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Is Resale Needed in Markets with Refunds?

Evidence from College Football Ticket Sales

By
Drew Vollmer[1]

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[1] Antitrust Division, U.S. Department of Justice. Email: Andrew.Vollmer@usdoj.gov.

Is Resale Needed in Markets with Refunds? Evidence from College Football Ticket Sales

Drew Vollmer*

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Abstract

When is resale valuable? And when can it be replaced with refunds? I study the performance of common reallocation mechanisms in perishable goods markets with demand uncertainty. Using primary and secondary market data on college football ticket sales, I design a structural model to evaluate the performance of 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. I find that refunds are more efficient than resale, but that resale is better for sellers and consumers than not reallocating.

*U.S. Department of Justice. Contact: drew.vollmer@gmail.com
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1 Introduction

Is resale valuable? The usual answer is yes, because it reallocates goods to consumers with high values. For instance, a consumer might buy a concert ticket, learn she cannot attend, and resell to someone who can. But there are other methods of reallocating, like refunds, that could reach the same result. With refunds, the consumer could return the ticket to the box office for a partial refund, allowing the seller to offer the recovered ticket to someone else. In fact, many sellers, like airlines and hotels, offer partial refunds instead of allowing resale. Would society be better off if resale were replaced with refunds, or is resale uniquely valuable? The question matters because reallocation is necessary when consumers receive stochastic demand shocks after initial purchases. They do so frequently: a consumer might make travel plans in advance and then learn she has a schedule conflict, or she might buy clothes online and then learn they do not fit.

In this paper, I evaluate the most common reallocation mechanisms, resale and refunds, in markets for perishable goods with demand uncertainty. I use data on college football ticket sales to study the performance of resale and two refund strategies, a partial refund and a menu of state-dependent refund contracts. With a partial refund, consumers who buy in advance can return the good for some money back; with a menu of refunds, consumers who buy in advance can choose among contracts that issue refunds in different states of the world. Football tickets are an ideal setting because consumers purchase in advance and then receive different demand shocks,[1] including schedule conflicts and aggregate shocks like news about team performance.

After presenting examples in which each strategy can be most efficient, I assess their performance empirically with a structural model in which consumers purchase football 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,

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

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 in the second period and thus depends on realized shocks. In counterfactual experiments, I replace the resale market with refund policies.

The results suggest that refunds perform as well as resale and are superior when consumers have heterogeneous preferences over an uncertain state of the world. By quantifying the effects of resale and comparing it to refunds, the findings inform the design of aftermarkets and government policies on resale rights.

The key difference between the strategies is that refunds are centralized in the primary market and resale is not. With refunds, consumers can return their tickets to the primary seller, who puts the recovered units back on sale. All transactions take place in the primary market at the seller's prices. But with resale, consumers can list their tickets on a third-party resale platform, like StubHub, at prices they choose. Centralization is beneficial because it reduces frictions and allows the seller to offer a menu of state-dependent refund contracts; it can be harmful when primary market prices are suboptimal because of rigidities and menu costs, unlike resale's flexible prices.

In numerical examples, I show that each strategy can be most efficient. Suppose that a sports team sells tickets in advance and cannot change its prices.[2] Some consumers will purchase early, then learn they have schedule conflicts and cannot attend. If the optimal price is uncertain, price rigidities can cause partial refunds to perform badly. For example, suppose the team's star player is injured, causing consumer values to fall. Consumers with conflicts will request a partial refund, but the seller's price will be too high to sell the recovered tickets after the injury. Some tickets will go unused. Resale would perform better because its prices are flexible: resellers would lower prices after the in-

[2]The strong assumption of complete rigidity holds in my setting, where prices are printed on the tickets. Weaker rigidities have a similar effect for other sellers, who do not adjust prices to *fully* reflect changes in demand. As shown in Section 4, observed demand shifts are empirically large.

jury so that all tickets are sold and used. But resale is less efficient when there is no need for price flexibility because it introduces additional frictions. For example, some consumers may be unaware of the resale market, or they may dislike browsing or distrust the platform. The choice between partial refunds and resale depends on the relative intensity of mispricing and frictions, which must be recovered in estimation.[3]

A separate force determines the value of state-dependent refund contracts: whether different consumers want the tickets in different states of the world. For instance, the consumers who value tickets the most in a state where covid-19 disappears might not be the same as the consumers who value them most in a state with widespread infection. With a menu of refund contracts, the seller could target each group with refunds that depend on the status of covid-19 or, more generally, an observable state.[4]

After estimating the model, I find in counterfactual experiments that the refund strategies are as efficient as resale when there is no uncertainty over states of the world. Total welfare is 0.5% higher with refunds and consumer welfare is unchanged, but the seller does earn 2.1% more in profit. The results are noteworthy because they suggest that, even in a market with inflexible prices and aggregate shocks, resale can be replaced. All parties benefit from resale and refunds compared to a market without reallocation: total welfare increases by 5.1%, consumer welfare by 6.9%, and profit by 2.8%. 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 offers marked benefits over resale, raising total welfare by 5.5%, consumer welfare by 8.8%, and profit by 4.5%.

The analysis has broad implications for our understanding of aftermarkets and resale. Evidence on the performance of reallocation

[3]Refunds are optimal when primary market prices are flexible, as for airlines and hotels.

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

mechanisms, and of the factors that affect them, is valuable for determining how to run aftermarkets. Yet there is little work on the matter. This paper contributes by highlighting the forces that determine when each strategy is efficient and evaluating the strategies empirically. It also contributes to our understanding of resale by quantifying its net effects. The effects of resale on both sellers and society have been hotly contested, with governments alternately restricting and protecting resale of event tickets.[5] Similarly, some sellers prohibit 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 application with state-dependent contracts is valuable because it quantifies the effects of screening when consumers are heterogeneous, which are frequently discussed in theory (Courty and Li, 2000) but rarely measured empirically.[8] The empirical application to covid-19 is relevant because of the return of mass gatherings despite uncertainty over the future status of covid-19 and the resistance offered by vaccination.

The analysis also offers suggestive evidence on alternatives to resale when there are rent-seeking brokers. Much of the resale literature focuses on markets where brokers purchase underpriced tickets in the primary market, as in Bhave and Budish (2017) and Leslie and Sorensen (2014). In fact, Courty (2019) proposes a refund system to eliminate

[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.

[8]An exception is Lazarev (2013), who measures the effects of screening airline passengers who receive schedule conflicts at different rates.

brokers similar to the one tested in this paper. Underpricing and brokers are not significant in this setting, but the performance of resale relative to refunds provides suggestive evidence on brokers because brokers magnify both the advantages and disadvantages of resale. Brokers funnel more tickets through the resale market, leading to more price flexibility and frictions from resale. However, the predictions are not definitive because estimated parameters and the initial allocation would be different with brokers. For example, resale frictions may be lower with fewer tickets left in the primary market. Similarly, refunds may perform worse with systematic underpricing because more tickets would be rationed.

The most important feature of the model is the set of demand shocks that affect consumer values between the time of initial purchases and the time of the game. The model includes three distinct shocks that are 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 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 good, like the skill of a sports team or weather in a vacation destination. It makes the mean valuation and 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 heterogeneous effect on consumer values. The recession state of a business cycle, for example, harshly affects some consumers but hardly affects others. In the market for tickets, the states can be interpreted as the future status of covid-19, which could ebb or continue to pose a risk to the vaccinated. The estimation captures the associated uncertainty using survey data on a similar shock, whether there will be a covid-19 vaccine (assumed to be effective) at the start of the season.[9]

[9] The survey was distributed in August 2020, when it was unclear if or when there would be a vaccine. When the survey was distribtued, consumers were unlikely to be aware of the possibility of breakthrough cases and the Delta variant had not yet been detected.

