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

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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, partial refunds, and a menu of state-dependent refund contracts. The optimal strategy depends on the properties of demand uncertainty, specifically whether shocks are idiosyncratic or aggregate and whether changes in consumer values across states of the world are heterogeneous. The model includes shocks with each property. I estimate the model using ticket sales data covering nearly 40,000 primary market transactions and over 6,000 resale market transactions, data on 576 annual resale prices for 76 college football teams, and 500 survey responses on willingness to pay for football tickets in states with and without a covid-19 vaccine. The data demonstrate that consumer values change after shocks: over 5% of all tickets are resold and resale prices often deviate by more than 25% from the average. Moreover, consumers have heterogeneous reactions to the state with no vaccine: almost a third report the same willingness to pay without a vaccine, but a fifth are willing to pay nothing without one. I find that partial refunds raise profit and total welfare relative to resale by 3.6% and 1.3%, but resale is better than not reallocating, improving profit by 1.8% and consumer welfare by 10.1%. When there is uncertainty from covid-19, state-dependent refund contracts substantially increase profit and welfare relative to not reallocating, boosting profit and total welfare by 10.3% and 7.7%.

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1 Introduction

It is only May, but fans of State U are already making plans for November's big football game against State A&M. Many of them have purchased tickets, but their values for using them can change. Some will have schedule conflicts that prevent them from attending. Others will be less interested if State U's star quarterback gets injured. And some will refuse to attend if a covid-19 vaccine is not widely distributed by game day. When demand is uncertain, what is the best way to allocate the tickets?

In this paper, I study the profit- and welfare-maximizing sales strategies for a seller of perishable goods facing demand uncertainty. As in the market for football tickets, the core problem is that the optimal price and allocation change after consumers receive preference shocks. I consider the performance of three sales strategies that reallocate after shocks: allowing resale, offering a partial refund, and offering a menu of refunds.

Each strategy is widely used. Sports teams and other sellers of event tickets allow resale but do not offer refunds; airlines and hotels offer refundable reservations but prohibit resale. However, we have little understanding of when each strategy is optimal. The decision to allow resale is particularly puzzling because resale platforms (e.g. StubHub) collect over 20% of the resale price as fees. Why do ticket sellers surrender so much of the gains from reallocation when they could avoid fees by using refunds?

I show that the optimal strategy depends on the properties of demand uncertainty, like whether shocks are idiosyncratic or aggregate. Despite fees, resale can be optimal when the optimal price after shocks is uncertain. A menu of refunds is valuable when the efficient allocation depends on observable states. I quantify the performance of each strategy in the market for college football tickets. Using ticket sales data covering the primary and resale markets and survey data on demand for tickets with and without a covid-19 vaccine, I develop and estimate a structural model of ticket sales in which consumers anticipate shocks and participate in resale markets. The model allows me to evaluate partial refunds and a menu of refunds in counterfactual experiments.

The analysis applies to a wide range of goods, including reservations (event tickets, airlines, hotels, rental cars, etc.), seasonal goods (fashion), and unreleased goods for which consumers pay deposits (cars). The relevant markets are large: online event ticket sales alone amounted to $56bn in 2019 (Statista (2020)). Moreover, this paper has broad implications for our understanding of resale and aftermarkets. Why are resale markets common for some perishable goods but not others? What are the net effects of resale of perishable goods on the seller and consumers? And what is the best way to run aftermarkets? Prior research has left these questions unanswered, but this paper offers theoretical and empirical evidence on each.

Ultimately, I find that the refund strategies outperform resale, but that resale is better for all parties than not reallocating. Specifically, partial refunds raise profit by

3.6% and total welfare by 1.3% relative to resale. However, the seller and consumers benefit from resale when the alternative involves no reallocation: profit increases by 1.8%, total welfare by 4.8%, and consumer welfare by 10.1%. In an application with states of the world with and without a covid-19 vaccine, the menu of refunds (implemented as state-dependent full refund contracts) also improves significantly on not reallocating, raising profit by 10.3% and total welfare by 7.7%. In both counterfactuals, refunds perform better because of fees and frictions associated with resale.

The performance of the sales strategies depends on three sources of demand uncertainty with distinct properties, all of which are present in the market for college football tickets. The first shock is purely idiosyncratic, like schedule conflicts. It causes consumers who bought tickets to have low values for using them, motivating reallocation. The second shock is a change in a common component of consumer values, like team performance. Changes in the common value make it difficult for the seller to predict the optimal price after shocks. The third shock is a realized state of the world, modeled as whether there will be a covid-19 vaccine at the start of the season. Consumers have heterogeneous reactions to the state with no vaccine: some are willing to pay the same amount for tickets if there is no vaccine while others would not pay a penny. The shock causes different consumers to have the highest values in each state.

The analysis relies on three data sources. The main source of data is transaction-level primary and resale market sales records for one season of college football from a large U.S. university. The records contain nearly 40,000 primary market transactions (including season ticket packages) and over 6,000 resale transactions on StubHub, the largest online resale platform (Satariano (2015)). I supplement the ticket sales with 576 observations of average annual resale prices for 76 college football teams, taken from the resale market SeatGeek. To learn about the effect of a covid-19 vaccine on consumer demand for tickets, I designed and conducted a survey asking 500 consumers, 250 of whom were 50 or over, for their willingness to pay in states with and without a vaccine.

To see how the properties affect the performance of each sales strategy, consider a seller of sports tickets that offers partial refunds and suppose that it cannot change prices after shocks. Some consumers will buy in advance, have schedule conflicts, and return their tickets to the seller's inventory for a refund. Whether partial refunds are optimal turns on whether there are also aggregate shocks in the market. If not, then the seller's price is optimal after shocks and all units are profitably and efficiently reallocated, making partial refunds optimal. But if there is an aggregate shock—for example, if there is unexpectedly no covid-19 vaccine, or if the team is bad—then the seller's price will be too high after shocks, leaving returned tickets unused. In this case, resale can maximize profit and welfare because resellers adjust their prices after shocks, ensuring that more tickets are sold and used. The downside of resale is that it incurs search frictions and fees paid to the resale market operator, which reduce its value when there is no aggregate uncertainty.

The choice between resale and partial refunds thus depends on a tradeoff between the intensity of aggregate shocks and the magnitude of fees and frictions. The data suggest that both factors are important, leaving the optimal strategy unclear. Reallocation is important because many consumers choose to resell: 6% of all seats were resold by consumers on StubHub. Aggregate uncertainty makes it difficult to predict the optimal price: nearly a third of the time, annual resale prices for a school deviate from the sample average by 25% or more. And resale fees are substantial: StubHub charges over 20% of the total price paid by the buyer, amounting to over $10 on each ticket resold.

The last strategy, a menu of refunds, is valuable when the efficient allocation varies across states of the world. Suppose it is uncertain whether there will be a covid-19 vaccine by the start of the season. The consumers with the highest values in the states with and without a vaccine may be different, making the efficient allocation dependent on the state. The seller can respond by offering a menu of state-dependent refund contracts, such as a contract giving a full refund in the state with no vaccine.[1] The principle of contracting on an observed state is used for financial derivatives; the NFL has also offered Super Bowl tickets only in the state when a certain team is in the game. The key property affecting the performance of the menu of refunds is the degree of heterogeneity in consumer values across states. When consumer responses to the state without a vaccine are more varied, the efficient allocations in the two states are less similar and the menu of refunds is optimal.

The survey results show that there is significant heterogeneity in consumer reactions to the state without a vaccine and hence in the efficient allocation across states. Almost a third of consumers report that it does not matter if there is a vaccine—they would pay the same amount in either state—while a fifth would pay something with a vaccine but nothing without one.

To compare the sales strategies, I develop a structural model of the market. In the model, consumers anticipate future shocks and participate in resale markets after shocks are realized. Specifically, in the first of two periods consumers know the distribution of shocks and decide whether to buy season tickets. Shocks are realized at the start of the second period. In the second period, consumers who bought season tickets decide whether to attend or resell; all other consumers decide whether to purchase tickets in the primary or resale markets.

