticket prices are prorated to reflect the canceled game.

[24] The figure excludes tickets sold directly to ticket brokers. I conservatively assume that all tickets sold to brokers are resold on StubHub.

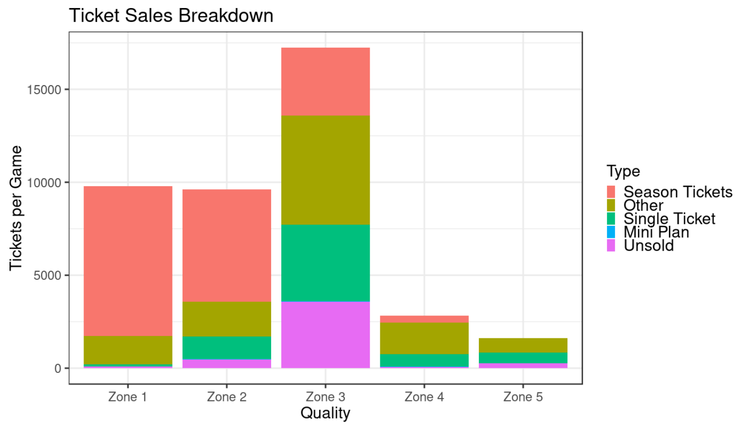


Figure 1: Sale types and volumes by quality group.

in resale rates across zones supports that interpretation. In zones 1 and 2, where advance sales are most common, the resale rate is 6.9%, but in the remaining zones, it is only 5.0%.[25]

The data support the idea that resale prices are flexible, which reflects the fact that resellers can adjust list prices at any time. Figure 3 demonstrates that resale prices adjust to differ from face value. It shows the distribution of face values and the distribution of the average resale price for each game-quality combination. The differences are likely to reflect changes in demand, and the variation in resale prices also suggests that consumers have different average values for each game.

Figure 2 provides further evidence of price flexibility. It shows the percent change in the quantity of single-game tickets sold for each game (in both primary and resale markets) from the season average. The changes in primary market quantities are practically always larger than the changes in resale quantities, usually by a large margin. The higher volatility in the primary market is unsurprising because primary market prices are fixed. In contrast, resale market prices adjust and smooth the quantity of tickets resold.

The last important feature of resale markets is that they include

[25]The difference between zones would be larger without the conservative assumption that brokers only resell on StubHub. The vast majority of tickets sold to brokers are from zones 1 and 2, causing the assumption to disproportionately lower the resale rate in those zones.

frictions that are not present in the primary market. StubHub charges buyers a fee of 15% of the advertised price and sellers a fee of 10%.[26] The average fee is $10.71 on each ticket resold, a substantial amount when the average resale price is under $40.

There is also evidence of non-monetary frictions. If there were no frictions, consumers would buy single-game tickets for a given section in whichever market is cheaper. But this is not true in the data hundreds of single-game tickets are sold in the primary market when cheaper resale tickets are available. For instance, the average resale ticket to game one is over $16 cheaper than the average primary market ticket, yet over 1,250 single-game tickets are sold in the primary market. There are several possible explanations for the friction. Consumers might not like or trust the resale market, they might find searching for tickets onerous, or they might be unaware that it has cheaper tickets.

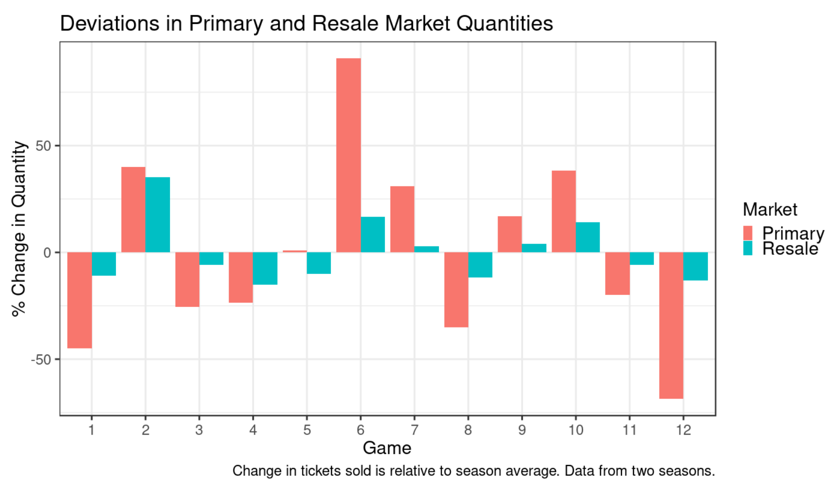


Figure 2: Percent deviation from season-average quantities sold for each game.

Annual Price Changes. Annual price changes for each team provide evidence of common value shocks. Using SeatGeek's records of average annual resale prices, I define the normalized price for university u in year y as

[26] StubHub's exact fee structure is not public (StubHub (2021)), but its typical fees are reported to be an additional 15% of the price from buyers and 10% from sellers (Goldberg (2019)).

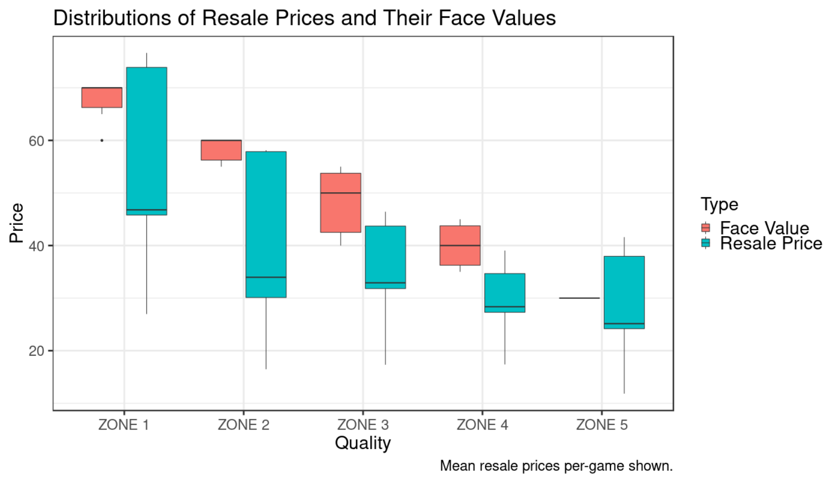


Figure 3: Distributions of mean per-game resale prices and face value.

$$\text{NormalizedPrice}_{uy} = \text{AvgResalePrice}_{uy} / \left(\frac{1}{Y} \sum_{y} \text{AvgResalePrice}_{uy} \right), \tag{1}$$

where Y denotes the number of years in the sample. Figure 4 shows the distribution of normalized prices for a random sample of 20 universities. The distributions demonstrate that within-university price variation is significant and ubiquitous. All but one university has a season where prices are 25% above the sample mean, and most have a season where prices are 25% below. There are several changes of 50% or more.

The dramatic swings in resale prices likely reflect common value shocks like changes in team performance. For instance, in Clemson's lowest-priced season they lost two of their first three games—as many as they lost in the entire previous season—whereas in their two highest-priced seasons they either played in or won the national championship game.

Figure 5 shows the combined distribution for all 76 teams in the data after adjusting for time trends. The distribution is approximately normal and has an estimated standard deviation of .25, implying that there is a roughly one-third chance that prices in any given season will be more than 25% away from the mean.

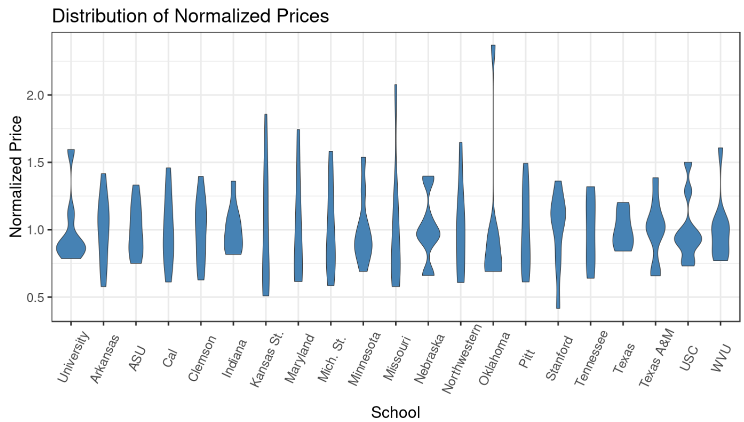


Figure 4: Distribution of average annual resale prices (normalized by school mean) for a random sample of 20 schools in similar conferences.

Covid-19 Survey. The key result of the survey is whether changes in reported willingness to pay (WTP) between states are heterogeneous. Figure 6 shows that they are. It plots reported WTP with a vaccine (the horizontal axis) against the change in WTP from the state with a vaccine to the state without (the vertical axis).[27] Reported values do not involve social distancing in the stadium. At all levels of WTP, some consumers report no change in value (the dots at zero), some report zero WTP without a vaccine (the diagonal line), and some report values in between. The changes in WTP are not visibly correlated with initial WTP. The correlation coefficient between the percent change in reported WTP and initial WTP is -.07.

5 Model

5.1 Outline, Utility, and Shocks

Let i index consumers and j index games. A monopolist seller has capacity K_q for each seat quality q and sells tickets over two periods,

[27] The lower triangle is empty because the change in WTP cannot exceed reported WTP.

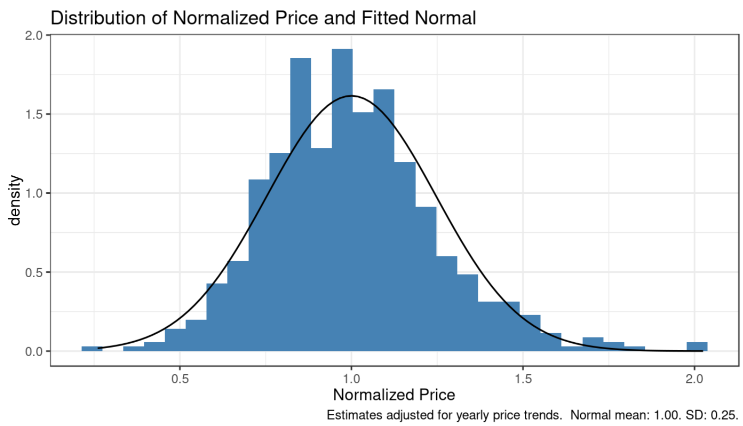


Figure 5: Distribution of resale prices normalized by team-mean in the sample. Adjusted for yearly trends. From SeatGeek annual average resale prices (76 teams, 576 team-seasons).

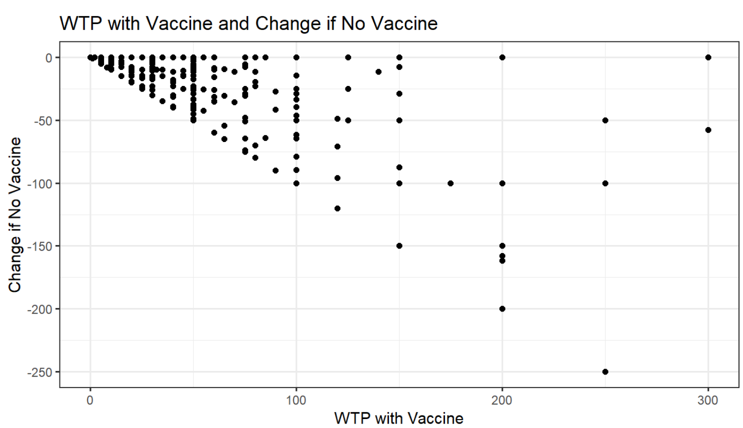


Figure 6: Scatterplot of reported willingness to pay with a vaccine and change in willingness to pay if there is no vaccine.