States of the world cause the efficient allocation to vary with the state, increasing the return to a menu of state-dependent refund contracts.[10]

I assemble a broad data set to learn about the market and shocks. The main data set consists of all primary and resale market ticket sales for one football season at a large U.S. university, covering 30,000 primary market transactions and 5,500 resale transactions on StubHub.[11] The data demonstrate that advance sales and resale are features of the market: 75% of tickets are sold months in advance and 6% of all tickets are resold on StubHub. The second data set includes annual resale prices for 76 college football teams from 2011–2019, which I gather from SeatGeek, another online resale market. Resale prices vary significantly, often differing from the sample average by 25% or more. The final source of data is a survey. In August 2020, I asked 500 consumers (250 of whom were 50 or over) their willingness to pay for football tickets in states with and without a covid-19 vaccine. Consumer reactions to the state with no vaccine are heterogeneous: among consumers with positive willingness to pay when there is a vaccine, almost a third would pay the same amount with no vaccine while a fifth would pay nothing.

I estimate the model in two stages. The key parameters in the first stage govern the demand shocks. The rate of idiosyncratic shocks is identified by the frequency of observed resale in the ticket sales data. The size of common value shocks, such as injuries and team performance, is identified by year-to-year price variation in the SeatGeek data. Heterogeneity in values between states with and without a vaccine is captured by a distribution of value changes. The distribution is identified by individual-level reports of changes in willingness to pay in the survey.

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

[10] 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.

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

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[12] 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 descriptive 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. 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)

[12]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.

and Cui et al. (2014).

A separate literature considers resale of durable goods. With durable goods, sellers compete against past vintages of their products, as in Chen et al. (2013).

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 in theory, but neither involves empirics or aggregate shocks.

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.

2 Examples

In this section, I present examples illustrating how demand shocks affect each sales strategy. The examples show that each strategy can maximize welfare and profit, 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. Consumers are forward-looking and one arrives in each period. Suppose that consumer i has value $u_i = \nu_i + V - b_i(\omega)$, where ν_i is consumer i's preference for the ticket, V is a common component to values shared by all consumers, and $b_i(\omega)$ is consumer i's individual-specific response to state of the world ω.

Values are affected by three potential shocks realized at the start of the second period. The first shock is purely idiosyncratic, like schedule conflicts: each consumer i receives a shock with probability ψ. Draws are independent and consumers who receive a shock have zero value. The second shock changes the common value V, like injuries or team performance. The third shock is a state of the world $\omega \in \{\omega^B, \omega^G\}$, like recessions or the status of covid-19, that affects the $b_i(\omega)$ term.

Suppose that resale incurs the friction s, so a resale purchase at price p_2^r earns utility $u_i - p_2^r - s$. (All resale takes place in the second period.) The friction could be due to search costs or distaste for the resale market. Furthermore, the resale market operator charges a multiplicative fee τ, so the buyer pays the fee-inclusive price p_2^r while the reseller receives $(1-\tau)p_2^r$. The reseller makes a take-it-or-leave-it offer of p_2^r in the examples, but the assumption is only used for simplicity.[13]

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

Example 1: Idiosyncratic Shocks. Suppose that there are only idiosyncratic shocks: $\psi = \frac{1}{5}$ but $V = 0$ 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 $p_1 = 41$, $p_2 = 40$.[14] 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; Bob then buys the ticket from the seller for $p_2 = 40$. Expected profit and total welfare equal 48, the highest possible value.

With resale, welfare would be lower because of frictions and profit would be lower because of frictions and fees. Suppose that $\tau = \frac{1}{10}$ and $s = 1$. In the second period, Alice would resell to Bob at price

[13] With many agents, as in the empirical model, the TILI assumption is not necessary. I use it here to simplify equilibrium with two agents.

[14] 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.

39 because of the resale friction, leading to lower total welfare of 47.8. Alice only receives 35.10 after fees, so the seller can only charge her 35.10 when she has a conflict, leading to profit of $p_1 = 47.02$.

Resale remains superior to not reallocating: total surplus and profit would be 40 without resale or refunds. However, resale is less valuable to the seller when there are many tickets to sell and resale merely displaces demand for tickets in the primary market.[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 the star player is injured with probability $\frac{1}{4}$, leading to $V = -20$, 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 purchases in the first period. The key difference is that Bob is unwilling to purchase at the seller's optimal price of $p_2 = 40$ after an injury. 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 equal 42.

But with resale, Alice could resell to Bob at both common values, setting $p_2^r = 39$ when $V = 0$ and $p_2^r = 19$ when $V = -20$. Expected total welfare rises to 42.8 and expected profit to 42.12 because the ticket is now reallocated and used when V is low.

The first two examples illustrate the tradeoff between resale's price flexibility and its frictions. When price flexibility is not valuable, as in the first example, partial refunds are superior because they avoid resale frictions (and, for profit, fees). But when price flexibility is valuable, as in the second example, resale can be efficient and profit-maximizing. An empirical model is needed to determine which effect dominates.

Example 3: States of the World. A menu of state-dependent contracts is best when the efficient allocation depends on the state of the world. Suppose there are are no idiosyncratic or common value shocks, $\psi = 0$

[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.

and $V = 0$, but that there are two states, ω^G with widespread vaccination or low caseloads and ω^B with higher risk, and that each occurs with probability $\frac{1}{2}$. The state is 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.[17] With resale, Alice could resell to Bob in the good state, but at the cost of fees and 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 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. Ticket sales are informative about demand for tickets and the extent of resale. 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.

[17] I assume that Alice's strategy depends only on her value and the refund.

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 clusters of 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.[18] 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 only the 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.

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.

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.

[18]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)).

Covid-19 Survey. In August 2020, 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.[19] Although there are several scenarios, including the possibility of social distancing at the game, responses mainly depend on whether a vaccine was available.[20] 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 E.

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 heterogeneity in values between states is informative about ongoing uncertainty regarding covid-19, like the spread of the Delta variant.

4 Descriptive Evidence

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

Market Background. The university is a monopolist seller of its tickets.[21,22] In the season used in the analysis, it sells tickets to five home games.[23]

[19]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).

[20]When the survey was distributed, public concern focused on whether a vaccine (assumed to be effective) would exist rather than distribution or mutations of the virus.

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

[22]Despite being a monopolist, quantity distortion is not critical because unversity employees report a desire to sell all tickets. In the model, the optimal quantity follows from demand.

[23] 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.

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.

Of tickets sold to the public, 75% are sold as season tickets, demonstrating the importance of advance sales in the market. The remaining tickets are sold as single tickets, in bundles of a subset of games ("mini-plans"), and unsold. I only consider season tickets and single-game tickets in the empirical analysis because the mini-plans account for a minuscule number of sales. I also disregard promotions and group ticket sales because they are not optimally priced and may only be available to targeted groups, like veterans.[24] For additional detail on the breakdown of ticket sales, see Figure 9 in Appendix C.

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.[25] Primary

[24]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.

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

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.

Resale Markets. Resale is a notable feature of the market, with 5.98% of all tickets sold to consumers resold on StubHub.[26] 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 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%.[27]

The data support the idea that resale prices are flexible, which is intuitive because resellers can adjust list prices at any time. Figure 1 demonstrates that resale prices adjust to differ from face value. It shows the distribution of face values and the distribution of the average fee-inclusive resale price for each game-quality combination. The differences reflect changes in demand, and the variation across games suggests that some games are more valuable.