[1] A menu of refund contracts can still be profitable when the shock is not an observable state. For example, contracts could consist of different levels of refunds (e.g. full or no refunds), as in Courty and Li (2000), and would still have implications for profit and welfare.

The model captures the effect of each source of demand uncertainty. Idiosyncratic shocks are modeled as independent Bernoulli draws for each game. Consumers receiving idiosyncratic shocks have no value for using the tickets. The rate at which consumers receive idiosyncratic shocks is identified by the rate of resale in the ticket sales data. The common value is a shared component of consumer utility. There is one draw of the common value per season, and the variance of the distribution is identified by the variation in annual resale prices in the SeatGeek data. The effect of the state with no covid-19 vaccine is modeled as a penalty to consumer values that varies across consumers. The distribution of penalties is identified by changes in individual-level reported willingness to pay in the covid-19 survey.

Other model parameters are estimated in structural simulations that match observed values for resale prices, season ticket quantities, and single-game ticket quantities. One such parameter affecting the performance of the sales strategies is the friction associated with searching both primary and secondary markets for tickets. The friction is identified by the number of consumers who choose to purchase tickets in the primary market when equivalent tickets are cheaper in the resale market.

The estimated model allows me to evaluate two core sets of counterfactuals. In the first, I consider a baseline model without uncertainty from covid-19 and compare resale to a partial refund. 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, I only consider uncertainty from the vaccine states[2] and compare the performance of a menu of refunds to resale.

The study has three broad implications. First, it informs our understanding of when to use resale markets. Resale is ubiquitous for some goods, like stocks, common for others, like event tickets, and rare for many more, like current fashions. What determines when resale of perishable goods is valuable? I provide a framework clarifying that resale is useful in markets where the clearing price is uncertain, the primary market price does not adjust easily, and resale frictions are sufficiently low. The empirical results suggest that the harms of frictions outweigh the benefits of price flexibility in the market for football tickets, making partial refunds more valuable. In markets where primary market prices are flexible, such as airlines, refunds may perform better than resale.

Second, the study has direct implications for the design of aftermarkets. Which aftermarket strategy produces the most efficient allocation after shocks, and how large are the changes in profit in welfare? Few prior studies have compared the strategies

[2]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 so the answers are, to this point, unknown.

Third, the study provides evidence on the value of resale. Despite much theoretical interest, there are few estimates of the net effects of resale of perishable goods on profit and consumer welfare because of the difficulty of assembling primary and resale market data.[3] Estimates are valuable because the net effect on profit is ambiguous in theory (Cui et al. (2014)) and the effect on consumers is informative for government policy on the right to resell. Consumers have a legal right to resell most legally purchased goods, but not event tickets or airline reservations.[4] After major concert tours prohibited ticket resale, several states passed laws extending the right to resell to ticket markets (Pender (2017)). This paper's predictions for the effects of resale on consumers provide evidence on whether such laws are beneficial.

The remainder of the introduction discusses the relevant literature. Section 2 presents several 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 from the data on the market for college football tickets and each source of uncertainty. 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, demand uncertainty, and price discrimination. For the resale literature, this paper provides estimates of how resale affects profit and welfare. The effects of resale on buyers and sellers are a traditional focus of the literature. Courty (2003) and Cui et al. (2014) examine whether resale is profitable in theory. 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. This paper does so by modeling both the 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, allowing me to provide estimates of the effect of resale on both profit and welfare. Other empirical studies of resale markets for event tickets include Sweeting (2012) and Waisman (2020).

A separate literature considers resale for sellers of durable goods. Unlike sellers of perishable goods, sellers of durable goods compete with past vintages of their products, and consumers may have heterogeneous preferences over the vintages. Examples of

[3] An exception is Leslie and Sorensen (2014), who provide estimates for consumer welfare. They do not consider profit because of systematic mispricing in their empirical setting.

[4] The first-sale doctrine prevents copyright holders from restricting the buyer's ability to resell in 17 U.S.C. §109. However, it does not apply to goods sold as revocable licenses, like tickets and reservations.

studies of durable goods include Chen et al. (2013), who find that resale is harmful for oligopolists in the market for cars, and Ishihara and Ching (2019), who find that sellers of video games benefit from resale markets.

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

Second, this paper relates to the literature on demand uncertainty, specifically studies that consider the effect of aggregate uncertainty on firms' strategic choices. Studies of aggregate demand uncertainty in this tradition include Kalouptsidi (2014), who studies the effect of uncertainty on investment when investment is lagged and irreversible, Jeon (2020), who studies how uncertainty creates boom and bust cycles in investment, and Collard-Wexler (2013), who studies how uncertainty affects entry, exit, and market structure. This paper differs because it does not emphasize industry-level outcomes, focusing instead on the sales strategies individual firms use when there is uncertainty.

The emphasis on how individual firms cope with uncertainty ties this paper to studies of airline pricing with stochastic demand, such as Lazarev (2013), Williams (2020), and Aryal et al. (2018). In these studies, stochastic consumer arrivals make it profitable for sellers to use dynamic pricing. In contrast, this paper focuses on non-price strategies like resale and refund contracts that reallocate goods after shocks. A branch of the management literature also considers non-price strategies. 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 contributes by providing empirical estimates for similar sales strategies.

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 are initially uncertain about unchanging model parameters and attempt to gather information about them over time. In this paper, agents are certain about the environment and uncertainty comes from the future realization of stochastic shocks.

Several features of this study have not yet been considered in the literature on demand uncertainty. Whereas earlier papers consider one non-price strategy, this study compares several and shows that their performance depends on the properties of demand uncertainty. Moreover, one property of uncertainty, heterogeneous value changes, has rarely been considered in empirical work.

Third, this paper connects to the literature on price discrimination, particularly studies in which sellers use future value shocks as a screening device. Courty and Li (2000) show that refund contracts are an optimal mechanism in a model in which consumers make purchase decisions before learning their values and different types of consumers have different distributions of values. The environment is similar to the one in this paper, where consumers can purchase season tickets before learning the state of the world. Despite significant attention from theorists, empirical evidence is rare because of the difficulty in identifying different effects of shocks for different types of consumers. I overcome the problem and estimate the returns to a menu of refund contracts by using survey data that identifies the distribution of changes in willingness to pay. One other study providing empirical evidence is Lazarev (2013), who considers two types of airline passengers with different probabilities of schedule conflicts and calculates the benefits of offering fully and non-refundable tickets. The application in this paper differs by using a full distribution of value changes rather than two types. It also considers an aggregate source of uncertainty, which allows the seller to offer state-dependent contracts. The fact that uncertainty comes from an aggregate shock also links this paper to Alexandrov and Bedre-Defolie (2014), who analyze product-state combinations as a bundling problem.

This study also relates to the literature on dynamic mechanism design. As in the dynamic mechanism design literature, consumer values evolve over time in this paper and the optimal mechanism may involve reallocation. This paper differs in that it tests the performance of several common reallocation mechanisms instead of investigating the theoretically optimal mechanisms studied in, for instance, Pavan et al. (2014) and Bergemann and Välimäki (2019). The literature on dynamic mechanism design also includes studies of dynamic pricing, such as Board and Skrzypacz (2016), Dilmé and Li (2019), and Sweeting (2012). This paper instead focuses on reallocation after preference shocks.

2 Uncertainty and Sales Strategies

In this section, I present three examples illustrating the connection between the types of uncertainty and sales strategies. Each example includes different types of uncertainty and implies that a different sales strategy maximizes profit and welfare.

In each example, there are two periods and the seller has one ticket to sell. The seller can set different prices for each period but, as in the data, 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 value ν_i and that the value is affected by three potential shocks:

1. Independently drawn (idiosyncratic) shocks that affect consumer i with probability ψ. Consumers who receive a shock have zero value.
2. An aggregate shock to a common value V that changes all consumers' values to $\nu_i + V$.
3. A realized state ω that changes consumer i's value to $\nu_i - b_i(\omega)$. The function $b_i(\omega)$ is specific to consumer i, so changes in values are heterogeneous. Possible states are $\omega \in \{\omega^B, \omega^G\}$. All consumers have $b_i(\omega^G) = 0$ and $b_i(\omega^B) \geq 0$.