$t = 1, 2$. In period one, it only sells a season ticket bundle including one ticket to each game, and in period two, it only sells single-game tickets. The seller's price for a season ticket bundle with seats in quality q is p_{Bq}; its price for single-game tickets of quality q to game j is p_{jq}. As in the data, it commits to its menu at the start of the first period and does not change it afterwards.

Three shocks are realized at the start of the second period and are modeled almost identically in Section 2. First, each consumer receives an independently drawn idiosyncratic shock for each game with probability ψ, and any consumer receiving a shock for game j has zero utility for that game. Second, there is a common component to values $V \sim N(0, \sigma_V^2)$ with a single realization for the season. Third, there is a state of the world ω that takes the value ω^{Vax} if there is a vaccine and ω^{NoVax} if there is not. There is a consumer-specific penalty to utility $b_i(\omega^{\text{NoVax}})$ in the state without a vaccine. (When there are no states of the world in the model, a baseline state ω^{BL} is realized with certainty.)

There are N consumers who want at most one ticket. A fraction a arrive in the first period and the rest arrive in the second. In the first period, consumers decide whether to buy season tickets or wait. In the second period, consumers who bought season tickets decide whether to resell tickets or attend each game. Consumers without season tickets decide whether to purchase in the primary market, secondary market, or not at all. Only season tickets are offered in the first period and only single-game tickets are offered in the second.

The model outline is depicted in Figure 7, which shows the timeline of choices on the right and a flowchart of consumer decisions on the left. Consumer decisions for a single game j are shown in period two but occur for all games.

Consumer i's utility for a ticket of quality q to game j is measured in dollars (relative to an outside option normalized to zero) and takes the form

$$u_{ijq}(V, \omega) = \alpha_j \left(V + \nu_i + \gamma_q - b_i(\omega) \right). \tag{2}$$

Consumer i's utility depends on a scalar α_j specific to game j, the

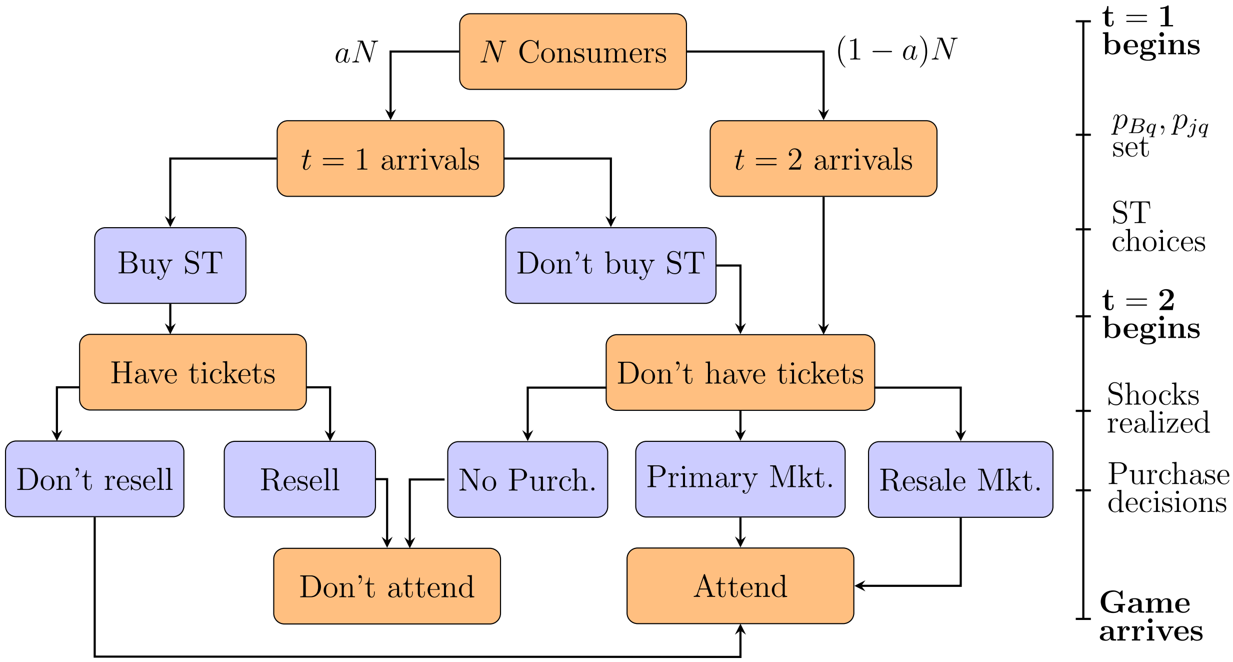


Figure 7: Model timeline and outline for consumer arrivals and choices. Decisions are shown in blue.

common value V, a consumer-specific taste parameter ν_i, a quality-specific parameter γ_q, and consumer i's distaste for attending sporting events in state ω, $b_i(\omega)$. I assume that the taste parameters ν_i follow an exponential distribution with parameter λ_ν.

Utility can be broken into two pieces. The piece in parentheses is constant across games and can be thought of as consumer i's base utility for all games. The base utility is multiplied by the second piece, the scalar α_j that describes which games are more desirable.

Changes in V affect each consumer's utility in the same way. The penalty $b_i(\omega)$ only applies to uncertainty from covid-19. Consumers experience no change if there is a vaccine, but are willing to pay weakly less if there is no vaccine: $b_i(\omega^{\text{Vax}}) = 0$, $b_i(\omega^{\text{NoVax}}) \geq 0$. Realizations when there is no vaccine are heterogeneous and independent of ν_i.[28] In

[28] The independence assumption follows from the lack of correlation between initial values and change in WTP in the survey.

the baseline model, all consumers have $b_i(\omega^{BL}) = 0$.

5.2 Period Two

At the start of period two, consumers learn the realizations of idiosyncratic shocks, the common value V, and the state of the world ω. Consumers who purchased season tickets decide whether to resell or attend; all other consumers decide whether to purchase tickets in the primary or resale markets. Resale prices are noted by $p^r_{jq}(V,\omega)$. They depend on the realizations of aggregate shocks because the shocks affect consumer values.

For simplicity, consider game j. Consumers who bought season tickets resell if

$$u_{ijq}(V,\omega) \leq (1-\tau)p^r_{jq}(V,\omega), \tag{3}$$

where τ is the percent commission charged by StubHub. Consumers who receive an idiosyncratic shock have value zero and always resell.

Consumers without season tickets decide whether and how to buy tickets to game j. They have three choices: make no purchase, purchase in the primary market, or purchase in the secondary market.

In addition to the familiar utility and price terms, surplus in the secondary market depends on the friction s_{ij}. I assume it follows an exponential distribution, $s_{ij} \sim \mathit{Exp}(\lambda_s)$, and is independently drawn across individuals and games. Consumers know the distribution in the first period but do not learn their realizations until the second. The friction explains why some consumers in the data purchase single-game tickets in the primary market when similar tickets are available for less in the secondary market.

Surplus from each option is

$$\mathit{No\ Purch.\ Surplus}_{ij} = 0, \tag{4}$$

$$\mathit{PM\ Surplus}_{ijq}(V,\omega) = u_{ijq} - p_{jq}, \tag{5}$$

$$\mathit{SM\ Surplus}_{ijq}(V,\omega,s_{ij}) = u_{ijq} - p^r_{jq}(V,\omega) - s_{ij}. \tag{6}$$

The equilibrium resale price $p^r_{jq}(V, \omega)$ makes the number of consumers willing to resell tickets of quality q, determined in equation (3), equal to the number of consumers who demand a ticket of quality q in the resale market.

If all tickets were available, consumer i would select the maximizer of the set

$$\mathcal{C}_i(V, \omega, s_{ij}) = \{0, \{SM\ \ Surplus_{ijq}(V, \omega, s_{ij})\}_{q=1}^{Q}, \{PM\ \ Surplus_{ijq}(V, \omega)\}_{q=1}^{Q}\}. \tag{7}$$

But some options might sell out, leaving the consumer unable to acquire his top choice. Stock-outs are possible in equilibrium because a high draw of the common value could leave single-game tickets underpriced in the primary market. I assume that tickets are rationed randomly. Let the probability of receiving a primary market ticket of quality q to game j be $\sigma_{jq}(V, \omega)$. (There is no rationing on the resale market at equilibrium resale prices.) Consumers rank all options in the choice set and request their first-choice ticket. They receive the ticket with the rationing probability and, if they do not receive it, request their next-preferred ticket.

5.3 Period One

In period one, aN consumers know their type $(\nu_i, b_i(\omega^{\text{NoVax}}))$ and decide whether to buy season tickets.[29] By buying season tickets, consumers receive the maximum of their value for attending game j and the after-fee resale price. Surplus depends on attendance values, resale values, the price of season tickets, and an additional parameter δ. The purpose of δ is to capture other factors that affect valuations for season tickets, such as perks for season ticket holders or diminishing returns from attending many games. Surplus from season tickets of quality q is

[29] In this section, I only consider season tickets with resale markets. In counterfactuals, I modify the decision rule to reflect different packages and reallocation strategies.

$$ST\ Surplus_{iq} = \sum_j \mathrm{E}_{V,\omega}\Big(\max\big\{(1-\psi)u_{ijq}(V,\omega) + \psi(1-\tau)p^r_{jq}(V,\omega), \\ (1-\tau)p^r_{jq}(V,\omega)\big\}\Big) + \delta - p_{Bq}. \tag{8}$$

The surplus from waiting until period two requires an expectation for surplus with rationing. Without rationing, surplus is the expected maximizer of equation (7).

With rationing, it is possible that the consumer must choose his m^{th}-best option. Let $c^{(m)}(\mathcal{C})$ be the m^{th}-largest element of $\mathcal{C}$, and let $\sigma_j(V,\omega,c)$ be the probability of receiving option c. The expected utility from waiting with choice set $\mathcal{C}_i$ when the common value is V, state is ω, and resale friction is s_{ij} can be defined recursively as

$$\begin{aligned} \mathit{WaitSurplus}_i(V,\omega,s_{ij},\mathcal{C}_i) = {} & \sigma_j(V,\omega,c^{(1)}(\mathcal{C}_i))c^{(1)}(\mathcal{C}_i) + \\ & (1-\sigma_j(V,\omega,c^{(1)}(\mathcal{C}_i)))\, \mathit{WaitSurplus}_i(V,\omega,s_{ij},\mathcal{C}_i \setminus c^{(1)}(\mathcal{C}_i)). \end{aligned} \tag{9}$$

Overall surplus from waiting is the expected value,

$$\mathit{WaitSurplus}_i = \mathrm{E}_{V,\omega,S}\left(\mathit{WaitSurplus}_i(V,\omega,S,\mathcal{C}_i(V,\omega,S))\right). \tag{10}$$

The consumer's choice set in period one is thus

$$\mathcal{C}_{i,ST} = \left\{\mathit{WaitSurplus}_i, \{ST\ Surplus_{iq}\}_{q=1}^{Q}\right\}. \tag{11}$$

Without rationing, the consumer would again select the maximizer. However, it is possible that some qualities of season tickets will sell out. I again assume random rationing under the same procedure discussed for the second period.

5.4 Equilibrium

I search for a fulfilled-expectations equilibrium. The seller anticipates consumer demand and selects profit-maximizing prices $\{p_{Bq}\}$ and $\{p_{jq}\}$. Consumers anticipate a set of resale prices $\{p^r_{jq}(V, \omega)\}$ and primary market purchase probabilities $\{\sigma_{jq}(V, \omega)\}$. In equilibrium, consumers make optimal choices in the first period given expectations for resale prices and probabilities, and their expectations are realized in the second period when they make optimal purchase choices.

