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

Drew Vollmer*

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Abstract

When is resale valuable? And when can it be replaced with refunds? I study common aftermarket policies in perishable goods markets with demand uncertainty. Using primary and resale market data on college football ticket sales, I estimate a structural model comparing resale, which has flexible prices but incurs frictions, to a partial refund scheme, which is centralized but has rigid prices. In the model, consumers anticipate shocks when making initial purchases, then engage in resale after shocks are realized. Because of resale frictions, refunds are more efficient on average. However, flexible prices make resale more efficient after large aggregate shocks.

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

Economists often argue that resale is valuable because it reallocates goods to consumers with high values. For instance, a consumer might buy a concert ticket, learn she cannot attend, and resell to someone who can. But other methods of reallocating, like refunds, could reach the same result. With refunds, the consumer could return the ticket to the box office; the primary market seller could then sell the same ticket to someone else. In fact, many primary sellers, like airlines and hotels, offer partial refunds instead of allowing resale.

The use of refunds and resale markets raises fundamental questions about how aftermarkets should be run. This paper focuses on resale and refunds and considers the question: is resale uniquely valuable, or would society be better off with refund policies? The answer matters in all markets where reallocation is necessary, such as those where consumers receive stochastic demand shocks after making an initial purchase. For example, a consumer might make travel plans in advance and then learn she has a schedule conflict, or she might buy clothes online and then learn they do not fit.

In this paper, I evaluate the performance of resale and refunds, the two most common reallocation mechanisms, in markets for perishable goods with demand uncertainty. The empirical setting is the market for college football tickets, where resale is common. I use primary and resale market data on college football ticket sales to estimate a structural model of the market. In the model, consumers make initial purchases under uncertainty, receive shocks that motivate reallocation, and then participate in a second phase of purchases that includes a resale market.

To compare the performance of resale and refunds, I use the model to conduct a counterfactual experiment in which resale is prohibited and the primary market seller offers a partial refund. The model predicts that partial refunds raise total welfare by 0.7% compared to resale, lower consumer welfare by 0.7%, and perform worse than resale when there are large aggregate shocks.

The empirical comparison of resale and refunds is valuable because, in theory, either strategy can maximize welfare. The core difference is that resale is decentralized, with flexible resale prices but additional frictions, whereas refunds are centralized, with all sales made by the primary market seller at its prices. Decentralized resale markets can be less efficient if the frictions associated with resale are substantial; the data suggest that they are significant in the resale market for college football tickets, possibly due to factors like a distaste for resale or the hassle associated with browsing another market. On the other hand, centralized refund policies perform poorly if primary market prices are suboptimal. One common reason for suboptimal prices—and the main explanation in the empirical setting and this paper—is that primary market prices are rigid but demand can change. Aggregate shocks to demand, such as unexpected changes in the team's performance, are common in the market for college football tickets.

I develop a framework implying that the optimal aftermarket policy depends on the relative importance of resale frictions and aggregate demand shocks. To quantify their effects, I develop a structural model in which consumers with uncertain demand decide whether to purchase football tickets over two periods. In the first period, the primary market seller announces a menu of prices that it will not revise, and consumers decide whether to purchase season tickets based on rational expectations of future shocks. Between the periods, consumers learn the realizations of two demand shocks. First, consumers may receive idiosyncratic (independently drawn) shocks. Idiosyncratic shocks are like schedule conflicts; they cause some consumers to have low values for their tickets and motivate reallocation. Second, consumers receive a purely aggregate shock, like news about the team's quality, that shifts the demand curve for tickets. In the second period, consumers know their values and decide whether to participate in the resale market or buy in the primary market. Buyers in the resale market incur frictions that are not present in the primary market, reducing the efficiency of resale. Outcomes in the second period, such as the quantity of tickets sold and the resale price, depend on the realized aggregate demand shock. The structural model is needed to predict market outcomes for circumstances not observed in the data, including different aggregate shocks and alternative aftermarket designs like refunds.

The main results come from a counterfactual experiment where the primary seller prohibits resale and offers a partial refund. I find that resale is not uniquely valuable because refunds are more efficient, raising total welfare by 0.7% despite lowering consumer welfare by 0.7%. Moreover, the primary seller prefers refunds because it raises profit by 2.5%. The changes imply that the harms of inflexible primary market pricing with refunds are outweighed by the elimination of resale market frictions. The welfare changes are meaningful relative to the number of tickets reallocated, roughly 8% with resale.

A second result is that resale performs better than refunds when there are large aggregate shocks. When the realized shock is one standard deviation above its mean, resale creates 10 percentage points more surplus in the second period relative to refunds than it does for an average shock. When the shock is one standard deviation below its mean, the corresponding advantage is five percentage points. Resale copes better because resale prices are flexible, rising $9.49 above average when the shock is one standard deviation above average and falling $8.55 when it is one standard deviation below. The difference in performance relies on the fact that model outcomes vary with realized shocks.

To estimate the model, I rely on a novel combination of data sets. The centerpiece is one season of primary and secondary market ticket sales records for a single university, with the secondary market records provided by the largest resale market, StubHub (Satariano, 2015). The sales records are at the transaction level and cover 30,000 primary market transactions and 5,500 resale transactions. The records are necessary to learn about demand for tickets and model the interaction between primary and resale markets.

The university ticket sales data, however, are not informative about the distribution of aggregate demand shocks because they only contain one season of data, and therefore one realization of season-level shocks. To learn about the distribution, which is essential for assessing the performance of refunds, I use annual resale prices for 76 college football teams from 2011–2019 from SeatGeek, another online resale market. The year-to-year variation in resale prices for each team provides a basis for the distribution of aggregate shocks. Resale prices for each school often differ from the average by 25% or more, suggesting that aggregate demand uncertainty is meaningful.

I estimate the model in two stages. In the first stage, I estimate a subset of parameters without simulating the model. The key parameters in the first stage govern demand shocks. I estimate the demand shock parameters using the frequency of observed resale, which is informative about idiosyncratic shocks like schedule conflicts, and annual variation in average resale prices for each university, which is informative about changes in aggregate demand.

In the second stage, I use the method of simulated moments to match the model's aggregate predictions for quantities sold and resale prices to the data. The computational challenge is finding a rational expectations equilibrium where consumers correctly anticipate second-period outcomes, like resale prices, in the first period.

The analysis has broad implications for our understanding of aftermarkets and resale. Evidence on the performance of reallocation mechanisms, and of the factors that affect them, is valuable for determining how to run aftermarkets. Yet there is little work on the matter. This paper contributes by measuring the relative performance of aftermarket policies and by highlighting the forces in an important class of perishable goods markets. It also contributes by quantifying the net effects of resale. The effects of resale on both primary market sellers and society have been hotly contested, with governments alternately restricting and protecting resale of event tickets (Squire Patton Boggs LLP (2017), Va. Code §59.1-38.2). Similarly, some primary market sellers prohibit resale—as U2 did for a 2017 tour (Pender, 2017)—while others, like the university in this paper, have an official resale partner. Some of the controversy is due to systematic underpricing, which is not present in this setting, but the net effect of resale on profit remains ambiguous in theory[1] and the benefits for consumers have rarely been measured. Additionally, the relevant class of perishable goods is large, covering items like reservation goods (e.g. live events, airlines, hotels, etc.) and seasonal goods (fashion). Online event ticket sales alone exceeded \$56bn in 2019 (Statista (2020)).

The analysis also offers suggestive evidence on alternatives to resale when there are rent-seeking brokers. Much of the resale literature focuses on markets where brokers purchase underpriced tickets in the primary market, as in Bhave and Budish (2023) and Leslie and Sorensen (2014). Courty (2019) proposes a refund system, similar to the one tested in this paper, to eliminate brokers in such a setting. Although underpricing and brokers are not significant for the university studied here, the model includes underpricing and rationing in equilibrium when realized demand is high in the second period. The results suggest that when primary market demand outstrips supply, resale produces significantly higher welfare than alternatives like refunds because fewer tickets are rationed. The effects of rationing imply that brokers could enhance welfare by shifting tickets to the resale market. However, the predictions are merely suggestive because the model does not include the costs of rent-seeking, featured in Leslie and Sorensen (2014), and cannot measure the potential impact of market power for brokers.

Related Literature. This paper contributes to several literatures, most directly those on resale and demand uncertainty. For the literature on resale of per-

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

ishable goods, this paper estimates how resale affects profit and welfare by modeling both primary and resale markets. Leslie and Sorensen (2014) use a similar model combining primary and resale markets to study whether resale increases welfare in the market for concert tickets, but they do not consider profit because tickets are systematically underpriced in their sample. Tickets in my setting are not underpriced and so I study both profit and welfare. Sweeting (2012) studies dynamic pricing in the resale market for sports tickets. Lewis et al. (2019) investigate the effect of resale on demand for season tickets in professional baseball but do not model how resale of season tickets affects sales of other tickets. The net effects of resale on buyers and primary market sellers are a traditional focus of the theory literature on resale, including studies such as Courty (2003) and Cui et al. (2014).

More broadly, this paper relates to other studies of how to run aftermarkets for perishable goods. Two recent papers, Cui et al. (2014) and Cachon and Feldman (2021), have compared resale and refunds in theory, but neither conducts an empirical study or considers the effect of aggregate shocks.

Aftermarket design and resale have also been studied in the context of durable goods. With durable goods, primary market sellers compete against past vintages of their products, as in Chen et al. (2013). The durable goods problem leads to alternative aftermarket designs, such as leasing, studied in Hendel and Lizzeri (2002), and buybacks, studied in Hodgson (2019).

The current analysis also relates to studies of demand uncertainty in which aggregate uncertainty affects firms' strategic choices, such as Kalouptsidi (2014), Jeon (2022), and Collard-Wexler (2013). This paper differs by focusing on strategies firms can use to cope with uncertainty.

The paper relates to a significant literature on how to sell perishable goods. The choice of sales mechanism is studied in Waisman (2021), who considers whether sellers should use auctions or posted prices when reselling sports tickets, and in Bhave and Budish (2023), who consider the differences between auctions and posted prices for the very best concert tickets.

The most significant literature on selling perishable goods concerns dynamic pricing. Recent empirical studies include Lazarev (2013) and Williams (2022), who study dynamic pricing in airlines when there is demand uncertainty. Sweeting (2012) uses data on resale of sports tickets to determine which classes of theoretical models are most appropriate.

The primary seller's need to commit to prices in this paper relates to another key issue in the dynamic pricing literature: whether the seller can commit to a pricing mechanism. The choice leads to different equilibria in Board and Skrzypacz (2016), where the seller can commit, and Dilmé and Li (2019), where the seller cannot and resorts to "flash sales."

2 An Example

In this section, I present an example illustrating that either refunds or resale can be most efficient, and that the key forces determining efficiency are demand uncertainty and resale frictions. The example establishes the need for an empirical study because the most efficient aftermarket policy is ambiguous in theory. It also clarifies that an empirical model must feature resale frictions and aggregate demand uncertainty.

The structure of the example closely matches the empirical model. A primary market seller has K tickets to sell over two periods. Additionally, the primary seller has rigid prices.

Assumption 1. *The primary market seller announces a menu of prices $\{p_1, p_2\}$ at the start of the first period and cannot adjust it afterwards. Primary market tickets are sold at price p_t in period t.*

There are two sources of demand uncertainty, both realized between the two periods. The first is an idiosyncratic shock: each consumer has a chance of receiving a shock (like a schedule conflict) and being unable to attend the game. If a consumer buys tickets in the first period and receives a schedule conflict, she has zero value for using the ticket and prefers to resell or request a refund. The purpose of idiosyncratic shocks is to motivate reallocation in the second period. The second source of uncertainty is an aggregate shock: the team might be worse than expected, causing all consumers to have lower values. Aggregate shocks make the optimal price in the second period uncertain. Consumer i's value for a ticket in the second period is

$$v_{i,2} = (\nu_i + V)(1 - H_i)\,. \quad (1)$$

Idiosyncratic shocks like schedule conflicts are reflected in the Bernoulli random variable H_i, which equals one with probability ψ and is independently drawn for each consumer. Consumers with schedule conflicts thus have $v_{i,2}$ set to zero. Aggregate shocks are reflected in changes to V, a common value for all consumers. It has two possible values in the example: a high value V_H and a lower value V_L. The different realizations V_H and V_L lead to different demand curves in the second period. Additionally, consumers differ in their tastes for football games ν_i.

Consumers consider whether to buy tickets in the first period or wait until the second, when there may be tickets available in the primary or resale markets. Consumers are forward-looking when deciding whether to buy tickets in the first period, considering the distribution of demand shocks and the aftermarket. I omit first-period decisions for both the primary market seller and consumers in this section to focus on how aftermarket strategies affect second-period allocations. The conclusions in this section hold in a two-period equilibrium, and the first period is fully developed in the empirical model.

For now, suppose that the primary market seller's prices and refund (if offered) cause consumers to buy in the first period if their expected value for tickets exceeds some threshold, $\mathrm{E}(v_{i,2}) > \bar{v}$. Suppose there are $\bar{Q}_1$ such consumers who purchase in the first period, and that a consumer i who purchases in the first period has $v_{i,2} > p_2$ whenever V_H is realized and H_i equals zero. Also suppose that the primary market seller always sets the price p_2 to just exhaust its inventory when V is realized as V_H.

Under both resale and refunds, a fraction ψ of consumers learns that they have schedule conflicts between the two periods, leaving $\psi\bar{Q}_1$ consumers who bought in the first period with no value for their tickets. The primary seller has an additional $K - \bar{Q}_1$ tickets in its inventory, leaving a total of $\bar{Q}_2 = K-(1-\psi)\bar{Q}_1$ that can be allocated to consumers with positive values. Different realizations of the shock V lead to two possible demand curves, the expected curve $D(p;V_H)$ and the lower curve $D(p;V_L)$. I suppress the first argument in the rest of the section.

Refunds. Suppose that the primary market seller prohibits resale and offers a refund r.

Assumption 2. *When the primary market seller offers a refund, it prohibits all other ticket transfers. It selects a refund r at the same time that it selects prices. Consumers who purchase tickets in the first period can return them in exchange for r at the start of the second period, and any refunded tickets are returned to the primary market seller's inventory.*

For simplicity, suppose that the primary seller sets a refund r so that the

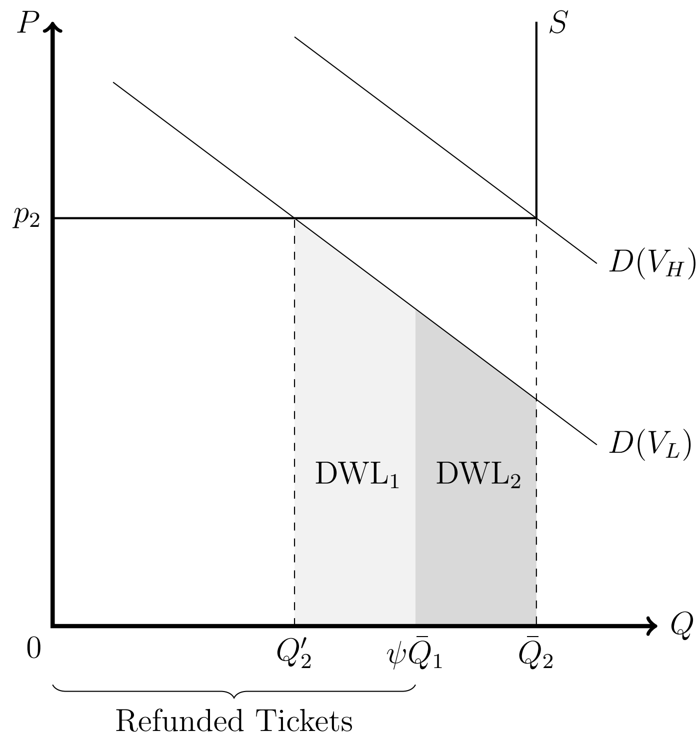


Figure 1: The second period of a market with refunds and uncertain demand.

only consumers who request refunds are the $\psi\bar{Q}_1$ who received schedule conflicts. (The assumption rules out the possibility that consumers request refunds because the realized common value V is low, which is permitted in the empirical model. It is ignored here for simplicity.) The primary seller puts all remaining tickets on sale, including those recovered through refunds, at the price p_2 it chose in the first period. I illustrate the second period in Figure 1.

The supply curve S for tickets is horizontal at p_2 up to the number of tickets in the primary seller's inventory, $\bar{Q}_2$, and vertical afterwards.

When demand is $D(V_H)$, the primary seller's price p_2 is optimal and allocates all tickets. But when demand is $D(V_L)$, only $Q_2' < \psi\bar{Q}_1$ tickets are sold. The price rigidity thus creates deadweight loss in the low-demand state. The deadweight loss region can be split based on whether the tickets were previously sold (DWL_1, the loss on refunded tickets) or not (DWL_2).

Resale markets. When there is a resale market, the primary market seller does not offer a refund. In the second period, consumers who bought in the first period can resell their tickets at prices of their choice; other consumers decide whether to purchase tickets in the primary and resale markets. I assume that the resale market is competitive, leading to an equilibrium with a single clearing price.

Assumption 3. *In the resale market, participants take the price as given, an auctioneer announces a single resale price p_2^r, and the resale market clears at the auctioneer's price.*

Because of Assumption 3, the equilibrium resale price changes when demand shifts from $D(V_H)$ to $D(V_L)$, making it a function of V, $p_2^r(V)$. The market clearing assumption is ostensibly quite strong, but several features of the empirical model prevent resale from being unrealistically efficient.

The most notable feature generating inefficiency is a friction s that consumers incur when purchasing in the resale market. It reflects factors like browsing costs and distaste for resale. Empirical evidence of frictions is shown in Section 4. Because of the friction, a consumer with value $v_{i,2}$ for a ticket is only willing to pay $v_{i,2} - s$ in the resale market. In the example, all consumers have the same friction s, an assumption I relax in the empirical model.

There are also fees in the resale market. Suppose resale market operator collects a fixed fee τ on each resold ticket, so a reseller who agrees to resell for p_2^r only receives $p_2^r - \tau$ after fees.