The three shocks closely track the ones observed in the data and are modeled almost identically in the empirical model. Consequently, the idiosyncratic shocks can be thought of as schedule conflicts, the common value as the quality of the team, and the realized state as whether there is a covid-19 vaccine at the start of the season. A more detailed explanation of the equilibrium of the following examples can be found Appendix A.

2.1 Idiosyncratic Uncertainty

When there is only idiosyncratic uncertainty, refunds maximize profit and welfare. 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 purchases the ticket in the first period 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 resale only incurs one friction, a multiplicative fee of $\tau = \frac{1}{10}$ on each transaction that is paid to the resale market. Also suppose 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 total welfare of 40.[6] However, Alice will

[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. For any such r, it can charge $p_1 = 40 + \psi r$ but will pay ψr in expected refunds.

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

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 would be lower if resale incurred other frictions, like a hassle cost of using the resale market.

2.2 Idiosyncratic and Common Value Uncertainty

When there is also aggregate uncertainty from a common value, resale can maximize profit and welfare. Continue to suppose that a seller has one ticket to sell to Alice and Bob and that $\psi = \frac{1}{5}$, but now there is also an 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 $p_2 = 40$.[7] 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, she returns the ticket. There are two cases where the ticket is returned. 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 72. 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 32. 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 earns profit of 42.3 by charging 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 frictions are low. With a higher fee or costs of using the resale market, refunds could have remained more profitable despite reallocating the tickets less effectively. Similarly, if there had been significant resale frictions, total welfare would 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.

[7] 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 States of the World

For the last example, suppose that there are states of the world but no idiosyncratic or common value uncertainty. When consumers have heterogeneous value changes across the states of the world, the menu of refunds can maximize profit and welfare. Suppose that the seller only makes sales in the first period, before the state of the world is known, and that each state of the world (ω^G and ω^B) occurs with probability $\frac{1}{2}$. 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 $p = 40$ and sell to Alice. But in state ω^G, Alice would have the ticket when Bob has a higher value. A single refund would not help because Alice would return her ticket in both states. With resale, Alice could resell to Bob in the good state, but doing so would incur frictions.

A menu of state-dependent contracts would avoid fees and maximize welfare and profit. The seller could offer a contract granting a full refund in state ω^B at price 50, which Bob would purchase, and another contract granting a full refund in state ω^G at price 40, which Alice would purchase. By implementing a state-dependent allocation, the contracts maximize welfare and profit when consumers have heterogeneous value changes.

3 Data

3.1 Primary and Resale Market Data

The main source of data is transaction-level ticket sales records from the primary and resale markets. The primary market records are provided by a large U.S. university and include all ticket sales for two years. Each record indicates the price paid, date of purchase, and seating zone. Seating zones are groups of similar seats sharing one price, which I use as a measurement of quality. The primary market records also indicate the type of sale, such as season tickets or promotions.

Similar transaction-level records for resale come from StubHub. The main difference between the resale and primary market data is that the transaction price is not included for resale transactions.

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 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.

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 SeatGeek data are informative about aggregate shocks. It shows that the average price of a resold ticket varies meaningfully from one year to the next. The changes are too large to be the result of purely idiosyncratic shocks like schedule conflicts; it is far more likely to reflect an aggregate shock to a common component of values.

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.[8] 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 come from only one resale market, resale is undercounted. 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 15%, with some discounts for large sellers. I assume that the standard fees apply to all buyers and resellers.

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

3.2 Covid-19 Survey

Data on how demand with and without a covid-19 vaccine 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.[9] 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.[10] (I combine responses for scenarios (iii) and (iv) because reported willingness to pay is similar.) 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 C.

The survey directly measures changes in willingness to pay in two states of the world. Descriptive evidence presented in the next section establishes that changes in consumer values are indeed heterogeneous. I use the resulting distribution of changes in values in the empirical model.

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.[11]

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 phase consists of season ticket sales, which are made 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

[9] 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).

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

[11] 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.

occur within a month of the game and 50% within two weeks. The gap between the two phases makes it plausible that consumers receive preference shocks. The empirical model reflects the timing of the market, with a first period in which only season tickets are sold and a second in which only single-game tickets and resale tickets are sold.

Figure 1 shows the average number of tickets sold to each game by type of sale and quality, including unsold tickets. Most tickets are sold as season tickets, and season tickets are fully 75% of tickets sold to the public (the "other" category consists of tickets that are not available to the public, like student tickets). Most of the rest are sold as single tickets or unsold. A minuscule number are sold in mini-plans, bundles of tickets to a subset of games that I exclude from the analysis. The single ticket purchases in Figure 1 include group sales and promotions. I only consider full-price single ticket sales in the analysis because promotions and group sales are not optimally priced and may only be available to targeted groups, like veterans.[12]

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 (excluding the cancelled game), including prorated season ticket prices, 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 always sell for \$30. Season tickets are \$25–\$35 cheaper than buying primary market tickets to each game. Prices vary slightly across games, but never by more than \$10.

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

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

[12]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.

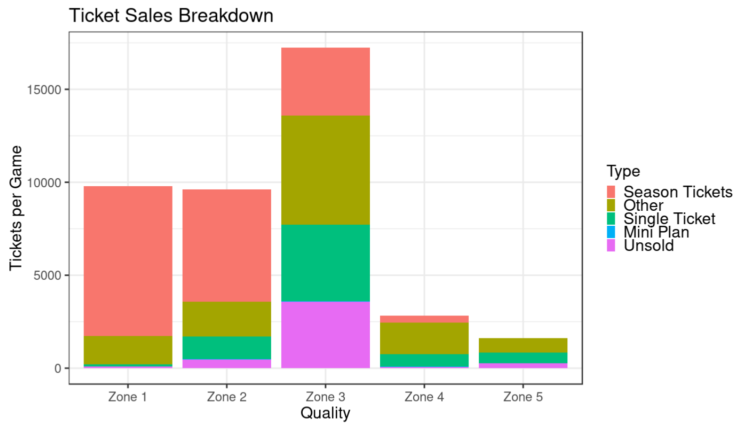


Figure 1: Sale types and volumes by quality group.

4.2 Resale Markets

Resale is a notable feature of the market, with 5.98% of all tickets sold to consumers resold on StubHub.[13] The true resale rate is higher because some tickets are resold on other resale markets.

An important feature of resale markets is that prices are flexible. Resellers set the price of their tickets when they list on StubHub and are free to change prices afterwards. The ability to change prices makes it plausible that the average transaction price adjusts after shocks.

Figure 3 establishes that resale prices adjust to differ from face value. It shows the distribution of face values and the distribution of the average resale price for each game-quality combination. The difference between the distributions suggests that resale prices adjust, presumably in response to demand. The variation in resale prices also suggests that consumers have different average values for each game.

Figure 2 provides further evidence of price flexibility. It shows the percent change in the quantity of single-game tickets sold for each game (in both primary and resale markets) from the season average. The changes in primary market quantities are practically always larger than the changes in resale quantities, usually by a large margin. The higher volatility in the primary market is unsurprising because its 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 buyers a fee of 15% of the advertised price and sellers a fee of 10%. The average fee is $10.71 on each ticket resold, a substantial amount when the average resale price is under $40. There is also evidence of non-monetary frictions. If there were no frictions, consumers would buy single-game

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

tickets for a given section in whichever market is cheaper. Table 2 shows that 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 1250 single-game tickets are sold in the primary market. There are several plausible interpretations for the friction. Consumers might not like or trust the resale market, they might find searching for tickets onerous, or they might be unaware that it has cheaper tickets.