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 frictions that are not present in the primary market. StubHub charges

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

[27]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.

fees amounting to roughly 22% of the amount paid by the buyer.[28,29] The average combined 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 of resale tickets.

Annual Price Changes. Annual price changes for each team provide evidence of common value shocks. Using SeatGeek's records of average annual resale prices for 76 universities, I define the normalized price for university u in year y as

$$\text{NormPrice}_{uy} = \text{AvgResalePrice}_{uy} / \left(\frac{1}{Y_u} \sum_{y} \text{AvgResalePrice}_{uy} \right), \quad (1)$$

where Y denotes the number of years in the sample for university u. Figure 3 shows the distribution of deviations from the team average for all 76 teams after adjusting for time trends.[30] Year-to-year variation for each university is significant: 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. Further, dispersion is not driven by a few outliers. The standard deviation of normalized prices is greater than .2 for more than 70% of all universities.

[28]Resale prices in this paper are fee-inclusive to reflect the amount paid by the buyer.

[29]StubHub's exact fee structure is not public (StubHub, 2021), but its typical fees are reported to be 15% of the fee-exclusive price from buyers and 10% from sellers (Goldberg, 2019). I use these values in the analysis.

[30]I regress the normalized prices on year dummies and take the residuals.

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—and prices were 30% lower than usual. In their highest-priced season they won the national championship game and prices were nearly 35% higher.

Covid-19 Survey. The key result of the survey is whether the same consumers have the highest willingness to pay (WTP) in all states. Figure 4 shows that they do not. 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).[31] Reported values do not involve reduced capacity in the stadium. There are consumers in the top right with high values in both states, consumers in the bottom right who only have high values with a vaccine, and consumers in the top middle who will only have relatively high values in the state with no vaccine. The changes in WTP are not correlated with initial WTP; the correlation coefficient between the percent change in reported WTP and initial WTP is -.07. Surprisingly, changes in WTP also do not correlate with age.[32]

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, no marginal costs for each ticket, and sells tickets over two periods, $t = 1, 2$. 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.

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

[32] For details, see Appendix E.

Three shocks are realized at the start of the second period, modeled almost identically as 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. To match the survey data, ω takes the value ω^{Vax} if there is a vaccine and ω^{NoVax} if there is not, but it can be interpreted more broadly as the prevalence of covid-19. There is a consumer-specific penalty to utility $b_i(\omega)$ that depends on the state. 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 5, which includes a timeline on the right. 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 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 have lower values without a vaccine, $0 \leq b_i(\omega^{\text{Vax}}) \leq b_i(\omega^{\text{NoVax}})$, and face no penalty in the baseline state predating covid-19, $b_i(\omega^{BL}) = 0$. Realizations when there is no vaccine are heterogeneous and independent of ν_i.[33]

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 include any fees paid by buyers and vary with realized shocks.

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 and receive surplus zero ($\textit{No Purch. Surplus}_{ij}$), purchase in the primary market and receive surplus $\textit{PM Surplus}_{ijq}(V, \omega)$, or purchase in the secondary market and receive surplus $\textit{SM Surplus}_{ijq}(V, \omega, s_{ij})$. The surplus terms are

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

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

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

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

Surplus in the secondary market depends on the friction s_{ij}, which I assume is independently drawn across individuals and games and follows an exponential distribution, $s_{ij} \sim Exp(\lambda_s)$. 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.

The equilibrium resale price $p^r_{jq}(V, \omega)$ clears the resale market based on supply in equation (3) and demand in equations (4), (5), and (6).

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

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

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 in 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 decide whether to buy season tickets.[34] 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

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

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

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

Overall surplus from waiting is the expected value,

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

The consumer's choice set in period one is thus

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

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

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 $\{p_{jq}\}$. (Equivalently, the seller maximizes revenue because tickets have no marginal cost.) Consumers anticipate the resale price function $\{p^r_{jq}(V,\omega)\}$ 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 under the assumption that StubHub represents 75% of the resale market.[35]

The data are not directly informative about how many consumers consider season tickets. 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.[36]

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.[37] 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

[35] Resale on other sites is not observed, so the total number of tickets is unknown. 75% is a conservative assumption for the overall amount of resale: Leslie and Sorensen (2014) assume a 50% share for StubHub and eBay and Satariano (2015) reports that StubHub has roughly half of the ticket resale market. If StubHub's market share is lower than 75%, the model underestimates the effects of reallocation and the differences between sales strategies.

[36] I discuss robustness in Appendix D.

[37] 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.

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 resale friction 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 with different qualities sell at different prices.

The variance of the common value, σ_V^2 is estimated using the distribution of normalized resale prices shown in Figure 3. 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 3 is approximately normal. Details can be found in Appendix D.

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.[38]

The last parameters estimated in the first stage define the effect of

[38]The university's distribution of normalized prices is similar to those of other schools. For evidence, see Figure 10 in Appendix C.

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.[39] 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 E 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 in the survey for September 2021, normalized to sum to one.[40]

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

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

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

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, $\mathrm{WTP}_i(\omega^{\mathrm{Vax}}) - \mathrm{WTP}_i(\omega^{\mathrm{NoVax}})$ and $\mathrm{WTP}_i(\omega^{BL}) - \mathrm{WTP}_i(\omega^{\mathrm{Vax}})$. The parameters for the first difference identify the distribution of $b_i(\omega^{\mathrm{Vax}})$ and are labeled ρ_1^{Vax} and ρ_2^{Vax}. The parameters for the second identify the distribution of $b_i(\omega^{\mathrm{NoVax}})$ 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. After adjusting for censoring, I estimate 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. Because all parameters are from the demand side,[41] I take the seller's price menu as given and simulate the model with 200,000 consumers who demand up to one ticket. Estimation moments are weighted by their inverse variances. Details are in Appendix D.

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 resale friction. For instance, if the resale price is \$5 less than the primary market price, any consumer with

[41] With fixed seating capacity and no marginal costs, there are no supply-side parameters to estimate. Although prices are treated as fixed in estimation, the monopolist chooses profit-maximizing prices in counterfactuals.

$s > 5$ 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.[42]

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.[43] 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%,

[42]The main motive for shared quality preferences γ_q is to reduce the search for resale prices to one dimension.

[43]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.

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.

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 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 D 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 D.

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 D.

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 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. Neither counterfactual allows 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. I implement the counterfactual as a partial refund (described below) with primary market prices responding to shocks as

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

Adjusting prices according to equation (16) is optimal when the sellers wants to sell all units for the realized value of V. Otherwise it is tractable and close to optimal.

Partial Refunds. To implement a partial refund, I close the resale market and let consumers with idiosyncratic shocks return their tickets to the seller's inventory. Tickets are only available in the primary market in the second period. Season ticket buyers only derive value from using tickets or returning them for a refund. As in Section 2, the exact level of the refund is not identified—any refund is optimal if consumers only request refunds after receiving an idiosyncratic shock.[44] I assume that the seller offers such a refund and do not consider uncertainty from covid-19 states.

Menu of Refunds. The menu of refund contracts is only studied with uncertainty over the two vaccine states. The seller offers three contracts: a non-refundable package that grants tickets in both states sold at $\{p_{Bq}^{NR}\}$, a package granting tickets in the state with a vaccine sold at $\{p_{Bq}^{FR}(\omega^{\text{Vax}})\}$, and a package granting tickets in the state with no vaccine sold at $\{p_{Bq}^{FR}(\omega^{\text{NoVax}})\}$. The state-specific packages can be thought of as conditional full refunds. The seller continues to offer single-game tickets at prices $\{p_{jq}\}$ in both states. There is no resale market. Consumers can only purchase primary market tickets in the second period, and consumer who buy season tickets get value from using their tickets or requesting a refund.