To easily compare to refunds, suppose the primary seller's prices make it optimal for the same $\bar{Q}_1$ consumers to purchase in the first period and that p_2 is the same as with refunds. The second period with resale is illustrated in Figure 2. Since consumers who bought early and received schedule conflicts are willing to accept any positive price, the supply curve is horizontal at zero up to $\psi\bar{Q}_1$. The supply curve is then horizontal at p_2 from $\psi\bar{Q}_1$ to $\bar{Q}_2$, reflecting the primary seller's remaining inventory. The supply curve then slopes upward because consumers with tickets and no schedule conflicts may be willing to resell at high prices.[2]

Resale frictions mean that consumers are willing to pay s less per unit in the resale market. For that reason, the demand curves $D(V_H)$ and $D(V_L)$ overstate demand for resale tickets—the first $\psi\bar{Q}_1$—by s. Consequently, there is a shaded region of height s that applies to both demand curves and represents surplus lost to frictions.

When demand is $D(V_H)$, the quantity sold is the same as with refunds. All $\bar{Q}_2$ tickets are sold at price p_2 (and resale price $p_2^r(V_H) = p_2 - s$). The price

[2] The final segment of the supply curve would be lower when demand is $D(V_L)$. I do not show the change because it would complicate the diagram and does not change the equilibrium.

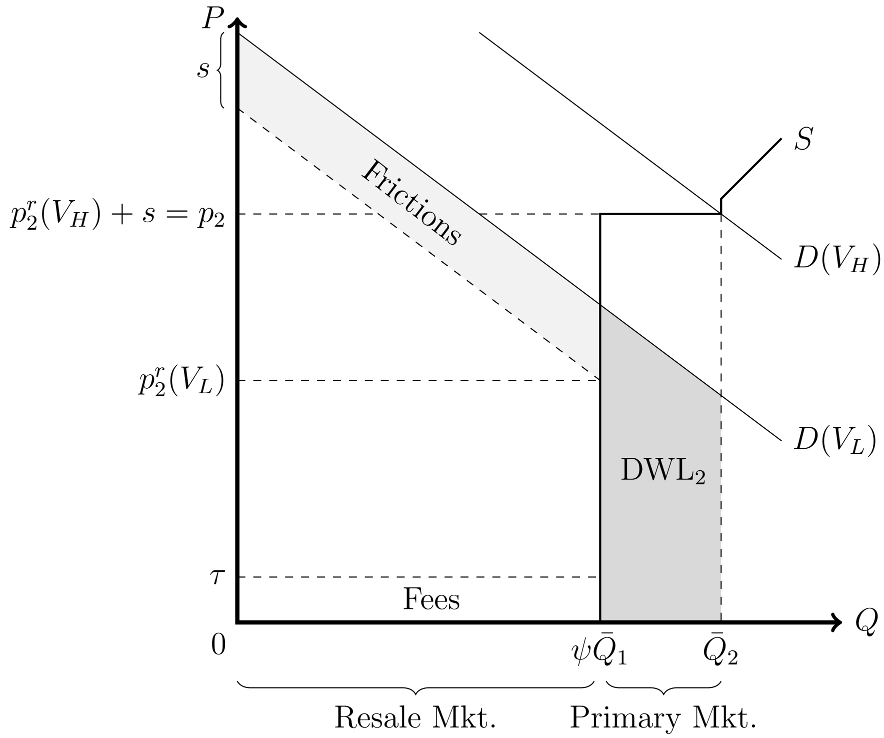


Figure 2: The second period of a market with resale and uncertain demand.

and quantity differ from refunds when demand falls to $D(V_L)$. At $D(V_L)$, $\psi\bar{Q}_1$ tickets are sold at resale price $p_2^r(V_L)$, more than the Q_2' sold with refunds. Resale fees do not affect total welfare in the example, but do affect profit by reducing consumers' expected after-fee resale revenue and hence willingness to pay in the first period.

Comparison and Summary. Because of resale's price flexibility, more tickets are sold in the low-demand state $D(V_L)$, raising welfare by up to DWL_1. But the gains are tempered by losses to resale frictions, which are realized in both states. The net change in total welfare with resale is $\Pr(V = V_L)DWL_1 - \textit{Frictions}$. ($DWL_2$ is lost with both strategies at $D(V_L)$ because the primary seller chooses p_2 under both strategies.)

The net effect thus depends on the degree of aggregate demand uncertainty and the magnitude of resale frictions. Greater aggregate uncertainty, reflected in the distribution of V, leads to larger potential losses with refunds from mispricing in the primary market. A larger friction s erodes more of the welfare gains from resale. The goal of the empirical exercise is to compare the two regions—DWL_1 and *Frictions*—in a model that features aggregate demand uncertainty, flexible resale prices, and resale frictions.

The example in this section focuses on a case where demand may be lower than expected, but the analysis is similar when demand may be higher than expected. When demand is unexpectedly high, there is still mispricing in the primary market, but now the price is too low, leading to shortages and inefficient rationing. The effects of rationing are mitigated with resale because resale prices would rise to direct tickets to higher-value consumers. However, resale still incurs frictions. The empirical model features both positive and negative aggregate shocks, and the welfare gains from resale when demand is high are significant.

The primary market seller's profit-maximizing aftermarket policy is also unclear. The ambiguity results from resale fees in addition to flexibility and frictions. The forces apply to the primary market seller's profit because it can charge consumers more in the first period when expected resale revenue increases. Thus it earns more when resale allocates more tickets or reduces rationing, but it earns less if frictions or fees reduce the proceeds from resale.

3 Data

The analysis relies on a novel combination of two data sets. The first consists of ticket sales for a single university, covering both the primary and resale markets. Ticket sales are informative about demand for tickets and the extent of resale. The second consists of annual resale prices for football tickets at many universities, which are informative about year-to-year demand changes that reflect aggregate shocks.

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

Resale transaction records for the same university come from StubHub. The data do not include all resale because consumers also resell on competing sites. However, StubHub is likely to account for most resale in this market for two reasons. First, the university has a partnership with StubHub and recommends that consumers resell on StubHub. Second, StubHub was the largest resale platform at the time, processing about half of all ticket resale in 2015 (Satariano (2015)).

The main difference between the resale and primary market data is that the resale data do not include the transaction price. To learn about the transaction price, I use daily records of all StubHub listings for the university's football games, which I gather using a web scraper. The listing data overlaps with the resale transaction data for only the season studied in this paper. Each listing includes a listing ID, price, number of tickets for sale, and location in the stadium (section and row).

The listing data scraped from StubHub do not directly give transaction prices because StubHub only shows tickets currently available for sale. To learn about transaction prices, I infer transactions from changes in listings. For example, if the number of tickets offered in a listing falls by two from one day to the next, then I assume two tickets were purchased at the last observed price.

The procedure leads to false positives because some listings are removed without being sold. I take two steps to correct them. First, I remove implausibly expensive transactions, defined as transaction prices more than 1.5 times the 75$^{\text{th}}$ percentile of price for similar quality seats. Second, I compare the number of inferred and actual transactions at the game-section-time level and assume that the lowest-price inferred transactions are the true ones. The removed transactions are generally outliers, either occurring earlier or containing more seats than typical transactions.

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

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

The combination of data sets is novel. Although several studies have combined primary and resale market ticket sales (e.g. Leslie and Sorensen (2014) and Bhave and Budish (2023)), to my knowledge, this is the first to add data on historic price fluctuations for similar events. The added SeatGeek data on annual price variation contributes by making it possible to study the effect of aggregate demand uncertainty.

4 Descriptive Evidence

In this section, I provide descriptive evidence about the market, focusing on features in the empirical model like advance sales and demand shocks.

Market Background. The university is a monopolist seller of its tickets in the primary market. There are other universities within driving distance, but they are not close substitutes because of local allegiances. In the season used in the analysis, the university sells tickets to five home games.[3]

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

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

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.

Figure 3 shows seating capacity and how tickets are sold in each zone. Season tickets account for 75% of tickets sold to the public, making them the dominant sales channel and cementing the importance of advance sales in the market. (Tickets in the "nonpublic" category are not available to the public

[3] An additional home game was scheduled but canceled. The canceled 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.

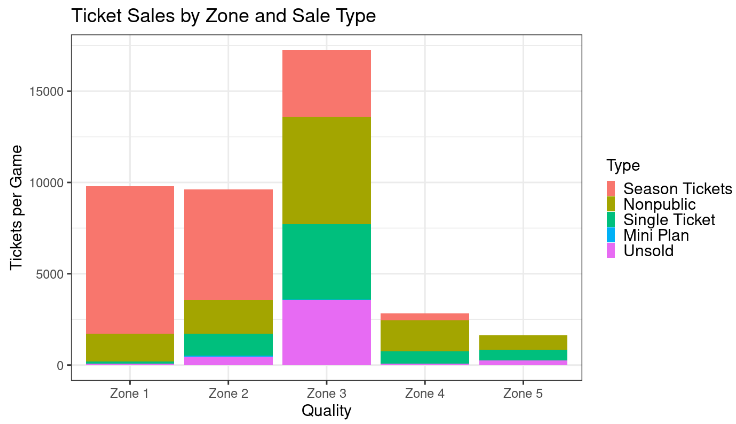


Figure 3: Sale types and volumes by quality group, averaged across games.

and include student tickets and tickets for athletics boosters.) The remaining tickets are sold as single tickets, in bundles of a subset of games ("mini-plans"), or unsold.

Capacity is concentrated in the first three zones, and the best seats are usually sold to season ticket holders. A meaningful number of tickets are shown as unsold in Figure 3—which shows an average across all games—but the unsold tickets are driven by a few less valuable games. Primary market tickets sold out for only one game in the season studied. In later seasons, the team performed better and a majority of games sold out.

I model sales for season tickets and single-game tickets in the empirical analysis. I exclude the nonpublic category because it is off limits to most buyers and I exclude mini plans because so few are sold. I also exclude single-game sales at promotional and group rates because they are not optimally priced and may only be available to targeted groups, like veterans.[4]

The menu of primary market prices is shown in Table 1. The table excludes the canceled game and shows season ticket prices that are prorated based on single-game prices. Primary market prices mainly vary by seat quality. Tickets in zone 1 cost \$60–\$70 depending on the game, but zone 5 tickets always sell for \$30. Prices vary slightly across games, but never by more than \$10.

Season tickets cost \$25–\$35 less than buying separate tickets to each game. Season ticket holders who are members of the university athletic club (which

[4]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.

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

is not required to buy season tickets) receive additional perks such as reserved parking, access to a pregame tailgate, and the chance to visit practice. Variation in values for the perks is one reason consumers might have heterogeneous preferences for season tickets. However, I do not model athletic club membership because of a lack of data and because other sports at the university are much more popular, providing a reason to join unrelated to football.

Resale Markets. Resale is a notable feature of the market, with 5.98% of all tickets sold to consumers resold on StubHub.[5] The true resale rate is higher because some tickets are resold on other resale markets. The rate at which consumers resell tickets will be used to estimate the frequency of schedule conflicts, captured in equation (1) as the probability ψ of activating the idiosyncratic shock term H_i.

The data support the idea that resale prices are flexible, reflecting the fact that resellers can adjust list prices at any time. Figure 4 demonstrates that resale prices adjust to differ from face value, akin to how resale prices $p_2^r(V)$ adjust in the example in Section 2. It shows the distribution of face values and the distribution of the average fee-inclusive resale price for each game-quality combination. The differences reflect changes in demand, and the variation across games suggests that some games are more valuable.

Figure 5 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 almost always larger than the changes in resale quanti-

[5] The primary market seller sells some tickets directly to brokers. I conservatively assume that all such tickets are sold on StubHub, so they are excluded from the 5.98% figure.

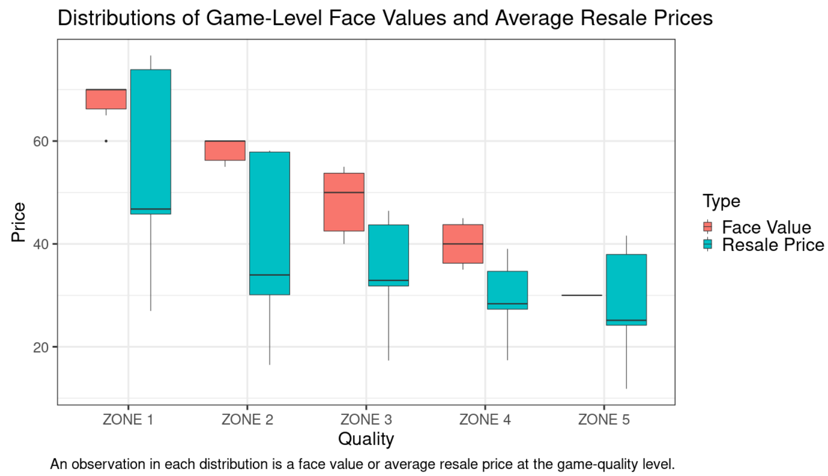


Figure 4: Distributions of mean fee-inclusive per-game resale prices and face value.

ties, usually by a large margin. The higher volatility in the primary market is unsurprising because primary market prices are fixed. In contrast, resale prices adjust and smooth the quantity of tickets resold.

The last important feature of resale markets is that they include fees and frictions that are not present in the primary market. StubHub charges a percent fee—analogous to the fixed fee τ in Section 2—amounting to roughly 22% of the amount paid by the buyer.[6,7] The average combined fee is \$10.71 on each ticket resold, a substantial amount when the average resale price is under \$40.

The data suggest that non-monetary frictions are also significant. If there were no frictions, consumers would buy single-game tickets in whichever market is cheaper. But this is not true in the data: hundreds of single-game tickets are sold in the primary market when comparable resale tickets are available for less. For instance, the average resale ticket to game one is over \$16 cheaper than the average primary market ticket, yet over 1,250 single-game tickets are sold in the primary market. There are several possible explanations for the friction. Consumers might not like or trust the resale market, they might find searching for tickets onerous, or they might be unaware of resale tickets. The frictions are reflected in the parameter s in the example in Section 2 and will be modeled as a distribution of frictions in the empirical model.

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

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

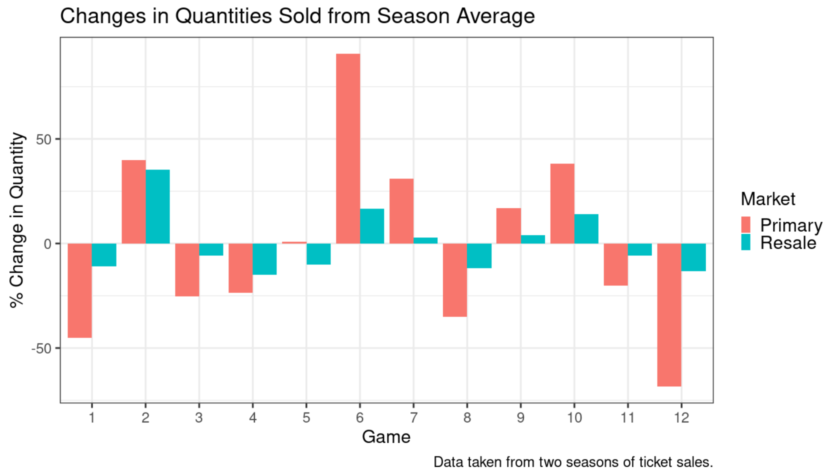


Figure 5: Percent deviation from season-average quantities sold for each game.

Annual Price Changes. The example in Section 2 includes shocks to a common component of values, V, that lead to different resale prices $p_2^r(V)$. SeatGeek's data on average annual resale prices for 76 universities provide observations analogous to $p_2^r(V)$ that can be used to learn about the underlying distribution of shocks V. Define the normalized price for university u in year y as

$$\text{NormPrice}_{uy} = \text{AvgResalePrice}_{uy} / \left(\frac{1}{Y_u} \sum_y \text{AvgResalePrice}_{uy} \right), \tag{2}$$

where Y_u denotes the number of years in the sample for university u. Figure 6 shows the distribution of normalized prices for all teams after using a regression on year dummies to adjust for time trends. Year-to-year variation for each university is significant: the distribution is approximately normal and has an estimated standard deviation of .25, implying that there is a roughly one-third chance that prices in any given season will be more than 25% away from the mean. Further, dispersion is not driven by a few outliers. The standard deviation of normalized prices is greater than .2 for more than 70% of all universities.

The dramatic swings in resale prices likely reflect aggregate demand shocks, such as changes in team performance that affect the common component of values V. For instance, in Clemson's lowest-priced season they lost two of their first three games—as many as they lost in the entire previous season—and prices were 30% lower than usual. In their highest-priced season they won the

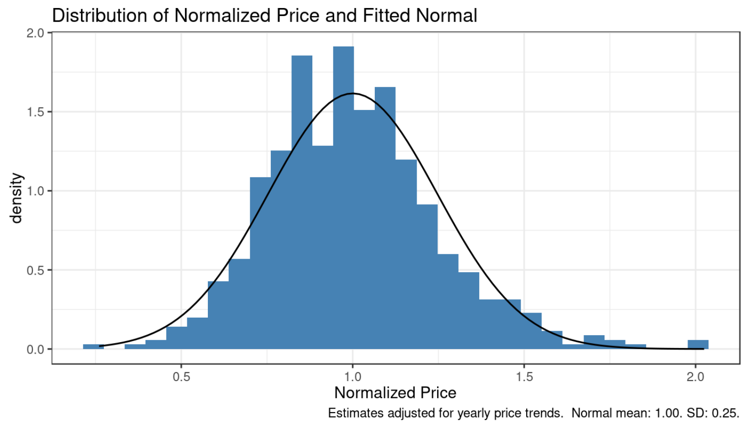


Figure 6: Distribution of resale prices normalized by sample university means, adjusted for yearly trends.

national championship game and prices were nearly 35% higher.

5 Model

In this section, I present the empirical model. The descriptive evidence of the market and the framework for comparing resale and refunds imply that the model must feature advance purchases, resale frictions, aggregate demand shocks, and a resale market whose outcome depends on aggregate shocks.

5.1 Outline, Utility, and Shocks

Let i index consumers. There are $j = 1, \ldots, J$ games in the season and $q = 1, \ldots, Q$ seat qualities. The model has two periods. On the supply side of the market, there is a monopolist primary market seller. I begin with two assumptions about the primary market seller.