6 Estimation and Results

There are two stages in the estimation strategy. The first stage includes all parameters that can be estimated without structural simulations, and the second estimates the remaining parameters using the method of simulated moments. I assume that the realized state is ω^{BL} when using the sales data because the season predates the covid-19 pandemic.

6.1 First Stage

The fee τ is the percentage of the fee-inclusive price paid by the buyer, calculated directly from StubHub's policies. The idiosyncratic shock rate ψ is identified by the frequency of resale. In the model, observed resale is explained by idiosyncratic shocks in equilibrium, so the parameter ψ equals the ratio of tickets resold by consumers to all tickets sold.[30]

The data are not directly informative about how many consumers consider season tickets. In the absence of data on browsing, I calibrate the fraction of consumers arriving in period one based on purchse data. Specifically, I take a to be the percentage of tickets sold 30 or more days in advance.

[30] The true number of all tickets resold is unknown because StubHub is not the only resale market. Moreover, the university sells some tickets to brokers for resale. I conservatively assume that all tickets sold to brokers are resold on StubHub and that 75% of consumers resell on StubHub. In contrast, Leslie and Sorensen (2014) assume that StubHub and eBay have a combined market share of 50%.

Next, the parameters α_j and γ_q affect consumer values and hence resale prices. Recovering the parameters requires a model for the price of resale transaction k. The resale price of listing k depends on all parameters affecting the relative surplus received in the primary and secondary markets in period two, including the realization of V, the distribution of resale market frictions, the distribution of consumer types, the menu of primary market prices, and characteristics X_k of listing k. The price can be written as a non-parametric function,

$$p^r_{jqk} = g(\alpha_j, \gamma_q, \lambda_s, V, \lambda_\nu, \mathbf{p}_j, X_k) + \varepsilon_{jqk}, \tag{12}$$

where X_k includes the number of tickets in the transaction and the number of days until the game.

Equation (12) can be simplified because most of its arguments are constant in the data. For instance, the common value, primary market prices, and type distribution do not change during the season. Moreover, the resale price is approximately linear in consumers' attendance values under mild assumptions.[31] Consequently, I assume that

$$g(\alpha_j, \gamma_q, \lambda_s, V, \lambda_\nu, \mathbf{p}_j, X_k) = \alpha_j(\beta_0 + \gamma_q + X_k\beta). \tag{13}$$

The right-hand side of equation (13) is the same as consumers' values for the game plus an additional term to capture features of listing k. The approximation does not capture one source of nonlinearity, substitution to the primary market from the cost of resale s_{ij}, but estimates are very similar with a polynomial form that allows nonlinearities.

The identifying variation for α_j and γ_q comes from across-game and across-quality variation in resale prices. More precisely, α_j explains why similar tickets for different games sell at different prices and γ_q explains why tickets to the same game in different quality zones sell at different prices.

The variance of the common value, σ^2_V is estimated using the dis-

[31] It is linear if the supply of tickets to the resale market does not change and resale prices are below primary market prices. The first assumption holds in equilibrium and the second is nearly always true in the data.

tribution of normalized resale prices shown in Figure 5. I multiply the distribution of normalized prices by the university's average resale price in the SeatGeek sample. Then, I adjust for the average value of α_j because the shocks enter utility as $\alpha_j V$. Finally, I take σ_V^2 as the variance of a normal fit to the distribution, which is sensible because the distribution in Figure 5 is approximately normal. Details can be found in Appendix C.

The identifying variation for the variance is entirely within each team. The normalized prices measure year-on-year variation relative to the team average, so σ_V^2 reflects the variation an individual team can expect from year to year.

The procedure makes three assumptions. First, the year-to-year variation in the SeatGeek data is the sole source of variation in the common value. It is not clear if the assumption understates or exaggerates the variance: it could understate the variance because annual prices smooth over game-specific shocks like rain, but it could exaggerate the variance if some part of the year-to-year change is predictable. Second, shocks to the common value pass through linearly to resale prices. This is the same assumption used to estimate α_j and γ_q in equation (13). And third, the university faces the same shocks to normalized prices as all other schools. This is plausible based on the distributions in Figure 4.

The last parameters estimated in the first stage define the effect of states of the world on preferences. The survey asks consumers about WTP in 2019 and in three scenarios, one with a vaccine and two without.[32] Consumers reported similar WTP in the two scenarios without a vaccine, so I combine them into a single no-vaccine state. The survey also asks for values with and without social distancing in each scenario. Social distancing also does not significantly affect consumer values, so I only consider reported WTP without it. See Appendix D for details.

The counterfactual considers sales for the college football season beginning in September 2021. The probabilities that there will and will not be a vaccine are taken as the average percent chance of each state

[32] The scenarios without a vaccine have different numbers of casess.

in the survey for September 2021[33], normalized to sum to one.[34]

There are two necessary adjustments for consumer preferences. The first is to find the function $b_i(\omega^{\text{NoVax}})$ describing the change in WTP from the vaccine to the no vaccine state. The second is to find the analogous function $b_i(\omega^{\text{Vax}})$ describing the change from the benchmark year (ω^{BL}, measured using reports for 2019) to the vaccine state. The second adjustment is necessary because the estimated distribution of values from the sales data reflects a typical year and reported values are lower with a vaccine.

I assume that each consumer's reported WTP in the survey is his utility for a representative game. I also assume that the representative game has the game-specific parameter $\bar{\alpha}$, an average of the estimated α_j. The change in consumer i's WTP from state ω to state ω' is

$$WTP_i(\omega) - WTP_i(\omega') = \bar{\alpha}(b_i(\omega') - b_i(\omega)). \tag{14}$$

I further assume that ω is a baseline state with $b_i(\omega) = 0$ and that $b_i(\omega')$ follows the parametric form

$$b_i(\omega') = \begin{cases} 0 & \text{w.p. } \rho_1 \\ \tilde{b}_i & \text{otherwise} \end{cases} \tag{15}$$

where $\tilde{b}_i \sim \text{Exp}(\rho_2)$. There is a mass point at zero to reflect the fact that many consumers report no change in WTP in the survey.

I estimate two sets of parameters to capture the two reported changes in WTP, $\text{WTP}_i(\omega^{\text{Vax}}) - \text{WTP}_i(\omega^{\text{NoVax}})$ and $\text{WTP}_i(\omega^{BL}) - \text{WTP}_i(\omega^{\text{Vax}})$. The parameters for the first difference identify the distribution of $b_i(\omega^{\text{Vax}})$ and are labeled ρ_1^{Vax} and ρ_2^{Vax}. The parameters for the second identify the distribution of $b_i(\omega^{\text{NoVax}})$ and are labeled ρ_1^{NoVax} and ρ_2^{NoVax}.

The reported differences in WTP almost directly identify the function b by equation (14). The sole complication is censoring: the change in WTP cannot be larger than WTP. I adjust for censoring and estimate

[33] We know now that vaccines became available before September 2021, but the survey remains valuable as a gauge of uncertainty related to covid-19.

[34] The normalization excludes a state in which there is no attendance at sporting events.

by maximum likelihood.

6.2 Second Stage

Three parameters remain for structural estimation: λ_s, which defines the distribution of resale market frictions; λ_ν, which defines the distribution of consumer values; and δ, which explains why values for season tickets differ from attendance and resale values. I estimate them using the method of simulated moments. In model simulations, I assume that there are 200,000 consumers who demand up to one ticket and weight moments by their inverse variances. Details are in Appendix C.

The estimation moments are the number of season tickets purchased, the average resale price for each game, and the quantity of tickets sold in the primary market for each game. With five games played, there are a total of 11 moments.

Each parameter is identified by a combination of the estimation moments. Start with the distribution of costs of purchasing in the resale market, which is parameterized by λ_s. In the model, consumers purchase in the primary market if the primary market price is less than the sum of the resale price and the cost of resale. For instance, if the resale price is $5 less than the primary market price, any consumer with $s > 5$ prefers the primary market. The distribution of s determines the number of consumers with $s > 5$ and hence the number of tickets sold in the primary market. It follows that λ_s is identified by primary market quantities and resale prices, which give an observed difference between resale and primary market prices and the number of consumers who prefer the primary market.

Next, consider the additional value of season tickets, δ. Values for season tickets equal the sum of attendance values, expected resale revenue, and the parameter δ. The role of δ is to explain why observed demand for season tickets differs from the demand predicted by attendance values and resale revenue. Consequently, it is identified by season ticket quantities, which capture demand for season tickets, and resale prices, which capture resale revenue.

The last parameter is the distribution of values for college football relative to the outside option, parameterized by λ_ν. Higher values cause purchase quantities and resale prices to rise, so λ_ν is explained by all estimation moments: season ticket quantities, primary market quantities, and resale prices.

Equilibrium requires a fixed point of the model: consumers must have correct expectations for resale prices and rationing probabilities as a function of V. Finding the fixed point for each set of candidate parameters is challenging. Moreover, each iteration of each fixed-point search requires a solution for resale prices for every realization of V.

I use several simplifications to make estimation feasible. First, shared quality preferences γ_q reduce the search for resale prices to one dimension. Second, I discretize continuous variables, taking 100 values for the common value and 400 for consumer values ν_i. Under these assumptions, iterating to find equilibrium expectations remains difficult: expectations for resale prices and primary market purchase probabilities vary by realization of V and game.

6.3 Results

Estimated parameters are in Tables 2, 3, 4, and 5. The resale fee is about 22% of the fee-inclusive price paid by the buyer.[35] The idiosyncratic shock rate suggests that 8% of buyers change their minds about attending the event between the first and second periods. The fraction of consumers arriving in the first period, a, is calibrated to 77%, indicating that most consumers consider whether to buy season tickets.

Consumer values vary widely across games and qualities. I normalize $\alpha_1 = 1$ and $\gamma_1 = 0$. The best game, game 2, has attendance values 67% higher than those for the baseline game; the worst game, game 5, has values nearly 50% lower. The best seats are worth roughly \$23 per ticket more than the worst seats for game 1, with the difference scaled by the relevant α_j for other games.

[35] For a listing with price p, StubHub charges the buyer $1.15p$ and gives the seller $.9p$. Ultimately, it collects $.25/1.15 \approx .22$ of the price paid by the buyer.

The standard deviation of the distribution of consumer values is \$7.85. The university thus faces consumer values for the baseline game that differ from the mean by more than \$7.85 about a third of the time.

State probabilities and parameters governing preference changes across vaccine states are contained in Tables 3 and 4. Conditional on there being attendance at sporting events, consumers report a 59% chance that there will be a vaccine in September 2021 and a 41% chance that there will not be one. 60% of consumers report no value change between the benchmark and the state with a vaccine, but other consumers report significant penalties, with a mean uncensored change in WTP of \$43.20. For the transition from the vaccine to the no vaccine state, 29% of consumers report no change in values. The remaining consumers again report a significant change in WTP, with an uncensored mean of \$52.27. Appendix C provides evidence of the fit.

In the second stage, the average consumer's friction associated with resale market purchases, s_{ij}, is \$48.95. Although the average value is large, the consumers who purchase in the resale market have much smaller realizations. Two-thirds of frictions are \$10 or less, and over 85% are \$20 or less. The full distribution of realized costs for resale market buyers is shown as Figure 14 in Appendix C.