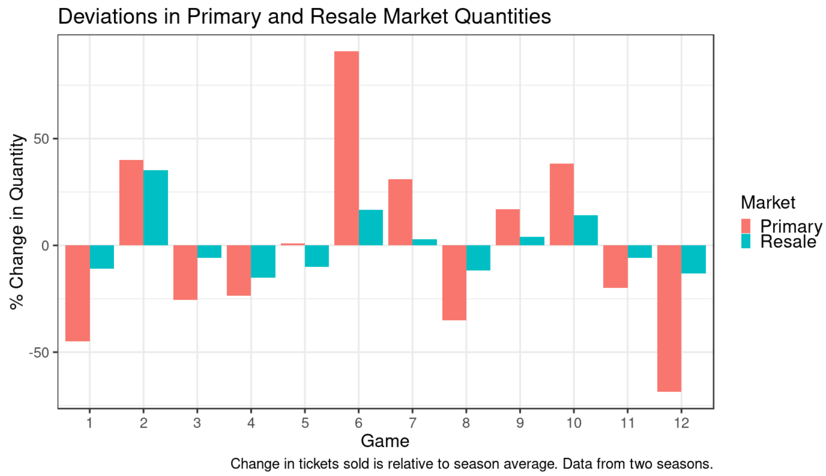


Figure 2: Percent deviation from season-average quantities sold for each game.

Table 2: Face value minus mean resale price and quantity of full-price primary market tickets sold for each game.

Game	Mean Price Diff.	PM Quantity
1	16.48	1266
2	-6.69	3373
3	16.94	991
4	-5.79	2383
5	28.21	493

4.3 Annual Price Changes

Annual price changes for each team provide evidence of aggregate shocks. Using Seat-Geek's records of average annual resale prices, I define the normalized price for university u in year y as

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

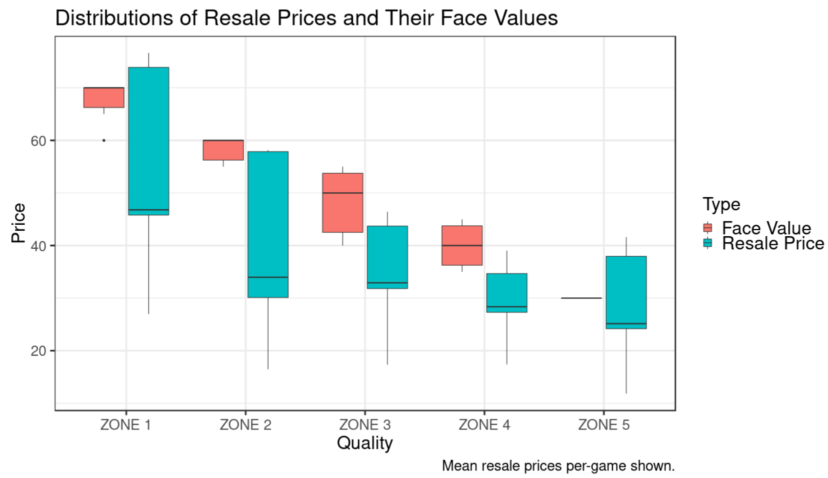


Figure 3: Distributions of mean per-game resale prices and face value.

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

The dramatic swings in resale prices likely reflect 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.

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

4.4 Covid-19 Survey

Figure 6 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.

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.

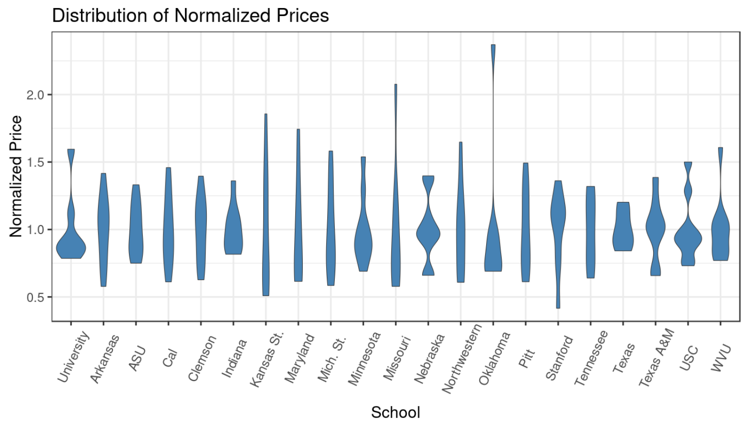


Figure 4: Distribution of average annual resale prices (normalized by school mean) for a random sample of 20 schools in similar conferences.

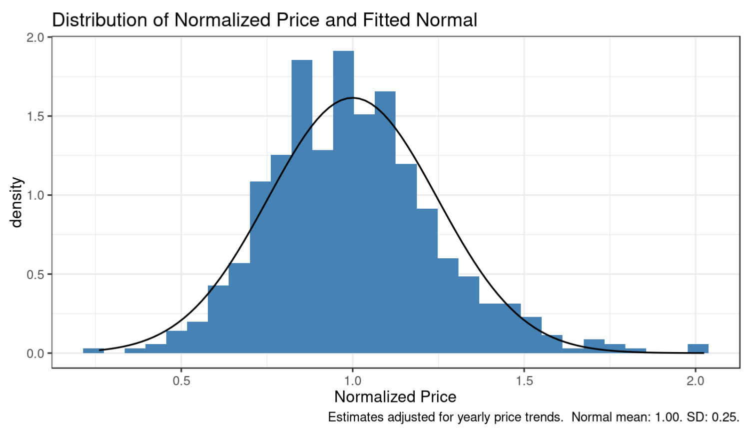


Figure 5: Distribution of resale prices normalized by team-mean in the sample. Adjusted for yearly trends. From SeatGeek annual average resale prices (76 teams, 576 team-seasons).

For evidence on individuals' changes in WTP across states, consider Figure 7. The figure shows the joint distribution of WTP with a vaccine and the change in WTP if there is no vaccine.[14] There is significant heterogeneity in the changes in WTP. Many report changes exceeding $50 while others report small or no change. Moreover, there is heterogeneity at each level of WTP with a vaccine, and the changes in WTP are not visibly correlated with initial WTP.

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

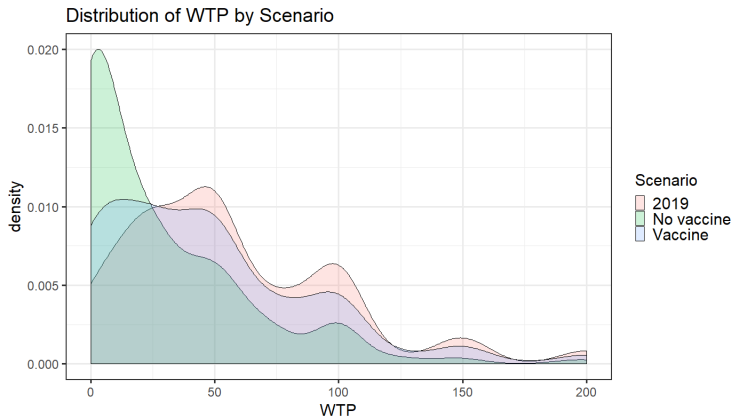


Figure 6: Distribution of reported willingness to pay without social distancing in 2019, with a vaccine, and with no vaccine.

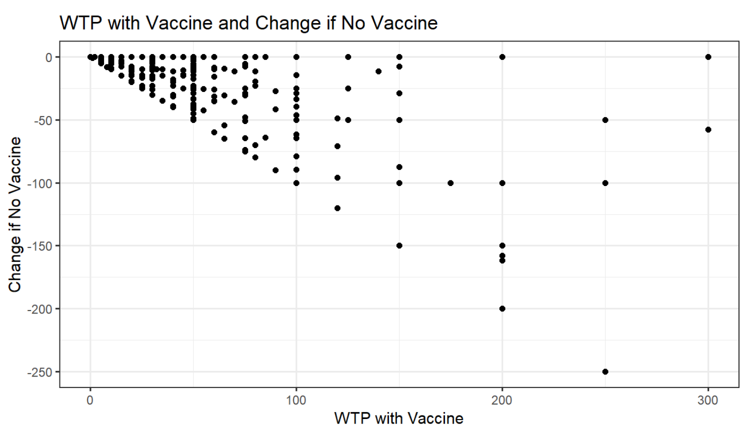


Figure 7: Scatterplot of reported willingness to pay with a vaccine and change in willingness to pay if there is no vaccine.

