Selling with Demand Uncertainty

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Abstract

What are the profit- and welfare-maximizing sales strategies for a seller of perishable goods facing demand uncertainty? I use a structural model of college football ticket sales that includes primary and resale markets to evaluate three sales strategies: resale, refunds, and a menu of refunds. The optimal strategy depends on the type of demand uncertainty, specifically whether shocks are idiosyncratic or aggregate and whether all consumers face the same degree of uncertainty. The model includes three sources of uncertainty: idiosyncratic shocks and aggregate shocks that affect consumers equally and an aggregate shock that has a heterogeneous effect on consumers. I estimate the model using primary and resale market data on ticket sales as well as survey data on demand for sports tickets with covid-19. I find that using refunds rather than resale raises profit by 3% and total welfare by 1%. Both strategies are better than not reallocating, with refunds producing gains of 5.2% for profit and 6.1% for welfare. Screening with a menu of refunds substantially increases profit and welfare, with gains of roughly 20%.

1 Introduction

It is only May, but State University is selling tickets for November's big football game against State A&M. Plenty of consumers already bought tickets, but not all of them will be able to go. These tickets might not be used. Other consumers plan to buy tickets later, but will lose interest if the star quarterback gets hurt. These tickets might not

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be sold. And some want to attend, but will only go if there is a covid-19 vaccine by game day. These consumers might not purchase because it is too risky. What is the best way to sell the tickets? The challenge is demand uncertainty: consumers receive preference shocks that make the initial prices and allocation suboptimal.

In this paper, I study the profit- and welfare-maximizing sales strategies for a seller of perishable goods facing demand uncertainty. I use primary and resale market data on college football ticket sales and a survey on demand for sports with covid-19 to estimate a structural model and evaluate three strategies: allowing resale, offering a refund, and offering a menu of refunds. All three strategies reallocate tickets after shocks. With resale, consumers transact amongst themselves at flexible prices, but there are frictions like fees paid to the resale market operator. With refunds, consumers cannot resell but can return their tickets to the seller for a partial refund. The seller then sells the recovered tickets at the prices it set before shocks. With a menu of refunds, the seller offers both fully and non-refundable tickets.

The choice of sales strategy matters because reallocation can improve both profit and welfare. Prior research on perishable goods, however, has left important questions unanswered. By how much do profit and welfare change? Few empirical studies can evaluate the changes because they do not model both primary market sales and reallocation.[1] Which strategies are most effective? No empirical studies have compared resale and refunds. And does the source of demand uncertainty matter? Past studies typically consider one source of uncertainty, like independently drawn shocks or an aggregate demand shock. I show that the type of uncertainty affects the performance of each sales strategy and include several types of uncertainty in the empirical model. I find that refunds raise profit by 3% and total welfare by 1% relative to resale. Both strategies are markedly better than not reallocating, resulting in profit gains of 5.2% for refunds and 2.1% for resale as well as total welfare gains of 6.1% for refunds and 4.9% for resale.

The results inform the policy debate on the right to resell. With few exceptions, consumers have a legal right to resell goods.[2] The exceptions are largely for tickets and reservations, like live events, airlines, and hotels. A few U.S. states have removed the exception for event tickets, but sellers can generally prohibit resale and some have done so (Pender (2017)). This paper's predictions for consumer welfare have a direct bearing on the debate.

Types of uncertainty are distinguished by two properties. The first is how much the overall post-shock distribution of consumer values differs across realizations of the

[1] Leslie and Sorensen (2014) are an exception. They model both primary and resale markets, but do not consider profit because of systematic mispricing in their empirical setting.

[2] The first-sale doctrine prevents copyright holders from restricting the buyer's ability to resell in 17 U.S.C. §109.

shock. The realization matters for aggregate shocks, like a potential injury to the star player. In the realization with an injury, all consumers have lower values and the dsitribution shifts leftward. But without an injury, values do not change. In contrast, the realization hardly matters for idiosyncratic shocks, like independently drawn schedule conflicts. Different realizations imply that different consumers will have conflicts, but the distribution is essentially the same as long as there are many consumers.

The second property is whether shocks have the same effects with the same probabilities for all consumers. When they do, like if each consumer has the same chance of having a schedule conflict, then uncertainty is homogeneous. When they do not, like if some consumers are willing to pay much less for sports tickets when there is no covid-19 vaccine and others are willing to pay the same amount, it is heterogeneous.

To see why the type of uncertainty affects the choice of strategy, consider a seller of college football tickets. In the data, the seller does not change its prices and essentially sells tickets in two phases: a season ticket phase months before the season and an individual-ticket phase (including the resale market) within a month of each game.[3] Suppose that shocks are realized in the lengthy gap between the two phases.

Whether to allow resale or offer refunds depends on the first property, the variance in the post-shock distribution of values. Suppose that buyers of season tickets will not attend some games because of idiosyncratic shocks. The seller and society can benefit by reallocating the tickets to consumers who would use them through resale or refunds. The core difference is the price at which tickets are reallocated: all sales with refunds take place at the prices the seller chose before shocks were realized, but resale prices are flexible and respond to shocks. For instance, suppose that an aggregate shock lowers consumer values and the seller offers refunds. Consumers with idiosyncratic shocks will return their tickets, but new consumers will not buy them because the price is too high. Resale prices, however, would fall to reflect the shock, enabling reallocation and boosting profit and welfare. The benefits of resale, however, come at the cost of fees paid to the resale market operator and other frictions. When there is no benefit to the flexibility of resale prices, as when there are no aggregate shocks and the optimal post-shock price is predictable, refunds are more profitable and efficient.

Whether to offer a menu of refunds depends on the second property, the degree of heterogeneity in uncertainty. Heterogeneous uncertainty is necessary so that some consumers prefer each contract. In the vaccine example, consumers who would not attend the game without a vaccine are much more likely to buy a fully refundable ticket, and the seller can discriminate by offering a contract granting a full refund

[3]Single-game tickets are on sale earlier and resale tickets are constantly available, but the bulk are purchased within a month of the game.

when there is no vaccine. In this example and the empirical application, the seller's refund contracts are contingent on an observed state: whether there is a covid-19 vaccine. The state-dependent contracts let the seller implement different allocations in different states of the world, potentially boosting both profit and welfare.

The ambiguity regarding which strategy is best requires an empirical study. The market for college football tickets is a suitable setting because it features three distinct types of uncertainty. Resale reflects idiosyncratic shocks like schedule conflicts that prevent consumers from attending the game. I use official resale transaction records from StubHub to measure the extent of resale and the importance of idiosyncratic shocks. Aggregate shocks are present because resale prices for college teams vary dramatically from year to year. I measure their importance using annual resale price data for all college football teams from another resale market, SeatGeek. I model the shocks as homogeneous. The final source of uncertainty, whether there will be a covid-19 vaccine at the start of the season, is both heterogeneous and aggregate. I capture heterogeneity in consumer responses to the state with no vaccine using a survey.

Each source of uncertainty is significant. For idiosyncratic uncertainty, over 5% of all seats were resold by consumers on StubHub alone. For homogeneous aggregate uncertainty, resale prices have a 25% chance to deviate from the average by 30% or more. And for heterogeneous aggregate uncertainty, a third of consumers do not care if there is a vaccine—they would pay the same amount with or without one—while a fifth have positive values with a vaccine but would pay nothing without one.

I develop a structural model of the market for college football tickets that includes all three sources of demand uncertainty. There are two periods, with shocks realized between them. In the first, consumers decide whether to buy season tickets. In the second, each game arrives and consumers participate in an endogenous resale market. Consumers who bought season tickets decide whether to attend or resell; all other consumers decide whether to purchase tickets on the primary or resale markets. Between the two periods, consumers receive independently drawn and aggregate preference shocks. There are two aggregate shocks, a common component to values (a homogeneous shock) and a state of the world inducing heterogeneous changes in values.

I estimate the model using survey data on covid-19 and primary and resale market data on ticket sales for a large U.S. university's football team. The model predicts the quantity of season tickets sold, the quantity of single-game tickets sold in the primary and resale markets, the resale price for each game, and the difference in willingness to pay without a vaccine. I match the model's predictions to the data and incorporate aggregate uncertainty using the distribution of annual resale prices from SeatGeek.