The mean of the distribution of consumer types is 16.18, suggesting that the average consumer (given the assumed size of the population) would pay \$16.18 for the worst seats to the baseline game in an average season. Finally, the benefits of season tickets are estimated to be \$25.61, suggesting that the convenience and perks of season tickets outweigh diminishing marginal returns. Evidence on the fit of the model is in Appendix C.

7 Counterfactuals

I use the structural estimates to evaluate several counterfactual policies. In each counterfactual, the seller chooses prices to maximize profit. In addition to the main experiments on partial refunds and a menu of refund contracts, I implement counterfactuals to measure the effects of

Parameter Description	Notation	Estimate	Std. Err.
Resale Fee (%)	τ	0.22	-
Idiosyncratic Shock Rate	ψ	0.08	-
% in First Period	a	0.77	-
Preference for Game 1	α_1	1.00	-
Preference for Game 2	α_2	1.67	0.032
Preference for Game 3	α_3	1.01	0.023
Preference for Game 4	α_4	1.60	0.029
Preference for Game 5	α_5	0.56	0.015
Preference for Quality 1	γ_1	0.00	-
Preference for Quality 2	γ_2	-12.05	0.581
Preference for Quality 3	γ_3	-17.58	0.55
Preference for Quality 4	γ_4	-22.65	0.62
Preference for Quality 5	γ_5	-21.95	0.687
SD of Common Value	σ_V	7.85	0.231

Table 2: Estimated parameters from the first stage.

Table 3: Expected state probabilities in September 2021

State	Probability
Vaccine	0.59
No Vaccine	0.41

market features like primary market price rigidities and resale fees.

7.1 Counterfactual Experiments

Benchmarks: No Reallocation and Flexible Prices. The first two counterfactuals, no reallocation and flexible prices, provide benchmarks for the value of reallocation and price rigidities. I evaluate both benchmarks without uncertainty over covid-19 states. In the no reallocation counterfactual, the university prohibits resale and does not offer refunds, helping to measure the net effect of resale and refunds on profit and welfare. To implement the counterfactual, I prevent resale transactions and adjust expectations in the first period accordingly.

A second benchmark allows the seller to adjust its prices and offer refunds, which measures the harm of primary market price rigidities.

Table 4: Estimated preference change parameters.

Parameter	Value	Std. Err
ρ_1^{NoVax}	0.29	0.02
ρ_2^{NoVax}	52.27	4.50
ρ_1^{Vax}	0.60	0.02
ρ_2^{Vax}	43.20	4.58

Table 5: Estimated parameters from the second stage.

Parameter Description	Notation	Estimate	Standard Error
Mean Resale Friction	λ_s	48.95	1.54
Mean Consumer Type	λ_ν	16.18	0.02
Mean ST Benefits	δ	25.61	0.34

I implement the counterfactual as a partial refund (described below) with primary market prices responding to shocks as

$$p_{jq}(V, \omega^{BL}) = p_{jq} + \alpha_j V. \tag{16}$$

Partial Refunds. To implement a partial refund, I close down the resale market and let consumers with idiosyncratic shocks return their tickets to the seller's inventory. As in Section 2, the exact level of the refund is not identified—any refund such that consumers only request refunds after receiving an idiosyncratic shock is optimal.[36] I assume that the seller offers a refund such that consumers only return their tickets if they receive an idiosyncratic shock. I do not consider uncertainty from covid-19 states with a partial refund.

Menu of Refunds. The menu of refund contracts is only considered in the application with uncertainty over the two vaccine states ω^{Vax} and ω^{NoVax}. The seller offers three types of state-dependent season ticket contracts: a non-refundable package sold at $\{p_{Bq}^{NR}\}$ granting consumers tickets in both realized states ω^{Vax} and ω^{NoVax}, a fully refundable

[36]Risk-neutral consumers pay ψr more for tickets with refund r (as long as they only return them after receiving a shock). The seller can charge them ψr more, but must pay them r with probability ψ, leaving profit unchanged.

package sold at $\{p_{Bq}^{FR}(\omega^{\text{Vax}})\}$ granting consumers tickets in the vaccine state ω^{Vax}, and another fully refundable package sold at $\{p_{Bq}^{FR}(\omega^{\text{NoVax}})\}$ granting consumers tickets in the no vaccine state ω^{NoVax}. The seller continues to offer single-game tickets, which are sold at prices $\{p_{jq}\}$ in both states.

In the counterfactual, I remove uncertainty from idiosyncratic shocks and the common value, $\psi = 0$ and $\sigma_V^2 = 0$. The extra sources of uncertainty are not important for measuring the returns to state-dependent contracts and removing them simplifies the results.[37] To implement the counterfactual, I use the estimated changes in willingness to pay from Section 6 to obtain consumer values with and without a vaccine. Using preferences in the vaccine state and the changes if there is no vaccine, consumers choose between the contracts.

I compare the performance of the menu of refunds to resale markets and no reallocation. The menu of refunds gives the seller more control over the final allocation and consequently should be more profitable. The contribution is to measure the size of the gain in profit and determine the change in welfare.

Frictions. The final set of counterfactuals measures the relative importance of fees and frictions, the two drawbacks of resale. The fees, which enter the model through the parameter τ, reduce the profitability of resale but not its effect on social welfare. The frictions, which enter as the random variable S, reduce both profit and welfare. To separate their effects, I simulate the model with no fees, $\tau = 0$, and no frictions, $\lambda_s = 0$, in the baseline model with state ω^{BL}.

7.2 Counterfactual Results

Table 6 presents counterfactual results for the baseline model, comparing the performance of resale and partial refunds with no reallocation and flexible prices included for comparison. Profit is 2.1% higher with

[37] With all forms of uncertainty, the seller would also need to choose between resale and refunds for consumers who receive tickets and idiosyncratic shocks. Focusing solely on uncertainty over states avoids the complication.

refunds than with resale, and 4.9% higher than with no reallocation. The results suggest that the harms of resale fees and frictions outweigh the harms of primary market price rigidities. Although a gain of 2.1% sounds small, it is significant because only 8% of tickets are resold.

Resale and partial refunds produce similar levels of welfare. Partial refunds also maximize total welfare, edging resale by 0.5%. Partial refunds lead to higher social welfare because they eliminate search frictions from having primary and secondary markets, but consumer welfare is similar under the two strategies.

The no reallocation counterfactual demonstrates that both resale and partial refunds are profitable and welfare-enhancing. It is not clear ex ante that resale should increase profit, but the results show that resale increases the seller's profit by 2.8%. The reallocation strategies should and do boost welfare. Total welfare rises by 5.1% for resale and 5.6% for refunds; consumer welfare rises by 6.9% for both resale and refunds. The predicted welfare gains are larger than the 2.9% gain estimated by Leslie and Sorensen (2014), but their paper included harms of resale that are not relevant for the team studied here.

The counterfactual with flexible prices, however, shows that resale and partial refunds do not maximize profit and welfare. If the seller could adjust its prices and offer a partial refund, it would earn 1.6% more than with refunds while generating 2.3% higher consumer welfare and 1.9% higher total welfare.

Table 7 presents the results for counterfactual experiments in simulations with two states of the world. The menu of refund contracts was expected to perform best in theory; the value of the counterfactuals is to quantify the improvement and the importance of heterogeneous preference shocks. Even relative to resale, the gains from contracting directly on states of the world are noteworthy: profit increases by 3.5% and total welfare by 2.8%. The substantial gains from reallocation underline the importance of heterogeneous preferences across the two states, with the menu of refunds and resale boosting welfare by 10.3% and 6.6% and total welfare by 7.7% and 4.8%. Consumers see few benefits, however, suggesting that the seller is able to extract surplus more effectively with state-dependent contracts. With resale, some gains to consumers are lost as frictions.

	Resale	Refunds	Flex. Prices	No Reall.
Profit (mn)	7.23	7.38	7.50	7.03
Consumer Welfare (mn)	2.64	2.64	2.70	2.47
Total Welfare (mn)	9.97	10.02	10.21	9.49
Resale Fees (mn)	0.10	0.00	0.00	0.00
Season Ticket Buyers (1000)	25.56	26.35	25.72	24.80
Season Ticket Base Price	32.38	30.45	30.90	31.40
Single Game Base Price	39.18	38.59	35.70	40.69

Table 6: Counterfactual results for the baseline model.

	No Reall.	Menu of Refunds	Resale
Profit (mn)	6.49	7.16	6.92
Consumer Welfare (mn)	2.35	2.35	2.31
Total Welfare (mn)	8.83	9.51	9.25
Resale Fees (mn)	0.00	0.00	0.02
Non-Refund. S. Tix (1000)	20.65	12.13	26.63
Vaccine S. Tix (1000)	0.00	6.25	0.00
No Vaccine S. Tix (1000)	0.00	12.64	0.00

Table 7: Counterfactual results for the model with different states of the world.

Although resale performs worse than partial refunds in the baseline model, the results in Table 6 do not clarify why. There are two possible reasons: resale fees and non-price frictions. Table 8 shows the results from counterfactuals that decompose the effects of fees and frictions. They suggest that fees are the major driver for profit and frictions are the driver for welfare. Removing resale frictions only closes 27% of the gap between profit with resale and partial refunds while removing fees closes 73% of the gap. For total welfare, removing fees covers roughly half the gap while removing frictions causes welfare to exceed its level with partial refunds.

	Resale	$\tau = 0$	$\lambda_s = 0$
Profit (mn)	7.23	7.33	7.04
Consumer Welfare (mn)	2.64	2.65	2.92
Total Welfare (mn)	9.97	9.98	10.16
Resale Fees (mn)	0.10	0.00	0.19
Season Ticket Buyers (1000)	25.56	25.56	26.03
Season Ticket Base Price	32.38	32.81	33.61
Single Game Base Price	39.18	38.68	31.86

Table 8: Counterfactual results for resale frictions in the baseline model.

8 Conclusion

When consumers receive stochastic demand shocks, the optimal price is not known in advance and the initial allocation of goods can be suboptimal. Both sellers and society can benefit from sales strategies that cope with uncertainty, but it is unclear which strategy is best. I showed that the optimal strategy depends on the properties of demand uncertainty, then estimated a structural model describing the salient sources of uncertainty in the market for college football tickets and used it to evaluate each strategy.

The results suggest that refunds, rather than the status quo of resale, maximize profit and welfare. In the counterfactual without uncertainty from covid-19, profit is 2.1% higher with partial refunds than with resale, and total welfare is 0.5% higher. With uncertainty from covid-19, profit is 3.4% higher with a menu of refunds than with resale, and total welfare is 1.7% higher. The menu of refunds could be particularly valuable because of uncertainty over the future status of covid-19. Resale remains valuable when the seller offers no way to reallocate. Resale raises profit by 2.8% and consumer welfare by 6.9% in the counterfactual without uncertainty from covid-19; in the other counterfactual it raises profit by 6.6% and lowers consumer welfare by 1.7%.

The paper has three core implications for our understanding of resale and aftermarkets. First, the theory demonstrates that resale can be valuable in markets with primary market rigidities, aggregate uncertainty, and low resale frictions. The market for college football tickets includes both rigidities and aggregate uncertainty, but resale fees and frictions are significant enough for refunds to be optimal. In similar markets without primary market rigidities, like airlines and hotels, refunds are a natural choice.

Second, the comparison between sales strategies informs how to run aftermarkets. The results imply that refund-based strategies are superior in a perishable goods market with a monopolist seller. A driver of the benefits is the reduction in search frictions when there is only one seller. Refunds may not perform as well in markets with many competing sellers.