Assumption 1′. *At the start of the first period, the primary market seller announces a menu of prices* $\{p_{Bq}\}_{q=1}^{Q}$ *for season tickets and* $\{p_{jq}\}_{q=1}^{Q}$ *for single-game tickets to each game* j*. Prices cannot be adjusted afterwards. Season ticket prices are only available in the first period and single-game prices are only available in the second.*

Assumption 1′ has the same content as Assumption 1 from the example in Section 2, but updates it to allow different games and seat qualities. Price rigidities and the different phases of primary market sales are based on the setting, as discussed in Section 4.

Assumption 4. *A monopolist primary market seller maximizes profit, has capacity K_q for each seat quality $q = 1, \dots, Q$, and has no marginal costs for each ticket.*

Assumptions $1'$ and 4 define the monopolist's problem and hence the supply side of the market. There are no cost parameters, so the model does not rationalize observed prices in estimation—estimation only involves the demand side of the model. However, the assumption that the primary market seller maximizes profit will matter in counterfactuals, where the primary seller sets different prices for each aftermarket policy.

The rest of the section explains the demand side of the model. There are N consumers who want at most one ticket. All consumers arrive in the first period, when they decide whether to buy season tickets or wait until the next period. 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.

Consumer i's utility for a ticket of quality q to game j is measured in dollars (relative to an outside option normalized to zero) and has a similar form to equation (1) in Section 2,

$$u_{ijq}(V, H_{ij}) = \alpha_j \left(\nu_i + V + \gamma_q\right)\left(1 - H_{ij}\right). \tag{3}$$

As before, the random variable H_{ij} captures idiosyncratic shocks like schedule conflicts and follows a Bernoulli distribution with success probability ψ. Consumer i receives independent draws of H_{ij} for each game and has no value for the game when H_{ij} equals one.

Similarly, the random variable V still acts as a common component of values for all consumers and so changes to it represent an aggregate shock, like an injury to the team's star player. The distribution of V is continuous, unlike in the two-type model in Section 2. There is a single realization of V for the season.

Consumer i's utility also depends on a consumer-specific taste parameter ν_i and two new terms, a scalar α_j specific to game j and a scalar γ_q specific to seat quality q. The parameters α_j and γ_q do not vary among consumers, implying homogeneous preferences for games and seat qualities.

The effect of the parameters is most easily seen if we separate equation (3) into pieces. The middle piece is constant across games and can be thought of as consumer i's base utility for a game. It is higher for better seat qualities q and higher consumer preferences for football games ν_i. The base utility is then multiplied by the leading term α_j to explain why some games are more desirable.

Consumer heterogeneity in equation (3) is primarily vertical, ranking consumers by their value of ν_i. The ordinal ranking of consumers is fixed until idiosyncratic shocks H_{ij} are realized, but the cardinal differences may be stretched across games (through α_j) or shifted by qualities and shocks (through V and γ_q). Heterogeneity in game and quality preferences is not essential to the research question and would make computation more challenging.

Although equation (3) does not include an error term, the model includes parameters and features that create random variation in choices over the products in a consumer's choice set, such as season tickets and resale tickets.

Two parameters in consumer utility, ν_i and V, require parametric distributions.

Assumption 5. *The common value V follows a normal distribution, $V \sim N(0, \sigma_V^2)$.*

Assumption 6. *The consumer taste parameter ν_i follows an exponential distribution, $\nu_i \sim Exp(\lambda_\nu)$.*

Assumption 5 follows from the distribution of normalized prices in Figure 6, which is approximately normal. I assume an exponential distribution for ν_i to limit the number of parameters to estimate.

The model outline is depicted in Figure 7. Consumer decisions in period two are depicted for a single game j but occur for all games.

5.2 Period Two

By the start of period two, consumers have already decided whether to buy season tickets. Consumers with season tickets decide whether to resell or attend, and all other consumers decide whether to purchase tickets in the primary market, resale market, or not at all. At the start of period two, consumers learn the realizations of random shocks: schedule conflicts H_{ij} and the common value V.

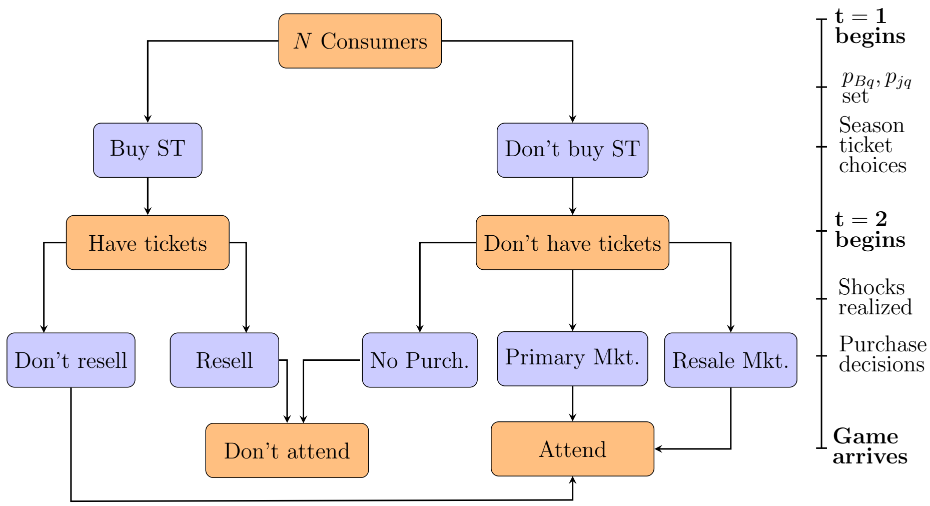


Figure 7: Model timeline and outline for consumer arrivals and choices, where the second period is shown for a single game j. Decisions are shown in blue.

The resale market operates as described in Assumption 3. Specifically, there is a single menu of resale prices $\{p^r_{jq}(V)\}_{q=1}^{Q}$ clearing the resale market for each game j, all resale market participants act as price takers, and the resale price varies with the realization of V and includes all fees paid by buyers. The purpose of the assumptions is to simplify the search for resale prices, which must be conducted for each realization of V. The assumptions do not imply a perfectly competitive market that maximizes welfare gains, however. Other features of the model, like resale frictions, will be calibrated to reduce the efficiency of resale based on observed purchase patterns in the data. The market-clearing price also implies that no resellers have market power, which may be inappropriate in a market where brokers resell in large volumes.

For simplicity, consider game j and begin by considering the supply side of the resale market. As in Section 2, consumers who bought season tickets resell if

$$u_{ijq}(V, H_{ij}) \leq (1-\tau)p^r_{jq}(V). \tag{4}$$

The resale fee τ is a percentage of the resale price to match the policies of resale markets like StubHub. The condition implies that all consumers receiving an idiosyncratic shock are willing to resell at any positive price.

Consumers without season tickets decide whether and how to buy tickets to game j. They have three choices: make no purchase and receive surplus zero (noted as *No Purch. Surplus*$_{ij}$), purchase in the primary market and receive surplus *PM Surplus*$_{ijq}$, or purchase in the resale market and receive surplus *SM Surplus*$_{ijq}$. The surplus terms are

$$\textit{No Purch. Surplus}_{ij} = 0, \tag{5}$$

$$\textit{PM Surplus}_{ijq}(V, H_{ij}) = u_{ijq}(V, H_{ij}) - p_{jq}, \tag{6}$$

$$\textit{SM Surplus}_{ijq}(V, H_{ij}, s_{ij}) = u_{ijq}(V, H_{ij}) - p^r_{jq}(V) - s_{ij}, \tag{7}$$

where s_{ij} is a friction that affects the surplus from buying in the resale market. Draws are independent for each consumer and game. As with the model's other shocks, consumers know the distribution of frictions in the first period but do not learn their realizations until the second. The friction introduces random variation in the choice between primary and resale market purchases. It explains why there are observed primary market purchases when similar tickets are available for less in the secondary market.

Assumption 7. *The frictions s_{ij} follow an exponential distribtion, $s_{ij} \sim Exp(\lambda_s)$, and are independently drawn for each individual and game.*

For each game, each consumer without season tickets chooses the option maximizing surplus among equations (5), (6), and (7). Together, the equations determine demand for primary and resale market tickets in period two.

Some alternatives may sell out, particularly in a state with a high draw of the common value V, and so the model must include rationing. (Although no games sell out in the season studied, all games sold out the following season.)

Assumption 8. *Tickets are rationed randomly when there is a stock-out. The probability of receiving a primary market ticket of quality q to game j is $\sigma_{jq}(V)$.*

The rationing process is as follows. A consumer starts by requesting his surplus-maximizing choice. He has some chance of receiving the requested choice: probability $\sigma_{jq}(V)$ if he requested a primary market ticket of quality q, and probability one if he requested a resale ticket of any quality or decided to make no purchase. (There are no stock-outs in the resale market because the resale market clears by Assumption 3.) If he does not receive his surplus-maximizing choice, he requests his next-preferred choice. The process continues until a request is accepted.

5.3 Period One

In period one, consumers decide whether to buy season tickets. In this subsection, I present a decision rule reflecting the ability to resell in the second period. I modify it in counterfactuals to reflect alternative aftermarket policies.

By buying season tickets, consumers receive the maximum of their value for attending game j and the after-fee resale price. Surplus also depends on the price of season tickets and an additional parameter δ_i. The purpose of δ_i is to capture heterogeneity in consumer values for season tickets, which could result from diminishing (or increasing) returns from attending many games or perks for season ticket holders in the university's athletics club[8]. Consumers sharing the same ν_i could make different season ticket decisions because of variation in δ_i. Consumer i's surplus from season tickets of quality q is

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

Assumption 9 limits the season ticket preferences δ_i to two values.

Assumption 9. *The parameter δ_i satisfies $\delta_i \in \{\delta_L, \delta_H\}$, where $\delta_L < \delta_H$. Values of δ_i are independently drawn. A fraction ζ of consumers have $\delta_i = \delta_H$, implying* $\Pr(\delta_i = \delta_H) = \zeta$.

The surplus from waiting until period two requires an expectation for each game j's surplus with rationing. Without rationing, surplus from waiting is the expected maximizer of the set of all seat qualities for each game j in the primary and resale markets, plus the ability to make no purchase. The complete set of alternatives for game j is

$$\begin{aligned} \mathcal{C}_{ij}(V, H_{ij}, s_{ij}) = \{0, & \{\mathit{SM\ Surplus}_{ijq}(V, H_{ij}, s_{ij})\}_{q=1}^{Q}, \\ & \{\mathit{PM\ Surplus}_{ijq}(V, H_{ij})\}_{q=1}^{Q}\}. \end{aligned} \tag{9}$$

With rationing, a consumer may have to choose her m^{th}-best option. Let $c^{(m)}(\mathcal{C}_{ij})$ be the m^{th}-largest element of $\mathcal{C}_{ij}$, and let $\sigma_j(V, c)$ be the probability

[8] I do not have data on membership in the athletics club and so omit it from the model. Membership may not be directly tied to preferences for football tickets because it grants benefits for other, more popular sports.

of receiving option c.[9] The expected utility in the second period from waiting with choice set $\mathcal{C}_{ij}$ can be defined recursively as

$$\begin{aligned} \mathit{WaitSurplus}_{ij}(V, \mathcal{C}_{ij}) = \; & \sigma_j(V, c^{(1)}(\mathcal{C}_{ij}))c^{(1)}(\mathcal{C}_{ij}) + \\ (1 - \sigma_j(V, c^{(1)}(\mathcal{C}_{ij}))) & \, \mathit{WaitSurplus}_i(V, \mathcal{C}_{ij} \setminus c^{(1)}(\mathcal{C}_{ij})). \end{aligned} \tag{10}$$

Overall surplus from waiting is the expected value in the first period,

$$\mathit{WaitSurplus}_i = \sum_j \mathrm{E}_{V,H_{ij},S_{ij}} \left(\mathit{WaitSurplus}_{ij}(V, \mathcal{C}_{ij}(V, H_{ij}, S_{ij})) \right). \tag{11}$$

The consumer's choice set in period one is thus

$$\mathcal{C}_{i,ST} = \left\{ \mathit{WaitSurplus}_i, \{ST \ \mathit{Surplus}_{iq}\}_{q=1}^{Q} \right\}. \tag{12}$$

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 procedure used in the second period.

5.4 Equilibrium

I search for a fulfilled-expectations equilibrium. The primary market seller anticipates consumer demand and selects profit-maximizing prices $\{p_{Bq}\}$ and $\{p_{jq}\}$. (Equivalently, the primary market seller maximizes revenue because the marginal cost of a ticket is zero.) Consumers know the equilibrium resale price function $\{p^r_{jq}(V)\}$ and primary market purchase probabilities $\{\sigma_{jq}(V)\}$. 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

Estimation has two stages. In the first stage, I estimate all parameters that can be identified without structural simulations. In the second, I estimate the remaining parameters using the method of simulated moments. Estimation

[9] The probability $\sigma_j(V, c)$ of receiving alternative c generalizes the earlier probability $\sigma_{jq}(V)$ of receiving primary market tickets of quality q to game j. When c is a primary market ticket, the two probabilities are equal. When c is a resale market ticket or no purchase, $\sigma_j(V, c)$ equals one.

focuses on the demand side of the model because there are no supply-side parameters to estimate.

6.1 First Stage

K_q. I use the university's designations for seating zones q and take K_q to be the number of seats in zone q.

τ. The fee τ is the percentage of the fee-inclusive price paid by the buyer, calculated directly from StubHub's policies.

ψ. The probability ψ of receiving an idiosyncratic shock (and having H_{ij} equal one) is identified by the frequency of resale. In the model, observed resale is explained by idiosyncratic shocks in equilibrium, so the parameter ψ equals the ratio of tickets resold by consumers to all tickets sold under the assumption that StubHub represents 75% of the resale market. (There is also resale on other sites, which I do not observe.) The 75% figure is conservative. Leslie and Sorensen (2014) assume a 50% share for StubHub and eBay and Satariano (2015) reports that StubHub has roughly half of the ticket resale market. If StubHub's market share is lower than 75%, the model understates the effects of reallocation and the differences between aftermarket policies.

α_j *and* γ_q. The parameters α_j and γ_q affect consumer values and hence resale prices. They can be recovered from resale prices with 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. As a result, the price can be written as a non-parametric function,

$$p^r_{jqk} = g(\alpha_j, \gamma_q, \lambda_s, V, \lambda_\nu, \mathbf{p}_j, X_k) + \varepsilon_{jqk}, \tag{13}$$

where X_k represents the characteristics of listing k, such as the number of tickets in the transaction and the number of days until the game.

Equation (13) can be simplified because many of its arguments are fixed within the observed season. The only arguments that vary are games, qualities, and listing characteristics. As a result, resale prices in the data only vary with α_j, γ_q, and X_k.

To estimate the parameters α_j and γ_q, I assume a specific form of $g(\cdot)$. The key assumption is that changes in consumer values pass through completely to resale prices. The assumption is acceptable if two conditions hold for the resale prices observed in the data. First, the supply of tickets available for resale must be roughly fixed. This is plausible in the model because, in equilibrium, only consumers who receive schedule conflicts choose to resell.[10] Second, a shift in demand for all tickets must produce a similar shift in demand for resale tickets. This is plausible if there is limited substitution between the primary and resale markets. Substitution is likely to be limited because resale prices are well below primary market prices in the observed season, but resale frictions imply that there is some substitution. The counterfactual results in Figure 10 suggest that the assumption holds in equilibrium.

The assumption that consumer values pass through completely to resale prices suggests that transaction prices should vary directly with consumer values. Accordingly, I assume that

$$g(\alpha_j, \gamma_q, \lambda_s, V, \lambda_\nu, \mathbf{p}_j, X_k) = \alpha_j(\gamma_q + X_k\beta). \tag{14}$$

Equation (14) is similar to equation (3), but differs by allowing the characteristics of listing k to affect the resale price through the vector of coefficients β. I estimate the model using nonlinear least squares and obtain standard errors using the bootstrap.

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

σ_V^2. The parameter σ_V^2 is the estimated variance of a normal fit to the set of observed aggregate demand shocks $\{V\}$. The challenge is that the set of shocks is not directly observed and must be constructed from the data.

The basis for the set of shocks is observed variation in annual resale prices for the wide range of teams in the SeatGeek data. The shocks faced by similar teams provide the most appropriate comparison, so I limit the SeatGeek data to universities in similar athletic conferences that, like the university studied,

[10] A caveat is that equilibrium requires optimal primary market prices, but estimation uses observed (and suboptimal) primary market prices. Thus, in estimation (but not counterfactuals), some consumers who do not receive shocks resell. However, they tend to resell for all games and so the supply of resale tickets remains fixed.

have not appeared in a national championship game or the College Football Playoff in the past 20 years.

The starting point is the normalized resale prices described in equation (2). The normalized prices give university u's percent deviation in resale prices in year y from university u's average across all seasons. I use the normalized prices to obtain a set of all observed shocks $\{V_{uy}\}$, then estimate σ_V^2 by fitting a normal distribution to the set $\{V_{uy}\}$. Observations for all universities and years are used—they are adjusted to apply to the university studied.

There are three adjustments needed to go from normalized prices to the shocks V_{uy}. First, I adjust for time trends by subtracting the relevant season's mean normalized price for all universities. Second, the normalized prices are percent deviations and must be converted to absolute changes in values for the university studied. To do so, I multiply by the studied university $\bar{u}$'s mean season-adjusted resale price, $\bar{p}^r_{\bar{u}}$. Third, resale price shocks reflect the mean across games of $\alpha_j V$ by equation (3), and the mean of the α_j is not necessarily one. I adjust by dividing by a weighted average of the α_j, taking game j's share of all resale transactions as the weight w_j. In total, the values V_{uy} are obtained according to

$$V_{uy} = \bar{p}^r_{\bar{u}} \left(\text{NormPrice}_{uy} - \overline{\text{NormPrice}}_y\right) \left(\sum_j w_j \alpha_j\right)^{-1}. \tag{15}$$

Because estimation is based on normalized prices, the identifying variation comes from season-to-season changes for each university. The estimate of σ_V^2 is not driven by differences between different universities.