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.[45] 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 frictions,

[44]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.

[45]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.

which enter as the random variable S, reduce both profit and welfare, but the fees, which enter through τ, only affect profit. 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. Total welfare is maximized with partial refunds, edging resale by 0.5%, but consumer welfare is similar under the two strategies. Profit, however, is 2.1% higher with refunds than with resale. The results suggest that resale does not confer a meaningful advantage despite the presence of primary market rigidities.

The counterfactual without reallocation demonstrates that both resale and partial refunds enhance welfare. The increase in welfare is unsurprising but rarely quantified. 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 changes are notable because only 8% of tickets are resold. The predicted welfare gains are larger than the 2.9% gain estimated in Leslie and Sorensen (2014), although their analysis includes harm from resale that is not relevant for the team studied here. It is not clear ex ante that resale should increase profit, but the results show that profit rises by 2.8%.

The counterfactual with flexible prices, however, shows that price rigidities prevent refunds from being optimal. If the seller could adjust its prices and offer a partial refund, it would generate 2.3% higher consumer welfare and 1.9% higher total welfare compared to refunds while earning 1.6% more profit.

Table 7 presents the results for counterfactual experiments in simulations with two states of the world. The menu of refund contracts is best in theory; the value of the counterfactuals is to quantify the improvement. Even relative to resale, the gains from contracting directly on states of the world are substantial: total welfare rises by 5.5%, consumer welfare by 8.8%, and profit by 4.5%. The benefits are particularly relevant as mass gatherings return despite uncertainty over covid-19.

The last set of counterfactuals, shown in Table 8, decompose the effects of fees and frictions on the core counterfactuals in Table 6. Removing only fees does little for efficiency, essentially transferring surplus from the resale market operator to the seller. Much of the welfare gains result from removing frictions. When there are fees, the resale market operator is the main beneficiary. Removing both fees and frictions allows an additional increase in total welfare, which is 3.3% higher than with fees and frictions.[46]

8 Conclusion

When consumers receive stochastic demand shocks, 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—namely the nature and strength of aggregate shocks—then estimated a structural model describing the salient shocks in the market for college football tickets and used it to evaluate each strategy.

The results suggest that refunds are no worse than, and can be more efficient than, the status quo of resale. In the counterfactual without uncertainty from covid-19, total welfare is similar, 0.5% higher with refunds, consumer welfare is similar, and profit is 2.1% higher. With uncertainty from covid-19, a menu of refunds is considerably better, raising total welfare by 5.5%, consumer welfare by 8.8%, and profit by 4.5% relative to resale. The menu of refunds could be particularly valuable because of uncertainty over the future status of covid-19. However,

[46]I emphasize total welfare rather than profit in Table 8 because the change in reduction in profit without fees and frictions is an artifact of the model. Setting fees to zero with a resale market creates small changes in consumers' willingness to substitute across qualities. The changes affect demand compared to the majority of counterfactuals.

resale is far superior to not reallocating.

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. Although brokers are not prominent in the data, the results suggest that refund policies are a potentially valuable alternative to resale when tickets are underpriced. Further investigation is needed because the results in this paper do not directly apply to markets with underpricing: the initial allocation and volume of resale may affect the comparison.

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. Total welfare falls significantly when sellers prohibit resale and do not offer refunds. Society would benefit from a legal right to resell tickets provided that the seller does not offer refunds instead.

References

Bhave, Aditya and Eric Budish (2017), "Primary-Market Auctions for Event Tickets: Eliminating the Rents of 'Bob the Broker'?" Working paper, National Bureau of Economic Research.

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

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 (2019), "Ticket resale, bots, and the fair price ticketing curse." *Journal of Cultural Economics*, 43, 345–363.

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.

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.

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.

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.

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

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 and 3	70	60	50	40	30
2 and 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

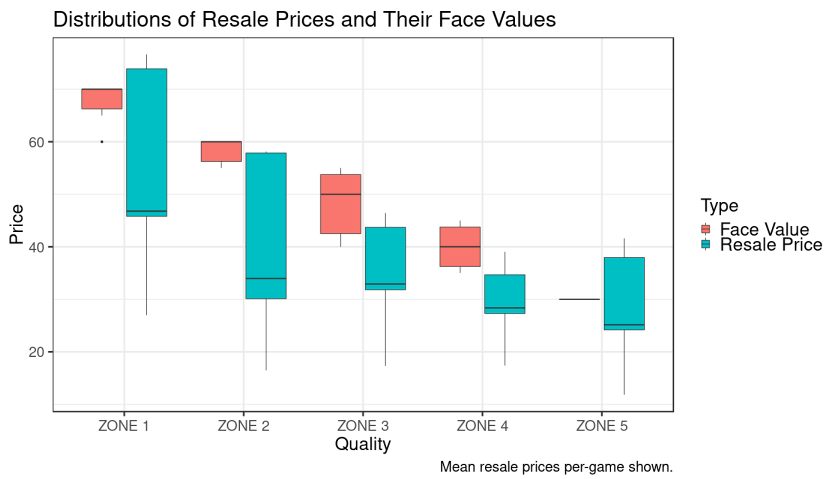


Figure 1: Distributions of mean fee-inclusive per-game resale prices and face value.

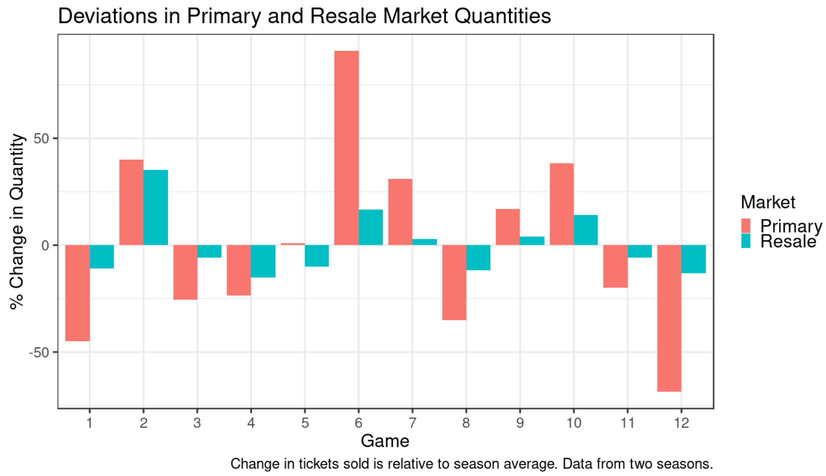


Figure 2: Percent deviation from season-average quantities sold for each game.

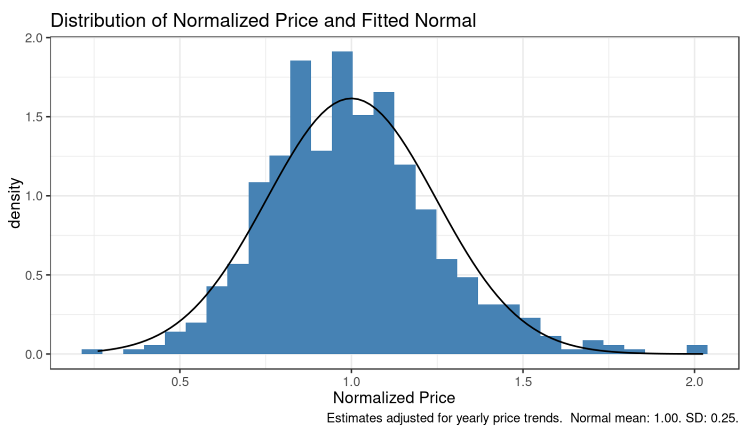


Figure 3: Distribution of resale prices normalized by team-mean in the sample. Adjusted for yearly trends. From SeatGeek annual average resale prices (76 teams, 576 team-seasons).