Third, the paper provides empirical evidence on the effects of resale. Whether sellers of perishable goods profit from resale is ambiguous in theory, and this paper shows that sellers benefit in practice. The effect of resale on consumer welfare informs policy on ticket resale. When sellers prohibit resale but do not offer refunds, consumer welfare falls by more than 6.9%. Consumers would benefit from a legal right to resell tickets provided that the seller does not offer refunds instead.

Finally, the analysis suggests several avenues for future research. The counterfactual experiments in this study suggest that refunds and menus of refunds boost profit and welfare. A next step would be to investigate the strategies' real-world performance. The results also suggest that frictions affect the performance of resale markets. Further investigation would advance our understanding of resale.

References

Bergemann, Dirk and Juuso Välimäki (2019), "Dynamic Mechanism Design: An Introduction." *Journal of Economic Literature*, 57, 235–274.

Board, Simon and Andrzej Skrzypacz (2016), "Revenue Management with Forward-Looking Buyers." *Journal of Political Economy*, 124, 1046–1087.

Cachon, Gérard P. and Pnina Feldman (2018), "Pricing Capacity Over Time and Recourse Strategies: Facilitate Reselling, Offer Refunds/Options, or Overbook?" Working paper.

Chen, Frank Youhua and Candace Arai Yano (2010), "Improving Supply Chain Performance and Managing Risk Under Weather-Related Uncertainty." *Management Science*, 56, 1380–1397.

Chen, Jiawei, Susanna Esteban, and Matthew Shum (2013), "When Do Secondary Markets Harm Firms?" *American Economic Review*, 103, 2911–2934.

Collard-Wexler, Allan (2013), "Demand Fluctuations in the Ready-Mix Concrete Industry." *Econometrica*, 81, 1003–1037.

Courty, Pascal (2003), "Ticket Pricing Under Demand Uncertainty." *Journal of Law and Economics*, 46, 627–652.

Courty, Pascal and Hao Li (2000), "Sequential Screening." *Review of Economic Studies*, 67, 696–717.

Cui, Yao, Izak Duenyas, and Özge Şahin (2014), "Should Event Organizers Prevent Resale of Tickets?" *Management Science*, 60, 2160–2179.

Fuster, Andreas and Basit Zafar (2021), "The Sensitivity of Housing Demand to Financing Conditions: Evidence from a Survey." *American Economic Journal: Economic Policy*, 13, 231–265.

Goldberg, Brett (2019), “Stubhub fees — the truth about buyer and seller fees.” https://www.tickpick.com/blog/stubhub-buyer-seller-fees/. Accessed March 19, 2021.

Ishihara, Masakazu and Andrew T. Ching (2019), “Dynamic Demand for New and Used Durable Goods Without Physical Depreciation: The Case of Japanese Video Games.” *Marketing Science*, 38, 392–416.

Jeon, Jihye (2020), “Learning and Investment under Demand Uncertainty in Container Shipping.” Working paper, Boston University.

Kalouptsidi, Myrto (2014), “Time to Build and Fluctuations in Bulk Shipping.” *American Economic Review*, 104, 564–608.

Lazarev, John (2013), “The Welfare Effects of Intertemporal Price Discrimination: An Empirical Analysis of Airline Pricing in U.S. Monopoly Markets.” Working paper, New York University.

Leslie, Phillip and Alan Sorensen (2014), “Resale and Rent-Seeking: An Application to Ticket Markets.” *Review of Economic Studies*, 81, 266–300.

Lewis, Michael, Yanwen Wang, and Chunhua Wu (2019), “Season Ticket Buyer Value and Secondary Market Options.” *Marketing Science*, 38, 973–993.

Pavan, Alessandro, Ilya Segal, and Juuso Toikka (2014), “Dynamic Mechanism Design: A Myersonian Approach.” *Econometrica*, 82, 601–633.

Pender, Kathleen (2017), “Think carefully before buying ‘paperless’ tickets that require credit card entry.” *San Francisco Chronicle*, URL https://www.sfchronicle.com/business/networth/article/Think-carefully-before-buying-paperless-11186609.php.

Potter, Simon M., Marco Del Negro, Giorgio Topa, and Wilbert Van Der Klaauw (2017), “The Advantages of Probabilistic Survey Questions.” *Review of Economic Analysis*, 9, 1–32.

Satariano, Adam (2015), "The Case of the Stubbed Hub." *Bloomberg Businessweek*, URL https://www.bloomberg.com/news/articles/2015-02-19/stubhub-faces-pressure-from-ticketmaster-and-ebay-its-own-parent.

Squire Patton Boggs LLP (2017), "Secondary Ticket Marketplace Guide to US Ticket Resale Regulations." Report, Squire Patton Boggs LLP.

Statista (2020), "Event tickets." https://www-statista-com.proxy.lib.duke.edu/outlook/264/100/event-tickets/worldwide. Accessed April 13, 2020.

StubHub (2021), "Stubhub's ticket fees." https://support.stubhub.com/en/support/solutions/articles/61000276392-stubhub-s-ticket-fees. Accessed March 19, 2021.

Su, Xuanming (2010), "Optimal Pricing with Speculators and Strategic Consumers." *Management Science*, 56, 25–40.

Sweeting, Andrew (2012), "Dynamic Pricing Behavior in Perishable Goods Markets: Evidence from Secondary Markets for Major League Baseball Tickets." *Journal of Political Economy*, 120, 1133–1172.

Waisman, Caio (2020), "Selling Mechanisms for Perishable Goods: An Empirical Analysis of an Online Resale Market for Event Tickets." Working paper, Kellogg School of Management, Northwestern University.

Williams, Kevin R. (2020), "Dynamic Airline Pricing and Seat Availability." Working paper, Cowles Foundation.

A Uncertainty and Sales Strategies Details

This section provides illustrations and derivations of the equilibria of the examples in Section 2. Recall that there is one ticket to be sold over two periods, that the seller commits to a menu of prices at the start of the first period, and that three demand shocks have known distributions in the first period and known realizations in the second. Consumer i has valuation ν_i before shocks arrive. The shocks are

1. An independently drawn shock with probability ψ that changes consumer i's value from ν_i to zero.
2. An aggregate shock V changing consumer i's value to $\nu_i + V$.
3. A realized state ω changing consumer i's value to $\nu_i - b_i(\omega)$. States are $\omega \in \{\omega^B, \omega^G\}$ with $b_i(\omega^G) = 0$ and $b_i(\omega^B) \geq 0$.

A.1 Diagrams

Figures 8, 9, and 10 illustrate the examples in Section 2.

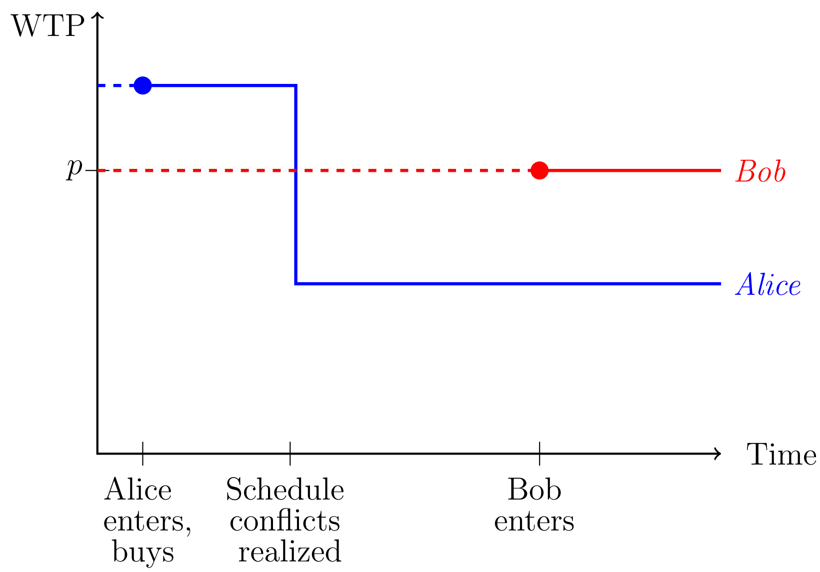


Figure 8: An illustration of the example with only idiosyncratic uncertainty. Although Alice receives an idiosyncratic shock, Bob does not and is willing to purchase the ticket at price p.

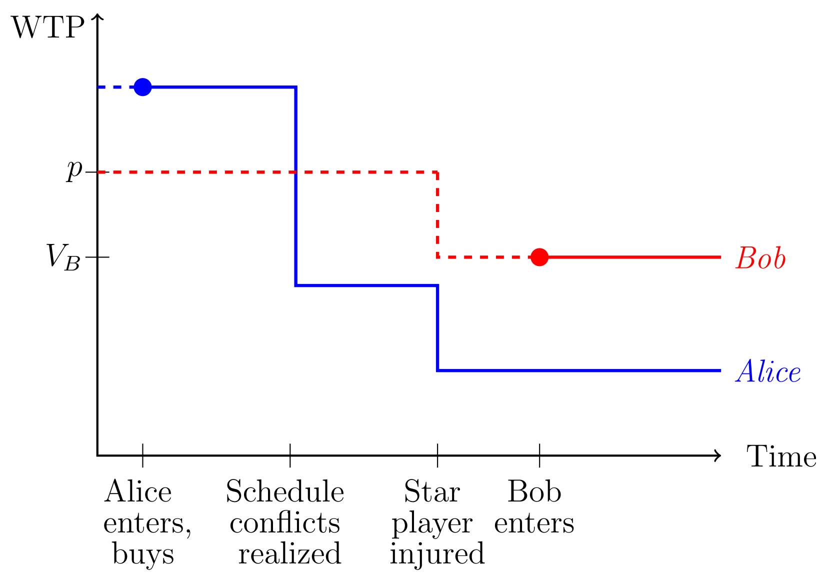


Figure 9: An illustration of the example with idiosyncratic and common value uncertainty. Alice receives an idiosyncratic shock and an aggregate shock lowers both her and Bob's values. Bob is unwilling to pay the primary seller's price p, but would purchase directly from Alice for a lower price.

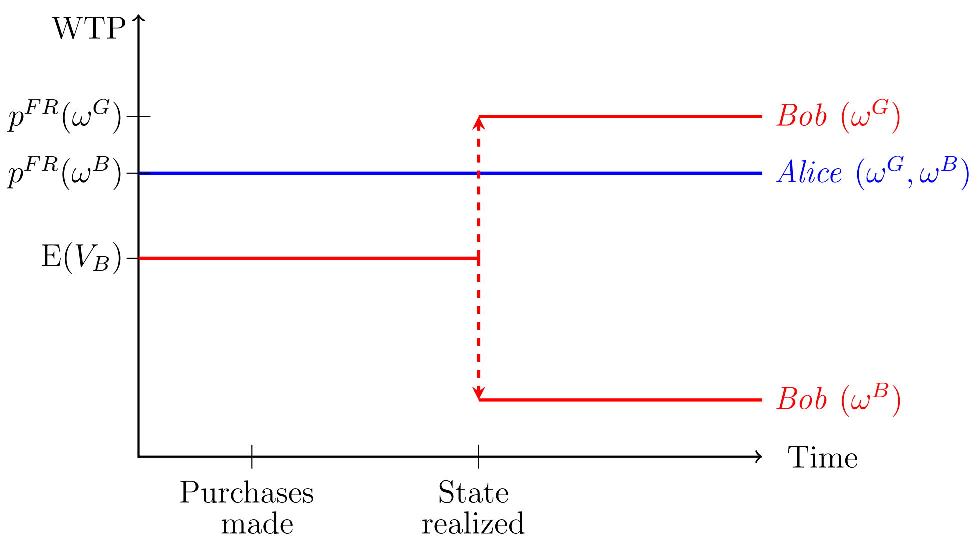


Figure 10: An illustration of the example with states of the world. Alice has the highest value in state ω^B and Bob has the highest value in state ω^G.