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 the year-to-year change is predictable, like when a star player graduates. Second, shocks to the common value pass through completely to resale prices, discussed earlier for the estimation of α_j and γ_q. And third, the university faces the same shocks to normalized prices as all other schools.[11]

[11] The university's distribution of normalized prices is similar to those of other schools. For evidence, see Figure 15 in Appendix B.

6.2 Second Stage

There are five parameters left to be estimated: λ_s, which defines the distribution of resale market frictions; λ_ν, which defines the distribution of consumer values; δ_H and δ_L, which define how consumer preferences for season tickets differ from attendance and resale values; and ζ, which defines the fraction of consumers with each value of δ_i.

I estimate the parameters using the method of simulated moments. For each set of candidate parameters, I take primary market prices as given and simulate the demand side of the model to predict 11 total moments: the number of season tickets sold, the average resale price for each of five games, and the quantity of primary market tickets sold for each of five games. MSM with aggregate moments is suitable because there are no closed-form expressions for model predictions as a function of parameters, and because many individual-level choices, such as to not purchase, are not observed.

An important detail for estimation is that the observed moments in the data result from one value of V realized for the season studied. I determine the value of V realized in the data using equation (15), which compares observed to average resale prices for the university. Then I estimate the model by comparing model predictions for the realized value of V to the observed data.

One factor affecting average resale prices in the data is the composition of seat qualities that are resold. I weight model-predicted resale prices, which are at the game-quality level, with the observed quality composition for resold tickets in the data to ensure they are comparable.

The weight matrix has zeros off the diagonal and treats a 1% deviation in each moment from its observed value equally. (The inverse covariance matrix cannot be recovered because estimation moments come from separate datasets.)

In simulations, I discretize the distributions of ν_i and V. The grid of values for ν_i ranges from 0 to 198 in increments of 0.1. The grid for V consists of 100 values, the evenly spaced quantiles of the distribution from 0.5% to 99.5%. The extreme values of V in the grid are ± 20.8.

Simulating the model is computationally demanding. Each simulation involves computing market outcomes for a grid of possible realizations of V. Moreover, equilibrium requires iteration to a fixed point where consumers correctly anticipate resale prices and primary market purchase probabilities for each game and realization—a $100 \times 5 \times 2$ array. The model iterates until expected and realized resale prices differ by no more than \$0.01 for any realization of V and the mean primary market purchase probability for each quality is within 1%. It takes over 20 minutes to converge at its optimal parameters.

I calculate standard errors for the second-stage parameters using the bootstrap. I draw a sample of 50 estimation moments, then estimate optimal parameters for each set with first-stage parameters fixed at their point estimates. The reported standard errors are derived from the set of estimated optimal parameters. To obtain the set of alternative estimation moments, I calculate each moment's variance and sample from the implied distributions. For each game's average resale price, I construct the variance by sampling from the distribution of transaction-level resale prices. For the number of season tickets and single-game primary market tickets sold, I do not observe individual-level choices and so cannot sample them. Instead, I assume that the underlying individual choices are based on Bernoulli draws and use the associated variance. For details, see Appendix C.1.

Each parameter is identified by a combination of the estimation moments. Start with the distribution of resale frictions, parameterized by λ_s. In the model, consumers purchase in the primary market if the primary market price is less than the sum of the resale price and the resale friction. For instance, if the resale price is \$5 less than the primary market price, any consumer with $s_{ij} > 5$ prefers the primary market. The distribution of s determines the number of consumers with $s_{ij} > 5$ and hence the number of tickets sold in the primary market. It follows that λ_s is identified by primary market quantities and the difference between primary and resale market prices.

Next, consider 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.

Finally, consider the parameters related to season ticket values, δ_H, δ_L, and ζ. They relate intuitively to season ticket purchases. The parameters either directly raise consumers' values for season tickets (δ_H and δ_L) or increase the fraction of consumers with high values for season tickets (ζ). However, the quantity of season tickets sold is not enough to identify all three parameters because raising δ_H while lowering δ_L or ζ could result in the same quantity of season tickets sold.

The remaining second-period moments identify the season ticket parameters. The connection between the moments and the parameters is that, by determining who buys season tickets, the season ticket parameters also determine who is left to shop for tickets in the second period. The values of second-period shoppers form the demand curves that determine resale prices and primary market quantities. For example, suppose that δ_H is raised and ζ lowered from their true values so that the number of season ticket buyers stays the same. The new high-type season ticket buyers would have lower values ν_i than earlier season ticket buyers. Therefore, consumers would have higher values than before in the second period, changing predicted resale prices and primary market quantities.

In fact, the estimation moments depend on all three parameters. (For details, see Appendix C.2.) The model produces a markedly worse fit when any of the season ticket parameters is normalized.

There is a special case in which the parameters δ_H and δ_L are partially identified, equilibria where all or no consumers of each type want to buy season tickets. For example, if no consumers with type L want to buy season tickets, they would not buy season tickets at any lower value of δ_L (holding other parameters constant). A range of δ_L would thus lead to the same allocation and model fit. As I explain below, the parameter δ_L is partially identified in the estimated equilibrium.

Partial identification would be consequential if the results of counterfactual experiments varied widely in the identified set. But if no consumers of type L purchase season tickets in the counterfactuals at any parameter combination in the identified set, then there is a single counterfactual prediction. This is the case in the data, making the partial identification of δ_L immaterial to the counterfactual experiments.

6.3 Results and Fit

Estimated parameters are in Tables 2 and 3. The resale fee is about 22% of the fee-inclusive price paid by the buyer.[12] The idiosyncratic shock rate suggests that 8% of buyers change their minds about attending the event between the first and second periods.

Consumer values vary widely across games and qualities. I normalize $\alpha_1 = 1$ and $\gamma_5 = 0$. 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%

[12] For a listing with price p, StubHub charges the buyer $1.15p$ and gives the reseller $.9p$, or $.25/1.15 \approx .22$ of the price paid by the buyer.

lower. The best seats are worth almost \$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 \$8.08. The university thus faces consumer values for the baseline game that differ from the mean by more than \$8 about a third of the time.

In the second stage, the parameter defining the exponential distribution of resale market frictions is 78.05. The substantial friction implies that the resale market does not allocate tickets to consumers with the highest values ν_i; many buyers in the resale markets have relatively low values ν_i but very low draws of the friction. Inefficiency from resale frictions reduces the effect of the assumptions that resale market participants are price takers and that there is a single clearing price in the resale market. For more details on resale market efficiency, see Appendix D.1.

The mean of the distribution of consumer types is 17.60, suggesting that the average consumer (given the assumed size of the population) would pay \$17.60 for the worst seats to the baseline game in an average season.

Consumers with high values for season tickets are estimated to represent 81% of the population and value season tickets \$5.60 more than buying tickets to each game separately.

The corresponding estimate for consumers with low values for season tickets is only partially identified. At the optimal parameters, the model predicts that no consumers with low values for season tickets will buy a season ticket package. Holding the other parameters constant, the model fit and allocation are the same for any δ_L such that no consumer of type L purchases season tickets. The identified set is $[-203.06, -\infty)$ and I report its upper bound. Similarly, the standard error reported for δ_L is based on the upper bounds of the identified sets for the alternative moments. The magnitude of δ_L ensures that some consumers with high values demand tickets in the second period.

Table 4 and Figures 8 and 9 assess the model fit, where second-period model predictions are for the value of V observed in the data. 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 parameters specifically designed to fit game-specific quantities. Finally, the model-implied number of season tickets purchased is within 10% of the true value.

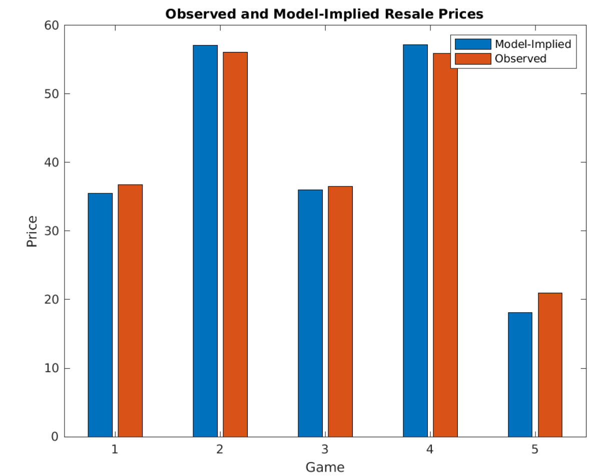


Figure 8: Observed resale prices and model-implied resale prices for the realized value of V for each game.

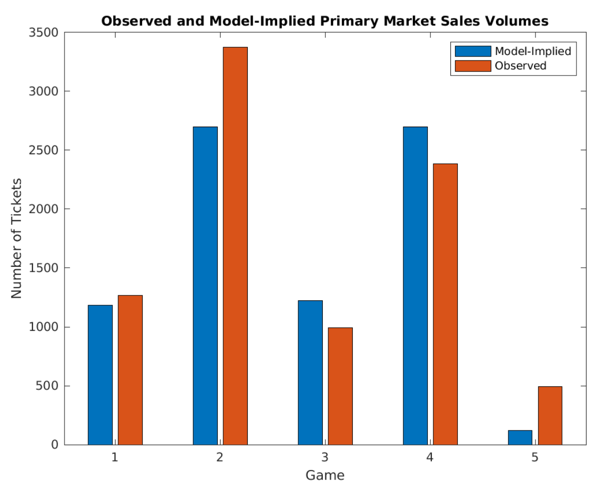


Figure 9: Observed primary market quantities and model-implied primary market quantities for the realized value of V for each game.

Parameter Description	Notation	Estimate	Std. Err.
Resale Fee (%)	τ	0.22	-
Idiosyncratic Shock Rate	ψ	0.08	-
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	21.95	0.689
Preference for Quality 2	γ_2	9.90	0.611
Preference for Quality 3	γ_3	4.37	0.569
Preference for Quality 4	γ_4	-0.70	0.619
Preference for Quality 5	γ_5	0.00	-
SD of Common Value	σ_V	8.08	0.293

Table 2: Estimated parameters from the first stage.

Table 3: Estimated parameters from the second stage.

Parameter Description	Notation	Estimate	Standard Error
Mean Resale Friction	λ_s	78.05	0.68
Mean Consumer Type	λ_ν	17.60	0.03
High-Type ST Benefits	δ_H	5.60	0.04
Low-Type ST Benefits*	δ_L	-203.06	1.67
Pct. High-Type ST Benefits	ζ	0.81	0.004

* Estimate and standards errors are for the upper bound of the identified set.

6.4 Robustness and Limitations

The available data and need for tractability place necessary limits on the model.

One limitation is the lack of data on brokers. Brokers are unlikely to be prominent in the market because tickets are not underpriced and do not sell out in the observed season, leaving little rent-seeking motive for resale. However, it is possible that some brokers are present in the data. If so, the estimate of the idiosyncratic shock rate ψ would be too high because some observed resale would be due to brokers who intended to resell. Further, brokers are more sophisticated than casual resellers and so may extract more surplus, for instance by using dynamic pricing strategies. As a result, the model would overstate consumer surplus if brokers are prominent. If brokers capture surplus by generating inefficiency, total surplus with resale would also be overstated.

A limitation of the data is that ticket usage and resale outside of the online

Table 4: Observed and model-implied quantities of season tickets.

Moment	Model-Implied	Observed
Season Tickets Sold	24543	22471

resale market are not observed. Due to the data, the model assumes that no one resells tickets to friends or coworkers and that all tickets are used. The assumptions are false but have an unclear effect on the counterfactual comparison of resale and refunds. Unobserved resale affects the comparison because refunds would make it impossible to transfer tickets to friends or colleagues. If recipients in unobserved transactions have high values, then the results may understate the performance of resale relative to refunds. If they have low values, the results may flatter resale. However, there is no data to settle the matter. I conduct robustness checks in Appendix D.3 and find that the welfare-maximizing aftermarket policy is unlikely to change.

The assumption that all tickets are used could affect the comparison of resale and refunds if one policy caused there to be more unused tickets. I evaluate how large the difference must be to change the results in Appendix D.2. The idea of unused tickets hints at a larger idea: that there is an entry process to the resale market that would also apply to refunds. An entry process implies an intensive margin to reallocation, but it is again unclear how it would affect the comparison of resale and refunds. Resale prices may motivate more reallocation than a lower refund, but refunds may get more takeup than the hassle of resale. In the absence of data, the exercise in Appendix D.2 helps assess the magnitude of any effect.

A limitation required by the model is Assumption 3, that the resale market is static with a single clearing price. The streamlined resale market is needed to compute a fulfilled-expectations equilibrium where outcomes vary with a distribution of shocks. But it would be inappropriate if it is more efficient than the true resale market, where dynamics and price dispersion produce misallocation. Although the modeled resale market is static, resale frictions cause misallocation and dispersion in effective prices paid (the resale price plus incurred frictions). I provide evidence on inefficiency in the model's resale market in Appendix D.1. I show that the model generates price dispersion similar to that in the data, and that it is far less efficient than a frictionless market conditional on the first-period allocation.

The model does not allow heterogeneous preferences for seat qualities, instead giving all consumers quality preferences defined by γ_q. The assumption prevents the primary seller from using seat quality to discriminate. The assumption has little effect on the purpose of the model and applies equally to the resale and refund counterfactuals.

The model also assumes there is no heterogeneity in how consumers value each game—everyone considers game 2 to be α_2/α_3 as good as game 3, for example—which has implications for the motives for resale. The assumption is necessary because there is no individual-level data to identify a joint distribution of values across games, but it is incorrect if consumers know in advance that they plan to resell. If heterogeneity in preferences across games is significant, then some resale is planned and the model overestimates the rate of idiosyncratic shocks. The difference would affect counterfactuals because the partial refund is likely to be lower than the resale price, causing consumers to resell when they have low values but not take the refund.

7 Counterfactuals

I use the structural estimates to evaluate several counterfactual policies. In addition to the main experiments on partial refunds and a menu of refund contracts, I implement counterfactuals to measure the effects of market features like primary market price rigidities and resale fees.

The model predicts allocations, welfare, and profit for each realization of the aggregate shock V. Reported counterfactual results integrate out over the distribution of shocks and so represent average outcomes.

Unlike the estimation procedure, the counterfactuals use the assumption that the primary market seller maximizes its profit. In each counterfactual, I solve for the primary market seller's optimal menu of prices and evaluate welfare at those prices. Solving for optimal prices is necessary because the aftermarket policy affects the optimal price menu.

I place a mild restriction the primary market seller's choice of prices to simplify the search for profit-maximizing prices.

Assumption 10. *The primary market seller chooses values p_B and p and then sets its menu of prices according to*

$$p_{Bq} = \left(\sum_j \alpha_j\right)(p_B + (1 - \psi\tau)\gamma_q) \tag{16}$$

$$p_{jq} = \alpha_j(p + \gamma_q). \tag{17}$$

Consumers who are indifferent between qualities choose the available quality with the highest value of γ_q*.*

The purpose of Assumption 10 is to simplify the search for the primary market seller's optimal prices by reducing it to two dimensions. The prices p_B and p are base prices that I report in counterfactual results.

Under the assumption, consumers are indifferent between all qualities and choose the best available quality. The main consequence is that the primary seller cannot set lower prices for one quality, which would create a shortage that pushes some high-value consumers to other qualities or the second period.

The only source of across-game variation in the primary seller's single-game prices is α_j. The assumption is reasonable because multiplication by α_j is the only difference between consumer values across games. Assumption 10 is even consistent with profit maximization in the second period if the primary seller cannot commit: the shared α_j term in consumer values and prices makes a single base price p optimal for all games.

I obtain standard errors using the bootstrap. I sample model parameters from the distribution obtained in the standard error calculations from Section 6 and run the counterfactual experiments for each sample to obtain a distribution of outcomes. Details are in Appendix C.3.

7.1 Resale and Partial Refunds

The primary empirical goal of the paper is to compare resale to a counterfactual where the primary market seller offers partial refunds. With resale, the market is as described in Section 5.

Partial Refunds. Partial refunds are as described in Assumption 2 in Section 2, except that the primary market seller now sets a refund for each game, r_j. As before, resale is prohibited. Analogous to the resale decision rule in equation (4), consumer i requests a refund when

$$u_{ijq}(V, H_{ij}) \leq r_j. \tag{18}$$

When consumers decide whether to buy season tickets, they know they can only purchase tickets in the primary market later. Consequently, the choice set for consumers without tickets in the second period, formerly equation (9), becomes

$$\mathcal{C}_{ij}(V, h_{ij}) = \{0, \{PM\ \ Surplus_{ijq}(V, h_{ij})\}_{q=1}^{Q}\}. \tag{19}$$

The value of buying season tickets now includes the ability to request a refund, but excludes revenue from resale. Season ticket surplus in equation (8) becomes

$$ST\ \ Surplus_{iq} = \sum_j \mathrm{E}_{V,H_{ij}}\Big(\max\big\{u_{ijq}(V, H_{ij}), r_j\big\}\Big) + \delta_i - p_{Bq}. \tag{20}$$

Additionally, any refunded tickets are added back to the primary market seller's inventory and can be sold at primary market prices in the second period.

Ideally, the primary market seller would choose the profit-maximizing menu of partial refunds r_j. The optimal menu cannot be too high, or else equation (18) implies that throngs of consumers would request refunds when the common value V is low. But refunds cannot be too low, either, because consumers would not bother returning their tickets for a pittance. Unfortunately, the data offer no guidance on what refund a consumer would accept.

In the absence of relevant data, I set the refund at \$20 for the first four games and \$10 for the last, least valuable game. The chosen refunds are high enough that consumers would exert some effort to receive the payment, making the return rule in equation (18) plausible. They are also low enough that the model predicts few redemptions due to low values.

Results. Table 5 shows the average performance of each counterfactual experiment over possible realizations of the common value V. Figure 10 includes plots of second-period outcomes for resale and refunds for each value of V.