I use the estimated model to evaluate several counterfactuals. In a baseline model without uncertainty from covid-19, I compare resale to a counterfactual in which the seller offers refunds. I also consider benchmark cases with no reallocation—neither resale nor refunds—and flexible prices. In the model with uncertainty from covid-19, I compare the performance of a menu of refunds to a single set of prices and resale. For simplicity, these counterfactuals do not include the other sources of uncertainty.[4]

The results predict that refunds are more profitable for the seller than resale, but both strategies produce similar levels of consumer and total welfare. The difference between resale and refunds is mainly due to resale frictions rather than the fees charged by the resale market operator. Results on menus of refunds with covid-19 are in progress.

Literature Review. This paper contributes to several literatures, most notably the literatures on demand uncertainty and resale. One branch of studies of demand uncertainty in industrial organization, including Kalouptsidi (2014), Jeon (2020), and Collard-Wexler (2013), focuses on how aggregate demand uncertainty affects strategic choices like investment, pricing, and entry.

In contrast, this paper considers the strategies firms use to cope with uncertainty, making it closer to studies of the airline industry in which consumers have stochastic demand. In Lazarev (2013), Williams (2020), and Aryal et al. (2018), stochastic demand affects the seller's dynamic pricing problem by changing the number of seats sold at each date. Lazarev (2013) also features individual-level uncertainty that prevents some consumers from using their tickets, as in this paper.

A branch of the management literature shares the emphasis on seller reponses to uncertainty. For example, Chen and Yano (2010) and Su (2010) consider different responses to aggregate uncertainty (offering retailers rebates and selling to brokers), while Xie and Gerstner (2007) study whether refunds are profitable when consumers have idiosyncratic preference shocks. All of these papers, however, have no empirical component. This paper differs by providing an empirical study with several strategies and sources of uncertainty.

The emphasis on uncertainty also relates to the literature on learning, such as Erdem and Keane (1996), Ching et al. (2013), and Hitsch (2006). In the learning literature, agents gather information over time about unchanging but initially uncertain parameters. This paper differs because agents receive stochastic preference shocks.

The second relevant literature concerns resale markets. A sizeable body of research considers ticket resale. Notable empirical studies include Leslie and Sorensen (2014), which studies whether resale boosts welfare in a model combining primary and resale

[4]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 permutations of the sales stratgies.

markets for concert tickets, and Lewis et al. (2019), which studies how the ability to resell boosts demand for season tickets in professional baseball. This study contributes by determining whether resale is profitable and whether it is better than alternative strategies like refunds. Although the profitability of resale is a primary concern of theoretical studies like Courty (2003) and Cui et al. (2014), it has not been evaluated empirically because few studies have built models combining primary market sales with endogenous resale markets. One study that does, Leslie and Sorensen (2014), does not consider profit because tickets are systematically underpriced in the empirical setting.

Other empirical studies of resale markets for event tickets include Sweeting (2012), Waisman (2020), and Zhu (2014). In the durable goods literature, Chen et al. (2013) find that resale is harmful for oligopolists in the market for cars.

This paper also contributes to the resale literature by comparing resale to alternative methods of reallocation. Only two studies, Cui et al. (2014) and Cachon and Feldman (2018), have compared resale and refunds. Both use theory models and find that one is always more profitable. This paper contributes by developing a model in which the choice is ambiguous and by providing empirical evidence.

The counterfactual testing a menu of refunds contributes to the literature on price discrimination. The idea of using refund contracts to screen consumers based on their uncertainty was first articulated in Courty and Li (2000). Despite significant attention in the theory literature, there is little empirical evidence estimating the returns. One study that does is Lazarev (2013), who considers airline passengers with different probabilities of schedule conflicts and calculates the benefits of offering fully and non-refundable tickets. The use of state-contingent tickets in this paper also provides an empirical application of Alexandrov and Bedre-Defolie (2014), who analyze product-state combinations as bundles.

Finally, this study considers sales strategies in a dynamic market and so relates to the literature on dynamic mechanism design. However, I do not investigate the theoretically optimal mechanisms studied in, for instance, Pavan et al. (2014) and Bergemann and Välimäki (2019). One dynamic mechanism used in resale markets for sports tickets is dynamic pricing. I do not consider dynamic pricing in this paper, but it is studied in theory by Board and Skrzypacz (2016) and Dilmé and Li (2019). Sweeting (2012) provides an empirical study of dynamic pricing in the market for event tickets.

2 Uncertainty and Sales Strategies

In this section, I present three examples illustrating the connection between types of uncertainty and sales strategies. Each example includes a different mix of the three types of uncertainty in the market—idiosyncratic, homogeneous aggregate, and heterogeneous aggregate—and implies that a different sales strategy is optimal.

There are two periods in each example. The seller can set different prices for each period, but it must commit to its menu at the start of the first period. Forward-looking consumers arrive in both periods but receive preference shocks at the start of the second period. Suppose that consumer i has willingness to pay ν_i. There are three potential shocks.

1. Independently drawn (idiosyncratic) shocks that arrive with probability ψ. Consumers who receive a shock have zero willingness to pay.
2. A homogeneous aggregate shock V that changes all consumers' willingness to pay to $\nu_i + V$.
3. A heterogeneous aggregate shock changing all consumers' willingness to pay to $\nu_i + b_i(\omega)$. The change in state ω is specific to consumer i. Possible states are $\omega \in \{\omega^B, \omega^G\}$. All consumers have $b_i(\omega^G) = 0$, and changes in state ω^B satisfy $b_i(\omega^B) \leq 0$.

The three shocks closely track the ones observed in the data. Moreover, they are modeled almost identically in the empirical model.

2.1 Only Idiosyncratic Uncertainty

Suppose that a seller has one ticket to sell to two buyers, Alice and Bob, and that there is only idiosyncratic uncertainty, $\psi = \frac{1}{5}$. 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. Bob always arrives in period two with $\nu_B = 40$. The seller optimally offers a refund $r = 5$ and sets $p_1 = 41$, $p_2 = 40$.[5] Alice finds it worthwhile to purchase the ticket despite the risk of a schedule conflict.

If Alice does not have a conflict, then total welfare is 50 and profit is 41. But if Alice does have a schedule conflict, she will return her ticket for a refund and the seller will sell the ticket on to Bob at $p_2 = 40$. In this case, the seller earns 76 in profit (a net of 36 from Alice and 40 from Bob) and total welfare is 40. Expected profit and total welfare equal 48.

What if the seller had not offered a refund, but had allowed resale? Suppose that the resale market charges a multiplicative fee $\tau = \frac{1}{10}$ on each transaction and that Alice buys the ticket in the first period. If she does not receive a shock, then total welfare is 50 as before. If she does, then she can resell to Bob at resale price 40, generating

[5] 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.

total welfare of 40. However, Alice will only receive 36 because 4 is paid to the resale market operator. The seller can thus charge Alice 50 for the state where she has no shock but only 36 for the state where she does, leading to $p_1 = 47.2$. Profit is lower than with refunds because of resale fees: the seller earned 40 when selling to Bob with refunds, but it only earns 36 when Alice resells to Bob. Total welfare is unchanged, but could be lower if resale introduces other frictions that limit reallocation.

2.2 Idiosyncratic and Homogeneous Aggregate Uncertainty

Continue to suppose that a seller has one ticket to sell to Alice and Bob, but now suppose that there is also a homogeneous aggregate shock arriving between the two periods: $V = 0$ with probability $\frac{3}{4}$, but $V = -20$ with probability $\frac{1}{4}$.

If the seller offers refunds, it will set $r = 5$, $p_1 = 37$, and $p_2 = 40$.[6] Alice is just willing to purchase the ticket. If she does not receive a shock, she uses the ticket and expected total welfare is 45. If she does receive a shock, there are now two cases. In both cases, she returns the ticket for the refund. Three quarters of the time, there is no aggregate shock and Bob is willing to buy the returned ticket for $p_2 = 40$, leaving total welfare of 40 and profit of 76. But one quarter of the time, Bob is only willing to pay 20 and refuses to buy the ticket. In this case, refunds do not reallocate the ticket because the seller's price is too high after shocks. When Bob refuses to purchase, total welfare is zero and profit is only 36. Refunds produce expected profit and welfare of 42.

Now suppose the seller allows resale and that Alice buys the ticket in period one. As before, Alice receives expected surplus of 45 when she does not have a shock. When she receives a shock, she can always resell to Bob, earning 36 when there is no aggregate shock and 18 when there is one. The key distinction between resale and refunds is that, because the resale price is flexible, Bob receives the ticket even when his value is low. Expected total welfare is 43 and the seller can charge Alice $p_1 = 42.3$, both higher than with refunds.

