Are "Buying Frenzies" Equitable? Distributional Effects of Congested Online Markets

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Abstract

In settings where goods are rivalrous and low fixed prices lead to excess demand, "buying frenzies" can create an inequitable allocation of consumption if some types of consumers are better at navigating congestion. Using transaction-level data for goods sold online via buying frenzy and random lottery, I show successful frenzy buyers are wealthier and more highly educated than those selected at random. The size of this effect increases with web site congestion, leads to a regressive distribution of consumption benefits and suggests a new type of digital divide that may exist in many online markets.

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1 Introduction

Economists have long been interested in the characteristics of "buying frenzies" where excess demand causes consumers to vie for the chance to purchase (DeGraba, 1995). Online product launches or "on-sale" events are of particular interest because they enable large numbers of consumers to participate simultaneously often resulting in congestion.[1] For instance, recent product launches for events industries, consumer electronics, hotel rooms, childcare, non-fungible tokens (NFTs) and COVID-19 vaccinations, have led to internet service disruptions, congestion and frustration on the part of consumers left unable to purchase.[2] While the literature has mainly focused on why such events occur, an important question is whether buying frenzies create distributional effects.

During an online buying frenzy, consumers employ strategies to improve their odds of successfully purchasing. They may arrive before sales begin, refresh their web browsers and attempt to time the exact moment the product launches. Individuals may utilize multiple internet connections or employ sophisticated computer programs ("bots") to automate purchases. Access to broadband internet technology and familiarity with specific online sales platforms may play important roles in allocating consumption. The extent to which these events favor wealthier or more technologically savvy consumers and disadvantage lower income or less "connected" consumers could create a digital divide in markets for a wide range of good and services. However, investigation into these types of effects has been hampered by the lack of examples where sales outcomes are observed for online buying frenzies and alternate allocation mechanisms.

I exploit novel features of markets for recreational permits on public lands in the United States to investigate whether online buying frenzies create distributional effects. The increasing popularity of outdoor recreation has led park managers to restrict use by requiring

[1] While buying frenzies associated with new product launches or Black Friday sales have existed for some time, online "on-sale" events may exacerbate buying frenzies because online queuing is less costly than in-person queuing.

[2] Frustration over from the Taylor Swift New Eras tour buying frenzy led to high profile Congressional hearings (Treisman, 2023). Similarly, Sony has struggled to appease consumers two years after release of the Playstation 5 console when "Mostly, obtaining a PS5 required getting very lucky in an on-the-spot release of new supply" (Fernandez, 2023). Many economists will also remember being unable to reserve a hotel room online for meetings of the American Economic Association.

permits for popular hiking, backpacking and river rafting sites. Permits are sold for modest fees and allocated either via lottery or using an online reservation system. The large number of recreational users, low permit prices and limited permit availability mean demand vastly exceeds permit supply. With a lottery system, permits are randomly allocated to users. With a reservation system, permits are made available during an on-sale event and the allocation depends on one's position in the digital queue when the sale begins. A buying frenzy results when users attempt to access the web page simultaneously.[3] Under these circumstances, the actual allocation of permits could be random, *i.e.* a so-called "cyber lottery" or it could disproportionately fall on groups who have an advantage in navigating online congestion. This feature is common to many e-commerce markets where only a portion of consumers who participate in an online buying frenzy are actually able to purchase the good.

Using transaction-level data for purchases on Recreation.gov, I compare purchases of identical goods allocated by both lottery and buying frenzy. In the first part of the paper, I show households that successfully purchase in the buying frenzy reside in higher income and more highly educated zip codes compared to those selected at random via lottery. Specifically, median household income is \$2,856 to \$3,027 (4%) higher and the fraction of college educated individuals is 1.57 to 1.87 percentage points (3% - 4%) higher. I rule out several mechanisms for the observed demographic effects including differences in preferences, time costs and scheduling costs. However, I find the estimated income effects grow in size with the number of page views (refresh activity) during the buying frenzy, suggesting online congestion plays an important role in the observed income effects.

In the second part of the paper I investigate the incidence of these effects in terms of the distribution of recreational trip benefits. I first use the user-level data on participation in permit lotteries to estimate the willingness to pay for different trip locations and start dates. The large numbers of users and trip choices in this setting make discrete choice modeling approaches quite difficult. Instead, I estimate mean willingness to pay with an expected utility approach based on equilibrium lottery outcomes. Then, using data from

[3] For instance, the recent online permit sale for the Boundary Waters Canoe Area Wilderness crashed Recreation.gov. Reservations for popular campsites in places such as Yosemite National Park are reserved within minutes of becoming available online.

recent reservation on-sales, I estimate the likelihood users in different income groups obtain a particular trip in a buying frenzy. Combining these two sets of estimates, I find the reservation system creates a regressive distribution of recreational benefits. Specifically, households in the fourth income quintile receive 25 percent *more* recreational trip value compared to households in the first income quintile.

This work is at the intersection of several literatures. First, I contribute to the literature on digital economics and the "digital divide." Online sales channels were predicted to be a "win" for consumers because lower search costs would increase competition and decrease price dispersion (Goldfarb and Tucker, 2019). However, empirical evidence suggests substantial price dispersion persists (Baye, Morgan, and Scholten, 2004; Orlov, 2011; Einav et al., 2015) and may enable new types of price discrimination (Fudenberg and Villas-Boas, 2012). Similarly, it was hypothesized online sales channels would improve access to goods and services by removing the requirement consumers appear in person to complete a purchase (Pozzi, 2013; Goldfarb and Tucker, 2019). However, improving access can also lead to congestion when there is excess demand for a good or service. Here, I show this can lead to a new type of digital divide where the distribution of consumption benefits is regressive.