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 a season ticket bundle including one ticket to each game, and in period two, it only sells single-game tickets. The seller sets the price p_{Bq} for a season ticket bundle containing tickets of quality q. It sets the price p_{jq} for quality q tickets to game j. It commits to its menu at the start of the first period and does not change it afterwards.

There are three sources of uncertainty, each realized at the start of the second period. 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 might cause one consumer, but not others, to change her mind about attending the game. Schedule conflicts are a natural interpretation.

The second is an aggregate shock. There is a single draw $V \sim N(0, \sigma_V^2)$ for the season that affects each consumer's value for attending the game. I refer to V as the common value. It captures changes (aside from whether there will be a vaccine) that affect annual aggregate demand for tickets, like team performance. There is only one draw of V per season and it affects all games.

The third is a state of the world ω. In the application with uncertainty over a covid-19 vaccine, the state is ω^{Vax} if there is a vaccine and ω^{NoVax} if there is not. Each consumer has weakly lower utility in the state with a vaccine, but the size of the change is heterogeneous across consumers. In the baseline model without uncertainty from covid-19, a baseline state ω^{BL} is realized with certainty.

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 in the primary market, secondary market, or not at all.

The model outline is depicted in Figure 8, which shows the timeline of choices on the right and a flowchart of consumer decisions on the left. Consumer decisions in period two are for one game j 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 with utility zero) and takes the form

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

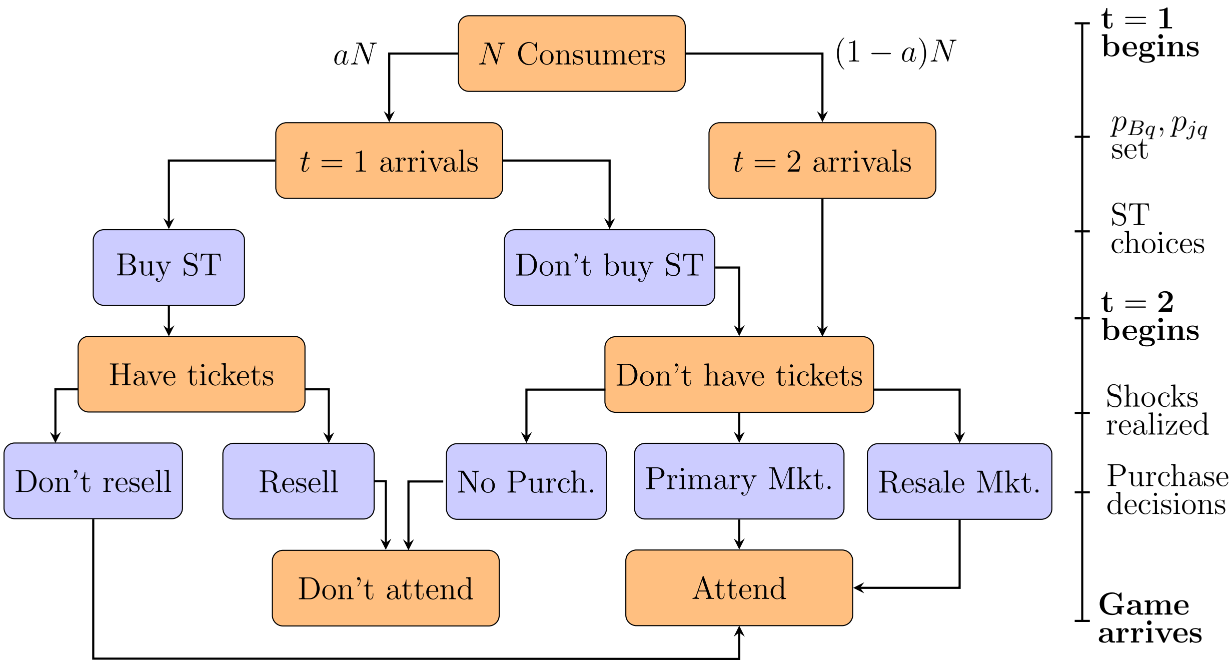


Figure 8: Model timeline and outline for consumer arrivals and choices. Decisions are shown in blue.

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 are aggregate, affecting all consumers' utilities in the same way. The penalty $b_i(\omega)$ only applies to uncertainty from covid-19. Consumers experience no change if there is a vaccine, but they are willing to pay weakly less if there is no vaccine: $b_i(\omega^{\text{Vax}}) = 0$, $b_i(\omega^{\text{NoVax}}) \geq 0$. Realizations when there is no vaccine are heterogeneous and independent of ν_i.[15] In the baseline model, all consumers have $b_i(\omega^{BL}) = 0$.

[15]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 7.

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; all other consumers decide whether to purchase tickets in the primary or resale markets. Resale prices are noted by $p^r_{jq}(V, \omega)$. They depend on the realizations of aggregate shocks because the shocks affect consumer values.

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

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

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

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

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

Surplus from each option is

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

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

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

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

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

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

5.3 Period One

In period one, aN consumers know their type $(\nu_i, b_i(\omega^{\text{NoVax}}))$ and decide whether to buy season tickets.[16] 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

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

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

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

Overall surplus from waiting is the expected value,

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

The consumer's choice set in period one is thus

[16] 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.

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

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 $\{p_{jq}\}$. Consumers anticipate a set of resale prices $\{p^r_{jq}(V,\omega)\}$ and primary market purchase probabilities $\{\sigma_{jq}(V,\omega)\}$. In equilibrium, consumers make optimal choices in the first period given expectations for resale prices and probabilities, and their expectations are realized in the second period when they make optimal purchase choices.

6 Estimation and Results

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

6.1 First Stage

The fee τ is the percentage of the fee-inclusive price paid by the buyer, calculated directly from StubHub's policies. The idiosyncratic shock rate ψ is identified by the frequency of resale. In the model, observed resale is explained by idiosyncratic shocks in equilibrium, so the parameter ψ equals the ratio of tickets resold by consumers to all tickets sold.[17]

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.

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

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

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

where X_k includes the number of tickets in the transaction and the number of days until the game. (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. Moreover, the resale price is approximately linear in consumers' attendance values under mild assumptions.[18] Consequently, I assume that

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

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

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

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

The identifying variation for the variance is entirely within each team. The normal-

[18]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 nearly always true in the data.

ized 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 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 4.

The last parameters estimated in the first stage define the effect of the states of the world with and without a vaccine on preferences. The survey asks consumers about WTP in 2019 and in three scenarios, one with a vaccine and two without. 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 C 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 $b_i(\omega^{\text{NoVax}})$ 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 $\bar{\alpha}$, which is an average of the estimated α_j. The change in consumer i's WTP from state ω to state ω' is

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

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

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

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

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

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

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

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

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 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 primary market purchase probabilities as a function of V. Finding the fixed point for each set of candidate parameters is challenging. Moreover, each iteration of each fixed-point search requires a solution for resale prices for every realization of V.

I use several simplifications to make estimation feasible. First, shared quality preferences γ_q reduce the search for resale prices to one dimension. Second, I discretize continuous variables. Consumer types and resale prices are both assumed to be a grid, with 100 values for resale prices and 200 for consumer types. 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 3, 4, 5, and 6. The resale fee is about 22% of the fee-inclusive price paid by the buyer.[19] The idiosyncratic shock rate suggests that 8% of buyers change their minds about attending the event between the first and second periods. The fraction of consumers arriving in the first period, a, is calibrated to 77%, indicating that most consumers consider whether to buy season tickets.

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

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

[19] 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.