Resale is valuable because prices adjust to reflect aggregate shocks, but it is only more profitable when the resale fee τ is relatively low. With a higher fee, refunds could have remained more profitable despite reallocating the tickets less effectively. Similarly, if there had been significant resale frictions, total welfare could be lower with resale. The choice between resale and refunds reduces to a trade-off between aggregate uncertainty and the importance of fees and frictions in resale markets.

[6] 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.

2.3 Only Heterogeneous Aggregate Uncertainty

For the last example, consider a different setting. A seller has two tickets that will only be sold in the first period, before the realization of a heterogeneous aggregate shock. The probability of each state is $\frac{1}{2}$. Alice and Bob both enter in the first period. Alice's value is 40 both with and without the shock—her response is $b_A(\omega^B) = 0$. 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 $p = 30$ and sell both tickets, earning profit of 60. Doing so extracts all of Bob's expected surplus, but leaves 10 for Alice. Neither resale nor a refund would help because no reallocation is necessary. It could, however, separate Alice and Bob by offering refund contracts. Only Alice would buy a non-refundable ticket priced at $p^{NR} = 40$, and only Bob would buy a fully refundable ticket priced at $p^{FR} = 50$. Bob would request a refund half the time, giving the seller an expected profit of 65. The downside is that, since Bob no longer holds a ticket when his value is low, total welfare falls from 70 to 65.

It is possible for total welfare to increase. Suppose that there is a third consumer in the market, Charlie, who is identical to Alice: $\nu_C = 40$ and $b_C(\omega^B) = 0$. The seller can offer full refund contracts that depend on the realized state. Suppose that the seller offers a non-refundable price of $p^{NR} = 40$ as before (equivalent to tickets in both state), but that it offers two fully refundable tickets, with each a full refund issued in a different state. The seller can set a contract for tickets in state ω^G at price $p^{FR}(\omega^G) = 50$ for Bob and one for tickets in state ω^B at $p^{FR}(\omega^B) = 40$ for Charlie. Expected profit and total welfare rise to 85, which is better than the 80 that could be achieved without state-contingent contracts.

The use of state-contingent refund contracts is helpful when there are different optimal allocations in different states. Differences between states result from heterogeneous aggregate uncertainty. The three examples demonstrate that the type of uncertainty affects the choice between resale and refunds and the returns to using state-contingent refund contracts.

3 Data

3.1 Primary and Resale Market Data

The main source of data is transaction-level ticket sales records from primary and resale markets. The primary market records were provided by a large U.S. university and include all ticket sales for two seasons of college football and one partial season. Each transaction record indicates the number of tickets purchased, the price paid, the date of the purchase, and the seating zone. A seating zone is a group of similar seats in the stadium that share the same price, which I use as a measurement of the quality of each seat. The primary market records also indicate the type of sale, such as season tickets or promotions. The exact section, row, and seat number of each ticket is not available.

The resale transaction records come from StubHub. They contain the same fields as the primary market data, except that the transaction price is not included.

To learn about the transaction price, I supplement the transaction records with daily records of all StubHub listings for the university's football games, which I gather using a web scraper. The listings are available for two full seasons and one partial season, but the listings and official resale transactions only overlap for the one full season studied in this paper. Each listing includes a listing ID, price, number of tickets for sale, and location in the stadium (section and row).

The final set of resale market data contain average annual resale prices for 76 college football teams, which I gather 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 StubHub listing records allow me 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, defined as those that are more than 1.5 times the 75$^{\text{th}}$ percentile of price for similar quality seats. 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.

Because the data comes from only one resale market, it undercounts total resale volumes. 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)).

StubHub charges fees for transactions on its platform. StubHub's exact fee structure is not public, but buyers usually pay an additional 10% of the listing price and sellers receive 15% less than the listing price, with some discounts for large sellers. I assume that these fees apply to all buyers and resellers.

3.2 Covid-19 Survey

Data on how demand responds to covid-19 come from a survey. 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.[7] The scenarios are (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. Respondents also report their demographic information and the percent chance of each scenario in January 2021, September 2021, and January 2022. The full survey and details can be found in Appendix B.

I distributed the survey to 500 users of Prolific.co, an online distribution platform. Half of respondents were aged 50 or over, and all were compensated at $9 per hour.

4 Descriptive Evidence

4.1 Market Background

The university is a monopolist because it is the sole primary market seller of its tickets. In the season used in the analysis, it sells tickets to five home games.[8]

The university's football team plays in a stadium with roughly 50,000 seats, of which around 30,000 are available to the public. The remainder are premium seats for athletics boosters, student seats, or seats reserved for visiting team fans.

Tickets are sold in two main phases. The first phase consists of season ticket sales, which are made months before the season—80% of season tickets are bought 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 for consumers to receive preference shocks.

Most tickets are sold as season tickets. Figure 1 shows the average number of tickets sold to each game by type of sale and quality, including unsold tickets. Tickets in the "Other" category are not available to the public. Fully 75% of seats available to the public are sold as season tickets. Most of the rest are sold as single tickets or unsold. A

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

[8] 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.

Game	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
1	65	55	40	35	30
2	70	60	50	40	30
3	70	60	55	45	30
4	70	60	50	40	30
5	70	60	55	45	30
6	60	55	40	35	30
Season Tickets	375	320	250	210	150
Total Face Value	405	350	290	240	180

Table 1: Primary market prices for each game, their sum, and season ticket prices.

minuscule number are sold in mini-plans, bundles of tickets to a subset of games that I exclude from the analysis. The single ticket purchases in Figure 1 include group sales and promotions. I only consider full-price single ticket sales in the analysis because promotions and group sales are not optimally priced and may only be available to targeted groups, like veterans.[9]

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 for single game tickets and season tickets is shown in Table 1. Primary market prices vary mainly by seat quality. Tickets in zone 1 cost \$60–\$70 depending on the game, but zone 5 tickets sell for \$30 apiece in all games. Season tickets are \$30–\$40 cheaper than buying primary market tickets to each game. Prices vary slightly across games, but never by more than \$10.

4.2 Resale Markets

Resale is a notable feature of the market. Figure 2 shows the percentage of all tickets in each zone that are resold. The resale rate exceeds 10% in zones 1 and 2 and the average resale rate in the market is 8.7%.

The prevalence of resale reflects the need for reallocation: many consumers holding tickets value them less than others. The degree of resale suggests that idiosyncratic shocks are important. Moreover, the concentration of resale in zones 1 and 2 suggests that season ticket holders, who disproportionately purchase tickets in those zones, are responsible for resale. This is consistent with the idea that season ticket holders receive

[9] 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.

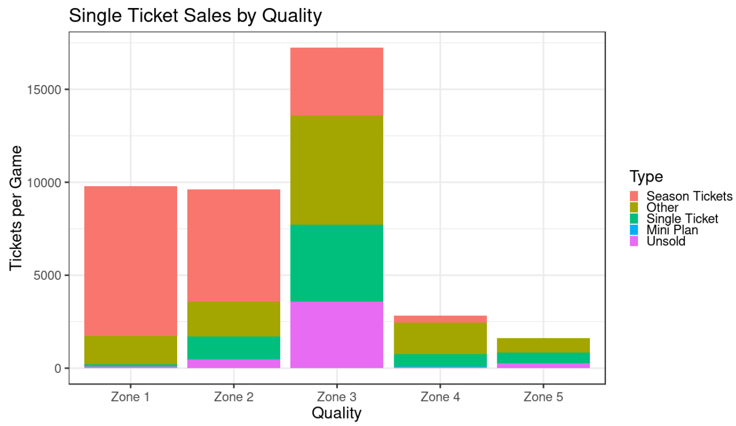


Figure 1: Sale types and volumes by quality group.

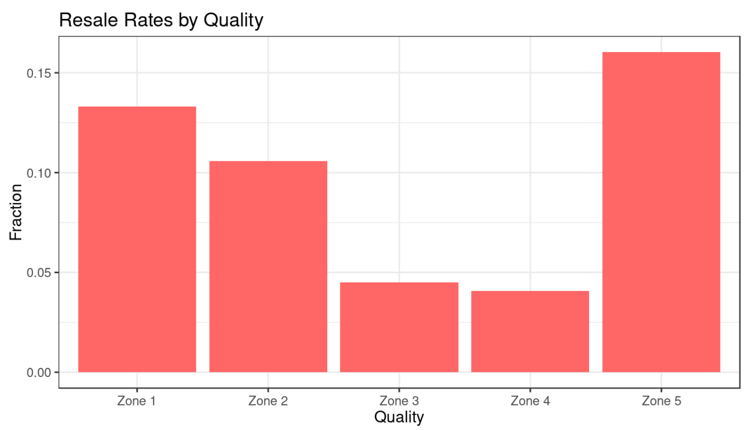


Figure 2: Resale rates in each quality. Rate is defined as total tickets resold on StubHub divided by total tickets sold in the primary market.