This result is closely related to results on discrimination in online markets where buyers with ethnically different names are at a disadvantage in purchasing used cars (Zussman, 2013), obtaining a short-term rental property (Edelman, Luca, and Svirsky, 2017) or hailing a ride-share (Ge et al., 2020). For instance, Edelman, Luca, and Svirsky (2017) find consumers with distinctly African American names are 16 percent less likely to be accepted for a short-term rental property than are consumers with distinctly white names. In online permit markets there is no discriminatory mechanism apart from buying frenzy itself. Yet, I find different types are consumers are at a substantial disadvantage in obtaining recreational permits. Households in the first income quartile are 32 percent less likely to obtain a permit during the frenzy compared with households in the fourth income quartile.

Improvements in information technology can have positive effects ranging from improved profits in artisanal fisheries (Jensen, 2007) to increased marriage rates (Bellou, 2015) and higher employment rates (Hjort and Poulsen, 2019). Similarly, Lakdawala, Nakasone, and

Kho (2023) show school-based internet access can have positive effects on educational outcomes.[4] A key theme in this work is that lower income households have poorer access to information technology and this fact, combined with the advantages these technologies create, leads to a regressive distribution of benefits. Here, I show lower income households are less successful in purchasing goods sold in online buying frenzies. Though it is difficult to determine the precise mechanism, the fact the income gap increases with online congestion and is not easily explained by different preferences, time or scheduling costs, suggests congested online marketplaces themselves disadvantage lower income users creating a digital divide.

Second, I contribute to the literature on buying frenzies. A monopolist can increase profits by creating a buying frenzy (DeGraba, 1995; Denicolo and Garella, 1999; Courty and Nasiry, 2016; Liu and Schiraldi, 2014; Loertscher and Muir, 2022) or by using excess demand to signal product quality (Becker, 1991; Balachander, Liu, and Stock, 2009).[5] For their part, consumers participate in the frenzy if they are uncertain of their valuations and rush to buy to avoid paying higher prices or the risk of being rationed in a later period (Bulow and Klemperer, 1994; DeGraba, 1995; Liu and Schiraldi, 2014; Courty and Nasiry, 2016). Here, I show how online buying frenzies can create distributional effects.

Third, the paper relates to work that studies managing access to public lands. Several authors consider the trade-off between the inefficiency of lotteries relative to auctions and potential inequities created by the latter. For instance, Evans, Vossler, and Flores (2009) study hybrid permit allocation systems that combine auction and lottery mechanisms. They show the hybrid mechanism preserves an efficient allocation of permits to individuals with the highest willingness-to-pay, but has an equity benefit of randomly allocating some permits. Arnosti and Randolph (2019), Reeling, Verdier, and Lupi (2020) and Verdier and Reeling (2022) study alternatives to simple lotteries that can approximate the efficient al-

[4]However, the results on computing technology are more mixed. In settings where school children were provided with laptop computers, computer skills increased (Malamud and Pop-Eleches, 2011; Beuermann et al., 2015). However for the most part, these skills did not lead to better educational outcomes (Fairlie and Robinson, 2013; Cristia et al., 2017).

[5]In the case of public lands, the motivation is obviously different from the monopolist. Park managers restrict use to prevent overconsumption and limit congestion externalities rather than to maximize profits. However, the results of scarcity induced by use-permit systems and rationing by a monopolist can ultimately be the same.

location while providing an equitable distribution of consumption. Here, I investigate the distributional effects of reservations systems, which are more commonly used by resource managers than either auctions or lotteries. I show these systems can also lead to an inequitable allocation of consumption when buying frenzies lead to online congestion. Since in my application there is no secondary market, these distributional effects are fundamental to the online buying frenzy and not due to subsequent reallocation.

The rest of this paper is organized as follows. In Section 2 I describe the institutional detail around permitted recreation. Section 3 lays out a theoretical framework describing user participation in permit lotteries and buying frenzies, including potential mechanisms for the distributional effects I observe. Section 4 presents the data and Section 5 presents results of the investigation into demographic effects of buying frenzies. In Section 6, I analyze the incidence of buying frenzies in terms of recreational benefits and Section 7 concludes.

2 Permits for recreation on public lands

Markets for recreational permits on public lands in the U.S. provides a novel setting for identifying the potential distributional effect of online buying frenzies. For many years, managers of public lands have struggled with the problem of managing use (The New York Times, 2021). Visitor use negatively impacts the experience of other visitors (United States Department of the Interior, 2020), raises safety concerns (Lawson et al., 2010) and can harm vegetation and animals (Dertien, Larson, and Reed, 2021). Since users do not consider the negative effects of their recreation, these costs are external costs and justify resource management. Since park managers have largely deemed higher user fees undesirable (Walls, 2022), limiting use via permits has become the predominant management strategy.[6]

Permits are obtained one of three ways: On a walk-up (call ahead) basis; via an online reservation system; or using a lottery, typically administered online. Walk-ups are rapidly being replaced by online reservations, even for day-ahead sales.[7] While some park managers

[6] Recreation.gov currently lists over 100 different use permits.

[7] Anecdotally, some parks that initially allocated permits using a reservation system moved to a lottery system over concerns of perceived fairness (Grand Canyon National Park, 2023).

administer their own online systems, many have elected to have their permits managed by Recreation.gov. The Recreation.gov site was conceived as "an interagency partnership among federal agencies to provide reservation services, sharable data, and recreation trip-planning tools for federal lands and waters across the United States." (United States Department of the Interior, 2016). Today, it manages use at approximately 4,200 facilities and over 110,000 reservable sites across the country (United States Department of the Interior, 2016).