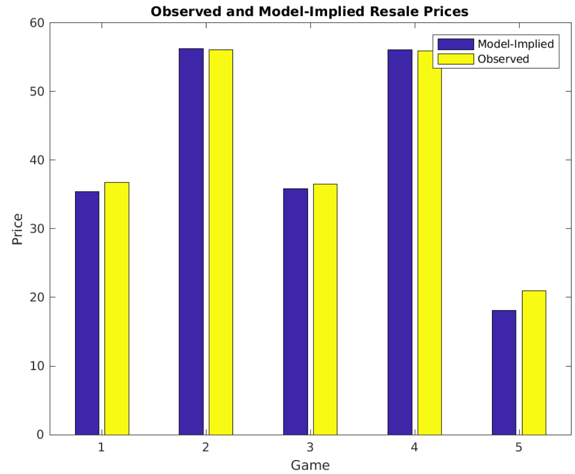


Figure 9: Observed and model-implied resale prices for each game.

more than \$7.85 about a third of the time.

State probabilities and parameters governing preference changes across vaccine states are contained in Tables 4 and 5. 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, 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 11 in Appendix B.

In the second stage, the average consumer's friction associated with resale market purchases, s_{ij}, is \$48.42. 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 nearly 90% are \$20 or less. The full distribution of realized costs for resale market buyers is shown as Figure 12 in Appendix B.

The mean of the distribution of consumer types is 16.02, suggesting that the average consumer would pay \$16.02 for the worst seats to the baseline game in an average season. Finally, the benefits of season tickets are estimated to be \$29.96, suggesting that the convenience and perks of season tickets outweigh diminishing marginal returns.

Table 7 and Figures 9 and 10 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.

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 3: Estimated parameters from the first stage.

Table 4: Expected state probabilities in September 2021

State	Probability
Vaccine	0.59
No Vaccine	0.41

Table 5: 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 6: Estimated parameters from the second stage.

Parameter Description	Notation	Estimate	Standard Error
Mean Resale Friction	λ_s	48.42	1.54
Mean Consumer Type	λ_ν	16.02	0.02
Mean ST Benefits	δ	29.96	0.34

Table 7: Observed and model-implied quantities of season tickets.

Moment	Model-Implied	Observed
Season Tickets Sold	25291	22471

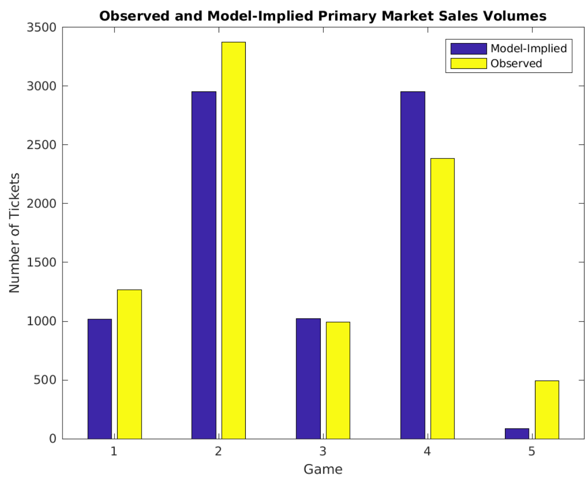


Figure 10: Observed and model-implied primary market quantities sold.

7 Counterfactuals

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

7.1 Benchmarks: No Reallocation and Flexible Prices

Start with counterfactuals that provide a benchmark for the focal sales strategies, which are only tested in the baseline state of the world. With no reallocation, the university prohibits resale and does not offer refunds. The comparison is useful because it measures the net effect of resale and refunds on profit and welfare. Whether sellers profit from resale is a primary concern of the theoretical literature (e.g. Courty (2003), Cui et al. (2014)), but empirical evidence is rare for sellers of perishable goods.

To evaluate the model without reallocation, I fix expected resale prices and supply at zero. 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 seller maximizes profit by optimally selecting its prices p_{Bq} and p_{jq}.

A second useful benchmark is to consider refunds if the seller has flexible prices. In this counterfactual, the seller can adjust its prices after shocks, eliminating the advantage of resale. I implement the counterfactual as a partial refund (described in the next subsection) with primary market prices for game j satisfying

$$p_{jq}(V, \omega^{BL}) = p_{jq} + \alpha_j V. \tag{17}$$

The counterfactual is useful because it measures the reduction in profit from fixed prices.

7.2 Partial 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 request refunds if and only if they receive idiosyncratic shocks.[20] As before, the seller chooses prices p_{Bq} and p_{jq}. I only evaluate partial refunds for the baseline model with state ω^{BL}.

[20]The reason is the same as in the example in Section 2. Risk-neutral consumers will 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.

7.3 Menu of Refunds

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

In the counterfactual, I remove uncertainty from idiosyncratic shocks and the common value, $\psi = 0$ and $\sigma_V^2 = 0$. The extra sources of uncertainty are not important for the returns to screening on uncertainty and removing them simplifies the results.[21] 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 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). 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.

State-dependent contracts differ from the strategy considered in Courty and Li (2000) by allowing the seller to offer a contract for the state with no vaccine. In Courty and Li (2000), consumers choose between contracts offering different refunds. With only two states, consumers would only request a refund in the state without a vaccine, making the menu equivalent to offering a contract for tickets with a vaccine and a contract for tickets in both states. State-dependent contracts also allow a contract for the state without a vaccine.

7.4 Counterfactual Estimates

I test the partial refund and benchmark couterfactuals against resale in the baseline model with one state of the world. The results, shown in Table 8, suggest that refunds are the most profitable strategy. Profit is 3.6% higher with refunds than with resale, and 5.5% higher than with no reallocation.

[21] 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.

The two strategies produce similar levels of welfare. Refunds also maximize total welfare, besting resale by 1.3%. Resale, however, produces consumer welfare that is 1.6% higher than refunds. Both strategies produce significant gains relative to no reallocation. The gains in total welfare are 4.8% for resale and 6.2% for refunds. For consumer welfare, it is 10.1% for resale and 8.3% for refunds. The predicted welfare gains are larger than the 2.9% gain estimated by Leslie and Sorensen (2014), but their paper included harms of resale that are not relevant in the present market.

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: 1.5% for profit, 1.3% 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 partial refunds. The seller's reliance on season ticket sales explain the small gains to flexible prices. By selling tickets before shocks are realized, the seller avoids relying on single-ticket sales when its prices may be suboptimal.

Results for the screening application are in Table 9. The comparison between state-based refunds and no reallocation establishes that screening results in significant gains for the seller. Profit increases by 10.3% and total welfare increases by 7.7%, but consumer welfare is unchanged. Gains are the product of the seller's ability to allocate tickets to different consumers in different states: thousands of tickets are sold in each type of contract.

Again, resale is a significant improvement over not reallocating, with gains in profit of 6.8% and total welfare of 4.7%. Consumer welfare falls slightly, by 1.7%. Resale, however, is worse in all respects than state-dependent refunds. The small size of resale fees implies that resale frictions drive the difference.

	Resale	Refunds	Flex. Prices	No Reall.
Profit (mn)	7.18	7.44	7.55	7.05
Consumer Welfare (mn)	2.50	2.46	2.48	2.27
Total Welfare (mn)	9.77	9.90	10.03	9.32
Resale Fees (mn)	0.09	0.00	0.00	0.00
Season Ticket Buyers (1000)	23.75	26.91	26.91	23.75
Season Ticket Base Price	33.45	30.80	30.90	32.48
Single Game Base Price	33.29	37.81	39.30	36.58

Table 8: Counterfactual results for the baseline model.

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

Table 9: Counterfactual results for the model with different states of the world.

There are two drawbacks to resale: non-price frictions and explicit fees. To decompose their effects, I simulate the market with the fee τ set to zero (column 2) and the non-price friction s set to zero (column 3).[22]

The results are shown in Table 10. They suggest that the non-price friction does not drive the difference in profit between resale and partial refunds: removing resale frictions only explains 27% of the difference in profit between resale and partial refunds. Instead, the difference is primarily due to resale fees. Eliminating fees explains 73% of the gap in profit. However, frictions drive the difference in total welfare.