The average results in Table 5 show that total welfare is maximized with partial refunds, besting resale by 0.7%, but consumer welfare is higher with resale by the same margin. Profit is 2.5% higher with refunds. The magnitude

	Resale	Refunds
Total Welfare (mn)	10.11	10.18
	(0.12)	(0.12)
Profit (mn)	7.17	7.35
	(0.09)	(0.09)
Consumer Welfare (mn)	2.84	2.82
	(0.04)	(0.04)
Resale Fees (mn)	0.10	0.00
	(0.00)	(0.00)
Season Ticket Buyers (1000)	25.83	27.03
Season Ticket Base Price	31.82	31.29
Single Game Base Price	42.22	40.97

Table 5: Average counterfactual results across realizations of V for resale and refunds. Standard errors shown in parentheses.

of the changes should be interpreted in the context of reallocation, which only affects 8% of tickets.

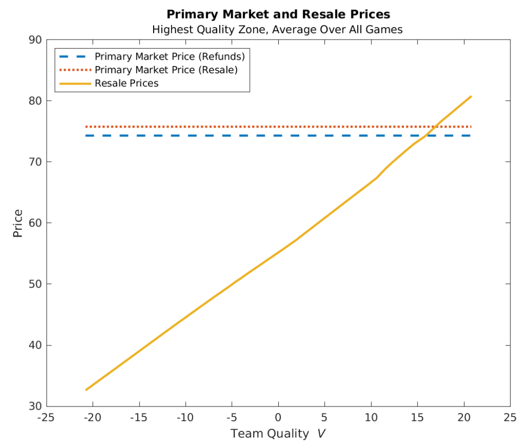
The framework presented in Section 2 suggests that the change in total welfare hinges on losses to resale frictions and the benefits of flexible resale prices. Losses to frictions are present in all states and take the form of both incurred frictions and frictions that are not incurred but lead to misallocation. The benefits of flexibility are more pronounced at extreme realizations of the common value V and are shown in Figure 10.

The top-left panel confirms that resale prices vary considerably depending on the level of aggregate demand.[13] Owing to frictions, they are sold at a discount to primary market tickets in most states.

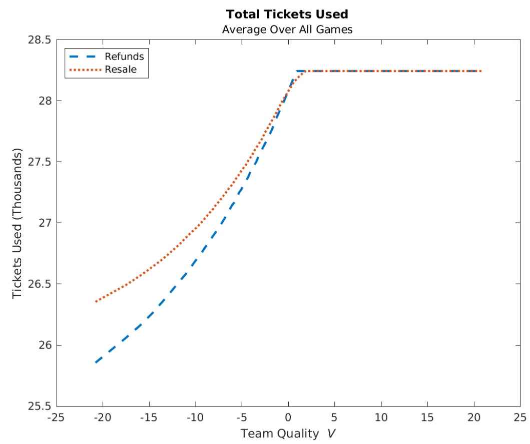
The effects of resale price variation are visible in the top-right and bottom-left panels. The top-right panel shows the number of tickets used at an average game. Although tickets sell out under both aftermarket policies when the team is good enough, more tickets are sold with resale than with refunds when the realization of V is low. When the realization of V is one standard deviation below its mean, 230 more tickets are used with resale. The difference in tickets sold, however, is small compared to the number of tickets sold in season ticket packages.

The bottom-left panel shows surplus created in the second period under each

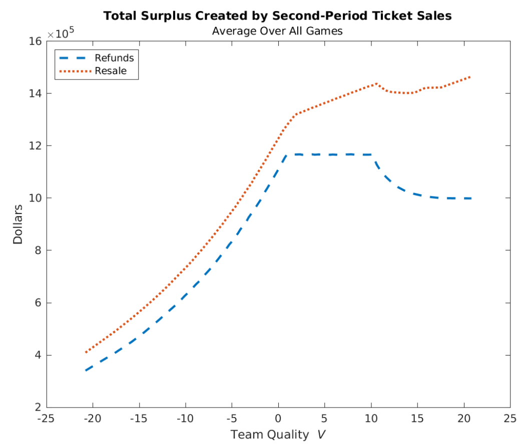
[13]The plot also demonstrates that value changes due to shocks to V are approximately passed through completely to resale prices, an assumption used to estimate α_j, γ_q, and σ_V^2.



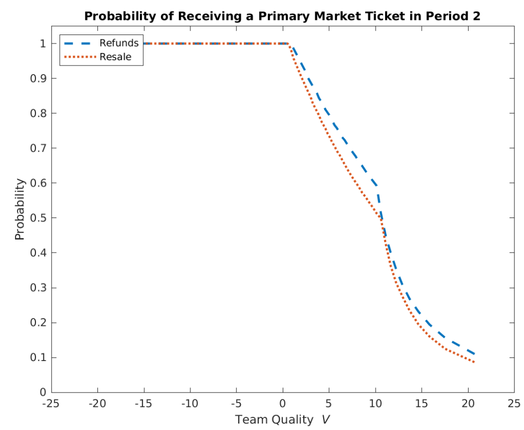
(a) Primary and resale market prices.



(b) Number of tickets used, average across games.



(c) Total surplus created from period two sales.



(d) Primary market rationing probability.

Figure 10: Market outcomes as the common value V varies.

policy. The key feature of the panel is not that resale creates more surplus—the comparison is distorted by the fact that fewer season tickets are sold with resale, leaving more surplus to be created in the second period—but that resale performs relatively better at the extremes. When the shock V is one standard deviation above its mean, resale produces welfare 21% higher than refunds, compared to an advantage of 11% at the mean realization. Resale also performs better when V is one standard deviation below its mean, producing 16% more welfare than refunds.

A central reason why resale performs better when V is high is that it causes fewer tickets to be rationed when there is excess demand in the primary market. The extent of rationing is shown in the bottom-right panel. As the shock to the common value grows, demand overwhelms supply in the primary market. The rationing probability falls to between .6 and .7 when V is one standard deviation above its average, and plummets below .3 at two standard deviations. Random rationing causes consumers with relatively low values to receive the tickets; the resulting misallocation leads to the decline in second-period surplus for refunds in the bottom-left panel. The effect is tempered for resale because of tickets available to the highest bidder in the resale market.

Despite the greater number of tickets allocated and the more efficient outcomes at high values of V, refunds are more efficient on average. The main reasons are that (i) the extreme shocks to V where resale outperforms do not occur often enough, and (ii) resale frictions diminish the potential benefits of resale.

Refunds have a clear advantage in profit, earning 2.5% more for the primary seller than resale. Interestingly, the primary seller earns more with refunds despite setting lower prices for season tickets and single-game tickets—even after accounting for expected resale revenue. The reason is that it earns more from sales of single-game tickets, including by capturing some of the fees and frictions lost to resale. In fact, the primary seller earns less on season ticket sales than with refunds—despite selling more season tickets—but makes up for it by increasing primary market revenue by 62%.

7.2 Benchmark Counterfactuals

I consider several other counterfactual experiments to provide benchmarks for the performance of observed resale markets. The first two counterfactuals are designed to evaluate the effects of reallocation and primary market price rigidities. The second set of counterfactuals explores the effects of resale frictions, which are important to the performance of resale.

No Reallocation. I measure the overall benefits of reallocation by conducting a counterfactual without reallocation. To eliminate it, I close the resale market, as in the partial refunds counterfactual. The primary market seller does not offer a way to return tickets—any ticket sold to a consumer who receives an idiosyncratic shock goes to waste.

Flexible Prices. Many of the benefits of resale could be realized with refunds if primary market prices were flexible. In this counterfactual, the primary seller offers a partial refund and commits in the first period to season ticket prices and a schedule of single-game prices $p_{jq}(V)$ that varies with the realization of V.

To reduce the number of choice variables the primary seller optimizes over, I assume that the primary seller sets a base price p_{jq} and derives a schedule according to

$$p_{jq}(V) = p_{jq} + \alpha_j V. \tag{21}$$

The price schedule is nearly optimal. The adjustment for the shock V in equation (21) is essentially the same as the one the primary seller chooses in simulations where it sets a profit-maximizing price in the second period after observing V.

Resale Frictions and Fees. To quantify the importance of resale frictions to the performance of resale, I conduct counterfactuals with resale markets but no resale frictions ($\lambda_s = 0$) and neither resale frictions nor fees ($\lambda_s = 0$ and $\tau = 0$).

Results. The results are contained in Table 6. The results of the counterfactual without reallocation confirm that there are substantial benefits to both aftermarket policies. Without reallocation, total welfare is 4.7% lower than with resale, consumer surplus is 7.0% lower, and profit is 2.4% lower. The results reinforce that primary market sellers can benefit from reallocation.

The results with flexible primary market prices suggest that a partial refund scheme would easily be optimal if there were no price rigidities in the primary market. Total welfare is 4.2% higher than in the main refund counterfactual, consumer welfare is 2.1% higher, and profit is 6.7% higher. A notable difference compared to the refund counterfactual with price rigidities is that fewer season ticket packages are sold and single-game tickets are generally cheaper, yet tickets

	Resale	Flex. Prices	No Reall.	$\lambda_s = 0$	$\lambda_s = \tau = 0$
Total Welfare (mn)	10.11	10.53	9.64	10.27	10.27
	(0.12)	(0.13)	(0.12)	(0.22)	(0.20)
Profit (mn)	7.17	7.64	7.00	7.23	7.43
	(0.09)	(0.09)	(0.09)	(0.13)	(0.13)
Consumer Welfare (mn)	2.84	2.90	2.64	2.84	2.84
	(0.04)	(0.05)	(0.04)	(0.09)	(0.08)
Resale Fees (mn)	0.10	0.00	0.00	0.20	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Season Ticket Buyers (1000)	25.83	25.83	24.96	27.18	27.18
Season Ticket Base Price	31.82	31.99	31.22	33.00	37.15
Single Game Base Price	42.22	35.80	41.47	41.08	41.08

Table 6: Average counterfactual results across realizations of V for experiments with flexible prices, no reallocation, and no resale frictions. Standard errors shown in parentheses.

sell out for all realizations of aggregate shocks. One reason for the difference is that selling tickets early is more appealing for the primary market seller when its prices are rigid in the second period. It can charge consumers for their predictable expected values in the first period, whereas realized values in the second period are volatile. The incentive to shift sales to the first period is weaker when prices are optimal in the second period.

The rightmost columns measure the effect of resale frictions. Without resale frictions, total welfare would be 0.9% higher than with refunds, and consumer welfare would be 0.7% higher. However, the primary market seller would still prefer refunds because profit remains 1.7% higher.

Removing fees in addition to resale frictions does not cause the primary market seller to change the allocation of tickets—the only effect is to transfer surpus from the resale market operator to the primary market seller. The primary market seller does so by raising its season ticket prices, charging consumers for the resale revenue gained when the fee disappears. The effects of removing fees would be different in a model with an intensive margin to resale.

Discussion. Although brokers are not expected to be important in the empirical setting, the results shed some light on their effects. When the realized aggregate shock is high, demand outstrips supply in the primary market, as it does in cases with systematic underpricing and brokers. The analogy is not perfect. Underpricing is known at the start of the market in settings with intentional resale and brokers. In contrast, underpricing is only known after shocks are realized in this paper and so the initial allocation is not affected. Moreover, consumers cannot buy underpriced tickets to resell within the second period.

The results are still illustrative for a central question regarding brokers: if there were no brokers (or resale), how severe would misallocation be? Figure 10 suggests that misallocation from primary market rationing is significant enough that resale, and brokers, could be valuable. As aggregate shocks grow, the welfare produced by resale increases, but misallocation from rationing causes welfare to decline with refunds. Brokers may reduce rationing and thus raise welfare in such cases. However, the model does not capture several harms of brokers.

One potential harm is that brokers could have market power. Further, there are costs to acquiring tickets in settings where they are underpriced in the primary market. The resulting costs—an important feature in Leslie and Sorensen (2014)—also reduce the benefits of brokers but cannot be measured in this setting.

The comparison between resale and refunds may change if primary and resale markets are sold in a single integrated market. The promise of integrated resale is that it could reduce the significant frictions associated with resale. But there are also risks. An integrated reseller may acquire market power in the resale market that lets it raise fees or gives it an incentive to distort the allocation of tickets. The model is not able to predict the effects of integrated resale because the change in frictions is unknown and there is no intensive margin to resale in the model, which would produce an incentive to change the resale fee.

The counterfactual results also inspire a practical concern: why are refunds rare in ticket markets? After all, many events—like concerts—have little demand uncertainty, which removes the benefits of resale studied in this paper. A likely reason is that restrictions on resale and ticket transfers are unpopular (Pender, 2017). Further, enacting a refund policy would require the primary market seller to consider market dynamics—refunding a ticket a week before the show is more valuable than refunding it an hour before—and the challenge may discourage event organizers from abandoning familiar resale policies. Finally, although the artists who set prices too low may not be trying to maximize welfare, the results suggest that the advantages of refunds may be reduced when tickets are underpriced.

8 Conclusion

When consumers receive stochastic demand shocks, the initial allocation of goods can be suboptimal. Society can benefit from aftermarket policies that cope with shocks, but it is unclear which policy is best. I show that the optimal aftermarket policy depends on the relative importance of aggregate shocks and resale frictions; I then estimate a structural model describing the salient shocks and frictions in the market for college football tickets and evaluate each policy in counterfactual experiments.

The results suggest that refunds are more efficient than the status quo of resale. In counterfactual experiments, total welfare is 0.7% higher with refunds and profit is 2.5% higher, although consumer welfare is 0.7% lower. The magnitudes are meaningful given that about 8% of tickets are reallocated in equilibrium.

However, the average performances of the policies mask important differences in performance as aggregate shocks vary. Resale performs relatively better when there are more extreme aggregate shocks, allocating more tickets when the shock is low and avoiding rationing when the shock is high. Such conclusions are only possible in a model with aggregate demand shocks.

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

Second, the comparison between resale and refunds informs how to run aftermarkets. The results imply that refund-based strategies are superior in perishable goods markets with significant aggregate demand uncertainty. The conclusion may change, however, in markets with more extreme uncertainty. A driver of the benefits is the removal of frictions associated with resale.

Third, the paper provides empirical evidence on the effects of resale. Whether primary market sellers of perishable goods profit from resale is ambiguous in theory, and this paper shows that primary sellers benefit in practice: resale raises profit by 2.4% compared to not reallocating. The effect of resale on consumer welfare informs policy on ticket resale. Total welfare falls significantly, by 7% compared to resale, when primary sellers prohibit resale and do not offer refunds. Society would benefit from a legal right to resell tickets in cases where the primary seller does not offer an alternative method of reallocation.

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A Application: Screening

A notable feature of refunds is that the primary market seller can offer a menu of contracts that screen consumers based on their future uncertainty. For example, consumers who are less certain about their future demand might be willing to pay a higher price to gain the security of a full refund. Because screening is only possible with consumer-specific payouts, it can be implemented with refunds but not resale. Its effects are therefore important for understanding the relative performance of resale and refunds. However, the analysis so far does not consider screening because there is no heterogeneity in consumer uncertainty: the consequences and probabilities of idiosyncratic and aggregate shocks H_{ij} and V are the same for all consumers.

In this section, I extend the model to include heterogeneous demand uncertainty and measure the effects of screening with refunds. Heterogeneous demand uncertainty comes from a state of the world realized in the second period. Consumers do not know which state will be realized, and the change in values in each state is heterogeneous.

The empirical motivation is the problem faced by primary ticket sellers during the covid-19 pandemic. When season tickets were sold, it was not clear if there would be a vaccine (the aggregate state ω^{Vax}) or not (the state ω^{NoVax}) by the start of the season. Consumers had varying responses to the state without a vaccine. Some were just as willing to attend without a vaccine, but others would not have paid as much. The variation in penalties without a vaccine is the source of heterogeneity in demand uncertainty. Crucially, if consumers know their preferences for attending without a vaccine when they purchase season tickets, they can sort into different refund contracts in the first period.

The structure of demand uncertainty suggests a simple menu of state-based refund contracts: one offering a full refund when there is no vaccine, one offering a full refund when there is a vaccine, and one without any state-based refund.

The fact that consumer values depend on the aggregate state means that the optimal allocation of tickets is different in the two states. The menu of state-based refunds effects a different allocation in each state, thus affecting total welfare. For that reason, state-based refunds should lead to a more efficient allocation than resale markets, and the value of the exercise is to quantify the benefits of refunds. The implications for total welfare also separate the setting from traditional studies of screening on uncertainty, where uncertainty is idiosyncratic and the focus is on an optimal sales mechanism.

Model Changes. There are two possible states of the world in the second period, $\omega \in \{\omega^{\text{Vax}}, \omega^{\text{NoVax}}\}$. The state is unknown in the first period and realized at the start of the second. All consumers expect state ω^{Vax} to occur with probability $\Pr(\omega^{\text{Vax}})$. Because of the new aggregate state ω, I do not allow uncertainty over V in the application.

There is an additional term in consumer utility reflecting the state of the world. Consumer i's utility for tickets of quality q to game j is

$$u_{ijq}(H_{ij}, \omega) = \alpha_j \left(\nu_i - b_i(\omega) + \gamma_q\right)(1 - H_{ij}), \tag{22}$$

where the realized state affects consumer values through the term $b_i(\omega)$. Consumers know their value of $b_i(\omega)$ in the first period, allowing it to influence season ticket decisions.

Assumption 11. *Consumer i knows the value of $b_i(\omega)$ throughout the model. The function satisfies $b_i(\omega^{\text{Vax}}) = 0$, $b_i(\omega^{\text{NoVax}}) \geq 0$, and $b_i(\omega^{\text{NoVax}}) \perp \nu_i$.*

Assumption 11 bridges the gap between the general form of equation (22) and the specific assumptions needed for the application. The assumption shows that the term b_i can be interpreted as consumer i's penalty for attending a game when there is no vaccine. Consistent with the penalty interpretation, no consumers have a higher value for tickets when there is no vaccine. The final component of Assumption 11, that penalties and values ν_i are independent, is based on descriptive evidence from the data.

Data and Descriptive Evidence. The extended model requires data to estimate the penalty $b_i(\omega)$ and the probability of each state. In this subsection, I describe the additional data and its main features.