There are nine river sites on Recreation.gov that allocate permits for rafting or float trips using both lotteries and reservation on-sales.[8] These sites are Desolation Canyon of the Green River (UT), Dinosaur National Monument Green and Yampa Rivers (CO and UT), Hell's Canyon of the Snake River (OR), the Middle Fork of the Salmon River (ID), the Rio Chama Wild and Scenic River (NM), the Salmon River (ID), the Salt River Canyon (AZ), the Selway River (ID) and the San Juan River (UT). The number of permits awarded per day depends on the river and time of year.

These sites are widely regarded as some of the premier float trip destinations in North America. Due to the large number of permit applications, park managers have implemented lottery systems for allocating permits. Users submit their lottery entry via Recreation.gov between December 1 and January 31. An entry consists of a site and specific trip start date. Users must specify a trip leader. A trip leader may not submit more than one entry per site per season. There is no secondary market for permits. Resales are prevented by verifying the trip leader's identity prior to the start of the trip. Each of these rivers also maintains a parallel permit system for commercially guided trips.

Following the entry period, winners are drawn at random for each trip start date.[9] Winners are notified several days after the end of the entry period, typically during the beginning of February. Winners then have several days to confirm (accept) their permit. Permits not

[8]There are also two hiking sites, the Enchantment are of Washington state and Mount Whitney in California. Here, I focus on river sites for consistency in modeling users' recreational choices.

[9]Lottery winners are selected using a sophisticated randomization algorithm. According to recreation.gov documentation "Each lottery is randomized by shuffling all the applications using the Fisher-Yates Shuffle, which produces an unbiased and random ordering of results. We also use a Cryptographically Secure Pseudo Random Number Generator (CSPRNG) to prevent any inadvertent bias in the lottery process. These random number generators are vetted to produce random numbers that cannot be predicted based upon past outputs, and they dont allow anyone to predict future or past numbers generated." (https://www.recreation.gov/lottery/how-they-work)

accepted during this confirmation period are made available to the public during a reservation on-sale.[10,11] Since the lottery for every site and start date has many entries, whether a trip appears subsequently in the buying frenzy depends on the probability the lottery winner claims the permit and not the number of lottery entries. The reservation on-sale is used to allocate unclaimed permits in order to avoid the administrative costs of running a second lottery. Most importantly for the work here, the sequential structure creates systems that allocate identical goods (river trips for specific dates) by both lottery and buying frenzy mechanisms at essentially the same moment in time.

(a) Lottery Entries and Reservations

(b) Web Traffic and Completed Orders

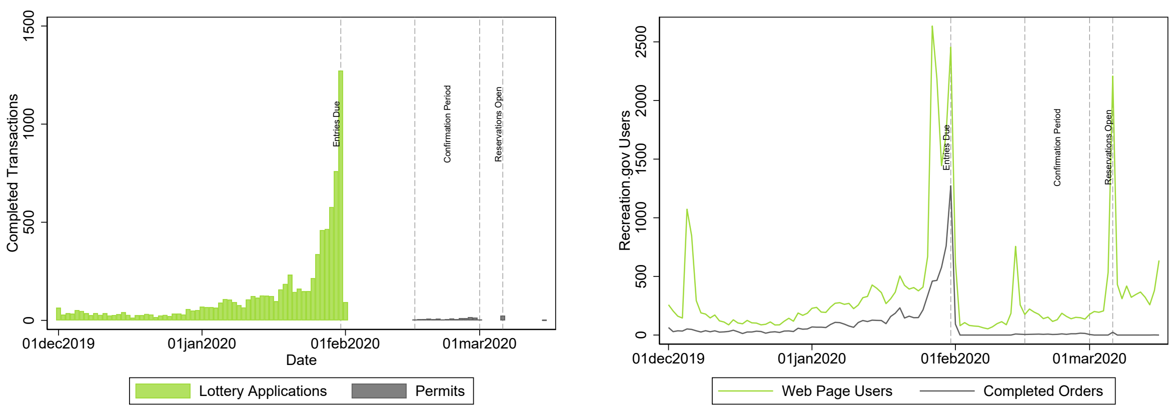


Figure 1: Lottery entries and online reservations activity for Green and Yampa River permits in Dinosaur National Monument (CO and UT). Lottery entries are accepted from December 1 through January 31. Lottery winners must confirm their permits between February 16 and March 1. The "on-sale" reservation period for unclaimed permits begins at 8am MST on March 6.

To better understand these systems, Figure 1 shows representative data for Green and Yampa River permits in Dinosaur National Monument (CO and UT). Figure 1a plots the

[10] Appendix Table A1 summarizes the relevant dates for 2020. Dates and times are set well in advance and published on Recreation.gov and the public land unit web pages. Specific dates vary occasionally from year to year for a variety of reasons including the recent federal government shut-down and other administrative disruptions. Relevant dates in the process described above are announced well in advance on Recreation.gov. Due to operational issues, on-sale events for each of the sites studied here begin at 8 am Mountain Time on the scheduled date. This is due to the desire to coordinate with the operating hours of the Recreation.gov call center which opens each day at 8 am Mountain time.