	Resale	$\tau = 0$	$\lambda_s = 0$
Profit (mn)	7.18	7.37	7.25
Consumer Welfare (mn)	2.50	2.46	2.58
Total Welfare (mn)	9.77	9.84	10.06
Resale Fees (mn)	0.09	0.00	0.22
Season Ticket Buyers (1000)	23.75	26.91	26.91
Season Ticket Base Price	33.45	32.86	33.01
Single Game Base Price	33.29	43.85	33.23

Table 10: Counterfactual results for resale frictions in the baseline model.

8 Conclusion

Demand uncertainty causes the initial allocation of goods to be suboptimal and can make it difficult to predict the optimal price in advance. Both sellers and society can benefit from sales strategies that cope with uncertainty, but it is unclear which strategy is best. I showed that the optimal strategy depends on the properties of demand uncertainty, then estimated a structural model describing the salient sources of uncertainty in the market for college football tickets and used it to evaluate each strategy.

[22] Frictionless resale, where τ and s both equal zero, is identical to the flexible price counterfactual.

The results suggest that refunds, rather than the status quo of resale, maximize profit and welfare. In the counterfactual without uncertainty from covid-19, profit is 3.6% higher with partial refunds than with resale, and total welfare is 1.3% higher. With uncertainty from covid-19, profit is 3.4% higher with a menu of refunds than with resale, and total welfare is 1.7% higher. However, resale is valuable when the seller offers no way to reallocate. Resale raises profit by 1.8% and consumer welfare by 10.1% in the counterfactual without uncertainty from covid-19; in the other counterfactual it raises profit by 6.6% and lowers consumer welfare by 1.7%.

The paper has three core implications for our understanding of resale and aftermarkets. First, the theory demonstrates that resale can be valuable in markets with primary market rigidities, aggregate uncertainty, and low resale frictions. The market for college football tickets has the potential to satisfy each requirement, but the results show that fees and frictions are significant enough in the resale market for refunds to be optimal. In similar markets without primary market rigidities, like airlines and hotels, refunds are a more 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. One benefit of refunds with a monopolist seller is to reduce search costs by leaving only one seller. The effect of refunds could be different in markets with many competing sellers.

Third, the paper provides empirical evidence on the effects of resale. Whether sellers of perishable goods profit from resale is ambiguous in theory, and this paper shows that sellers benefit in practice. The effect of resale on consumer welfare informs policy on ticket resale. When sellers prohibit resale but do not offer refunds, consumer welfare falls by more than 10%. Consumers would benefit from a legal right to resell tickets provided that the seller does not offer refunds instead.

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

References

Alexandrov, Alexei and Özlem Bedre-Defolie (2014), "The Equivalence of Bundling and Advance Sales." *Marketing Science*, 33, 259–272.

Aryal, Gaurab, Charles Murry, and Jonathan W. Williams (2018), "Price Discrimination in International Airline Markets." Working paper.

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

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

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

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

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

Ching, Andrew T., Tülin Erdem, and Michael P. Keane (2013), "Learning Models: An Assessment of Progress, Challenges, and New Developments." *Marketing Science*, 32, 913–938.

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

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

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

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

Dilmé, Francesc and Fei Li (2019), "Revenue Management without Commitment: Dynamic Pricing and Periodic Flash Sales." *Review of Economic Studies*, 86, 1999–2034.

Erdem, Tülin and Michael P. Keane (1996), "Decision-Making under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets." *Marketing Science*, 15, 1–20.

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

Hitsch, Günter J. (2006), "An Empirical Model of Optimal Dynamic Product Launch and Exit Under Demand Uncertainty." *Marketing Science*, 25, 25–50.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Xie, Jinhong and Eitan Gerstner (2007), "Service Escape: Profiting from Customer Cancellations." *Marketing Science*, 26, 18–30.

A Uncertainty and Sales Strategies Details

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

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

A.1 Idiosyncratic Uncertainty

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

A.1.1 Partial Refunds

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

$$p_1 = (1 - \psi) \cdot 50 + \psi r. \tag{18}$$

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

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

A.1.2 Resale

The seller sets $p_2 = 40$ to ensure that Alice purchases in the first period.[23] Alice knows that if she receives a shock, she can resell to Bob at 40 and will receive $(1-\tau)40 = 36$. She is thus willing to pay

$$p_1 = (1-\psi) \cdot 50 + \psi p_2^{\text{resale}} = 40 + \frac{1}{5}36 = 47.2. \tag{19}$$

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

A.2 Idiosyncratic and Common Value Uncertainty

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

A.2.1 Partial Refunds

The seller again offers $p_2 = 40$.[24] In the first period, it can charge Alice

$$p_1 = (1-\psi)(\frac{3}{4} \cdot 50 + \frac{1}{4} \cdot 30) + \psi r, \tag{20}$$

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

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

A.2.2 Resale

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

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

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

$$p_1 = (1-\psi) \cdot (\frac{3}{4} \cdot 50 + \frac{1}{4} \cdot 30) + \psi(\frac{3}{4} \cdot 36 + \frac{1}{4} \cdot 18) = 42.3. \tag{21}$$

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

A.3 States of the World

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

A.3.1 No Reallocation

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

A.3.2 Resale

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

$$p = \frac{1}{2} \cdot 50 + \frac{1}{2} 36 = 43. \tag{22}$$

Profit is 43 and total welfare is maximized at 45.

A.3.3 State-Dependent Refund Contracts

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

B Estimation Details

B.1 Distribution of V

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

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

The distribution of V is based on residuals from the regression

$$\text{NormalizedPrice}_{uy} = \beta_y Season_y + \varepsilon_{uy}. \tag{23}$$

The residuals form the distribution in Figure 5, 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,

$$\text{NormalizedPrice}_{uy} - 1 = V_y \sum_j w_{jy} \alpha_j \tag{24}$$

$$(\text{NormalizedPrice}_{uy} - 1) \left(\sum_j w_{jy} \alpha_j \right)^{-1} = V_y \tag{25}$$

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.

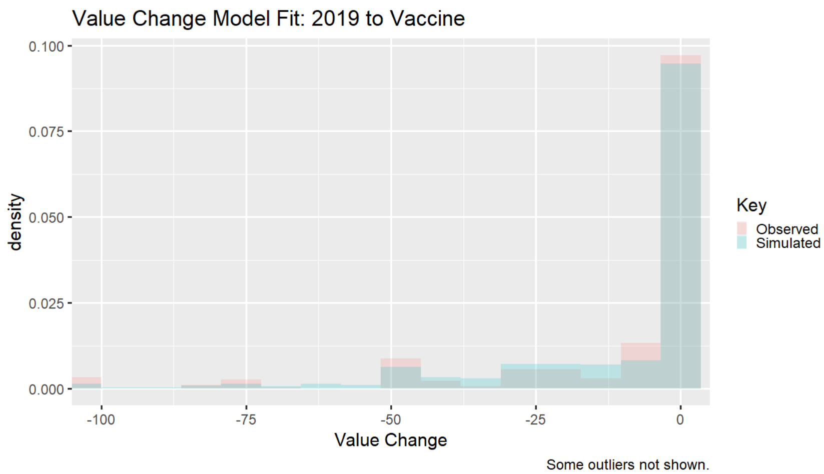
B.2 Vaccine Demand

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 6.