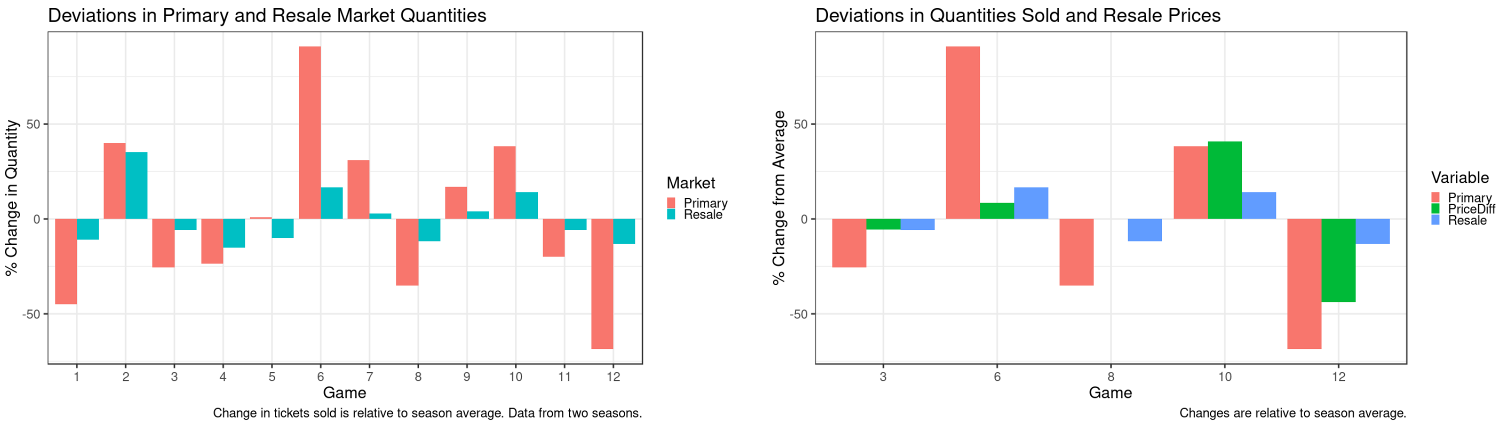
idiosyncratic shocks between the time of purchase and the game. The data, however, do not indicate who resells each ticket.

Two features of resale markets affect the seller's choice of sales strategy. The first is the level of fees on the resale market, which limit the monopolist's ability to profit from resale. StubHub charges buyers a fee of 15% of the advertised price and sellers a fee of 10%. For the median ticket resold in zone 1, the fee is more than $10.

The second feature is that resale prices are flexible. It is impossible to show a direct response of resale prices to shocks because shocks are not directly observed. Instead, I present evidence that resale prices adjust to reflect demand.

Figure 3 shows the percent change from the season average for each game for the quantity of tickets sold and resale prices. The left panel includes two seasons for quantity changes only; the right panel includes a subset of games for which resale price changes are available. The figure suggests that resale prices are flexible because the changes in resale prices in the right panel are in the same direction as changes in primary market quantities sold. Further, the quantities sold in the primary market are far more volatile than those in the resale market, which is consistent with resale prices adjusting to reflect demand.

Figure 4 provides additional evidence of price flexibility. It shows that the distribution of face values is much less dispersed than that of average per-game resale prices. The difference between the distributions suggests that primary market prices are not optimal for realized demand and that resale prices adjust to reflect demand.



(a) (b)

Figure 3: Percent deviation from season-average quantities sold for each game (both panels), and percent deviation from season-average resale prices (right panel).

4.3 Annual Price Changes

Annual price changes for each team provide evidence of aggregate shocks. Using SeatGeek's records of average annual resale prices, I define the normalized price for univer-

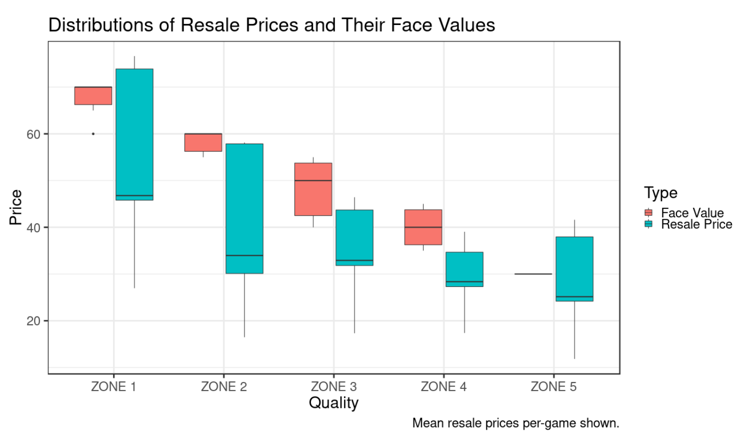


Figure 4: Distributions of mean per-game resale prices and face value.

sity u in year y as

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

where Y denotes the number of years in the sample. Figure 5 shows the distribution of normalized prices for a random sample of 20 universities. The distributions demonstrate that within-university price variation is significant and ubiquitous. All but one university has a season where prices are 25% above the sample mean, and most have a season where prices are 25% below. There are several changes of 50% or more.

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

Combining the distributions for all 76 teams in the data and adjusting for annual time trends give the distribution in Figure 6. The distribution is approximately normal and has an estimated standard deviation of .25, implying that there is a roughly one-third chance that prices in any given season will be more than 25% away from the mean.

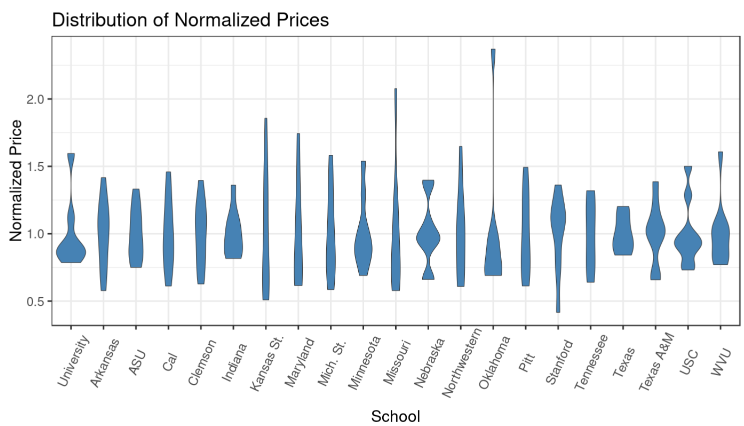


Figure 5: Distribution of average annual resale prices (normalized by school mean) for a random sample of 20 schools in similar conferences.

4.4 Covid-19 Survey

Figure 7 shows the distribution of reported willingness to pay (WTP) in the survey in three scenarios without social distancing. There is significant variation in how much respondents will pay for college football tickets, with many reporting WTP of $100 or more in the 2019 season.

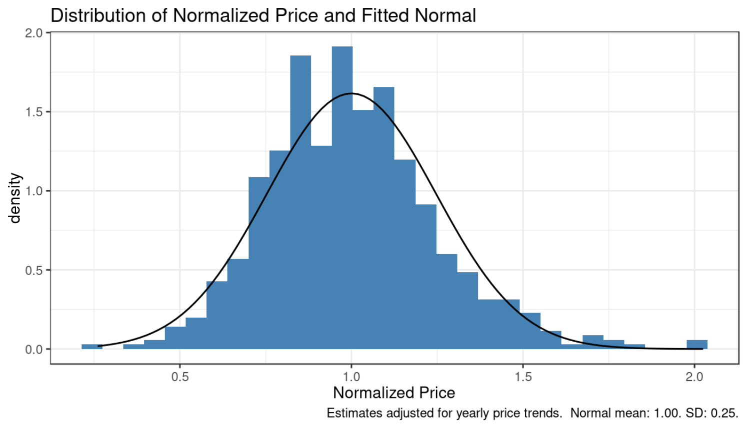


Figure 6: Distribution of resale prices normalized by team-mean in the sample. Adjusted for yearly trends. From SeatGeek annual average resale prices (76 teams, 576 team-seasons).