[11] The two-part permit allocation scheme is presumably due to the time required in advance to plan for these trips and travel to these site. Late cancellations would likely go un-used since users would not have time to plan and organize a trip on short notice. Forcing an early confirmation or cancellations reallocates permits in a manner that allows sufficient planning time.

number of completed transactions, either lottery entries or completed reservations, for the 2020 season. Several features are worth noting. First, lottery entries greatly outnumber available permits. For instance, during the 2020 season there were approximately 8,000 entries for approximately 300 permits. This suggests the permit system substantially curtails river use in the monument. Second, the majority (72%) of successful reservations outside of the initial lottery, occur during the first two hours of the reservation period. This suggests timing is critically important to obtaining a permit during the on-sale period. Third, lottery entries increase at a steady rate during the entry period and peak around the deadline of January 31, 2020. This suggests entrants value waiting.[12] Since entrants must submit trip start dates, waiting could reduce uncertainty regarding the most favorable river conditions during the season, for instance as winter snowfall totals are realized. There is similar late peaking behavior during the lottery confirmation period when lottery winners obtain permits based on the dates submitted to the lottery.

Figure 1b provides additional insight into congestion by investigating web page traffic from Google Analytics. I plot the number of visitors to the Dinosaur National Monument page on Recreation.gov during the lottery and reservation periods. I also plot completed orders (lottery entries and permit purchases) for comparison. During the lottery entry period there are approximately twice as many users as completed orders. This could indicate repeat visits to check trip dates or lottery information. During the reservation on-sale on March 6, 2020, over 2000 users visited the Monument web page. Again, only 24 permits were awarded on this day. This suggests intense competition for available permits during the on-sale period consistent with a buying frenzy. Transaction and web traffic data for the other sites in the sample look quite similar to those for Dinosaur National Monument presented here.

To see whether the congestion during the on-sale period favors different types of users, Figure 2a plots median household income of successful frenzy reservations versus lottery entrants for river permits in Dinosaur National Monument. I see evidence the distribution of household income for reservation permits is right-shifted. The mean household income for permits awarded by lottery is approximately $74,000 versus over $85,000 for permits

[12] Appendix Section A.1 argues that although users appear to value waiting, high and low income users do not appear different in this regard.

obtained during the buying frenzy. Figure 2b plots the distribution of median household income for permit holders at the nine different river sites. Again, there is evidence the income distribution is right-shifted for users successful in the buying frenzy. Mean income is approximately \$72,000 for lottery permit holders and nearly \$76,000 for users who were successful in the buying frenzy.[13] These results suggest higher income households have an advantage in the reservation on-sale. Section 3 describes potential mechanisms and Section 5 investigates these mechanisms empirically.

(a) Dinosaur National Monument (b) All Rivers

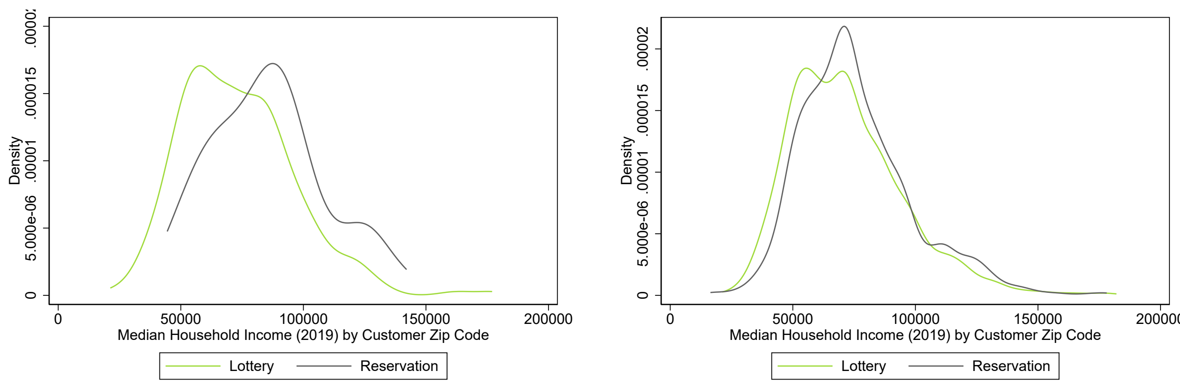


Figure 2: The distribution of median household income by customer zip code for users awarded permits by lottery and reservation on-sale buying frenzy.

3 User participation in lotteries and reservation systems

This section presents a simple framework to motivate the empirical work below. Users choose to participate in the lottery or reservation on-sale buying frenzy (or both). Understanding these decisions sheds light on the potential mechanisms of any distributional effects.

[13] Interestingly, I observe similar income shifts in other settings including permits to climb Half Dome and Mount Whitney in California and for backpacking permits in the popular Enchantment wilderness area in Washington state.

3.1 Lotteries

A number of authors have modeled the behavior of consumers in recreational goods lotteries (Boyce, 1994; Kerr, 1995; Scrogin and Berrens, 2003; Scrogin, 2005; Yoder, Ohler, and Chouinard, 2014). The approach adopted here most closely follows Yoder, Ohler, and Chouinard (2014). Consider a multi-attribute good $\mathbf{x} \in \mathbf{X}$, where $\mathbf{X} = [\mathbf{x}_0\ \mathbf{x}_1\ \mathbf{x}_2 \ldots \mathbf{x}_N]'$ and the goods $\mathbf{x}$ are trips at a given site defined by different start dates, *e.g.* day-of-week and week-of-season. Good $\mathbf{x}_0$ is the outside option awarded to lottery non-participants with probability one. I assume an individual can enter the lottery for only one good and that each good is allocated using a separate lottery.[14] Lottery entries for good $\mathbf{x}_i$ are selected at random with probability π_i that depends on the number of available permits Q_i and the number of entrants A_i, such that $\pi_i = \frac{Q_i}{A_i}$. While the actual probabilities are deterministically determined, users must make their entry decisions before the final number of entries is realized. Therefore, they choose based on the expected probability $\hat{\pi}_i = E[\pi_i] = \frac{Q_i}{\hat{A}_i}$, where $\hat{A}_i$ is the predicted number of entries $\hat{A}_i = E[A_i]$. In practice, users can estimate $\hat{A}_i$ based on past lotteries since many lotteries publish detailed reports on prior years' results.