A.2 Idiosyncratic Uncertainty

Alice arrives in the first period with $\nu_A = 50$ and has probability $\psi = \frac{1}{5}$ of receiving an idiosyncratic shock. If she waits to purchase until the second period, her value falls to 40. Bob arrives in the second period with $\nu_B = 40$ and does not receive a shock. When there is a resale market, the fee charged by the resale market operator is $\tau = \frac{1}{10}$.

A.2.1 Partial Refunds

The optimal price in the second period is $p_2 = 40$. In the first period, Alice knows that she will earn zero surplus by waiting to purchase so she can be charged up to her expected surplus from buying in the first period,

$$p_1 = (1 - \psi) \cdot 50 + \psi r. \tag{17}$$

Any (p_1, r) pair with $50 \geq r \geq 0$ satisfying the expression achieves the same final allocation, profit, and welfare. For simplicity, suppose that the seller offers $r = 5$, leaving $p_1 = 41$. Alice purchases the ticket.

With probability $\frac{4}{5}$, Alice does not receive an idiosyncratic shock and uses the ticket, generating total welfare of 50 and profit of 41. With probability $\frac{1}{5}$, Alice returns the ticket, yielding a net profit of $41 - 5 = 36$ on the first sale and 40 when the ticket is sold again to Bob. The total profit in this case is 76 and welfare is 40. Expected profit and welfare are 48.

A.2.2 Resale

The seller sets $p_2 = 40$ to ensure that Alice purchases in the first period.[38] Alice knows that if she receives a shock, she can resell to Bob at 40 and will receive $(1 - \tau)40 = 36$. She is thus willing to pay

$$p_1 = (1 - \psi) \cdot 50 + \psi p_2^{\text{resale}} = 40 + \frac{1}{5}36 = 47.2. \tag{18}$$

[38] Doing so is optimal because the seller wants to sell to Alice in the first period: expected profit exceeds 40 when $p_2 = 40$.

The seller can again extract all of Alice's surplus and sets $p_1 = 47.2$, earning profit of 47.2. Total welfare remains 48.

A.3 Idiosyncratic and Common Value Uncertainty

Suppose there is also an aggregate shock: $V = 0$ with probability $\frac{3}{4}$ and $V = -20$ with probability $\frac{1}{4}$.

A.3.1 Partial Refunds

The seller again offers $p_2 = 40$.[39] In the first period, it can charge Alice

$$p_1 = (1 - \psi)(\frac{3}{4} \cdot 50 + \frac{1}{4} \cdot 30) + \psi r, \tag{19}$$

where $r \leq 30$ so that Alice only returns the ticket after an idiosyncratic shock. There are again many optimal pairs of (p_1, r). Without loss of generality, the seller offers $r = 5$ and charges $p_1 = 37$.

Alice contributes 37 to profit and 45 (in expectation) to total welfare with probability $\frac{4}{5}$. The remaining $\frac{1}{5}$ of the time, the seller earns a net of 32 from Alice and 40 from Bob with probability $\frac{3}{4}$ and 0 from Bob with probability $\frac{1}{4}$. Profit and total welfare differ from the optimal level because of the case where Alice returns the ticket and Bob does not purchase because $V = -20$ and $p_2 = 40$. Expected profit and welfare both equal 42.

A.3.2 Resale

With resale, the seller sets $p_2 = 40$ so that Alice buys the ticket in the first period. If Alice has an idiosyncratic shock she resells to Bob at price 40 when $V = 0$, earning 36 after fees, or 20 when $V = -20$, earning 18 after fees. The seller sets p_1 to extract Alice's full surplus,

[39] Setting $p_2 = 20$ is not optimal because, even if the seller extracted all of Alice's surplus in the first period, it would prefer to earn $\frac{3}{4} \cdot 40 + \frac{1}{4} \cdot 0 > 20$ when Alice has an idiosyncratic shock.

$$p_1 = (1-\psi)\cdot(\frac{3}{4}\cdot 50 + \frac{1}{4}\cdot 30) + \psi(\frac{3}{4}\cdot 36 + \frac{1}{4}\cdot 18) = 42.3. \tag{20}$$

With resale, the ticket is always allocated to the consumer with the highest value, yielding total welfare of $\frac{4}{5}\cdot 45 + \frac{1}{5}\cdot 35 = 43$. Profit is 42.3 because .7 is paid as fees to the resale market operator in expectation.

A.4 States of the World

The states ω^G and ω^B each occur with probability $\frac{1}{2}$. Alice has value 40 in each state, but Bob has value 50 in state ω^G and 10 in state ω^B. All sales must occur in the first period, but the state is not realized until the second period.

A.4.1 No Reallocation

Without reallocation, the seller prefers to sell to Alice at $p = 40$ than to Bob at $p = 30$. Profit and welfare are both 40.

A.4.2 Resale

With resale, Bob can resell to Alice in state ω^G at price 40, earning 36. The seller can thus charge Bob up to

$$p = \frac{1}{2}\cdot 50 + \frac{1}{2}36 = 43. \tag{21}$$

Profit is 43 and total welfare is maximized at 45.

A.4.3 State-Dependent Refund Contracts

The seller can offer a contract granting a full refund in state ω^G at price 40, which Alice is willing to purchase, and another granting a full refund in state ω^B at price 50, which Bob is willing to purchase. Total welfare is again maximized at 45. Profit is now $\frac{1}{2}40 + \frac{1}{2}50 = 45$.

B Data Construction

I use StubHub listings to infer the distribution of resale transaction prices. Resale transaction prices are not directly observable from listings because the StubHub listings only contain tickets currently available for sale. I start by inferring transactions from changes in listings. For example, if the number of tickets offered in a listing falls by two from one day to the next, then I assume two tickets were purchased at the last observed price.

The procedure leads to false positives because some listings are removed without being sold. I take two steps to correct them. First, I remove implausibly expensive transactions.[40] Second, I compare the number of inferred and actual transactions at the game-section-time level and assume that the lowest-price inferred transactions are the true ones. The removed transactions are generally outliers, either occurring earlier or containing more seats than typical transactions.

C Estimation Details

C.1 Distribution of V

The estimation procedure for the distribution of V uses the normalized prices defined in equation (1),

$$\text{NormalizedPrice}_{uy} = \text{AvgResalePrice}_{uy} / \left(\frac{1}{Y} \sum_{y} \text{AvgResalePrice}_{uy} \right). \tag{1 revisited}$$

The distribution of V is based on residuals from the regression

$$\text{NormalizedPrice}_{uy} = \beta_y Season_y + \varepsilon_{uy}. \tag{22}$$

The residuals form the distribution in Figure 5, which can be interpreted as percent deviations from mean prices. To recover the magni-

[40] These are defined as transactions sold at more than 1.5 times the 75^{th} percentile of price for similar quality seats

tude of the deviations for the university, I multiply the residuals by the university's mean price, which is adjusted to reflect time trends for the relevant year.

To recover σ_V^2, the distribution must be adjusted for the effect of α_j. The adjustment is necessary because changes in V affect utility and hence resale prices as $\alpha_j V$. Under the assumptions that changes in V linearly affect resale prices and that deviations in annual resale prices are solely due to changes in V,

$$\text{NormalizedPrice}_{uy} - 1 = V_y \sum_j w_{jy}\alpha_j \tag{23}$$

$$(\text{NormalizedPrice}_{uy} - 1)\left(\sum_j w_{jy}\alpha_j\right)^{-1} = V_y \tag{24}$$

where the vector w_{jy} sums to one and determines the relative importance of each game. SeatGeek does not describe how their averages are computed, so I assume that they are an average of all transactions on their platform and weight the α_j parameters by number of resale transactions. The resulting standard deviation is 7.85.

C.2 Vaccine Demand

Recall from Section 6 that the estimated distribution of values from structural estimation, parameterized by λ_ν, reflects demand before covid-19. The survey results suggest that demand with a vaccine is different, as illustrated in Figure 15.

Section 6 explains how the change in values $b_i(\omega^{\text{Vax}})$ is estimated. In the application with states of the world, I adjust values to reflect the change by defining

$$\nu_i' = \nu_i + b_i(\omega^{\text{Vax}}). \tag{25}$$

I use the distribution of ν_i' as the distribution of consumer values in the application. The value changes $b_i(\omega^{\text{NoVax}})$ are independent of ν_i'.

Figure 11 demonstrates that the parametric form of $b_i(\omega)$ fits the data.

C.3 Weights

The weight matrix used in the second stage of estimation has moment variances on the diagonal and zeros elsewhere. Although the inverse covariance matrix is asymptotically optimal for GMM, I am unable to recover the covariances of most estimation moments because they come from separate data sources. Even for resale prices for different games, an observation only contains information about one game and so a sample is not informative about the covariance between games. The resulting weight matrix is consistent but not asymptotically optimal.

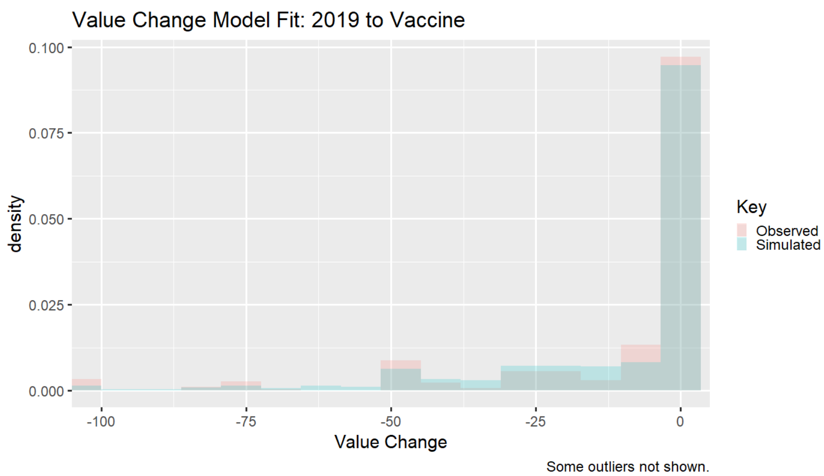
I calculate the variance of each moment using the bootstrap. Resale prices for each game are the simplest case. The data contain records of resale transactions and their prices. If there are N_j observed resale transactions for game j, I repeatedly sample N_j draws from the population of transactions and take the variance of the sample average price as the variance for game j.

Calculating the variance is less straightforward for season ticket and primary market quantities because the decision to not purchase is unobserved. In each bootstrap sample, I suppose that there are M total consumers and and take M Bernoulli draws with success probability N_j/M, where N_j is the observed number of tickets purchased. I censor each sample to ensure that no more tickets are sold than are available, then take the variance of the resulting sample means as the moment variance.