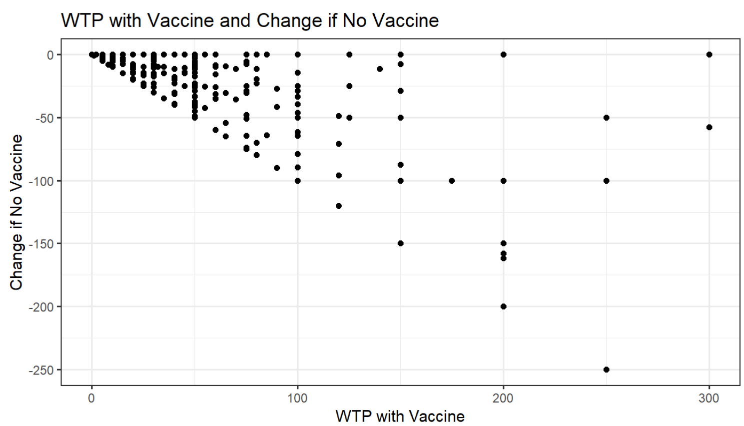


Figure 4: Scatterplot of reported willingness to pay with a vaccine and change in willingness to pay if there is no vaccine.

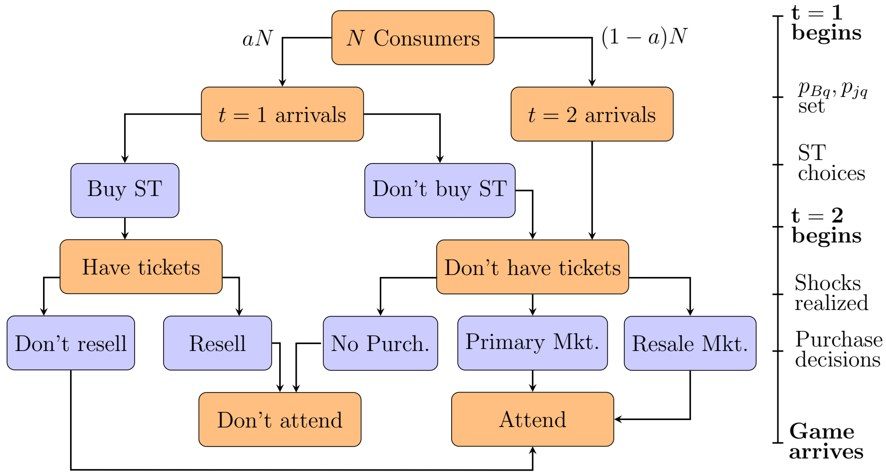


Figure 5: Model timeline and outline for consumer arrivals and choices. Decisions are shown in blue.

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

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	51.43	1.56
Mean Consumer Type	λ_ν	16.45	0.11
Mean ST Benefits	δ	21.89	1.46

	Resale	Refunds	Flex. Prices	No Reall.
Profit (mn)	7.23	7.38	7.50	7.03
	(0.09)	(0.09)	(0.09)	(0.08)
Consumer Welfare (mn)	2.64	2.64	2.70	2.47
	(0.04)	(0.04)	(0.04)	(0.04)
Total Welfare (mn)	9.97	10.02	10.21	9.49
	(0.12)	(0.12)	(0.12)	(0.11)
Resale Fees (mn)	0.10	0.00	0.00	0.00
	(0.00)	(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. Standard errors shown in parentheses.

	No Reall.	Menu of Refunds	Resale
Profit (mn)	6.62	7.17	6.86
	(0.08)	(0.08)	(0.07)
Consumer Welfare (mn)	2.52	2.59	2.38
	(0.04)	(0.04)	(0.09)
Total Welfare (mn)	9.13	9.76	9.25
	(0.11)	(0.11)	(0.12)
Resale Fees (mn)	0.00	0.00	0.02
	(0.00)	(0.00)	(0.00)
Non-Refund. S. Tix (1000)	24.60	12.06	24.60
Vaccine S. Tix (1000)	0.00	5.79	0.00
No Vaccine S. Tix (1000)	0.00	13.10	0.00

Table 7: Counterfactual results for the model with different states of the world. Standard errors shown in parentheses.

	Resale	$\tau = 0$	$\lambda_s = 0$	$\tau = 0$ and $\lambda_s = 0$
Profit (mn)	7.23	7.33	7.28	7.17
	(0.09)	(0.09)	(0.09)	(0.09)
Consumer Welfare (mn)	2.64	2.65	2.66	3.13
	(0.04)	(0.04)	(0.04)	(0.19)
Total Welfare (mn)	9.97	9.98	10.14	10.30
	(0.12)	(0.12)	(0.13)	(0.18)
Resale Fees (mn)	0.10	0.00	0.20	0.00
	(0.00)	(0.00)	(0.01)	(0.00)
Season Ticket Buyers (1000)	25.56	25.56	26.19	28.18
Season Ticket Base Price	32.38	32.81	33.50	31.91
Single Game Base Price	39.18	38.68	34.23	27.61

Table 8: Counterfactual results for resale frictions in the baseline model. Standard errors shown in parentheses.

A Example 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 value $u_i = \nu_i + V - b_i(\omega)$ and consumers incur a friction s when buying in the resale market.

A.1 Diagrams

Figures 6, 7, and 8 illustrate the main implications of Section 2. The diagrams, however, do not explicitly illustrate resale's fees and frictions.

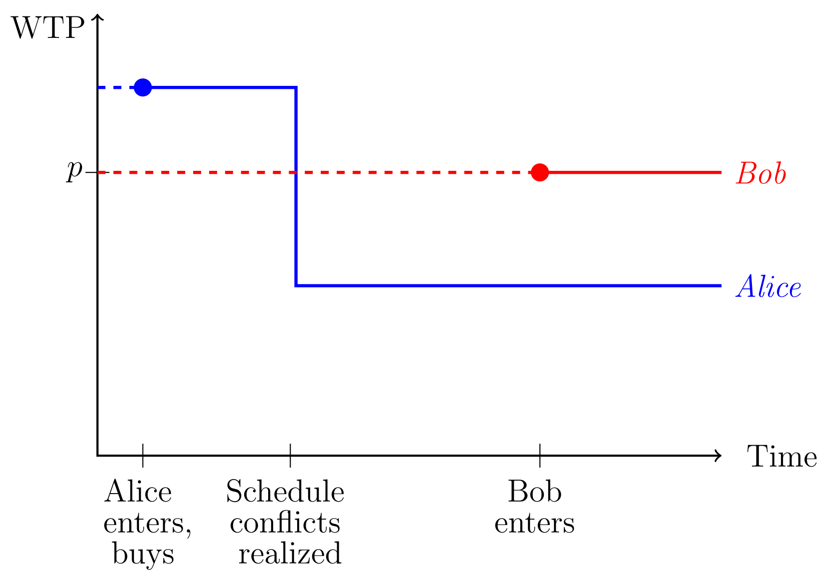


Figure 6: An illustration of the example with only idiosyncratic uncertainty. Although Alice receives an idiosyncratic shock, Bob does not and is willing to purchase the ticket at price p.