Individuals have preferences over the goods defined by the utility function $U(\mathbf{x})$.[15] I denote the utility individual l gains from consuming good $\mathbf{x}_i$ as $U_l(\mathbf{x}_i)$. When deciding whether to participate in a site lottery, users weigh the expected utility from a lottery trip net of transaction costs against that of the outside option.[16] Each user solves:

$$max\ (\hat{\pi}_i U_l(\mathbf{x}_i) - C, U(\mathbf{x}_0)) \tag{1}$$

where C are transaction costs of participating in the lottery. Costs of participating in a permit lottery are small, entry fees range from \$6 to \$16 and time costs are minimal. Therefore, the analysis below ignores lottery transaction costs, *i.e.* assumes $C = 0$. Expected

[14] In practice, each "trip leader" may enter the lottery for a given site only once. However, since a party may consists of several people, each may enter the lottery separately as trip leader to increase the group's entries of enter a separate lottery by choosing a different trip start date.

[15] Utility for the outside option can be normalized to zero such $U(\mathbf{x}_0)$ is the utility gained from "winning" a lottery trip.

[16] While monetary transaction costs of lottery participation may be small, the fact some outside options may disappear while entrants are awaiting results generates an opportunity cost.

utility depends on both the consumption utility from that trip and the probability of winning. Since users may only enter the lottery for a given site once per year, the utility-maximizing user chooses the good with largest expected utility. Here this equates to picking the start date defined in $\mathbf{x}$ such that:

$$\hat{\pi}_i U_l(\mathbf{x}_i) > \hat{\pi}_j U_l(\mathbf{x}_j) \; \forall \; j \neq i \tag{2}$$

This means users may choose less desirable trip start dates (e.g. late season or mid-week start) to improve the odds of winning the lottery.

3.2 Reservation on-sale buying frenzies

Reservation on-sales are modeled as a type of discriminatory lottery with non-trivial entry costs. The details of this process determine the types of users that participate in the frenzy and whether they are successful in obtaining a permit. The reservation process effectively consists of two stages. The first stage consists of the decision whether or not to participate in the reservation on-sale buying frenzy. Since entering the reservation on-sale is time-consuming, users weigh the expected utility of participation net of time and scheduling costs against the consumption utility from the outside option $U_l(\mathbf{x}_0)$. In the second stage, participants who are successful in obtaining a permit have the choice of accepting the permit or choosing the outside option.

Buying frenzy participation

During a reservation on-sale, a particular site start date trip i appears in the on-sale with probability $\pi_{a,i}$.[17] Conditional on being listed, users are able to reserve a particular trip with probability $\pi_{r,li}$ that depends on factors such as the number of other users online, internet speed, timing and savviness in navigating Recreation.gov. As such, this probability varies not only by site and trip start date but also, potentially, by individual user l. As before, the

[17] Recall, the reservation on-sale is populated by unclaimed lottery trips and cancellations that occur during the confirmation period.

consumption utility of a given trip is $U_l(x_i)$. Unlike the lottery, users participating in the reservation system may incur non-trivial time (scheduling) costs T_l that vary by individual. For instance, the opportunity cost of sitting in front of one's computer rather than being elsewhere or the cost of being available at a specified time and date to participate in the reservation on-sale. Under these assumptions, the user solves:

$$max\ (\hat{\pi}_{a,i}\hat{\pi}_{r,li}U_l(x_i) - T_l, U_l(x_0)) \tag{3}$$

User l participates in a buying frenzy when the expected trip utility exceeds the consumption utility of the outside option.

Permit purchase

Once trips are revealed at the start of the reservation on-sale, users must then decide whether on not to compete for a particular permit. In practice, rivalry/congestion necessitates quickly selecting a single trip from amongst the available trip start dates. Users who successfully add a permit to their online shopping cart must then decide whether to actually accept or purchase the permit. For permits purchased during the reservation on-sale: $U_l(x_i) > U_l(x_0)$.[18]

3.3 Potential mechanisms

The discussion above highlights factors determining whether users participate in reservation on-sales. To the extent these criteria differ systematically across groups of users they also illustrate potential mechanisms of the observed demographic differences between those who obtain their permit via lottery and those who are successful during the buying frenzy. I discuss four main channels through which the demographic effects may operate in this online sales environment: trip availability; differences in preferences (willingness-to-pay); time or scheduling costs; and web page congestion that affects success during the buying frenzy.

[18] This feature is unobserved in the data. In other words, I do not observe users who add a permit to their "shopping cart" but ultimately decide not to purchase.

Trip availability

In this particular setting, permits that appear in the reservation on-sale are those left unclaimed by initial lottery winners. One may therefore worry these permits are for less desirable trips and systematically vary with users' incomes. If this is the case, the probability a trip appears during the on-sale $p_{a,i}$ may be non-random and correlated with the choices of certain types of users who participate in the buying frenzy.

Preferences

Users that receive larger utility ($U_l(x_i)$) from obtaining a permit are more likely to participate in a buying-frenzy. Therefore, if preferences (willingness-to-pay) vary systematically by type of user, we would expect high value users to appear more often and expend more effort during reservation on-sale buying frenzies and could therefore receive a larger share of permits.