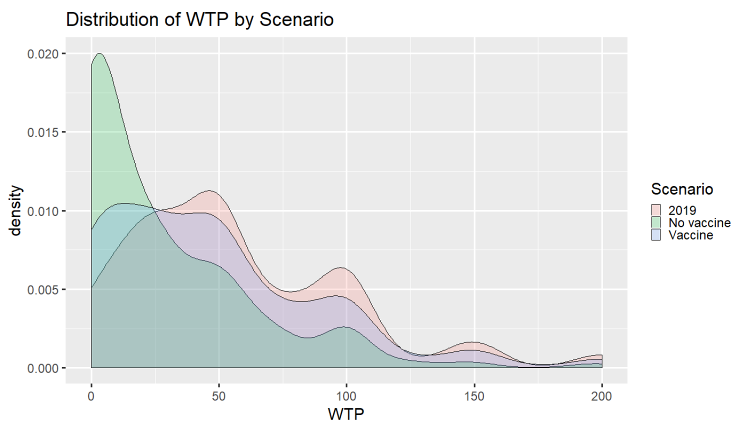


Figure 7: Distribution of reported willingness to pay without social distancing in 2019, with a vaccine, and with no vaccine.

As expected, WTP is highest for the 2019 scenario. Consumers report somewhat lower WTP even if there is a covid-19 vaccine and WTP falls markedly in the case where there is no vaccine. Many consumers, however, are still willing to pay $50 or more if there is no vaccine.

For evidence on individuals' changes in WTP across states, consider Figure 8. The figure shows the joint distribution of WTP with a vaccine and the change in WTP if there is no vaccine. There is ample variation in both variables. Many consumers report WTP over $50, and some consumers report small changes in WTP at each level of WTP. The lower triangle is empty because the change in WTP cannot exceed reported WTP.

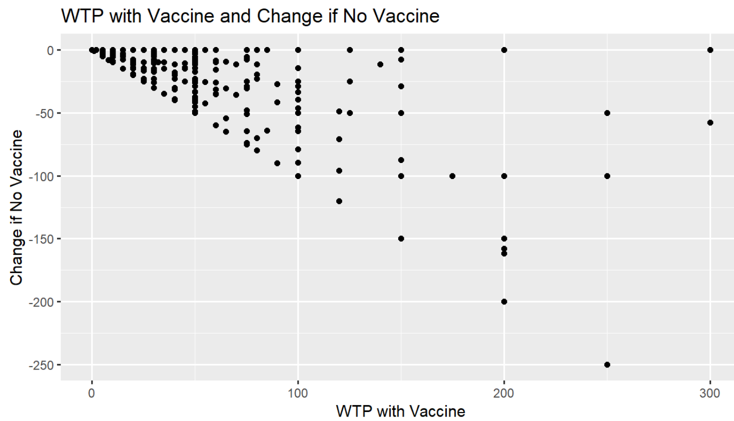


Figure 8: Scatterplot of reported willingness to pay with a vaccine and change in willingness to pay if there is no vaccine.

5 Model

5.1 Outline, Utility, and Uncertainty

Let i index consumers and j index games. A monopolist seller has capacity K_q for each of q seat qualities and sells tickets over two periods, $t = 1, 2$. In period one, it only sells season tickets, and in period two, it only sells single-game tickets. A state of the world ω is realized between the first and second periods. In the baseline model without uncertainty from covid-19, the state is always ω^{BL}. When there is uncertainty from covid-19, the state is ω^{V} if there is a vaccine and ω^{NV} if there is not.

The seller offers a season ticket bundle containing tickets of quality q to each game at price p_{Bq} and a single-game ticket of quality q to game j at price p_{jq}. The seller commits to a menu of season ticket prices and single-game ticket prices at the start of the first period and cannot change it afterwards.

There are N consumers who each 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 and, if so, whether to buy in the primary or secondary market.

The model outline is depicted in Figure 9. The bottom half depicts one game j but occurs for all J games.

Consumer i's utility for a ticket of quality q to game j is measured in dollars and takes the form

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

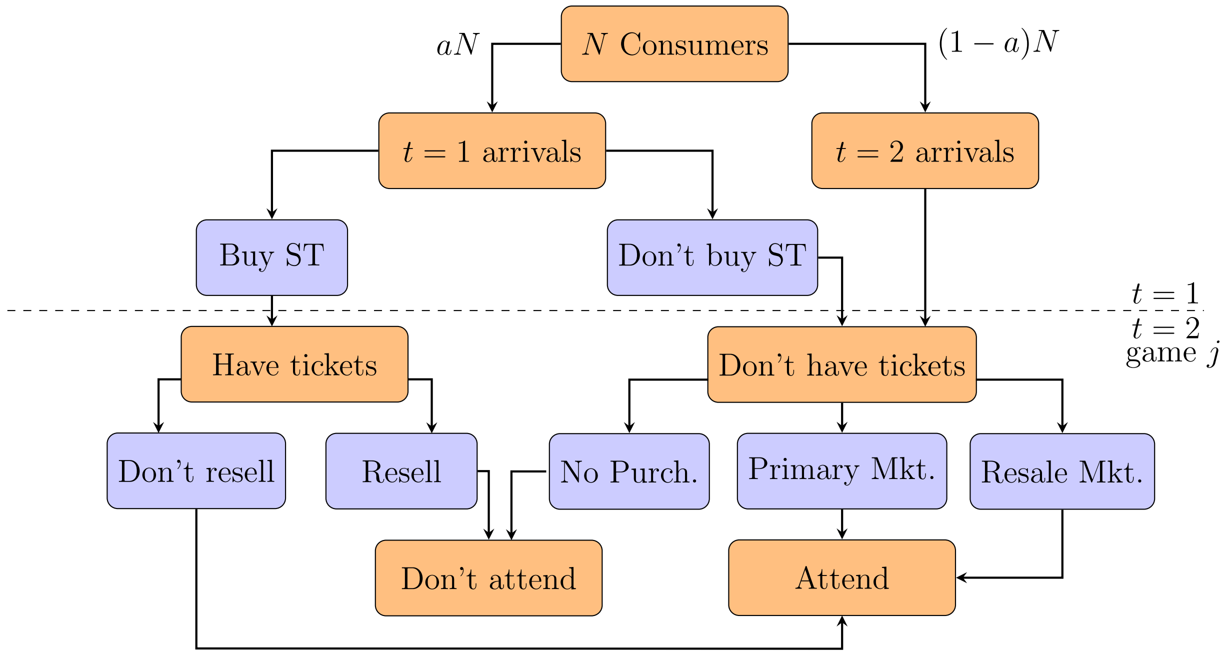


Figure 9: Model outline for consumer arrivals and choices. Decisions are shown in blue.

The utility of the outside option is normalized to zero. Consumer i's utility can be broken into a base utility for tickets of quality q, given by the term in parentheses, and a game-specific component α_j that allows values to vary across games. The base utility term depends on a random draw V that affects all consumers, the consumer's taste for football games ν_i, the quality q of the seats,[10] and the consumer's response to the state of the world ω. Consumer taste parameters are distributed according to $\nu_i \sim Exp(\lambda_\nu)$.

There are three sources of uncertainty, all of which are realized between the first and second periods. The first is an idiosyncratic preference shock. Consumers receive independently drawn shocks for each game with probability ψ, and any consumer receiving a shock for game j has zero utility for that game. The idiosyncratic shock captures anything that affects one consumer's value without affecting the average value, such as schedule conflicts.

The second is a homogeneous aggregate shock. There is a single draw $V \sim N(0, \sigma_V^2)$ for the season that has the same effect on all consumers' willingness to pay in equation (2). I refer to V as the common value. It captures changes (aside from the vaccine state) that affect annual aggregate demand for tickets, like team performance. There is only one draw of V per season and it affects all games.

[10] All consumers share the same quality preferences to simplify estimation. The simplification is necessary for computation because it converts a Q-dimensional search for resale prices to a one-dimensional search. Resale prices are calculated thousands of times in estimation.

The third is a heterogeneous aggregate shock that varies with the realized state and enters utility as $b_i(\omega)$ in equation (2). The shock only applies to uncertainty from covid-19. Consumers experience no change if there is a vaccine, but they are willing to pay weakly less if there is no vaccine: $b_i(\omega^V) = 0, b_i(\omega^{NV}) \leq 0$. Realizations when there is no vaccine are heterogeneous and independent of ν_i.[11] Without risk from covid-19, the only state is ω^{BL} and all consumers have $b_i(\omega^{BL}) = 0$.

5.2 Period Two

At the start of period two, consumers know 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 and all other consumers decide whether to purchase tickets in the primary or resale markets. Resale prices are noted by $p^r_{jq}(V, \omega)$ because post-shock consumer values affect the resale price.