The data come from a survey, conducted in August 2020, asking consumers about their demand for tickets with and without a covid-19 vaccine. Respondents report the maximum they are willing and able to pay for one ticket to a college football game in several scenarios related to covid-19. The scenarios include (i) 2019, as a pre-pandemic benchmark, (ii) a case with a widely available vaccine, and (iii) cases with no vaccine and varying caseloads and social distancing policies. Respondents also report their demographic information and the percent chance of each scenario in September 2021.[14] Eliciting willingness to pay (WTP) and assessments of probabilties by asking directly is used in other surveys (see Fuster and Zafar (2021) and Potter et al. (2017)).

I distributed the survey to 500 users of Prolific.co, an online distribution platform, in August 2020. Half of respondents were aged 50 or over. The full survey and details can be found in Appendix E.

Although there are several scenarios without a covid-19 vaccine (including ones with and without social distancing), reported willingness to pay is similar in each. The observation that reported values depend mainly on whether there is a vaccine motivated the two-state structure. To combine reported willingnesses to pay from the scenarios without a vaccine to a single no-vaccine state, I average reports across the different caseload scenarios when there is no social

[14]The survey also asks about other dates, but only September 2021 is used in the analysis.

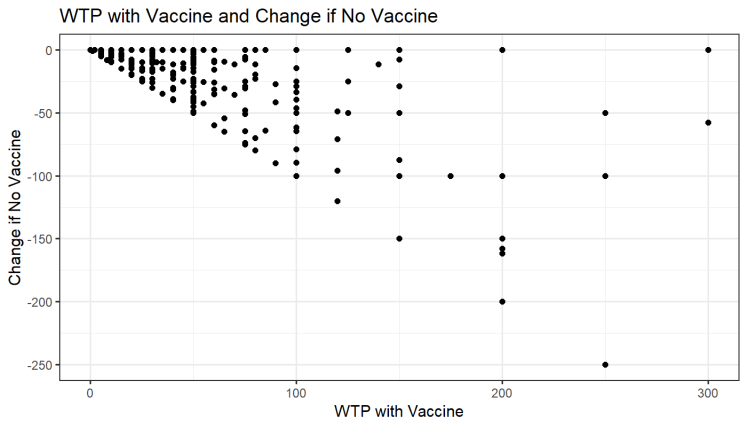


Figure 11: Scatterplot of reported willingness to pay with a vaccine and change in willingness to pay if there is no vaccine. Reported values are for games without reduced seating.

distancing, weighting by the average likelihood of each scenario in September 2021 from the survey.

To illustrate consumer heterogeneity, Figure 11 shows reported WTP with a vaccine (the horizontal axis) against the change in WTP from the state with a vaccine to the state without one (the vertical axis).[15] The main conclusion is that there is variation in consumer preferences that can be used for screening. A significant number of consumers have high values in both states of the world (the top right), but many others only have high values when there is a vaccine (the lower diagonal).

A secondary conclusion is that the changes in WTP (similar to $b_i(\omega)$) are not correlated with initial WTP (similar to ν_i). Consumers report proportionately large changes in WTP at all levels of initial WTP, and the correlation between the percent change in reported WTP and initial WTP is -.07. The results motivate the independence of $b_i(\omega)$ and ν_i in Assumption 11. Surprisingly, changes in WTP also do not correlate with age. For details, see Appendix E.

Estimation. I use the survey results to estimate two objects: the probability of each state of the world and the distribution of penalties $b_i(\omega^{\text{NoVax}})$.

For the state probabilities, I take the average reported probability from the survey for the states in September 2021, normalized to sum to one. The normalization excludes a case where there is no attendance at sporting events and so no tickets are sold.

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

For the penalty function, the informative data is the difference in reported willingness to pay between the states with and without a vaccine. For each consumer i, the survey provides observed penalties $\Delta\, WTP_i = WTP_i(\omega^{\text{Vax}}) - WTP_i(\omega^{\text{NoVax}})$. Assuming that survey responses are for a generic game with game-specific parameter α, and that responses are for the same quality level γ_q, equation (22) implies that the observed differences $\Delta\, WTP_i$ are

$$\Delta\, WTP_i = \alpha b_i(\omega^{\text{NoVax}}). \tag{23}$$

There are two complications that must be addressed before using equation (23) to estimate the penalty function. First, the parameter α is unknown. I assume that it equals the average of the game-specific parameters α_j, $\bar{\alpha}$. Second, consumer reports of $\Delta\, WTP_i$ are censored: consumers tend not to report negative values of $WTP_i(\omega)$, so the true penalty may be larger than the observed value of $\Delta\, WTP_i$ indicates. Equation (23) must be adjusted to reflect censoring and the use of $\bar{\alpha}$, giving

$$\Delta\, WTP_i = \min\left\{\bar{\alpha} b_i(\omega^{\text{NoVax}}),\, WTP_i(\omega^{\text{Vax}})\right\}. \tag{23$'$}$$

Finally, I assume a parametric form for $b_i(\omega^{\text{NoVax}})$.

Assumption 12. *The function $b_i(\omega^{\text{NoVax}})$ equals zero with probability ρ_1 and is otherwise distributed according to an exponential with parameter ρ_2,*

$$b_i(\omega^{\text{NoVax}}) = \begin{cases} 0 & \textit{w.p. } \rho_1 \\ \tilde{b}_i & \textit{otherwise, where } \tilde{b}_i \sim \textit{Exp}(\rho_2). \end{cases} \tag{24}$$

I estimate ρ_1 and ρ_2 by maximum likelihood. The likelihood functions are derived from equations (23$'$) and (24) and are shown in full in Appendix C.4. I calculate standard errors using the bootstrap, repeatedly sampling from the distribution of survey responses.

The estimated state probabilities are shown in Table 7. The parameters defining $b_i(\omega^{\text{NoVax}})$ are shown in Table 8. 29% of consumers have no change in values between states, but the remaining consumers are significantly less willing to attend, reporting a mean penalty of over \$52 for the base game.

Figure 12 shows that observed values of $\Delta\, WTP_i$ are very similar to simulated results. The simulated distribution is not a smooth exponential because, as in the survey, $\Delta\, WTP_i$ is censored at $WTP_i(\omega^{\text{Vax}})$.

Table 7: Expected state probabilities in September 2021

State	Probability
Vaccine	0.59
No Vaccine	0.41

Table 8: Estimated preference change parameters.

Parameter	Value	Std. Err
ρ_1	0.29	0.02
ρ_2	52.27	4.58

One final change is that the screening application uses a different distribution of values ν_i than estimated in Section 6. The reason is that the pandemic may have changed demand for sporting events in September 2021. Therefore, the relevant distribution of values is the distribution of $\nu_{i,Vax}$, not the distribution of $\nu_{i,2019}$ used in the main counterfactuals.

To recover the distribution $\nu_{i,Vax}$, I use survey data on the difference in reported WTP between the 2019 and vaccine states. Using a similar argument to the one used to derive equation (23′), the observed changes in WTP $WTP_{2019} - WTP_{Vax}$ are equal to $\bar{\alpha}(\nu_{i,2019} - \nu_{i,Vax})$. The difference thus looks similar to the penalty function in equation (24). Observed changes are also similar to the earlier penalty, with many responses unchanged between the states but others falling significantly. For that reason, I estimate the difference between $\nu_{i,2019}$ and $\nu_{i,Vax}$ using the same parametric penalty function as in equation (24). Applying the estimated penalty then gives the distribution of $\nu_{i,Vax}$ used below. For details, see Appendix C.

Counterfactual. I consider three aftermarkets: no reallocation, resale, and a menu of state-based refund contracts. The rules of the no reallocation and resale counterfactuals are the same as in the main counterfactuals.

With a menu of refund contracts, the primary market seller prohibits resale and offers three contracts: a non-refundable package that grants tickets in both states sold at $\{p^{NR}_{Bq}\}$, a full refund package granting tickets in the state with a vaccine sold at $\{p^{FR}_{Bq}(\omega^{\text{Vax}})\}$, and a full refund package granting tickets in the state with no vaccine sold at $\{p^{FR}_{Bq}(\omega^{\text{NoVax}})\}$.

The primary seller continues to offer single-game tickets at prices $\{p_{jq}\}$ in both states. Consumers can only purchase primary market tickets in the second period, and consumers who buy season tickets get value from using their tickets

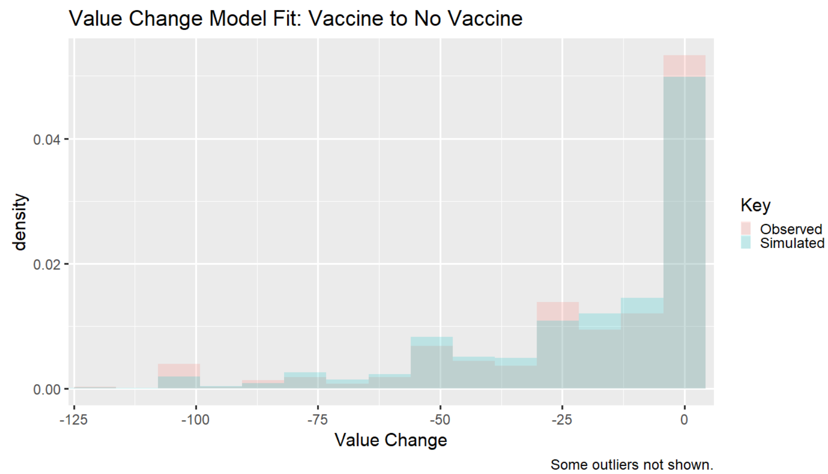


Figure 12: Observed and simulated changes in willingness to pay between states of the world.

or requesting a refund. As before, the primary market seller maximizes profit by choosing its prices in the counterfactual experiments.

In the counterfactual, I remove uncertainty from idiosyncratic shocks and the common value, $\psi = 0$ and $\sigma_V^2 = 0$. The extra sources of uncertainty are not important for measuring the returns to state-dependent contracts and removing them simplifies the results.

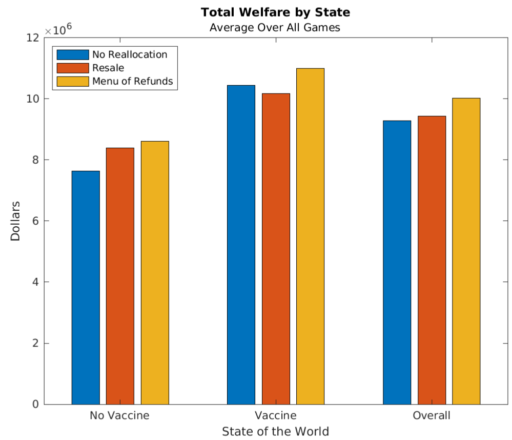
Each consumer i is described by a pair $(\nu_i, b_i(\omega^{\text{Vax}}))$ and chooses between the contracts. As in Section 5, consumers weigh the surplus from season tickets against the expected surplus from waiting.

Results. The menu of refunds gives the primary seller more control over the final allocation than resale and no reallocation, so it should be more profitable. The contribution of the exercise is to measure the gain in profit and determine the change in welfare.

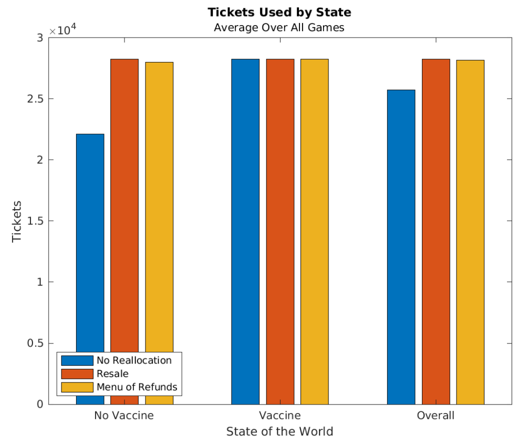
Table 9 presents the results and demonstrates that the menu of refunds produces significant gains for both consumers and the primary seller. Relative to resale, the menu of refunds boosts total welfare by 6.0%, consumer welfare by 4.5%, and profit by 7.0%.

The partial identification of δ_L has a small effect on the results because a small number of consumers with type L purchase season tickets in the resale counterfactual. I show in Appendix D.5 that the results are virtually unchanged for other values of δ_L in the identified set.

Figure 13 provides evidence on why the menu of refunds performs bet-



(a) Total welfare.



(b) Attendance.

Figure 13: Counterfactual results for total welfare and attendance by state of the world.

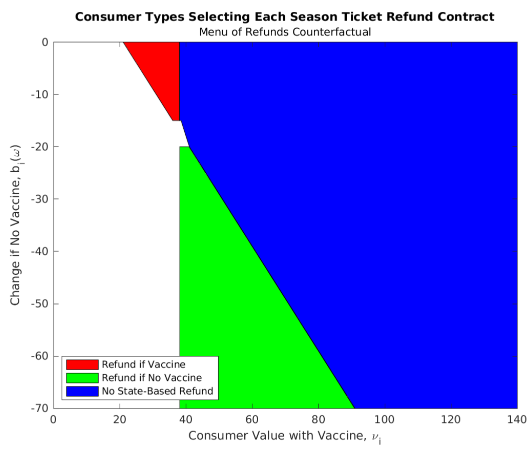


Figure 14: Regions of consumer types selecting each refund contract.

	No Reall.	Menu of Refunds	Resale
Total Welfare (mn)	9.28	10.01	9.44
	(0.12)	(0.12)	(0.24)
Profit (mn)	6.59	7.23	6.76
	(0.08)	(0.09)	(0.17)
Consumer Welfare (mn)	2.69	2.79	2.67
	(0.04)	(0.04)	(0.10)
Resale Fees (mn)	0.00	0.00	0.01
	(0.00)	(0.00)	(0.00)
Non-Refund. S. Tix (1000)	20.03	12.76	25.87
Vaccine S. Tix (1000)	0.00	5.80	0.00
No Vaccine S. Tix (1000)	0.00	13.07	0.00

Table 9: Counterfactual results for the model with different states of the world. Standard errors shown in parentheses.

ter. The counterfactual without reallocation performs worst because many consumers with tickets do not want to use them in the state without a vaccine, causing markedly fewer tickets to be used in that state. Resale and the menu of refunds manage to allocate virtually all tickets in both states, but the menu of refunds avoids the frictions associated with resale.

Figure 14 shows the consumer types in (ν_i, $b_i(\omega^{\text{NoVax}})$) space choosing each refund contract. The results match the intuition on sorting. Consumers with low penalties (or values so high that the penalty is unimportant) choose the contract without a refund. Consumers with high penalties choose the contract that only grants tickets when there is a vaccine. And consumers with moderate values but relatively low penalties choose the contract that only grants tickets when there is not a vaccine.

B Additional Descriptive Evidence

Figure 15 shows the distribution of normalized prices for the focal university and a random sample of 20 universities. The distributions demonstrate that within-university price variation is significant and widespread. Nearly all universities have a season where prices are 25% above and 25% below the sample mean.

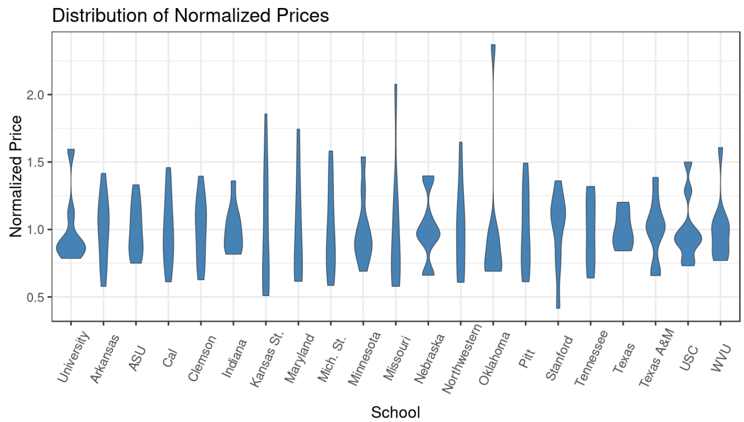


Figure 15: Distribution of average annual resale prices (normalized by school mean) for a random sample of 20 schools in similar conferences.

C Estimation Details

C.1 Sampling Estimation Moments

This subsection describes the process used to sample estimation moments, which are then used to calculate standard errors of parameters included in the second stage of estimation. The overall process is to estimate the variance of each moment using the bootstrap, then take a random sample of moments from the implied distribution. I am unable to consider the covariance of moments when sampling because I only observe one draw of each moment in the data, and the sampling processes do not imply linkages between moments.

Calculating the variance is easiest for each game's resale prices. The data contain records of transaction-level resale prices that can be repeatedly sampled. 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 I do not observe consumer-level choices to purchase or not. To handle unobserved choices, I create a data set of simulated choices that matches the data. Specifically, 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 of the relevant type (season tickets, single-game 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,

$$M\frac{N_j}{M}(1-\frac{N_j}{M}) = N_j(1-\frac{N_j}{M}). \tag{25}$$

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 10.

Table 10: 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

C.2 Identifying Season Ticket Parameters

The goal of this subsection is to establish that the season ticket parameters δ_H, δ_L, and ζ are identified. For ease of exposition, assume that all other parameters are fixed at their true values. Start by observing that a candidate value δ_H causes high-type consumers with $\nu_i \geq \nu^*(\delta_H)$ to purchase season tickets. There is an analogous threshold for low types, $\nu^*(\delta_L)$, where $\nu^*(\delta_L) > \nu^*(\delta_H)$.

The most intuitive estimation moment for identification is the number of consumers buying season tickets. For a distribution of ν given by $F_\nu(\nu)$ and market size N, the number of consumers buying season tickets is

$$STQuantitySold = N\left(\zeta\left(1 - F_\nu(\nu^*(\delta_H))\right) + (1-\zeta)\left(1 - F_\nu(\nu^*(\delta_L))\right)\right). \quad (26)$$

Although equation (26) provides a concrete connection between the parameters and the estimation moments, it leaves two free parameters. Additional conditions are needed.