Time and scheduling costs

Buying frenzies can give rise to substantial time and scheduling costs T_l. For instance, high web traffic may lead to long delays in loading web pages, site crashes and payment processing errors. Transactions that would normally require several minutes may instead last five or ten times as long. From Equation (3) we see that increasing time cost decreases the likelihood of participating in the on-sale and instead choosing the outside option. The issue is particularly acute since on-sales occur at a specified time, 8 am MT for these river sites and often on weekdays. This may exacerbate time costs if users must modify work or childcare schedules to accommodate the on-sale. High scheduling costs may prevent certain groups from participating in the buying frenzy due to the timing of the particular event. For instance, if higher (lower) income users have more (less) flexible work arrangements, scheduling costs may alter the types of users participating.

While the time of the on-sale itself may not immediately suggest a digital divide effect, it is precisely because online sales can more easily be operated during "normal business hours" that creates the potential for high scheduling costs among certain groups of users. Further, the morning start time is not unique to Recreation.gov. A survey of recent on-sale events indicates weekday mornings are the preferred times for online product launches in goods as varied as concert tickets (AXS, 2023), sporting events (Denver Broncos, 2023), theatre (LEO Weekly, 2023), game consoles (Pettit, 2023), vodka (WWJ Newsradio 950, 2023) and NFTs (Kauflin, 2023).

On-sale success probabilities

In addition to cost differences, there may also be substantial heterogeneity in access to information technology and familiarity with online sales platforms across groups of users. Such differences are captured in the probability of obtaining a reservation during a buying frenzy ($p_{r,ijt}$) in Equation 3. While the time that reservations become available for purchase is known in advance, small differences in clock times mean the exact start time is uncertain. As a result, users arrive at the reservation web page several minutes before sales start and refresh their web browsers in order to access the reservation system at the moment sales begin. Under some circumstances, users with faster computers and faster internet connections can do this more quickly and thus have an advantage in this process. Further, lower-income households often lack a broadband connection and may rely on a mobile phone as their primary connection to the Internet (Swenson and Ghertner, 2020). These households may face an additional disadvantage if reservation web sites are difficult to display and navigate on a small screen. Finally, less frequent visitors to Recreation.gov may be further disadvantaged if they are less familiar with the online reservation process. For instance, users who have failed to create a Recreation.gov account or who have not signed in to their account prior to the start of the on-sale lose valuable minutes at the start of the buying frenzy.[19]

[19]For instance, Rocky Mountain National Park recently migrated their backcountry permit system to Recreation.gov. In notifying potential users of this change, park staff advised "Take time to become familiar with the site prior to March 2, when reservations go live. To be prepared, those interested in booking a wilderness backpacking camping trip this summer should set up an account with Recreation.gov in advance of March 2." (National Park Service, 2022). Conversely more savvy users may be more adept at navigating on-sale systems or selecting suitable options from available trips.

4 Data

Transaction-level data on lottery entries and reservations are from Recreation.gov via the Recreation Information Database (RIDB) system (Recreation.gov, 2021). The data include information on the type of purchase (lottery entry, permit, campground reservation, etc.), site, purchase date and time, and customer state and zip code for the 2019 and 2020 seasons. Note the effects of the COVID-19 pandemic are likely minimal since permit allocations concluded in mid-March 2020. I use the purchase type, transaction date and time to classify each purchase as being either a lottery entry, a permit purchase as a result of a successful lottery entry or a permit purchase during the buying frenzy. For the later, I restrict the reservation on-sale period to the first day permits become available, though effectively nearly all of these transactions occur during the first hours of the buying frenzy. I eliminate permits purchased after the first day since these are permits made available due to cancellations.[20]

	Number Orders			Fees Paid	
Site	Lottery Entries	Lottery Permits	Reservation Permits	Lottery Entry Fee	Permit Fee
Desolation Gray - Green River Permit	4,243	193	114	$6	$229
Dinosaur Green And Yampa River Permits	7,950	124	24	$15	$71
Hells Canyon - Snake River (4 Rivers)	3,807	228	39	$6	$2
Middle Fork Of The Salmon (4 Rivers)	13,438	384	18	$6	$194
Rio Chama Wild and Scenic River Permits	2,693	98	23	$6	$16
Salmon River (4 Rivers)	10,457	271	28	$6	$209
Salt River Canyon Wilderness Permit	1,976	165	101	$16	$40
San Juan River Permit Lottery And Reservations	5,989	295	201	$6	$76
Selway River (4 Rivers)	6,050	57	4	$6	$0

Table 1: Summary of permits allocated using lottery and reservation by river site for the 2020 season. Individual-level permit and lottery entry data are from Recreation.gov obtained via the Recreation Information Database (RIDB) system.

Table 1 summarizes orders by site for the 2020 season. The number of lottery entries ranges from 1,976 for the Salt River Canyon to 13,438 for the Middle Fork of the Salmon. The number of successful reservations varies from 4 for the Selway River to 201 for the San Juan. The ratio of permits, both lottery and reservation, to lottery entries is a measure

[20]Reservations due to cancellations after the initial on sale are likely made by a different type of user, for instance those with unusual scheduling flexibility or individuals using bots or subscription services to monitor the site for cancellations.

of recreational demand for each site. The ratio is also an empirical measure of the ex-post probability of winning the lottery. In general, the odds of a successful lottery entry are low, less than one in ten for every river site except the Salt River Canyon (one in eight). The odds of getting a Selway permit are approximately one in a hundred.

The righthand-side of Table 1 summarizes fees paid for lottery entries and ultimately, permits. Costs to enter a permit lottery are low, between \$6 and \$16. Permit fees are somewhat higher, averaging in the dollars or tens of dollars, but can be as high as \$200 on some rivers, depending on party size and trip length.