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

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

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

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

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

Surplus from each option is

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

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

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

The equilibrium resale price $p^r_{jq}(V, \omega)$ makes the number of consumers willing to

[11] There is no correlation between reported WTP with a vaccine and the percent change in valuation from the vaccine to the no vaccine state. The lack of correlation is evident in Figure 8.

resell tickets of quality q, determined in equation (3), equal to the number of consumers who demand a ticket of quality q on the resale market.

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

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

But some tickets might sell out, leaving the consumer unable to acquire his preferred option. Stock-outs are possible in equilibrium; a high realized value V would make primary market tickets underpriced. I assume that tickets are rationed randomly. Let the probability of receiving a primary market ticket of quality q to game j be $\sigma_{jq}(V, \omega)$. (There is no rationing on the resale market because resale prices adjust.) 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. The process continues until they receive a ticket or all tickets are sold.

5.3 Period One

In period one, aN consumers know their type $(\nu_i, b_i(\omega^{NV}))$ and decide whether to buy season tickets.[12] 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

[12] In this section, I only consider the traditional season ticket package with resale markets. I modify the decision rules to reflect refunds and alternative contracts in Section 7.

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

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

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

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. Consumers anticipate a set of resale prices $\{p^r_{jq}(V,\omega)\}$ and primary market purchase probabilities $\{\sigma_{jq}(V,\omega)\}$. The market is in equilibrium when consumer choices in the first period are consistent with the expectations and the expected prices and probabilities are realized in the second period.

6 Estimation and Results

There are two steps 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. The sales data predates the covid-19 epidemic, so I assume that the realized state is ω^{BL} and that $b_i(\omega^{BL}) = 0$ when using the sales data.

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.[13]

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

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,

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

where X_k includes the number of tickets in the transaction and the number of days until the game. (For a full discussion of how these factors affect price, see Sweeting (2012).)

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. Under mild assumptions, the resale price is approximately linear in consumers' attendance values.[14] Consequently, I estimate α_j and γ_q using the reduced form

$$p^r_{jqk} = \alpha_j(\beta_0 + \gamma_q + X_k\beta). \tag{13}$$

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

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

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

[14]The assumptions are that the supply of tickets to the resale market does not change and that resale prices are below primary market prices. The first assumption holds in equilibrium and the second is true in the data.

quality zones 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 6. 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. Details can be found in Appendix A.

The variance is identified by the year-to-year variation in resale prices for the average college football team. The normalized prices used to estimate σ_V^2 come entirely from within-team variation and so reflect within-team variation in annual resale prices.

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 the weather, but it could exaggerate if some part of the year-to-year change is predictable. Second, shocks to common values pass through linearly to resale prices. This is the same assumption used to estimate α_j and γ_q in equation (13). And third, the university faces the same shocks to normalized prices as all other schools. This is plausible based on the distributions in Figure 5.

The last parameters estimated in the first stage define the effect of covid-19 on preferences. The survey asks consumers about WTP in three scenarios, each with and without social distancing. Consumers reported similar WTP in the two scenarios without a vaccine, so I combine them into a single no-vaccine state. Social distancing also does not significantly affect consumer values, so I only consider reported WTP without it. See Appendix B 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. (The normalization excludes a state in which there is no attendance at sporting events.)

There are two necessary adjustments for consumer preferences. The first is to find the function $b_i(\omega^{NV})$ describing the change in WTP from the vaccine to the no vaccine state. The second is to find the analogous function $b_i(\omega^{V})$ describing the change from the 2019 benchmark (ω^{BL}) to the vaccine state. The second adjustment is necessary because the estimated distribution of values reflects a typical year, but 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 $\bar{\alpha}$, which is an average of the estimated α_j. The change in consumer i's

WTP from state ω to state ω' is

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

I further assume that $b_i(\omega')$ follows the parametric form

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

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

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

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

$$\left(\text{WTP}_i(\omega) - \text{WTP}_i(\omega')\right)/\bar{\alpha} = \begin{cases} 0 & \text{w.p. } \rho_1^{NV} \\ \min\{\text{WTP}_i(\omega)/\bar{\alpha}, \tilde{b}_i\} & \text{otherwise.} \end{cases} \tag{16}$$

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 values. I estimate them using the method of simulated moments. In model simulations, I assume that there are 200,000 consumers who demand up to one ticket and weight moments by their inverse variances. Details are in Appendix A.

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 on the resale market, which is parameterized by λ_s. In the model, consumers purchase in the primary market if the primary market price is less than the sum of the resale price and the cost of resale. For instance, if the resale price is \$5 less than the primary market price, any consumer with $s > 5$ prefers the primary market. The distribution of s determines the number of consumers with $s > 5$ and 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 the solution to a fixed-point problem: consumers must have correct expectations for resale prices and primary market purchase probabilities as a function of V. Estimation is computationally challenging because it requires the solution to a fixed point problem for each set of candidate parameters. Moreover, each iteration of each fixed-point search requires a solution for resale prices for every realization of V.

I use several simplifications to make estimation feasible. First, homogeneous quality preferences reduce the search for resale prices to a one dimensional. Second, I discretize continuous variables. Consumer types and resale prices are both assumed to be a grid representing 100 evenly-spaced quantiles. Under these assumptions, iterating to find equilibrium expectations remains difficult: expectations for resale prices and primary market purchase probabilities vary by realization of V and game, giving two $100 \times J$ matrices.

6.3 Results and Fit

Estimated parameters are in Tables 2 and 5. The resale fee is about 22% of the price paid by the buyer.[15] The idiosyncratic shock rate suggests that 8% of buyers change their minds about attending the event between the first and second periods. The fraction of consumers arriving in the first period, a, is calibrated to 77%, indicating that most consumers consider whether to buy season tickets.

Consumer values vary widely across games and qualities. I normalize $\alpha_1 = 1$ and $\gamma_1 = 0$. The best game, game 2, has attendance values 67% higher than those for

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

the 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.

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

State probabilities and parameters governing preference changes across vaccine states are contained in Tables 3 and 4. 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, only 29% of consumers report no change in values. The remaining consumers again report a significant change in WTP, with a mean of \$52.27. For proof of the fit of the model, see Figure 12 in Appendix A.

In the second stage, the friction associated with resale market purchases is substantial, with an average of \$56.68. The realized frictions for resale buyers, however, are modest. 66% of resale purchases involve a friction of \$10 or less. The full distribution of realized costs is shown as Figure 13 in Appendix A.

The mean of the distribution of consumer types is 16.04, suggesting that the average consumer would pay \$16.04 for the worst seats to the baseline game in an average season. Finally, the benefits of season tickets are estimated to be \$30.00, suggesting that the convenience and perks of season tickets outweigh diminishing marginal returns.

Table 6 and Figures 10 and 11 assess the model fit. The model-implied number of season tickets purchased is within 12% of the true value and simulated resale prices match the data in both levels and in variation across games. The same is true of simulated primary market quantities, although the fit is a bit looser.

7 Counterfactuals

I use the structural estimates to evaluate several counterfactual policies. The central counterfactuals are to consider refunds and a menu of refunds, but I also consider benchmark cases with no reallocation and refunds with flexible prices.

7.1 Benchmarks: No Reallocation and Flexible Prices

Start with counterfactuals that provide a benchmark for the focal sales strategies. With no reallocation, the university prohibits resale and does not offer refunds. The comparison is useful because it measures the total effect of resale on profit and welfare,

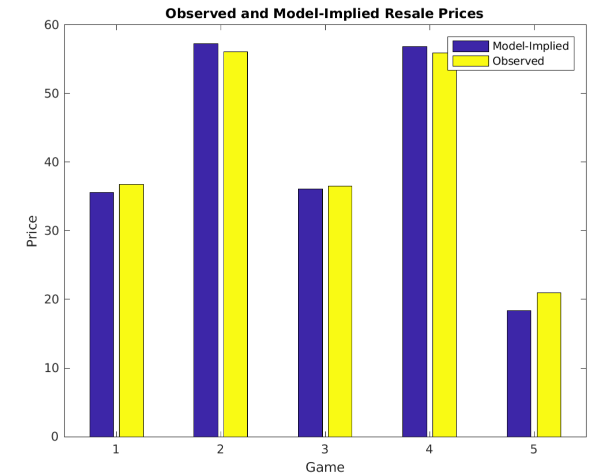


Figure 10: Observed and model-implied resale prices for each game.