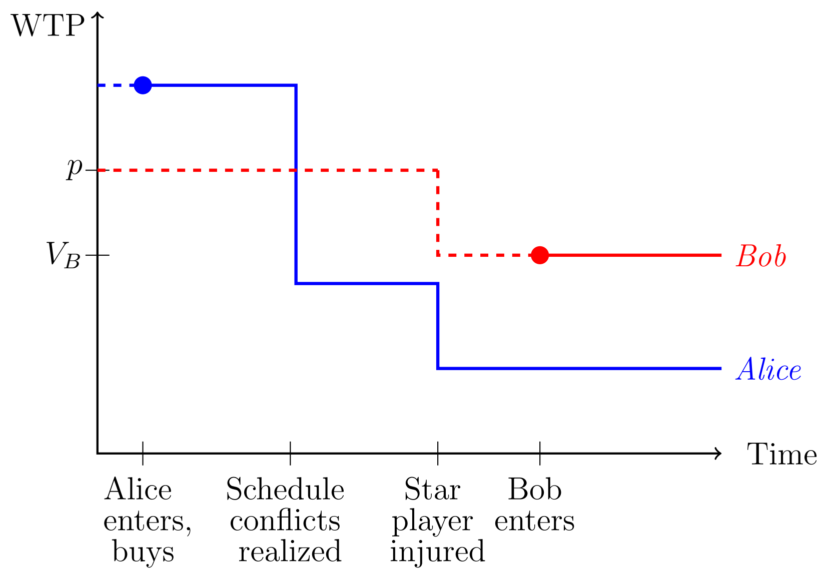


Figure 7: An illustration of the example with idiosyncratic and common value uncertainty. Alice receives an idiosyncratic shock and an aggregate shock lowers both her and Bob's values. Bob is unwilling to pay the primary seller's price p, but would purchase directly from Alice for a lower price.

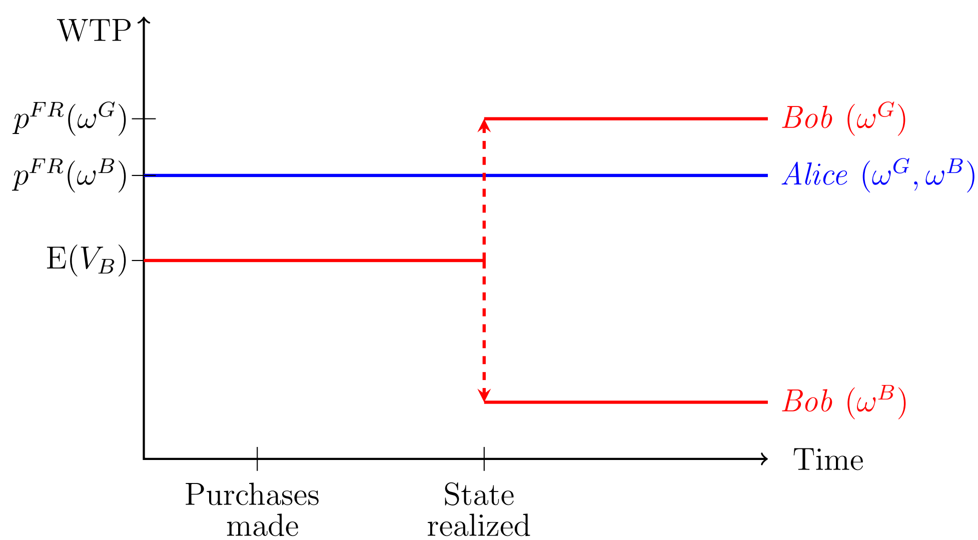


Figure 8: An illustration of the example with states of the world. Alice has the highest value in state ω^B and Bob has the highest value in state ω^G.

A.2 Idiosyncratic Uncertainty

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 $0 \leq r \leq 50$ 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.

Resale. The seller sets $p_2 = 40$ to ensure that Alice purchases in the first period.[47] Alice knows that if she receives a shock, she can resell to Bob for 39. Total welfare is thus $.8 \cdot 50 + .2 \cdot 39 = 47.8$.

When reselling, Alice sets $p_2^r = 39$ and receives $(1 - .1)39 = 35.1$. She is thus willing to pay

$$p_1 = (1 - \psi) \cdot 50 + \psi p_2^r = 40 + \frac{1}{5} 35.1 = 47.02. \tag{18}$$

The seller can again extract all of Alice's surplus and sets $p_1 = 47.02$, earning profit of 47.02.

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 $\frac{1}{4}$.

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

Partial Refunds. The seller again offers $p_2 = 40$.[48] In the first period, it can charge Alice

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

where $0 \le r \le 30$ 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.

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 39 when $V = 0$, earning 35.1 after fees, or 19 when $V = -20$, earning 17.1 after fees. The ticket is always allocated to the consumer with the highest value, yielding total welfare of $\frac{4}{5}\cdot 45 + \frac{1}{5}\cdot 34 = 42.8$.

The seller's profit is its price p_1, which it sets to extract Alice's full surplus,

$$p_1 = (1-\psi)\cdot(\frac{3}{4}\cdot 50 + \frac{1}{4}\cdot 30) + \psi(\frac{3}{4}\cdot 35.1 + \frac{1}{4}\cdot 17.1) = 42.12. \quad (20)$$

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.

[48] 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.

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.

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.

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.[49] 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.

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

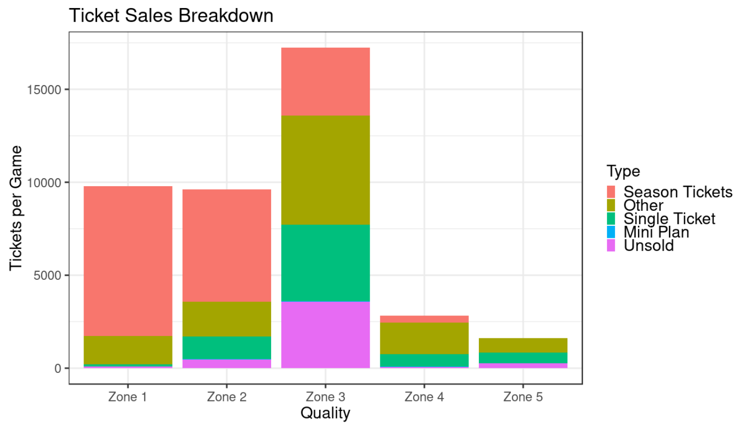


Figure 9: Sale types and volumes by quality group.

C Additional Descriptive Evidence

Figure 9 shows the average number of tickets sold (across games) for each sales format and quality zone. As expected, season tickets are dominant. The "other" cateogry of tickets is also significant, but is not available to the public. It includes student tickets and tickets for athletics boosters.

Figure 10 shows the distribution of normalized prices for the focal university and a random sample of 20 universities. The distributions demonstrate that within-university price variation is significant and widespread. Nearly all universities have a season where prices are 25% above and 25% below the sample mean.

D Estimation Details

D.1 Distribution of V

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

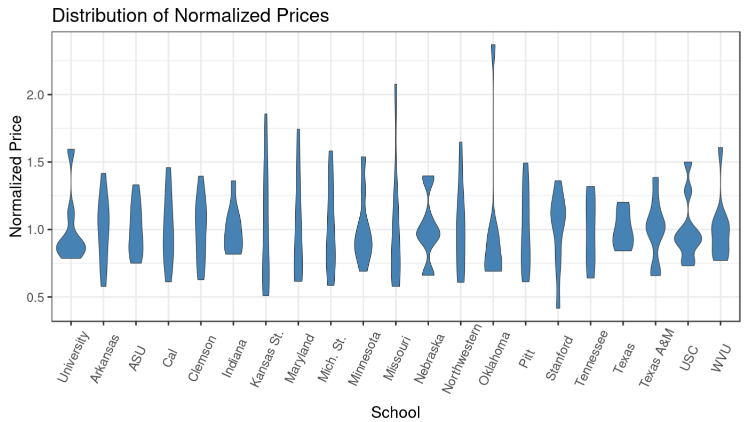


Figure 10: Distribution of average annual resale prices (normalized by school mean) for a random sample of 20 schools in similar conferences.