I collect zip code level demographic data from the U.S. Census American Community Survey (U.S. Census Bureau, 2021) and match these data to Recreation.gov transactions using customers' zip codes. The main dependent variable in the empirical analysis below is median household income by zip code. Several additional specifications explore educational attainment and ethnicity as alternate dependent variables. Table 2 presents summary statistics for various demographic characteristics of lottery entrants and successful on-sale reservations. The unconditional means (again) suggest differences in the demographic characteristics of users who obtained their recreational permit via the lottery with those that obtained their permit during the buying frenzy. Households that were successful in obtaining a permit during the on-sale period come from higher income zip-codes with a larger percentage of college graduates and slightly higher broadband internet penetration. Because these demographics may be correlated with recreational site and trip characteristics, the empirical models below control for these factors in studying differences in user characteristics across allocation mechanisms. Finally, I utilize detailed data from Google Analytics, provided by Recreation.gov, to analyze web congestion. Google Analytics provides high frequency estimates of the number of users, sessions and page views for Recreation.gov. Sessions refer to a group of user interactions on a web page. Users are individuals or devices accessing a web page. Page views count the number of times a page is accessed and capture page refresh activity.

Customer Zip Code Demographics	N	Mean	sd	Min.	Max.
Lotteries					
Median Inc.	3,187	$ 72,052	$ 23,507	$ 21,250	$ 223,859
College (%)	3,223	44.6	16.4	0.0	100.0
Broadband (%)	3,223	89.0	7.1	0.0	100.0
Median Age	3,226	39.7	7.7	16.0	73.3
White (%)	3,226	87.4	10.4	2.0	100.0
	N	Mean	sd	Min.	Max.
Reservations					
Median Inc.	939	$ 75,662	$ 22,804	$ 16,406	$ 178,056
College (%)	947	46.9	15.9	0.0	100.0
Broadband (%)	947	89.2	7.8	0.0	100.0
Median Age	948	40.0	7.4	16.0	62.9
White (%)	948	88.1	9.6	11.5	100.0

Table 2: Comparison of zip-code level demographics for permits allocated by lottery and reservation on-sale buying frenzy. Demographics are 2019 zip code level demographic data from the U.S. Census American Community Survey. "Median Inc." and "Median Age" are the median household income and median age. "College," is the percent of individuals over the age of 25 who are college educated. "Broadband" is the percent of households with a broadband internet connection and "White" is the percent of individuals who report their race as white.

5 Demographic effects

Here I more rigorously compare the demographics of users awarded permits in permit lotteries with those in reservation on-sale buying frenzies. In these comparisons, I am implicitly assuming the population of potential users, and their preferences over different trips, is constant over the (short) time between the lottery and buying frenzy periods. I provide evidence this assumption is reasonable in Section A.1 of the Appendix. The remaining identification challenge is accounting for unobserved trip factors (site-specific timing) that may be correlated with user characteristics. These factors could lead to selection bias in who participates in the reservation on-sale buying frenzy via the trip availability probability $p_{a,jt}$.[21]

[21] For example, high income and low income households may prefer start dates on different days of the week. The distribution of lottery winners will reflect these preferences. However, if high income users are less likely to confirm a winning permit or are more likely to cancel during the confirmation period the distribution of trips available during the reservation on-sale will be skewed toward the preferences of the higher income users. If these trends are known ahead of time, this could result in fewer lower income users participating in the reservation on-sale.

I employ two different strategies to address this issue. The first approach uses parametric controls and various fixed-effects to account for unobserved factors that may be correlated with demographics and trip characteristics. Specifically, I first estimate models of the form:

$$Y_{li} = \delta_r + \Gamma_{it} + \alpha_s + \epsilon_{li} \tag{4}$$

Y_{li} is the outcome of interest, *e.g.* income or education, for a permit for site i received by individual l and where δ_r is an indicator variable equal to one if user l's permit was obtained during the reservation on-sale buying frenzy period. Because river conditions and weather affect users' willingness to pay for a particular trip (Yoder, Ohler, and Chouinard, 2014), Γ_{it}, is a vector of trip characteristics to control for site-specific time-varying factors. In the preferred specification, Γ_{it} is made up of site-by-week and site-by-day of week effects. Alternatively, some specifications directly control for river conditions by including historical data on stream flow and air temperatures in Γ_{it}. Finally, some specifications include customer state fixed-effects α_s to account for mean effects that vary by state.[22] Estimates produced with Equation 4 have the advantage of utilizing all the observations in the sample. The main disadvantage, of course, is that the somewhat coarse controls and fixed-effects may not completely account for unobserved factors that are correlated with both trips and demographics. In particular, if the subset of trips appearing during the buying frenzy is different in ways that are more or less valuable to different types of users, different choice sets, rather than the allocation mechanisms themselves, could explain the observed demographic effects.[23]

To address this concern, the second strategy uses trip fixed-effects (site by start-date) such that δ_r is identified by variation in permit allocation method (lottery versus reservation on-sale buying frenzy) within a particular trip.[24] This approach has the advantage that it

[22] For instance, a site in California may be less distant from large population centers, and hence be in high demand, but may also be visited by a larger proportion of higher-income households.

[23] It is also possible for some users to conclude remaining trips appearing during the buying-frenzy are less valuable. However, this perception would need to vary systematically by type of user in order to explain the observed demographic effects.