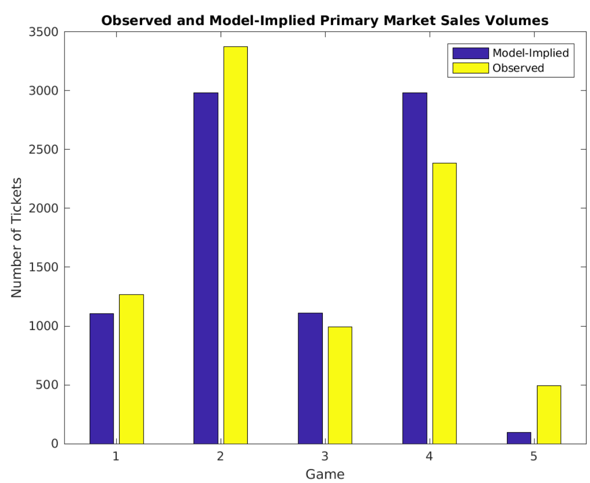


Figure 11: Observed and model-implied primary market quantities sold.

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

which is a fundamental concern of the theoretical literature (e.g. Courty (2003), Cui et al. (2014)). Empirical studies have not provided estimates in perishable goods markets that account for substitution between primary and resale markets: the only prior study with a full interaction between the two is Leslie and Sorensen (2014), which does not consider profit because tickets are systematically underpriced in their setting.

To evaluate the model without reallocation, I fix expected resale prices at zero and assign each consumer zero utility from the resale market. Consumers who buy season tickets and have idiosyncratic shocks neither use nor reallocate them, and all other consumers can only buy tickets in the primary market. The university maximizes profit by optimally selecting its price p_{Bq} and p_{jq}.

A second useful benchmark is to consider refunds if the seller adjusted its prices after shocks, eliminating the advantage of resale over refunds. I implement the counterfactual by assuming that the seller sets a partial refund r and changes the single-game ticket price for game j by $\alpha_j V$. The counterfactual is useful because it measures the reduction in profit from the seller's sticky prices.

Table 4: Estimated preference change parameters.

Parameter	Value	Std. Err
ρ_1^{NV}	0.29	0.02
ρ_2^{NV}	52.27	4.39
ρ_1^{V}	0.60	0.02
ρ_2^{V}	43.20	4.56

Table 5: Estimated parameters from the second stage.

Parameter Description	Notation	Estimate	Standard Error
Mean Resale Friction	λ_s	56.68	1.77
Mean Consumer Type	λ_ν	16.04	0.01
Mean ST Benefits	δ	30.00	0.26

7.2 Refunds

To implement refunds in the model, I close down the resale market and have consumers with idiosyncratic shocks return their tickets to the seller. The exact level of the refund cannot be determined—all refunds are equally profitable as long as consumers only request refunds when they receive idiosyncratic shocks.[16]

7.3 Menu of Refunds

The final sales strategy is only considered for the covid-19 application with two states of the world, ω^V and ω^{NV}. The seller offers three types of state-dependent season ticket contracts: a non-refundable package sold at $\{p_{Bq}^{NR}\}$ granting consumers tickets in both realized states ω^V and ω^{NV}, a fully refundable package sold at $\{p_{Bq}^{FR}(\omega^V)\}$ granting consumers tickets in the vaccine state ω^V, and another fully refundable package sold at $\{p_{Bq}^{FR}(\omega^{NV})\}$ granting consumers tickets in the no vaccine state ω^{NV}. The seller continues to offer single-game tickets, which are sold at prices $\{p_{jq}\}$ in both states.

In the counterfactual, I remove uncertainty from idiosyncratic shocks and the common value, $\psi = 0$ and $\sigma_V^2 = 0$. Although the added uncertainty is important for the seller's problem, it is not crucial for measuring the returns to screening on uncertainty, which is the objective of the counterfactual.[17] To implement the counterfactual, I use

[16]To see why, consider that consumers are risk neutral and receive idiosyncratic shocks with probability ψ. As long as they do not request refunds because they have low values, a refund of r increases willingness to pay for tickets by ψr. The seller can raise the price by ψr, but will pay out r to the fraction ψ of consumers who need a refund, making profit invariant to the level of the refund.

[17]With all forms of uncertainty, the seller would also need to choose between resale and refunds for consumers who get tickets and then receive idiosyncratic shocks. Focusing solely on uncertainty from covid-19 avoids the complication.

Table 6: Observed and model-implied quantities of season tickets.

Moment	Model-Implied	Observed
Season Tickets Sold	25262	22471

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, I let consumers consider choose between the contracts.

I compare the performance of the menu of refunds to resale markets and not allowing reallocation. The case without reallocation provides a benchmark for the benefits of price discrimination, adding new empirical evidence related to Courty and Li (2000) and Alexandrov and Bedre-Defolie (2014). The comparison to resale allows the allocation of tickets to vary across states, but incurs fees and frictions as before. The performance of resale is important because it is the option ticket sellers are most likely to select for the coming season.

7.4 Counterfactual Estimates

Results for the baseline model without uncertainty from covid-19 are shown in Table 7. The results suggest that refunds are the most profitable strategy when there is no heterogeneous uncertainty. Profit is 3% higher with refunds than with resale, and 5.2% higher than with no reallocation. The difference between resale and refunds is not a result of the fees charged in the resale market. Fees only explain 41% of the gap between profit with refunds and resale, implying that the frictions associated with purchasing on the resale market are substantial.

The two strategies produce similar levels of surplus. Refunds also maximize total surplus, but it is only better than resale by 1%. Similarly, resale produces higher consumer surplus, but the advantage is only 1.2%. Both strategies produce significant gains relative to no reallocation. The gains in total welfare are 4.9% for resale and 6.1% for refunds. For consumer welfare, it is 9.2% for resale and 7.8% for refunds. The results are in the same range as the estimates in Leslie and Sorensen (2014), which pin the total welfare increase due to resale at 2.9%.

The patterns in season ticket volumes are unsurprising. The seller chooses to sell more season ticket packages for strategies that reallocate more profitably, in this case refunds and flexible prices. By contrast, when it cannot reallocate or when there are fees and frictions associated with reallocation, it chooses to sell fewer packages.

As expected, the counterfactual with flexible prices is more profitable than all other strategies. However, the gains relative to refunds are relatively small: 1.4% for profit, 1.1% for total welfare, and 0.8% for consumer welfare. The results suggest that aggregate uncertainty does not significantly reduce the profitability or efficiency of reallocation with refunds.

Results for the screening application are in Table 8. State-based refunds deliver significant increases in profit and total welfare compared to the counterfactual with no reallocation. Profit increases by 23.9% and total surplus increases by 16.8%, but consumer surplus falls by 7.2%.

	Resale	Refunds	Flex. Prices	No Reall.
Profit (mn)	7.25	7.47	7.58	7.10
Consumer Surplus (mn)	2.49	2.46	2.48	2.28
Total Surplus (mn)	9.83	9.94	10.05	9.37
Resale Fees (mn)	0.09	0.00	0.00	0.00
Season Ticket Buyers (1000)	23.82	26.98	26.98	23.82
Season Ticket Base Price	33.60	30.84	30.90	32.53
Single Game Base Price	34.78	39.59	41.30	37.59

Table 7: Counterfactual results for the baseline model.

	No Reall.	Full Refunds
Profit (mn)	5.89	7.12
Consumer Surplus (mn)	1.81	2.12
Total Surplus (mn)	7.70	9.24
Resale Fees (mn)	0.00	0.00
Non-Refund. S. Tix (1000)	13.16	0.00
Vaccine S. Tix (1000)	0.00	11.79
No Vaccine S. Tix (1000)	0.00	14.02

Table 8: Counterfactual results for the model with different states of the world.

8 Conclusion

Demand uncertainty poses a serious challenge for sellers, who find their initial prices suboptimal and early sales misallocated. Both sellers and society benefit from sales strategies that cope with uncertainty, and the type of demand uncertainty affects the performance of each strategy. I estimated a structural model that captures salient sources of uncertainty in the market for college football tickets and used it to evaluate each strategy.

The results suggest that refunds, rather than the status quo of resale, maximize profit and welfare. Profit is 3% higher with refunds than with resale, and total welfare is 1% higher. The difference in welfare between refunds and resale suggests that the method of reallocation is not pivotal. Reallocating, however, is hugely valuable. Compared to offering no method of reallocation, resale increases total welfare by 4.9% and consumer welfare by 9.2%. For refunds, the figures are 6.1% and 7.9%.