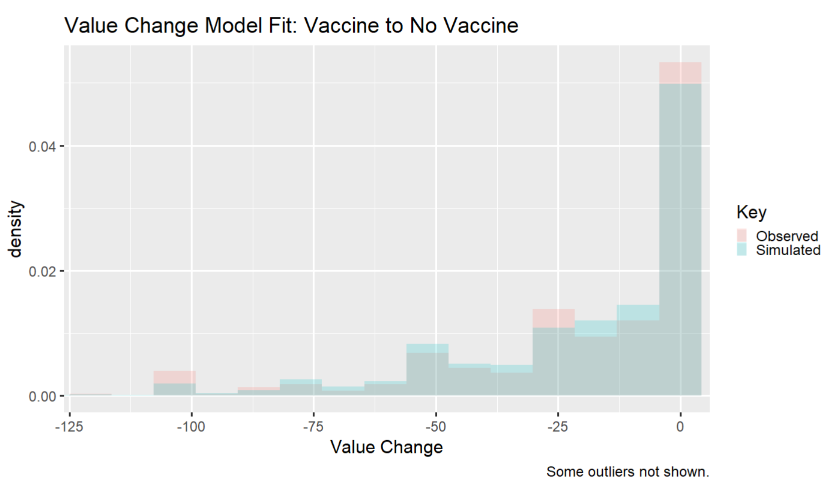
One concern with this strategy is that the variance depends on the market size M, which is assumed to be 200,000. If there were no censoring, the variance would follow from M Bernoulli draws with success probability N_j/M,

$$M\frac{N_j}{M}(1-\frac{N_j}{M}) = N_j(1-\frac{N_j}{M}). \tag{26}$$

The only dependence on M is mild because M is large relative to



(a)



(b)

Figure 11: Observed and simulated changes in willingness to pay. Top panel shows change from 2019 WTP to vaccine WTP. Bottom shows vaccine WTP to no vaccine WTP.

the quantity purchased. Consequently, the last term is close to one and the variance is robust to different values of M.

Moment variances are presented in Table 9.

Table 9: Variance of estimation moments.

Moment	Variance
Season Tickets Sold	19899.16
Avg. Resale Price: Game 1	0.30
Avg. Resale Price: Game 2	0.43
Avg. Resale Price: Game 3	0.31
Avg. Resale Price: Game 4	0.53
Avg. Resale Price: Game 5	0.16
PM Tickets Sold: Game 1	1262.01
PM Tickets Sold: Game 2	3286.64
PM Tickets Sold: Game 3	994.04
PM Tickets Sold: Game 4	2394.55
PM Tickets Sold: Game 5	495.96

I make two adjustments to model output so that it is comparable to the estimation moments. First, I only use the model's predicted resale prices and quantities for the value of V realized in the data. The model predicts resale prices and quantities for all possible realizations, but only the one for the realized V is comparable. Second, I weight resale prices by the observed average quantity of tickets resold in that quantity for the season. Weighting is necessary because the model predicts resale at the game-quality level and the mix of qualities resold affects the resale price.

C.4 Model Fit

Table 10 and Figures 12 and 13 assess the model fit. Observed and model-implied resale prices are extremely close. The model captures the patterns in primary market sales across games, but does not fit them exactly. The looser fit is expected because there are no game-specific quantity parameters. Finally, the model-implied number of season tickets purchased is within 13% of the true value.

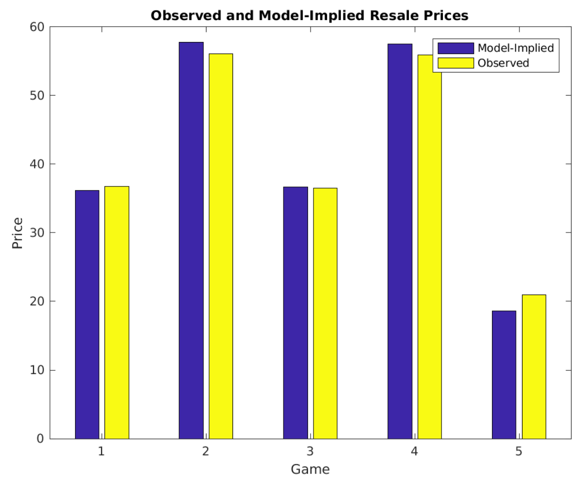


Figure 12: Observed and model-implied resale prices for each game.

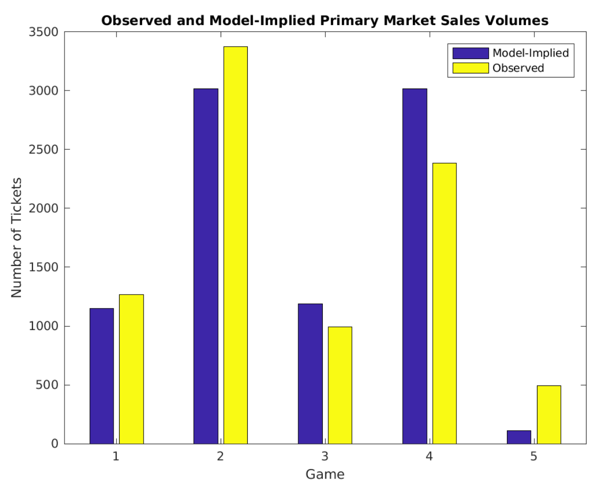


Figure 13: Observed and model-implied primary market quantities sold.

Table 10: Observed and model-implied quantities of season tickets.

Moment	Model-Implied	Observed
Season Tickets Sold	25226	22471

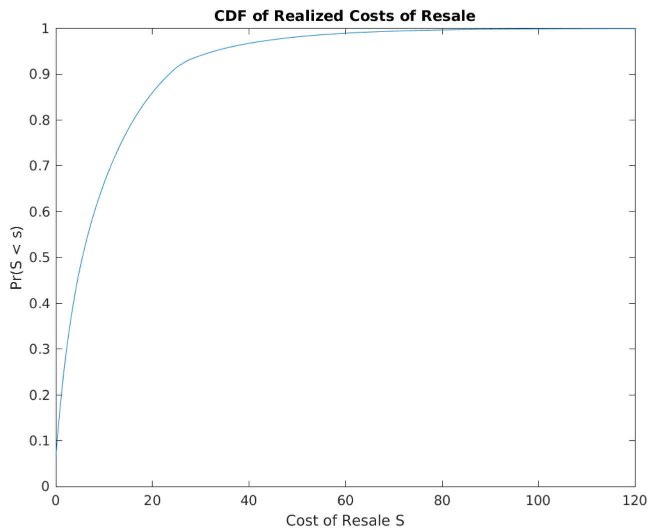


Figure 14: CDF of realized costs of resale for resale buyers in equilibrium.

C.5 Parameter Standard Errors

Standard errors for the first stage are calculated using the bootstrap and the properties of MLE. The errors for the α_j and γ_q parameters are calculated using the bootstrap for samples of resale prices. Similarly, the standard errors for ρ_1^{NoVax}, ρ_2^{NoVax}, ρ_1^{Vax}, and ρ_2^{Vax} are bootstrapped using repeated sampling of survey responses. The standard error of σ^V follows from maximum likelihood.

Standard errors for structural estimation are also calculated using the bootstrap. I draw a sample of 50 sets of moments from the covariance matrix used to weight moments in estimation and estimate optimal parameters for each set. The first stage parameters are fixed at their point estimates.

D Survey

I surveyed 250 Americans under the age of 50 and 250 Americans aged 50 or over, ultimately receiving a total of 457 usable responses. I distributed the survey through Prolific.co, an online survey distribution platform. Respondents were paid \$9.34 per hour and live in nine states that each have one dominant college football team: Arkansas, Georgia, Louisiana, Michigan, Minnesota, Nebraska, Ohio, West Virginia, and Wisconsin. Respondents from each state were asked to consider one ticket for that team throughout the survey.

I asked for the amount they are willing and able to pay in four scenarios: (i) the 2019 season, (ii) a covid-19 vaccine, (iii) no vaccine but the number of cases falls below the CDC's near-zero benchmark, and (iv) no vaccine and the number of cases is above the CDC's near-zero benchmark.

The CDC's benchmark for a near-zero number of new cases is 0.7 new cases per 100,000 people. Respondents were given the benchmark and a practical illustration, that a 25,000-seat stadium filled with randomly selected people would contain an average of 2.5 sick people if each case lasts two weeks. They were also told that the true number of infected people would be lower, on average, because some people would know that are ill and decide not to attend.

The survey includes respondents with a wide range of reported WTP. Figure 15 shows the distribution of reported WTP for three scenarios without social distancing: a 2019 baseline, a state with a vaccine, and a state without one. In each state, some consumers report values for tickets exceeding \$50 and \$100.

In the absence of a true measure of the probability of each scenario in the future, I ask respondents how likely they consider each one at three future dates. The average percent chances are shown in Figure 16. Respondents do not expect a vaccine in January 2021, but think the chance exceeds 40% in September 2021 and 60% in January 2022.

Figure 17 shows that the distribution of reported WTP is similar

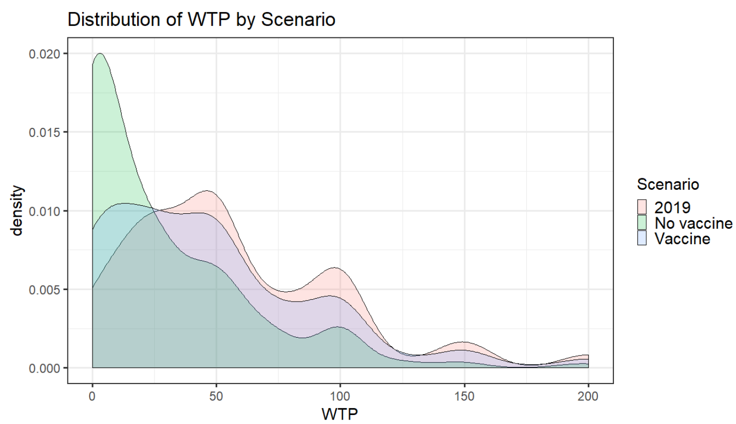


Figure 15: Distribution of reported willingness to pay without social distancing in 2019, with a vaccine, and with no vaccine.

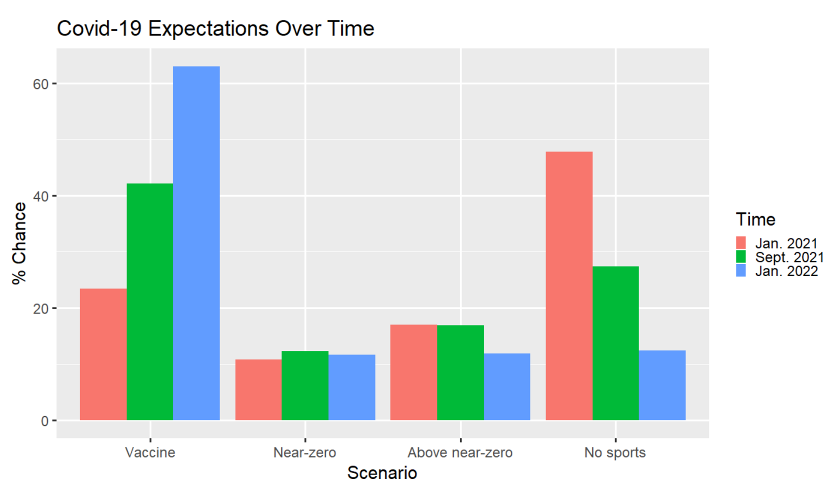


Figure 16: Average reported percent chance of each scenario occurring in each month.

for the near-zero and above near-zero scenarios.[41] The distributions are not exactly the same—consumers are more reluctant to attend when there are more cases—but the differences are small enough for the two to be consolidated into a single state without a vaccine. I consolidate WTP as a weighted average, taking the relative probability of the states in September 2021 as the weights.