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

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 3, which can be interpreted as percent deviations from mean prices. To recover the magnitude 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.

D.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

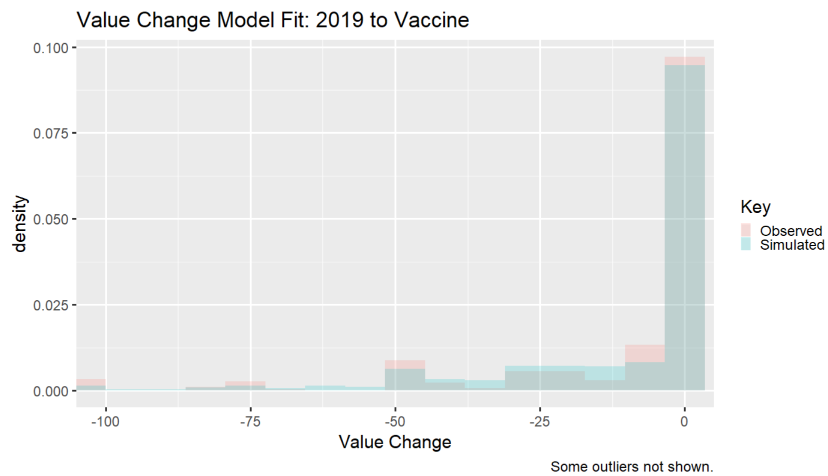
$$\nu_i' = \nu_i + b_i(\omega^{\text{Vax}}). \tag{25}$$

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'.

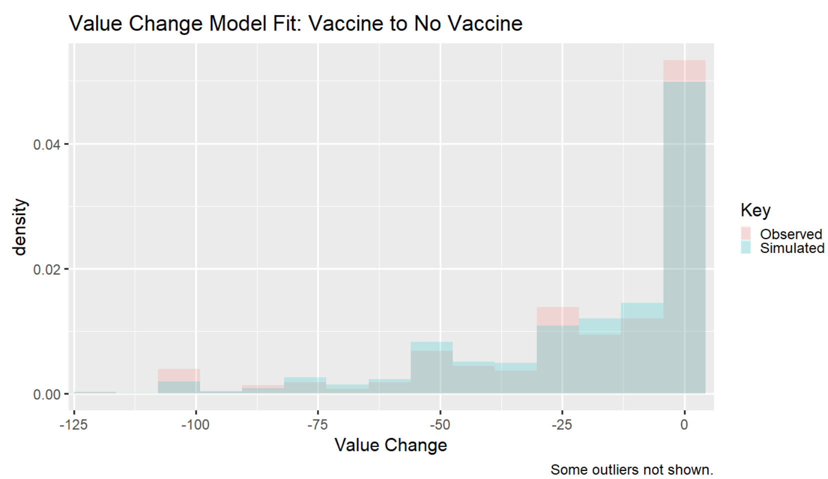
Figure 11 demonstrates that the parametric form of $b_i(\omega)$ fits the data.

D.3 Second Stage Details

The second stage of estimation includes a grid of values ν_i stretching from \$0 to \$198 in increments of \$0.10. There are 100 values in the grid for V, the evenly spaced quantiles from 0.5% through 99.5%. The model iterates until expected and realized resale prices and primary market purchase probabilities converge, defined as the maximum resale price difference being within \$0.01 and the mean primary market purchase probability for each quality is within 1%.



(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 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 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.

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

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

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.

D.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.

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

Moment	Model-Implied	Observed
Season Tickets Sold	25226	22471

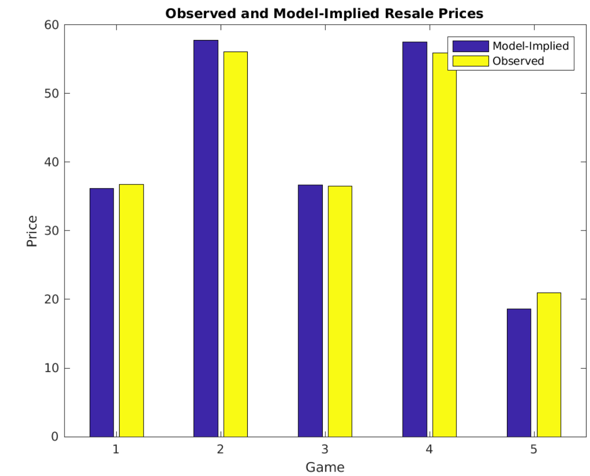


Figure 12: Observed and model-implied resale prices for each game.

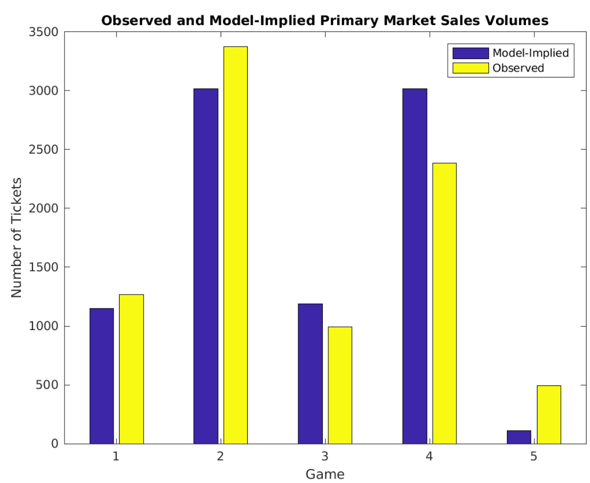


Figure 13: Observed and model-implied primary market quantities sold.

D.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.6 Counterfactual Standard Errors

Standard errors for counterfactual estimates such as profit are also calculated using the bootstrap. I evaluate each counterfactual 50 times using 50 sets of input coefficients. The ideal sampling would draw parameters from their joint distribution, but the full joint distribution is unknown since not all parameters are estimated jointly.

I account for the correlation between parameters that are jointly estimated but assume that draws are independent for parameters that are estimated separately. For example, draws of $(\lambda_s, \lambda_\nu, \delta)$ are correlated because they are estimated together; the draws are taken from the set of bootstrapped parameter estimates. The same is true of draws of the vector (α, γ). However, values of λ_s and each α_j are assumed to be independent because they are taken from separate estimation processes.

D.7 Robustness of a

The parameter a is calibrated as the percentage of tickets sold 30 or more days in advance. To evaluate its effect on the model, I estimate the second stage using several alternative values. Results are shown in Table 11. Changing the value of a has a relatively mild effect on frictions

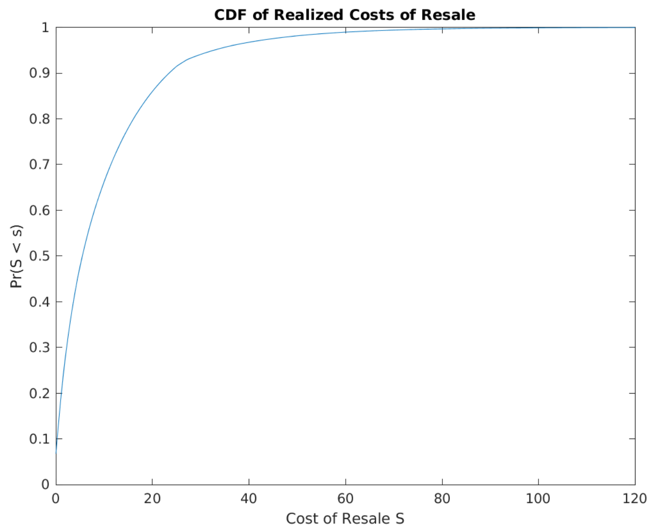


Figure 14: CDF of realized costs of resale for resale buyers in equilibrium.

and valuations, λ_s and λ_ν, but a significant effect on the parameter δ that calibrates the appeal of season tickets. The change in δ is not surprising. It helps fit the number of consumers who purchase season tickets. As the number of consumers who consider season tickets varies with a, it is only natural that δ must change to match the number of season ticket buyers in the data.