The basis for the additional conditions is that each configuration of parameters defines a unique distribution of values among consumers shopping for tickets in the second period. As long as the estimation moments depend on the full distribution, only the true distribution of second-period values is consistent with observed moments. Denote the distribution by $F_{\nu,2}(\nu)$. Its CDF is

$$F_{\nu,2}(\nu) = \begin{cases} (1-\zeta)F(\nu^*(\delta_L)) + \zeta F(\nu^*(\delta_H)) & \text{if } \nu > \nu^*(\delta_L) \\ (1-\zeta)F(\nu) + \zeta F(\nu^*(\delta_H)) & \text{if } \nu^*(\delta_H) < \nu \le \nu^*(\delta_L) \\ F(\nu) & \text{if } \nu \le \nu^*(\delta_H), \end{cases} \quad (27)$$

If any parameter deviates from its true value, then the empirical analogue $\hat{F}_{\nu,2}(\nu)$ will be incorrect on at least one interval. I show that two estimation moments, resale prices and the quantity of tickets sold in the primary market, depend on the distribution $F_{\nu,2}(\nu)$.

The number of primary market tickets sold in quality $\bar{q}$ for game j is

$$\begin{aligned} PMTicketsSold_{j\bar{q}} &= (N - STQuantitySold)\Pr(Consumer\ i\ buys\ PM\ ticket\ for\ j,\ \bar{q}| \\ &\quad Did\ not\ buy\ at\ t=1) \\ &= (N - STQuantitySold) \prod_{\{q: u_{ijq}(V) - p_{jq} > u_{ijq}(V) - p_{j\bar{q}}\}} (1-\sigma_{jq}(V))\sigma_{j\bar{q}}(V) \\ &\quad \Pr(\mathbb{I}\left[s_{ij} > p_{j\bar{q}} - p^r_{j\bar{q}}(V)\right]\mathbb{I}[u_{ij\bar{q}}(V) \ge p_{j\bar{q}}]|Did\ not\ buy\ at\ t=1) \\ &= (N - STQuantitySold) \prod_{\{q: u_{ijq}(V) - p_{jq} > u_{ijq}(V) - p_{j\bar{q}}\}} (1-\sigma_{jq}(V))\sigma_{j\bar{q}}(V) \\ &\quad \Pr(s_{ij} > p_{j\bar{q}} - p^r_{j\bar{q}}(V))\left(1 - F_{\nu,2}(\frac{1}{\alpha_j}p_{j\bar{q}} - V - \gamma_{\bar{q}})\right). \end{aligned}$$

With sufficient variation in primary market prices p_{jq} relative to the game-specific parameters α_j, the total number of primary market tickets sold—the sum of the $PMTicketsSold_{jq}$ over q—depends on the full distribution of values in the second period.

A similar argument holds for resale prices. Let the function $ResaleSupply$ capture the supply side of the resale market (which does not depend on the season ticket parameters). The resale price function $p^r_{j\bar{q}}(V)$ solves the equilibrium condition

$$\begin{aligned}
ResaleSupply_{j\bar{q}}(p^r_{jq}(V), V) &= ResaleDemand_{j\bar{q}}(p^r_{jq}(V), V) \\
&= (N - STQuantitySold) \cdot \Pr(Consumer\ i\ buys\ resale \\
&\quad ticket\ for\ j,\ \bar{q} | Did\ not\ buy\ at\ t = 1) \\
&= (N - STQuantitySold) \int \prod_{\{q: p_{jq} \leq p^r_{jq}(V)+s\}} (1 - \sigma_{jq}(V)) \\
&\quad \Pr(u_{ij\bar{q}} \geq p^r_{jq}(V) + s | s, Did\ not\ buy\ at\ t = 1)\, dF_s(s) \\
&= (N - STQuantitySold) \int \prod_{\{q: p_{jq} \leq p^r_{jq}(V)+s\}} (1 - \sigma_{jq}(V)) \\
&\quad \Pr(\alpha_j \nu - s \geq p^r_{jq}(V) - \alpha_j(V + \gamma_q) | \\
&\quad s, Did\ not\ buy\ at\ t = 1)\, dF_s(s).
\end{aligned}$$

The expression depends on $F_{\nu,2}(\nu)$ through the probability term in the integral. Variation in the frictions s make it so that equilibrium resale prices depend on a wide range of the support of ν in the second period.

C.3 Counterfactual Standard Errors

Standard errors for counterfactual outcomes are calculated using the bootstrap. I obtain the distribution of counterfactual outcomes by running the counterfactual experiments for samples from the distribution of model parameters. The distribution of optimal parameters is taken from the optimal parameters obtained when calculating parameter standard errors in Section 6.

When sampling from the distribution of parameters, I am forced to assume that some parameters are uncorrelated with each other. The reason is that the estimation procedures for some parameters are completely separate, making it impossible to determine their covariance. For example, the parameter λ_s is estimated in the second stage, but the set of α_j are estimated based on (14) and there is no link between the two processes.

The sampling procedure accounts for covariance between parameters whenever possible. For example, the parameters α_j and γ_q are estimated jointly and so their draws are correlated. The same is true of the second-stage parameters λ_s, λ_ν, δ_H, δ_L, and ζ.

C.4 Vaccine Demand

Estimating ρ_1 and ρ_2. For the likelihood function used to estimate ρ_1 and ρ_2, let $G(\Delta\, WTP; \rho_2)$ be an exponential CDF with density $g(\cdot)$. The likelihood function can be written as

$$\mathcal{L}(\rho_1, \rho_2) = \mathcal{L}_1(\rho_1)\mathcal{L}_2(\rho_2), \tag{28}$$

$$\mathcal{L}_1(\rho_1) = \prod_{i=1}^{N} \left(\rho_1^{\mathbb{I}[\Delta\, WTP_i = 0]}(1-\rho_1)^{\mathbb{I}[\Delta\, WTP_i > 0]}\right)^{\mathbb{I}[WTP_i(\omega^{\text{Vax}})>0]}, \tag{29}$$

$$\begin{aligned}\mathcal{L}_2(\rho_2) = \prod_{i=1}^{N} \Big(& g(\Delta\, WTP_i; \rho_2)^{\mathbb{I}[\Delta\, WTP_i < WTP(\omega^{\text{Vax}})]} \cdot \\ & (1 - G(\Delta\, WTP_i; \rho_2))^{\mathbb{I}[\Delta\, WTP_i = WTP(\omega^{\text{Vax}})]}\Big)^{\mathbb{I}[\Delta\, WTP_i > 0]}.\end{aligned} \tag{30}$$

The likelihood function can be separated into two pieces, one evaluating the likelihood of observing zero change in willingness to pay ($\mathcal{L}_1$) and the other evaluating the likelihood of a positive change ($\mathcal{L}_2$). The function $\mathcal{L}_2$ accounts for censoring: when the observed change $\Delta\, WTP_i$ is the same as initial willingness to pay $WTP(\omega^{\text{Vax}})$, the exact value of the penalty b_i is not observed. Instead, we only know that it is higher than initial willingness to pay, and in such cases the likelihood must be evaluated using the CDF. The case where $WTP_i(\omega^{\text{Vax}})$ equals zero does not affect the likelihood because $\Delta\, WTP_i$ then equals zero with probability one.

Standard errors are calculated using the bootstrap, where samples are drawn from the distribution of survey responses.

Adjusting the Distribution of Values. 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 18. Accordingly, I use the survey data to adjust the distribution of ν_i to reflect post-pandemic demand.

Assuming that reported WTP is for a representative game and quality and that there are no relevant penalties, equation (24) implies that the observed differences in WTP from 2019 to the vaccine state are

$$WTP_{i,2019} - WTP_{i,Vax} = \nu_{i,2019} - \nu_{i,Vax}. \tag{31}$$

For that reason, it is appropriate to adjust the distribution of ν_i in the screening application. The data suggest that there is no change in WTP for many consumers, but there is a long tail of consumers who report lower values. The pattern resembles the changes in WTP for the transition in values from the state with a vaccine to the state without one. Therefore, I model the difference as a penalty b_i' using the parametric form in equation (24). The new distribution of values follows

$$\nu_{i,Vax} = \nu_{i,2019} - b_i', \tag{32}$$

where b_i' is parameterized by ρ_1^{2019} and ρ_2^{2019}. The estimation procedure is the same as for the original penalty function $b(\omega^{\text{Vax}})$; estimation is by maximum likelihood and standard errors are obtained using the bootstrap.

The results are shown in Table 11. Compared to the transition between states with and without a vaccine, many more consumers experience no change in values, 60% as opposed to 29%, and consumers who do receive a penalty have a slightly smaller one, \$43 as opposed to \$52 for the average game. Figure 16 demonstrates that the model fits the observed WTP changes in the data.

Table 11: Estimated preference change parameters for the transition from 2019 to the vaccine state.

Parameter	Value	Std. Err
ρ_1^{2019}	0.60	0.02
ρ_2^{2019}	43.20	4.58

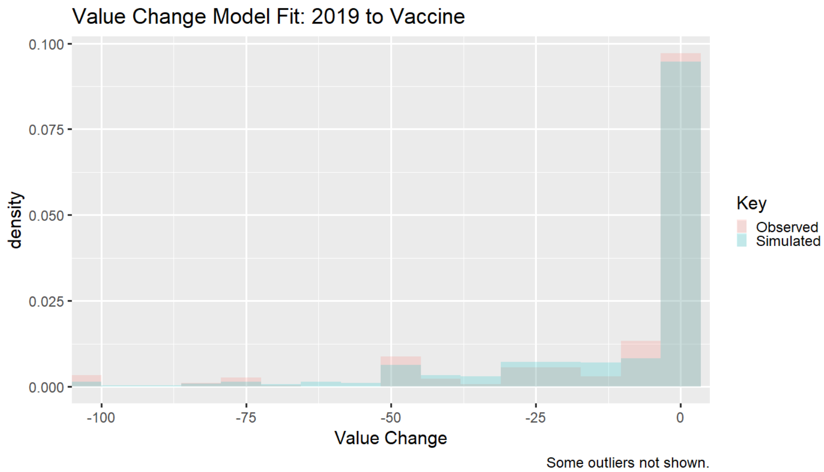


Figure 16: Observed and simulated changes in willingness to pay from 2019 to the state with a vaccine.

D Additional Robustness Checks and Counterfactuals

D.1 Resale Market Efficiency

This subsection considers how the efficiency of the resale market in the model compares to the effiency of the observed resale market. The issue is worthwhile because there are sources of inefficiency in the real world—such as dynamics, imperfect browsing, and potentially market power—that are not explicitly modeled. In contrast, the resale market in the model is static and, by Assumption 3, has a single clearing price. A concern is whether the modeled resale market is too efficient, and whether it affects the comparison to refunds.

There are two important items to note before presenting robustness checks. First, the resale market in the model has a source of inefficiency, the resale friction s_{ij}, which also creates dispersion in the effective prices paid by resale buyers. For that reason, the clearing price assumption should not be treated as an indicator that the resale market is perfectly efficient.

Second, I do not have a full model of the resale market that would quantify its inefficiencies. Although I can measure inefficiency in the model, there is no benchmark indicating the correct amount of inefficiency.

Welfare Gains from Resale. Given the lack of a benchmark resale market, one useful exercise is to compare the welfare gains from resale in a market with

Percentile	Game 1	Game 2	Game 3	Game 4	Game 5
15	-3.5	-7.0	-3.5	-5.5	-2.5
25	-2.5	-6.0	-2.5	-4.5	-2.0
75	6.0	13.5	6.0	12.5	4.0
85	10.5	24.5	10.0	23.0	8.0

Table 12: Model-implied dispersion from the median in effective resale prices.

Percentile	Game 1	Game 2	Game 3	Game 4	Game 5
15	-11.5	-10.4	-11.3	-11.4	-8.6
25	-7.9	-5.9	-8.4	-7.5	-4.6
75	9.1	8.2	11.2	10.3	5.9
85	14.4	14.3	17.5	15.9	11.2

Table 13: Observed dispersion in resale transaction prices.

and without the resale frictions s_{ij}. Essentially, if the resale market were truly efficient and lacked price dispersion, how would the results differ from those in the model?

In an out-of-equilibrium comparison, I take the first-period allocation from estimation as given and compare welfare created through resale to the welfare that would be created if there were no resale frictions. Welfare gains with estimated frictions are only half as high as they would be without frictions. Total welfare generated in the second period would be 11.4% higher without frictions.

The counterfactual experiment with λ_s set to zero provides an equilibrium comparison. Total welfare increases by 1.6%, again based on 8% of tickets that are resold. The difference is large enough for resale (without resale frictions) to become more efficient than refunds.

Price Dispersion. A second exercise is to compare observed price dispersion to the distribution of effective prices paid in the resale market, defined as $p_j^r + s_{ij}$. (Dispersion does not depend on seat quality; I compare dispersion for the common value V realized in the data.) Price dispersion is not a perfect metric because a model can capture inefficiency without necessarily matching price dispersion, but it is easily observed and so provides a convenient benchmark.

Tables 12 and 13 show various percentiles of the distribution of resale prices minus the median (using effective resale prices paid by buyers for the model, which include incurred frictions).

In general, the model implies less price dispersion than is observed in the data, but the results depend on the game. The model-implied results vary more across games, so popular games like 2 and 4 have similar or larger interquartile price spreads in the model than in the data. In all other cases, the price dispersion in the data is greater. The model matches a meaningful amount of the price variation observed in the resale market.

D.2 Partial Entry to the Resale Market

One significant assumption in the paper is that all tickets are used. In reality, we expect that some tickets are neither used nor resold, and the number of wasted tickets affects the welfare gains from reallocation.

For the paper's central comparison of resale and refunds, the salient issue is whether there will be more or less waste with one policy. In theory, the effect could go either way. Resale markets are more of a hassle than pushing a button that says "claim refund," so there could be more reallocation with refunds. But resale prices should generally be higher than the primary seller's partial refund (so that fewer consumers ask for refunds when the team is bad), leading to relatively more reallocation through resale. Which effect dominates is an empirical question that I cannot resolve with the data at hand.

Nonetheless, it is worth looking at simulations with partial take-up to get a sense of the magnitude of the effect. I introduce a probability ϕ that a consumer will forget to resell or claim a refund, causing some tickets to go unused. The rate of idiosyncratic shocks ψ is fixed, so the volume of reallocation decreases as ϕ increases.

The probability ϕ is a simple way to capture the idea that consumers face hassle costs that prevent them from entering the resale market or from seeking a refund. The probability is known throughout the model, but the realization is not known until the second period. Thus consumers in the first period do not know if they will resell or request a refund. To gauge the magnitude of the effect, I run the counterfactual experiments for values of ϕ ranging from 0.1 to 0.5, in increments of 0.1.

The results confirm that the takeup rate for reallocation could affect which aftermarket policy maximizes welfare. For example, although refunds produce higher total welfare at each level of ϕ considered, society prefers resale with no waste to refunds with a probability of forgetting exceeding 0.2. For levels of ϕ up to 0.3, total welfare with resale is equivalent to welfare with refunds when

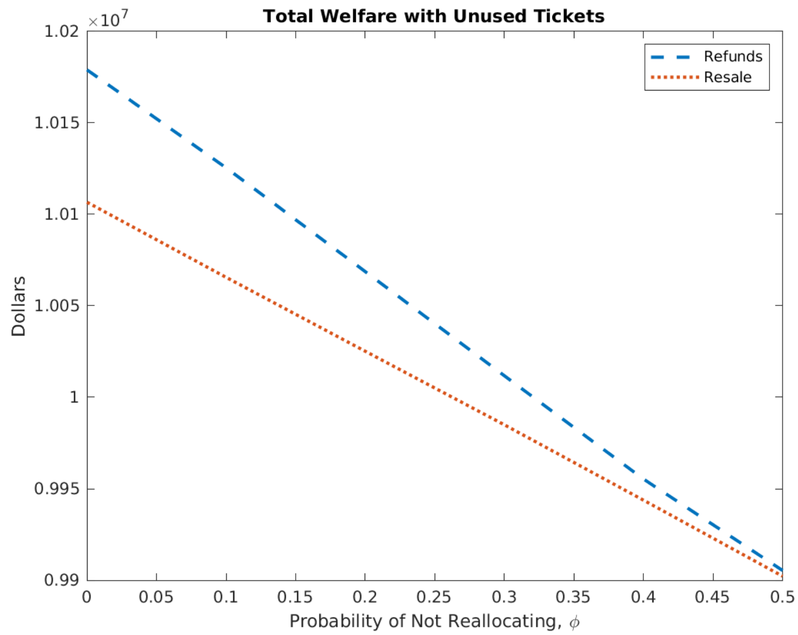


Figure 17: Total welfare in the resale and refunds counterfactuals as ϕ varies.

10–15 percentage points more consumers receiving idiosyncratic shocks fail to reallocate with refunds. The gap narrows as ϕ grows because the volume of idiosyncratic shocks ψ is fixed, causing welfare with both policies to approach the welfare level without reallocation as ϕ approaches one.

D.3 Unobserved Reallocation

There is undoubtedly reallocation outside of the primary and online resale markets, like when people give tickets to friends or sell offline. However, those transactions are unobserved and I have not been able to find data on their scope.

The issue is potentially important to the counterfactual results because the refund policy would shut down the alternative channels. (The primary seller must prohibit private transfers of tickets to prevent resale when implementing a refund.) If reallocation in the unobserved channels is efficient, then the counterfactuals understate the performance of resale. If it is not, then refunds should hold a bigger advantage. The issue also affects whether the model features the right degree of reallocation.

Unobserved reallocation thus warrants attention, but the lack of data raises challenging questions in designing a robustness exercise. The central issue, which is pivotal to the results, is whether the consumers who get tickets through alternative channels have high values. Beyond that, any exercise requires an assumption about the volume of reallocation in alternative channels. Because consumers are forward-looking when buying season tickets, it also matters whether the alternative channels are giveaways or transactions and, if transactions, at what price.

An additional issue is whether the consumers who give tickets to friends would bother to collect a refund. If they currently give away tickets for free, it is not certain they would request the primary seller's partial refund. The implications of partial takeup are addressed by the partial entry counterfactual above, so I do not consider them here.

The changes to the model are as follows.