The counterfactual results have implications for policies on ticket resale. Guaranteeing that consumers can resell tickets hardly benefits consumers if the alternative is a refund, but the benefits are significant if the seller would not otherwise permit reallocation.

The application to covid-19, using novel survey data, provides rare empirical estimates for the value of sequential screening. These results are not yet finished.

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A Estimation Details

A.1 Distribution of V

Let p_{ht} be the average annual resale price for university h in season t and let $\bar{p}_h$ be the average for university h across seasons. The basis for estimating the distribution of V is the distribution of prices p_{ht}, normalized by the university average $\bar{p}_h$ and adjusted for time trends. Specifically, the distribution of V is based on residuals from the regression

$$p_{ht}/\bar{p}_h = \beta_t Season_t + \varepsilon_{ht}. \tag{17}$$

The residuals form the distribution in Figure 6, 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.

The distribution must also be adjusted for the game-specific parameters α_j before it is possible to recover σ_V^2. Observed changes in resale prices are due to changes in utility, and changes ΔV in the common value produce changes of $\alpha_j \Delta V$ in utility. 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,

$$\bar{p}_h - p_{jt} = \sum_j w_{jt} \alpha_j V_t \tag{18}$$

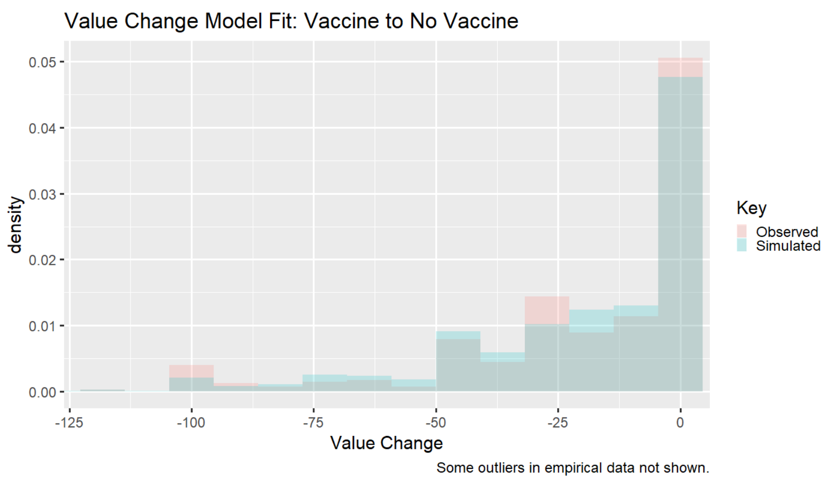
$$(\bar{p}_h - p_{jt}) \left(\sum_j w_{jt} \alpha_j \right)^{-1} = V_t, \tag{19}$$

where the vector w_{jt} 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 taking an average of all transactions on their platform and weight the α_j parameters by number of resale transactions. The exact manner of weighting does not strongly affect results: the sum is 1.15 with weighting and 1.11 without. The resulting standard deviations are 8.25 with weighting and 8.56 without.

A.2 Covid-19 Demand

The application to covid-19 requires two distributions of values, if there is and is not a vaccine, and the transition between them. The second stage of estimation produces a distribution of consumer values parameterized by λ_ν, but those values are derived for a normal year. In the survey results, consumer demand with a vaccine is lower than

(a)



(b)

Figure 12: 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.

in a normal year, requiring a three-step procedure. First, I use the survey results to transform demand in a normal year (2019 in the survey) to demand with a covid-19 vaccine. Second, I again use survey results to transform consumer types with a vaccine to types without one.

A.3 Weights

The weight matrix used in the second stage of estimation has moment variances on the diagonal and zeros elsewhere. Although the inverse covariance matrix is asymptotically optimal for GMM, I am unable to recover the covariances of most estimation moments. The reason is that moments come from separate data sets, as with resale prices and primary market quantities, making it impossible to draw a sample that reveals how they covary. 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. Instead, I assume the covariances are equal, resulting in a weight matrix that is consistent but not asymptotically optimal.

I calculate the variance of each moment using a 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 take bootstrap samples of N_j draws and take the variance of the sample averages as the variance for game j.

Calculating the variance is less straightforward for season ticket and primary market quantities because decisions to not purchase are unobserved. I recover the variance by supposing that there are M total consumers and, for each bootstrap sample, taking a random sample of M Bernoulli draws. The success probability for each draw is 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,

$$M\frac{N_j}{M}(1-\frac{N_j}{M}). \tag{20}$$

The only dependence on M in the result is in the last term. The dependence, however, is mild because any reasonable value of M is large relative to the quantity purchased, leaving the last term close to one. The result is that the variance is robust to different values of M.

Moment variances are presented in Table 9.

Table 9: Variance of estimation moments.

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

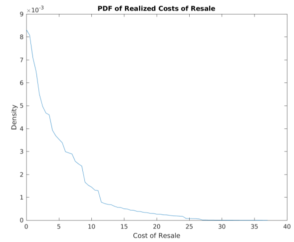


Figure 13: Realized costs of resale for resale buyers in equilibrium.

A.4 Standard Errors

Standard errors 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. I calculate the standard error as the standard deviation of the set of 50 optimal parameters. I construct 95% confidence intervals by multiplying the standard errors by the relevant quantiles of the normal.

B Covid-19 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 came from 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.

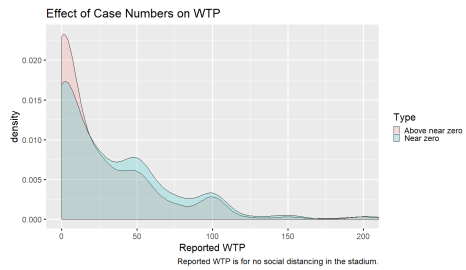
The survey refers to the CDC's benchmark for the number of new cases to be near zero, which is 0.7 new cases per 100,000 people. Respondents were given the benchmark and a practical illustration, that a 25,000-seat stadium filled with randomly selected people would contain an average of 2.5 sick people 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.

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 14. Respondents do not expect a vaccine in January 2021, but think the chances exceed 40% in September 2021 and 60% in January 2022.

Figure 15 shows that the distribution of reported WTP is similar for the near-zero and above near-zero scenarios.[18] The distributions are not exactly the same—

[18]The figure shows reported WTP without social distancing. The analogous figure with social distancing

consumers are more reluctant to attend when there are more cases—but the differences are small enough for the two to be consolidated into a single state without a vaccine. I consolidate WTP as a weighted average, taking the relative probability of the states in September 2021 as the weights.



(a)

Figure 15: WTP distributions with near-zero and above near-zero levels of cases.

Figure 16 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.

The full survey is included below.

is similar.

Event Expectations (General)

Start of Block: Intro

Q1 This study is conducted by [redacted].

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 [redacted]. For questions about your rights as a participant contact the [redacted] Institutional Review Board at [redacted].

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

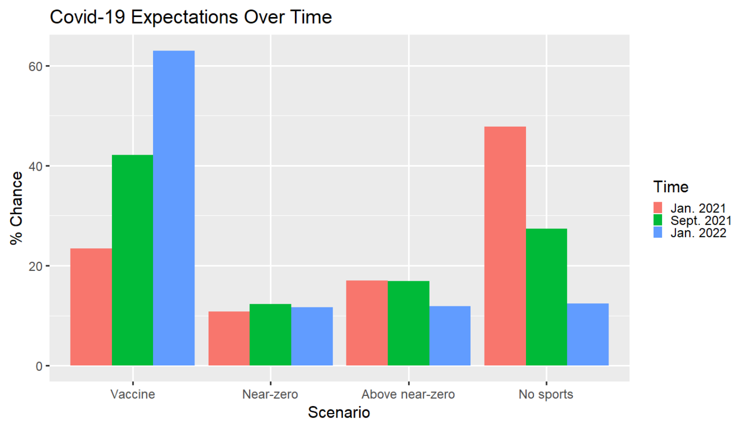
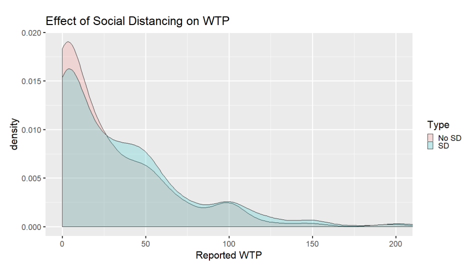


Figure 14: Average reported percent chance of each scenario occurring in each month.



(a)

Figure 16: WTP distributions with near-zero and above near-zero levels of cases.