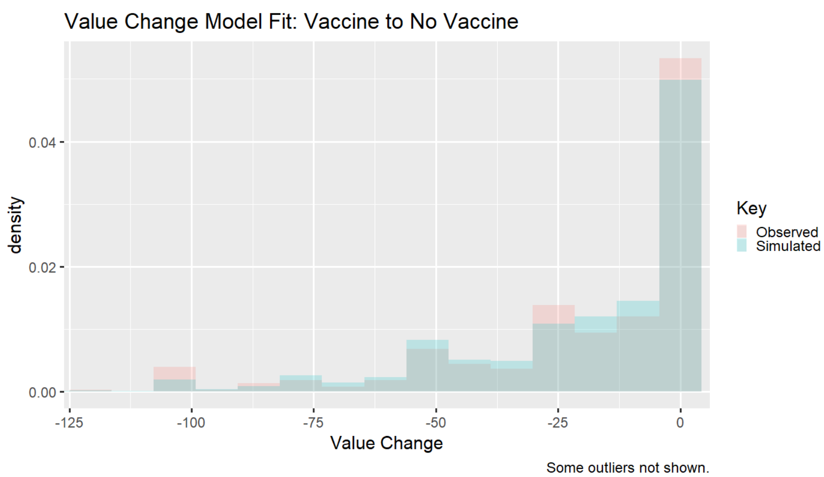
Section 6 explains how the change in values $b_i(\omega^{\text{Vax}})$ is estimated. In the application with states of the world, I adjust values to reflect the change by defining

$$\nu_i' = \nu_i + b_i(\omega^{\text{Vax}}). \tag{26}$$

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'.



(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.

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

B.3 Weights

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

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

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

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

$$M\frac{N_j}{M}(1-\frac{N_j}{M}) = N_j(1-\frac{N_j}{M}). \tag{27}$$

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 11.

Table 11: Variance of estimation moments.

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

I make two adjustments to model output so that it is comparable to the estimation moments. First, I only use the model's predicted resale prices and quantities for the value of V realized in the data. The model predicts resale prices and quantities for all possible realizations, but only the one for the realized V is comparable. Second, I weight resale prices by the observed average quantity of tickets resold in that quantity

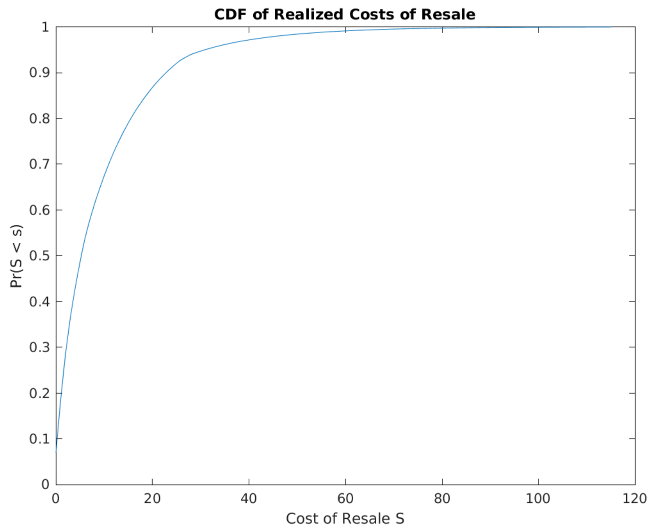


Figure 12: CDF of realized costs of resale for resale buyers in equilibrium.

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.

B.4 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.

C 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.

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 13. Respondents do not expect a vaccine in January 2021, but think the chance exceeds 40% in September 2021 and 60% in January 2022.

Figure 14 shows that the distribution of reported WTP is similar for the near-zero and above near-zero scenarios.[25] The distributions are not exactly the same—consumers are more reluctant to attend when there are more cases—but the differences are small enough for the two to be consolidated into a single state without a vaccine. I consolidate WTP as a weighted average, taking the relative probability of the states in September 2021 as the weights.

Figure 15 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.

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

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)

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

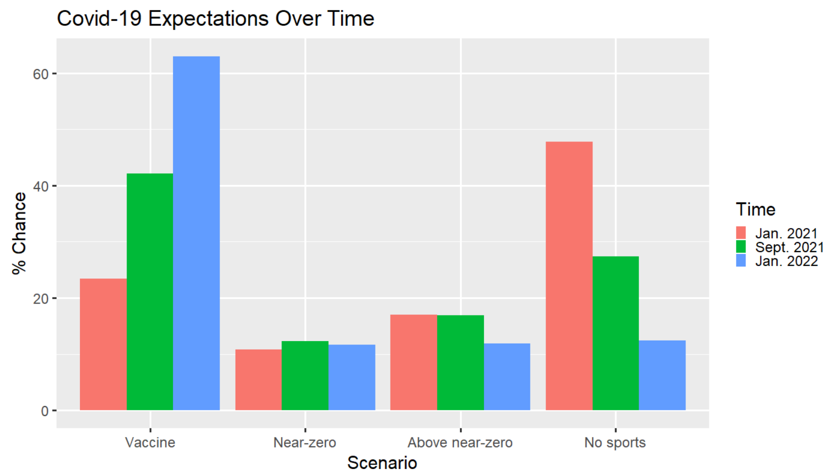


Figure 13: Average reported percent chance of each scenario occurring in each month.

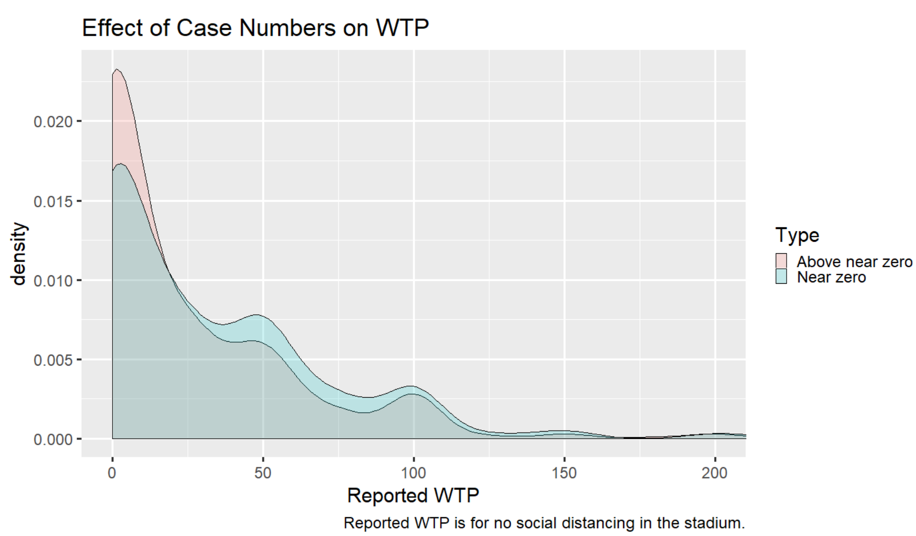


Figure 14: WTP distributions with near-zero and above near-zero levels of cases.

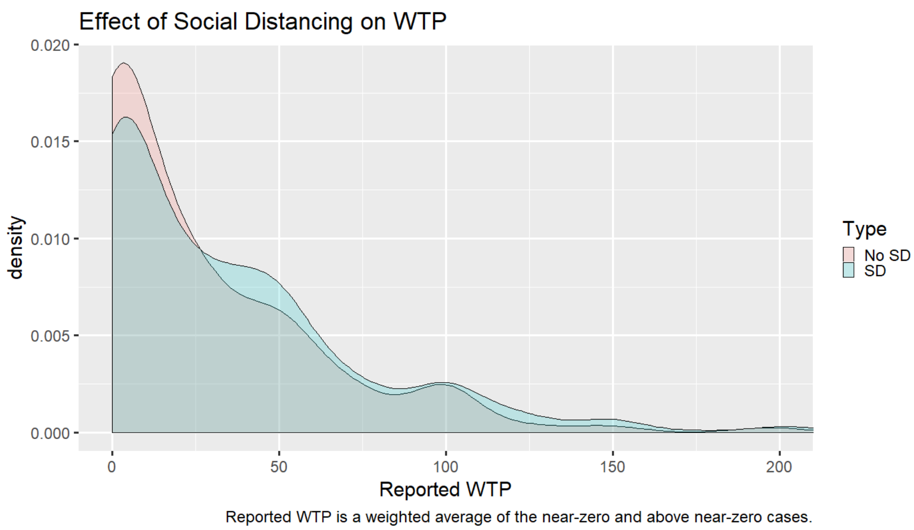


Figure 15: WTP distributions with near-zero and above near-zero levels of cases.