Table 11: Second-stage parameter estimates for different values of a.

a	λ_s	λ_ν	δ
0.60	39.73	14.25	60.51
0.70	47.19	15.13	41.78
0.77	51.43	16.45	21.89
0.85	60.84	18.46	-4.34

E 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 for the near-zero and above near-zero scenarios.[50] 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

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

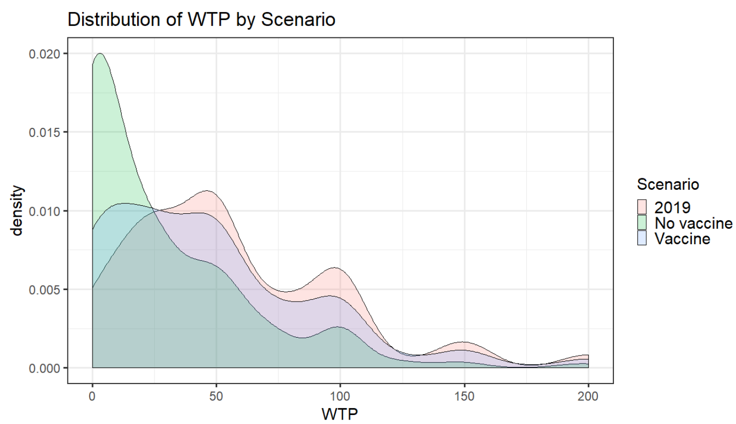


Figure 15: Distribution of reported willingness to pay without social distancing in 2019, with a vaccine, and with no vaccine.

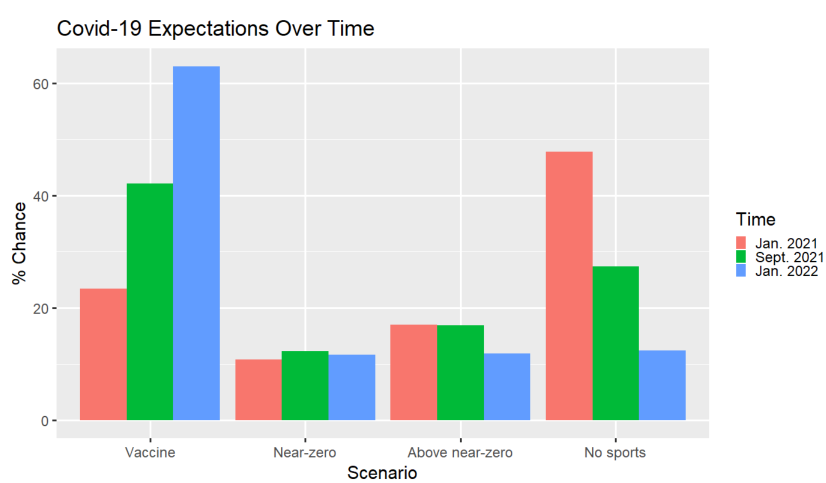


Figure 16: Average reported percent chance of each scenario occurring in each month.

WTP as a weighted average, taking the relative probability of the states in September 2021 as the weights.

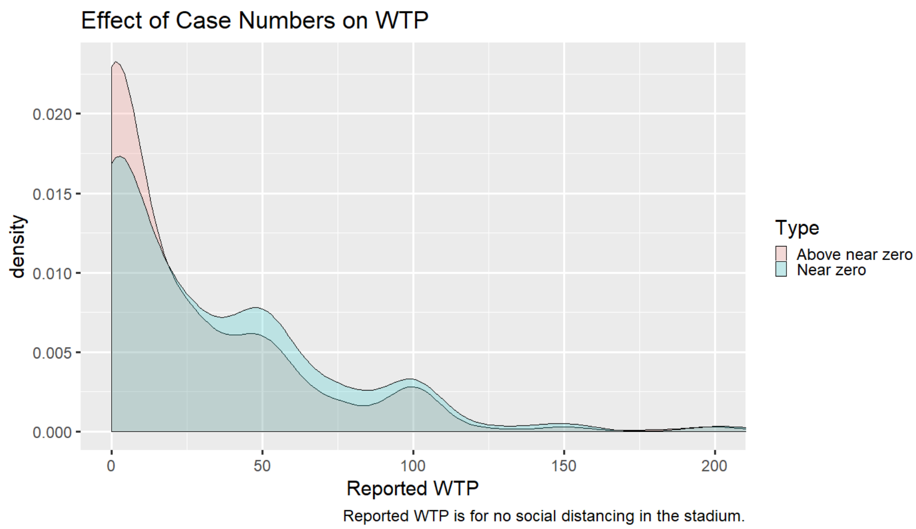


Figure 17: WTP distributions with near-zero and above near-zero levels of cases.

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

$$\Delta WTP_i = \alpha Age_i + \beta Race_i + \gamma State_i + \varepsilon_i, \qquad (27)$$

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 12.

Table 12: 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: Age coefficients relative to respondents aged 22–29. Race coefficients relative to respondents who are American Indians or Alaska Natives.

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.

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%.

JS *

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)

JS *

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

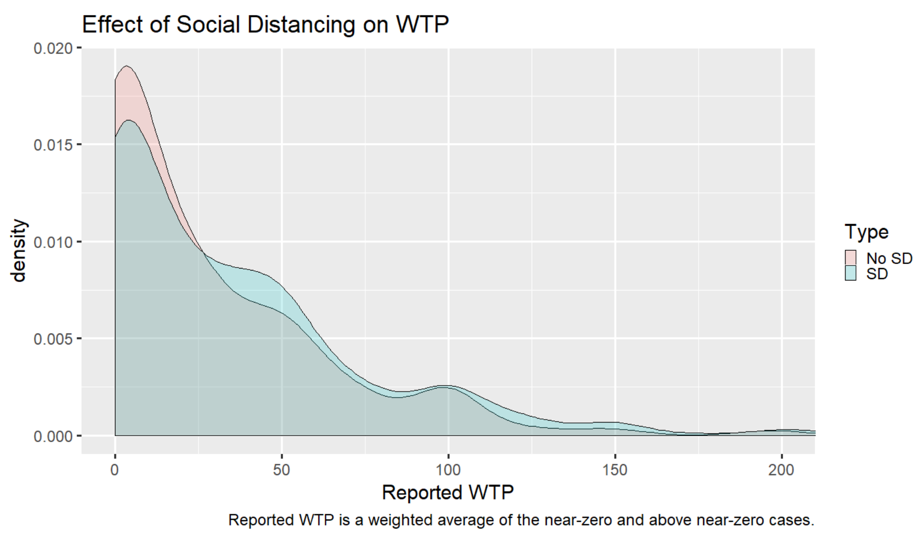


Figure 18: WTP distributions with near-zero and above near-zero levels of cases.