- I assume that the volume of unobserved reallocation is half the volume of reallocation attributed to resale markets in the model. Specifically, I set $\psi' = 1.5\psi$ as the idiosyncratic shock rate and assume that consumers receiving the additional shocks reallocate offline. The assumed increase in shocks shows how the market would operate if alternative channels are significant.
- I assume that only consumers above a certain value threshold $\bar{\nu}$ are eligible to receive tickets in alternative channels. The idea is that there is some point where consumers are not interested in attending and would not be offered the ticket. However, it is not clear what that point is, so I perform the counterfactual for several thresholds.
- For sellers, I assume that some sellers are randomly selected to reallocate in alternative channels. Specifically, of the fraction ψ' of consumers with season tickets who receive an idiosyncratic shock to each game, two-thirds (corresponding to the original shock rate ψ) resell and the remaining one-third (the additional resellers) use alternative channels. Selection into each channel is random and the consumer does not know which channel she will use until the second period.
- For buyers, I randomly sample consumers without season tickets whose value ν_i exceeds the threshold $\bar{\nu}$. I sample the number needed to transact with the selected season ticket holders.
- Buyers and sellers for game j and quality q all transact at $\min\{\alpha_j(\bar{\nu}+\gamma_q+$

$V), \frac{3}{4}p^r_{jq}(V)\}$. The price ensures that all participants have positive surplus in the transaction and matches the likely scenario where sales to friends or acquaintances are discounted. There are no fees or frictions so that the only parameter controlling the inefficiency of unobserved resale is the threshold $\bar{\nu}$. The lack of frictions is not without consequence, and boosts the performance of resale. The transaction price is necessary because it enters the season ticket decision for forward-looking consumers.

- Consumers are forward-looking and so the changes affect first-stage decisions. When assessing values for season tickets, consumers know the probability of receiving an idiosyncratic shock. They also know that they would resell two-thirds of the time with a shock and would use the alternative resale channels one-third of the time. Similarly, when deciding whether to wait for tickets, consumers know the threshold $\bar{\nu}$ and consider the chance that they would be offered tickets.

Because of the many assumptions and unknowns, the modified model cannot assess how wrong the main counterfactual results are. But it provides information on two questions that help assess the main counterfactual results. First, how different are the main resale results from the likely results when alternative channels matter? And second, how would refunds compare to resale when both reflect reallocation through unobserved channels?

Before presenting the results, there are two weaknesses of the experiment worth discussing. First, consumers are randomly selected to participate in the alternative resale channels. It is not an optimal choice for sellers, and buyers may be conscripted even if another choice is preferable. Second, consumers do not know in advance if they are the type that would engage in resale through alternative channels, which is unlikely in reality.

Both choices are meant to simplify the necessary changes to the model. Rationalizing participation in alternative channels would require additional assumptions on how unobserved resale works, and would require significant new machinery in the model. Making participation in alternative channels a dimension of consumer types would make it difficult to control the number of consumers who participate in alternative channels, and would also require larger changes to the code base.

Results. Results of the counterfactual are shown in Table 14. The leftmost column provides the main resale results from Section 7 for comparison. The

	Resale (Benchmark)	Refunds	$\bar{\nu} = 10$	$\bar{\nu} = 20$	$\bar{\nu} = 30$
Tot. Welfare (mn)	10.11	10.05	9.95	10.02	10.06
Profit (mn)	7.17	7.23	6.86	6.91	6.95
Cons. Welfare (mn)	2.84	2.82	2.99	3.00	3.01
Resale Fees (mn)	0.10	0.00	0.10	0.10	0.10

Table 14: Counterfactual results for the main resale experiment, a partial refund experiment with the rate of idiosyncratic shocks used in the unobserved resale experiments, and unobserved resale experiments with varying thresholds for consumers to randomly receive tickets.

refunds column implements the same partial refund scheme from Section 7 with the new idiosyncratic shock rate ψ' to provide a fair comparison for the counterfactuals with alternative channels. The remaining columns consist of the counterfactuals of interest and differ by the value threshold $\bar{\nu}$ used.

The first comparison is between the resale results with different values of $\bar{\nu}$. As the value threshold climbs from 10 (a consumer without particular fondness for college football) to 30 (a consumer who is on the fence about buying season tickets), total welfare and profit change significantly relative to the scope of reallocation. The details of offline reallocation are therefore potentially important.

The next comparison is between the resale results and the modified refund counterfactual that reflects the higher rate of idiosyncratic shocks. Refunds are clearly more profitable and worse for consumers than resale, but whether they are more efficient depends on the true value of $\bar{\nu}$. However, given that resale only produces a slightly higher level of total welfare when offline resale is limited to high-value consumers, it is likely that refunds remain more efficient.

The final comparison is between the resale results in the main text and resale with offline reallocation. If offline reallocation is significant, the resale results in the main text would exaggerate the profit and welfare earned through resale, although consumer welfare would be understated.

The overall conclusion from the exercise is that offline resale, if significant, would change the levels of predicted welfare and profit in the market, but that it is not likely to change the assessment that refunds are more efficient and profitable.

D.4 Integrated Resale

In recent years, there has been understandable interest in integrated resale, defined as offering both primary and resale tickets on a single platform. The most notable example is Ticketmaster, which controls primary market sales for a variety of high-profile events and now shows "Verified Resale Tickets" alongside primary market inventory on its platform.

Integrated resale could have a range of effects. One is to enhance Ticketmaster's market power, enabling it to charge higher fees. Ticketmaster does not disclose its fee structure, but adds 23% of the before-fee price to what buyers pay on a listing for an upcoming event. If Ticketmaster charges resellers a similar amount as StubHub, its fees are indeed higher. A second effect is that, by making resale tickets easier to find, integration may reduces the frictions associated with participating in the resale markets. A third effect is that any of the other changes may affect brokers' incentives to participate.

The empirical model of resale in this paper can be modified to feature an integrated resale market, but it cannot provide evidence on the effects above. Brokers are not prominent in the data and so do not feature in the model. The model is thus not tailored to determine how integrated resale would affect their behavior. For frictions, the model allows me to assess the effect of different levels of frictions, but there is no basis for judging how resale frictions should change in an integrated resale market. As in other robustness checks, I provide a range of estimates but cannot be sure which is correct.

The model also cannot assess how an integrated seller would change fees. One reason is that I do not model competition between resale platforms, which could affect fees. The other is that the model cannot find the optimal fee, even if the integrated seller were a monopolist in the resale market, because there is no intensive margin to reallocation. Without an intensive margin, a change in fees can be exactly offset by a change in the season ticket price in the model, resulting in the same allocation and profit.

In more detail, consumers only resell in equilibrium when they receive an idiosyncratic shock. When buying season tickets of quality q, they thus expect to receive $\psi(1-\tau)\alpha_j(\bar{p}_j^r+\gamma_q)$ in resale revenue for each game j. (For convenience, let $\bar{p}_j^r$ be an average over all realizations of V.) When deciding whether to buy season tickets, consumers consider the price p_{Bq}, defined in equation (16), minus resale revenue. The difference is

$$
\begin{aligned}
& p_{Bq} - \left(\sum_j \alpha_j\right) \psi(1-\tau)(\bar{p}_j^r + \gamma_q) \\
= & \left(\sum_j \alpha_j\right) \left(p_B + (1 - \psi\tau\gamma_q) - \psi(1-\tau)(\bar{p}_j^r + \gamma_q)\right) \\
= & \left(\sum_j \alpha_j\right) \left(p_B + (1-\psi)\gamma_q - \psi(1-\tau)\bar{p}_j^r\right) .
\end{aligned}
$$

An increase in fees of $\Delta\tau$ can thus be offset exactly by a reduction in p_B of $\psi\Delta\tau\bar{p}_j^r$, which would result in the same season ticket choices, resale prices, allocations, and profit. For this reason, eliminating the fee τ only shifted surplus from the resale market operator to the monopolist in Section 7, and it will do the same here.

As before, a counterfactual still shows the range of possible changes if the resale friction changes. The model changes required for the resale counterfactual are as follows.

1. The primary market seller controls the entire resale market and earns all fees, which now count towards primary market profit. (Resale fees are still listed separately in the results.)
2. As before, the primary market seller chooses its optimal primary market prices.
3. The resale fee τ is fixed at the level observed in the data.

The first assumption states that the integrated seller controls the entire resale market. In reality, there would be competing resale platforms.

The third assumption is primarily motivated by the fact that the model cannot identify an optimal fee, but the integrated seller's choice of fee could also be constrained if it competed with other resale platforms.

The results of the exercise are shown in Table 15. The leftmost column shows the counterfactual results for resale without an integrated resale market. The next column shows results for an integrated resale market with the value of resale frictions observed in the data, and subsequent columns differ by varying the level of frictions.

	Not Int.	Int.	Int., $\lambda_s = 60$	Int., $\lambda_s = 40$	Int., $\lambda_s = 20$
Total Welfare (mn)	10.11	10.11	10.12	10.14	10.18
Profit (mn)	7.17	7.27	7.28	7.30	7.35
Consumer Welfare (mn)	2.84	2.84	2.84	2.84	2.84
Resale Fees (mn)	0.10	0.10	0.10	0.11	0.12
Season Ticket Base Price	31.82	31.83	31.89	32.08	32.34
Single Game Base Price	42.22	42.22	42.17	41.78	39.85

Table 15: Counterfactual results with an integrated resale market and the fee τ fixed at the observed level in the data.

The results show that, as in the counterfactual in Section 7 where the fee τ is removed, integrated resale is a pure transfer of surplus to the primary market seller. In the main comparison, between the leftmost columns, the only difference is that the primary market seller's profit is higher by the amount of fees. Therefore, in the empirical model, integrating the resale market does not change the primary market seller's incentives enough to affect the allocation of tickets. The results in the rightmost three columns are driven by the reduction in frictions, which raise total welfare. However, the increase in welfare is captured entirely by the primary market seller.

D.5 Screening Counterfactuals

The discussion of the resale counterfactual in Appendix A noted that some type L consumers purchased season tickets when δ_L was set to its upper bound. As a result, there may be different counterfactual results for different identified sets of parameters. In this section, I show that the results of the counterfactual are virtually the same at lower values of δ_L.

I ran the counterfactual experiment again after setting δ_L to -1000. At the chosen value, no consumers of type L purchase season tickets. It is therefore a useful comparison to assess the spread of outcomes within the identified set of parameters. The results are shown in Table 16 and hardly differ. The partial identification of δ_L therefore has a negligible effect on interpreting the counterfactual results.

	δ_L Upper Bound	$\delta_L = -1000$
Profit (mn)	6.76	6.77
Consumer Welfare (mn)	2.67	2.66
Total Welfare (mn)	9.44	9.44
Resale Fees (mn)	0.01	0.01
Non-Refund. S. Tix (1000)	25.87	25.83
Type L S. Tix (1000)	0.24	0.00

Table 16: Counterfactual results for the resale counterfactual in the screening application when δ_L is set to the upper bound of the identified set (-203) and a value low enough that no type L consumers purchase season tickets ($-1,000$).

E Survey

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

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

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

The survey includes respondents with a wide range of reported WTP. Figure 18 shows the distribution of reported WTP for three scenarios without social distancing: a 2019 baseline, a state with a vaccine, and a state without one. In each state, some consumers report values for tickets exceeding \$50 and \$100.

In the absence of a true measure of the probability of each scenario in the future, I ask respondents how likely they consider each one at three future dates. The average percent chances are shown in Figure 19. Respondents do

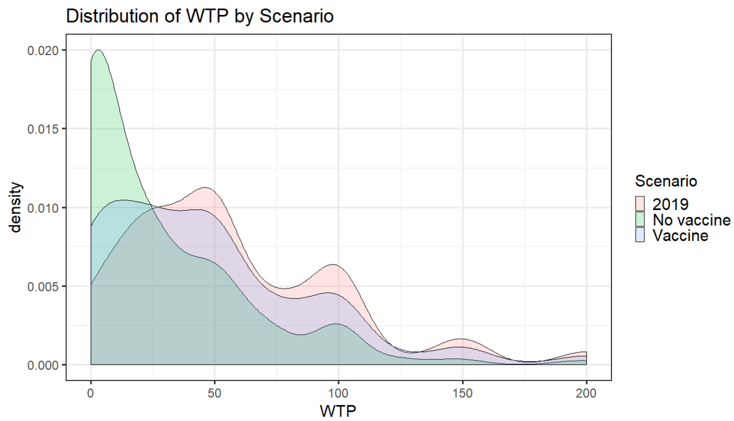


Figure 18: Distribution of reported willingness to pay without social distancing in 2019, with a vaccine, and with no vaccine.

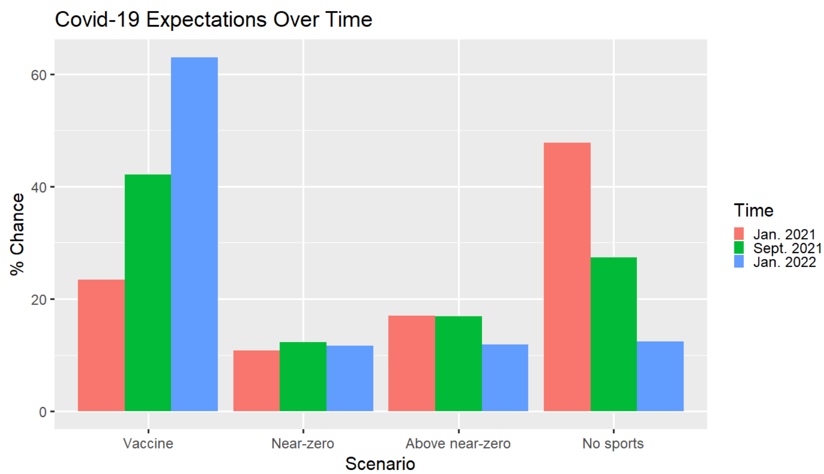


Figure 19: Average reported percent chance of each scenario occurring in each month.

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

Figure 20 shows that the distribution of reported WTP is similar for the near-zero and above near-zero scenarios.[16] 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.

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

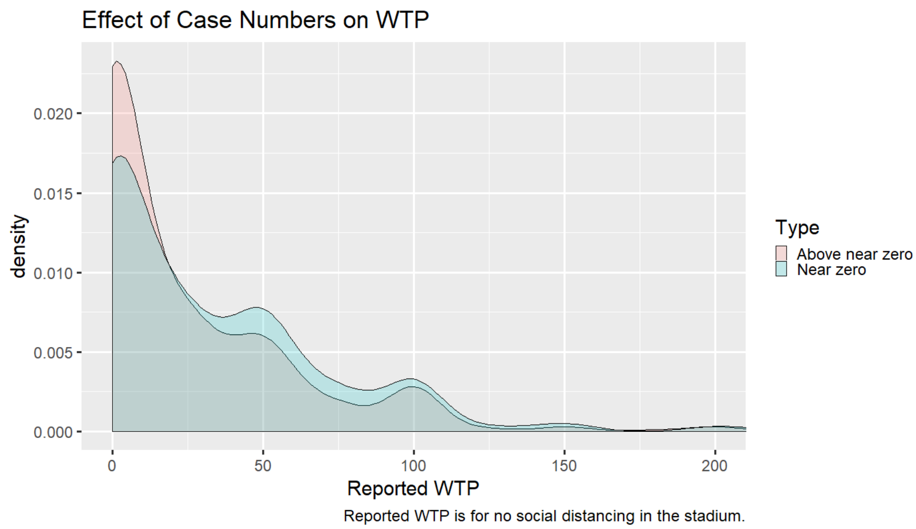


Figure 20: WTP distributions with near-zero and above near-zero levels of cases.

Figure 21 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 primary market seller can offer.

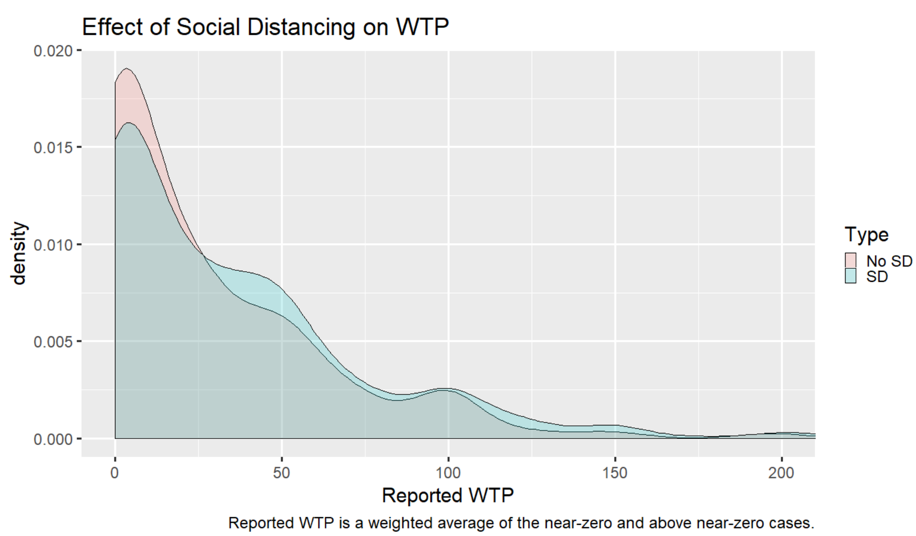


Figure 21: WTP distributions with near-zero and above near-zero levels of cases.

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

$$\Delta WTP_i = \alpha Age_i + \beta Race_i + \gamma State_i + \varepsilon_i, \tag{33}$$

where Age_i is a set of age dummies (with decade-long bins, e.g. ages $30--39$), $Race_i$ is a set of dummies for race, and $State_i$ is a dummy for the state of the respondent. The response variable is measured both as an absolute number of dollars and as a percentage of initial WTP. Lower values denote greater sensitivity to the state without a vaccine. Results are shown in Table 17.

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

The full survey is included below.

Table 17: Regression output for equation (33).

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

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

Event Expectations (General)

Start of Block: Intro

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

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

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

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

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

End of Block: Intro

Start of Block: Block 4

Q16 In which state do you currently reside?

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

End of Block: Block 4

Start of Block: WTP

JS

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

End of Block: WTP

Start of Block: Probabilities

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

JS *

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

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

JS *

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

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

JS *

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

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

End of Block: Probabilities

Start of Block: Demographics

*

Q12 What is your year of birth?

____

Q13 What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Prefer not to answer (3)

Q14 What is your ethnicity?

- ○ Hispanic or Latino/Latina (1)
- ○ Not Hispanic or Latino/Latina (2)

Q15 What is your race?

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

End of Block: Demographics