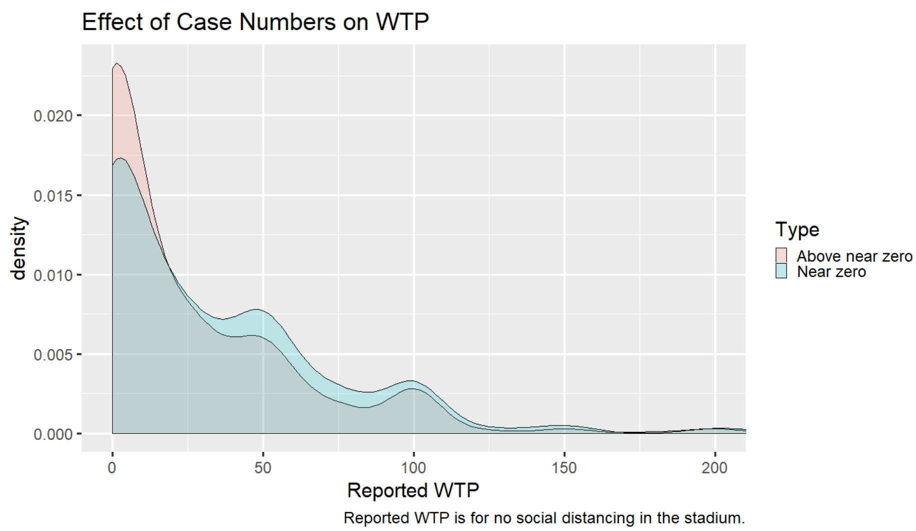


Figure 17: WTP distributions with near-zero and above near-zero levels of cases.

Figure 18 shows that the distribution of reported WTP is also similar with and without social distancing. As before, there are some changes, but they are not large enough to treat separately. I use reported values without social distancing because distancing would greatly reduce the number of tickets the seller can offer.

Surprisingly, demographics were not an important determinant of the change in WTP across states. I evaluated regression models of the form

$$\Delta WTP_i = \alpha Age_i + \beta Race_i + \gamma State_i + \varepsilon_i, \tag{27}$$

[41] The figure shows reported WTP without social distancing. The analogous figure with social distancing is similar.

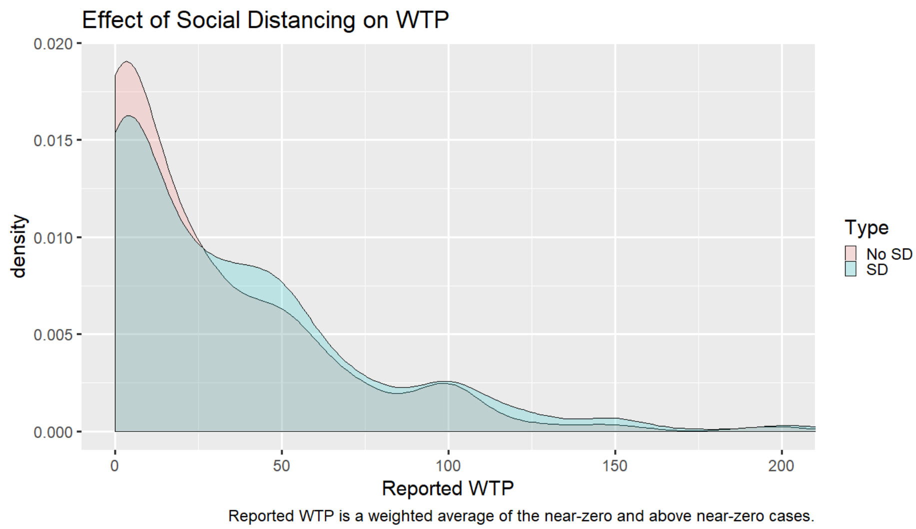


Figure 18: WTP distributions with near-zero and above near-zero levels of cases.

where Age_i is a set of age dummies (with decade-long bins, e.g. ages $30--39$), $Race_i$ is a set of dummies for race, and $State_i$ is a dummy for the state of the respondent. The response variable is measured both as an absolute number of dollars and as a percentage of initial WTP. Lower values denote greater sensitivity to the state without a vaccine. Results are shown in Table 11.

Although all groups were more sensitive than the reference group of respondents aged 22–29, those aged 50 and over did not report greater sensitivity to the state without a vaccine than those aged 30–49. (Respondents 70–79 are not numerous and only show a stronger response in one model.) Responses vary by race, but no coefficients are significant and the groups with large changes have few respondents. Because the covariance of value differences with demographics is not a critical feature of the data, I make value changes independent in the empirical model.

The full survey is included below.

Table 11: Regression output for equation (27).

	Dependent variable:	
	Value DIfference	Value Difference (%)
	(1)	(2)
Age 30-39	−12.821	−0.220**
	(8.713)	(0.088)
Age 40-49	−12.419	−0.051
	(8.806)	(0.089)
Age 50-59	−19.863**	−0.169*
	(8.911)	(0.090)
Age 60-69	−7.068	−0.125
	(9.574)	(0.097)
Age 70-79	−10.209	−0.390***
	(10.736)	(0.109)
Asian	28.256	−0.156
	(33.078)	(0.335)
African American	43.199	−0.267
	(32.337)	(0.328)
Other	35.790	−0.495
	(36.947)	(0.374)
White	50.867	−0.034
	(30.960)	(0.314)
White, Asian	−36.666	−0.078
	(60.378)	(0.612)
White, African American	74.146	0.447
	(48.460)	(0.491)
Constant	−59.122*	−0.213
	(32.724)	(0.331)
State Fixed Effects	Yes	Yes
Observations	382	382
R^2	0.070	0.114
Adjusted R^2	0.013	0.060
Residual Std. Error (df = 359)	41.706	0.422
F Statistic (df = 22; 359)	1.233	2.105***

Note: *p<0.1; **p<0.05; ***p<0.01
Age coefficients relative to respondents aged 22–29.
Race coefficients relative to respondents who are American Indians or Alaska Natives.

Event Expectations (General)

Start of Block: Intro

Q1 This study is conducted by Drew Vollmer, a doctoral student researcher, and his advisor, Dr. Allan Collard-Wexler, a faculty researcher at Duke University.

The purpose of the research is to design sales strategies that cope with uncertainty over the covid-19 pandemic. You will be asked about how much you would pay for tickets to an outdoor college football game under several scenarios related to covid-19. The survey should take 5-10 minutes.

We do not ask for your name or any other information that might identify you. Although collected data may be made public or used for future research purposes, your identity will always remain confidential.

Your participation in this research study is voluntary. You may withdraw at any time and you may choose not to answer any question. You will not be compensated for participating.

If you have any questions about this study, please contact Drew Vollmer. For questions about your rights as a participant contact the Duke Campus Institutional Review Board at campusirb@duke.edu.

End of Block: Intro

Start of Block: Block 4

Q16 In which state do you currently reside?

▼ Alabama (1) ... I do not reside in the United States (53)

End of Block: Block 4

Start of Block: WTP

JS

Q2
In this section of the survey, you will be asked how much you are **willing and able to pay for one ticket to a football game**. Your responses should be dollar amounts.

In some questions, you will be given a scenario related to COVID-19. You should respond with the amount you would pay if that scenario occurs. You should not consider how likely the scenario is.

---

*

Q3 What is the **maximum** you would be **willing and able to pay** for **one** ticket...

	Amount (dollars) (1)
one year ago, in Fall 2019? (1)	
if there had not been a global COVID-19 outbreak and the virus had not spread to the US? (2)	
if there is a widely available COVID-19 vaccine? (3)	

Q4
In the next two questions, suppose that there is **no COVID-19 vaccine**, but that fans are allowed to attend sporting events.

You will be asked to consider two levels of risk from the virus:

The CDC says that new cases are **near zero**. The CDC says that new cases are **more than near zero,** but **risk is low enough** to allow fans at sports games.

The CDC standard for new cases to be near zero is 0.7 new cases per 100,000 people or fewer. This means that filling a 25,000-seat stadium with randomly selected people would imply an average of **2.5 sick people** in the stadium if each case lasts two weeks. The true number of infected people at any event, however, would be lower because some people would know they are sick and would not attend.

---

*

Q5
Suppose that there is **no social distancing in the stadium**.

What is the **maximum** you would be **willing and able to pay** for **one** ticket if...

	Amount (dollars) (1)
the CDC says that the number of new cases is **near zero**? (4)	
the CDC says that the number of new cases is **higher than near-zero**, but that the risk from attending mass gatherings is **low enough** to allow fans at sports games? (5)	

---

*

Q6
Suppose that there is **social distancing in the stadium**.

What is the **maximum** you would be **willing and able to pay** for **one** ticket if...

	Amount (dollars) (1)
the CDC says that the number of new cases is **near zero**? (4)	
the CDC says that the number of new cases is **higher than near-zero**, but that the risk from attending mass gatherings is **low enough** to allow fans at sports games? (5)	

Q7
Suppose that fans can return their tickets if the number of new virus cases is higher than near-zero. Tickets are sold out, but there is a **wait list** in case fans who bought tickets return them because of the virus.

What is the maximum you would be willing to pay for a ticket on the wait list?

	Amount (dollars) (1)
No social distancing in the stadium (1)	
Social distancing in the stadium (3)	

End of Block: WTP

Start of Block: Probabilities

Q8
In this section, you will be asked about the likelihood of COVID-19 scenarios. Your answers should be *percent chances*. So, if you believe an outcome has a one-in-four chance of occurring, the percent chance is 25%.

Q34 What is the *percent chance* of each outcome in **January 2021**? Chances must sum to 100.

Current total: 0 / 100
________ There is a widely available COVID-19 vaccine. (1)
________ There is no COVID-19 vaccine and new cases are **near zero**, as defined by the CDC. (2)
________ There is no COVID-19 vaccine and new cases are **higher than near-zero**, but the CDC considers the risk from mass gatherings is **low enough** to allow fans at sports games. (3)
________ There is no COVID-19 vaccine, new cases are **higher than near-zero**, and the CDC judges that the risk from mass gatherings is **high enough** that fans cannot attend sports games. (4)

Q36 What is the *percent chance* of each outcome in **September 2021**? Chances must sum to 100.

Current total: 0 / 100
________ There is a widely available COVID-19 vaccine. (1)
________ There is no COVID-19 vaccine and new cases are **near zero**, as defined by the CDC. (2)
________ There is no COVID-19 vaccine and new cases are **higher than near-zero**, but the CDC considers the risk from mass gatherings is **low enough** to allow fans at sports games. (3)
________ There is no COVID-19 vaccine, new cases are **higher than near-zero**, and the CDC judges that the risk from mass gatherings is **high enough** that fans cannot attend sports games. (4)

JS *

Q35 What is the *percent chance* of each outcome in **January 2022**? Chances must sum to 100.

Current total: 0 / 100
________ There is a widely available COVID-19 vaccine. (1)
________ There is no COVID-19 vaccine and new cases are **near zero**, as defined by the CDC. (2)
________ There is no COVID-19 vaccine and new cases are **higher than near-zero**, but the CDC considers the risk from mass gatherings is **low enough** to allow fans at sports games. (3)
________ There is no COVID-19 vaccine, new cases are **higher than near-zero**, and the CDC judges that the risk from mass gatherings is **high enough** that fans cannot attend sports games. (4)

End of Block: Probabilities

Start of Block: Demographics

*

Q12 What is your year of birth?

____

Q13 What is your gender?

○ Male (1)

○ Female (2)

○ Prefer not to answer (3)

Q14 What is your ethnicity?

○ Hispanic or Latino/Latina (1)

○ Not Hispanic or Latino/Latina (2)

Q15 What is your race?

- ▢ White (1)
- ▢ Black or African American (2)
- ▢ American Indian or Alaska Native (3)
- ▢ Asian (4)
- ▢ Native Hawaiian or Pacific Islander (5)
- ▢ Other (6) ____

End of Block: Demographics