[24] For example, trips beginning on July 3, 2020 in Desolation Canyon where one permit was awarded by lottery and two were awarded during the reservation on-sale would be included in the restricted sample. However, a trip in Desolation Canyon on July 4, 2020 where all three permits were awarded by lottery (or all three permits awarded by reservation) would not be included.

non-parametrically controls for unobserved factors at the trip level. The disadvantage of this approach is that the sample is limited to only those trips that have within-trip variation in δ_r.[25] This could limit external validity if, for instance, the sample includes only less desirable trips. Using this sub-sample I estimate models of the form:

$$Y_{li} = \delta_r + \gamma_{it} + \epsilon_{li} \tag{5}$$

where γ_{it} are trip fixed-effects. Results from both identification strategies are discussed below.

5.1 Results

Table 3a presents estimates for Equation 4 for several demographic variables beginning with median household income. Users who were successful in obtaining a permit during a reservation on-sale buying frenzy come from zip codes with higher median household income, \$3,027 (4%) more than users who obtained their permit from the lottery. There are differences in other demographic characteristics as well. Column two presents results for educational attainment. Users successful in obtaining a permit during the reservation on-sale period come from zip codes where the fraction of college educated persons over the age twenty-five is approximately 1.6 percentage points (3.5%) higher than lottery winners. Broadband Internet penetration, age and percentage of the population that is white are all higher, though these effects are not statistically significant.

Table 3b presents estimates of Equation 5 using the second identification strategy and the sub-sample of trips allocated by both lottery and buying frenzy. The estimated effects are quite similar to those in Panel a. The average income for users who were successful in obtaining a permit during the reservation on-sale is \$2,856 higher than users who obtained their permit, *for the same site and start date*, through the lottery. Users successful in obtaining their permit during the reservation on-sale come from zip codes where the percentage of college-educated individuals is 1.87 percentage points higher. The estimates for broadband,

[25]Practically speaking, this restriction reduces the sample of trips by about half.

age and percent white are again statistically insignificant.

Reservation On-Sale Demographic Effects

Panel A.)	Income ($)	College (%)	Broadband (%)	Age	White (%)
Reservation	$ 3,027.47	1.57	0.44	0.11	0.82
	(833.59)	(0.57)	(0.36)	(0.36)	(0.55)
Mean of Dependent Variable	$ 72,873	45.1	89.0	39.7	87.6
Site by Day-of-Week Effects	Yes	Yes	Yes	Yes	Yes
Site by Week-of-Season Effects	Yes	Yes	Yes	Yes	Yes
Observations	4126	4170	4170	4174	4174
Adj. R-sq.	0.01	0.01	0.00	0.01	0.01

Panel B.)	Income ($)	College (%)	Broadband (%)	Age	White (%)
Reservation	$ 2,856.13	1.87	0.39	-0.21	0.64
	(1339.03)	(0.69)	(0.34)	(0.30)	(0.79)
Mean of Dependent Variable	$ 73,951	45.8	89.0	39.9	87.5
Trip Effects (Site by Start Date)	Yes	Yes	Yes	Yes	Yes
Observations	2023	2044	2044	2047	2047
Adj. R-sq.	0.03	0.04	0.01	0.00	0.00

Table 3: Demographic effects of online buying frenzies. The dependent variables are median household income, percent population over age 25 college educated, percent households with broadband internet, median population age and percent white by customer zip code. Standard errors clustered at the site level. Results are also robust to clustering at the start-date level and are available upon request.

Table 4 investigates the robustness of the main income results to several alternate specifications. Column one reproduces the unconditional comparison of means. Households that are successful in making permit reservations during the reservation on-sale buying frenzy come from zip codes with median household income approximately $3,611 higher than the average lottery winner. Column two adds site fixed-effects and column three adds site by day of week fixed-effects. The estimated income effects are somewhat smaller in these specifications, approximately $3,253 to $3,367 higher for reservation on-sale permits compared with lottery entrants. Column four reproduces estimates from Equation 4 using site by week and site by day-of-week effects. Column five replaces site-specific time effects with weekly average temperature and stream flows. The estimated income effect, $3,371 is quite similar to the base specification. Column six adds customer state effects. Here, the point estimate decreases somewhat to $2,754 but remains fairly large and statistically significant. This change could be due to the propensity for more affluent users to recreate in more congested sites nearer to their home state. Finally, column seven reproduces results from Equation 5 using within-trip variation in allocation mechanism.[26] Overall, these results support the conclusion users who are successful in navigating congestion in the buying frenzy reside in higher income zip codes compared to those selected at random via permit lottery.

Reservation System Mean Income Effects

	Unconditional Mean	Add Site Mean-Effects	Add Site-by-DOW Effects	Add Site-by-Week Effects	Stream Conditions	Customer State Effects	Site-by-Start Date Effects
Reservation System	3611.0	3253.4	3366.9	3027.5	3371.2	2754.0	2856.1
	(1049.80)	(985.11)	(914.23)	(833.59)	(966.23)	(635.01)	(1386.46)
Site Fixed-Effects	No	Yes	No	No	No	No	No
Site by Day-of-Week Effects	No	No	Yes	Yes	Yes	Yes	No
Site by Week Effects	No	No	No	Yes	No	Yes	No
Temp. and Flow Controls	No	No	No	No	Yes	No	No
Customer State Efffects	No	No	No	No	No	Yes	No
Site by Start Date Effects	No	No	No	No	No	No	Yes
Observations	4126	4126	4126	4126	4117	3973	2023
Adj. R-sq.	0.00	0.02	0.02	0.01	0.02	0.15	0.02

Table 4: Robustness checks on the main income effect. The dependent variable is median household income by customer zip code. Temperature is predicted daily high temperature from a regression of week and day-of-week effects on 10 years of pre-period daily maximum temperatures. Stream flow is logged predicted discharge from a regression of week and day-of-week effects on 10 years of daily discharges. Standard errors clustered at the site level. Results are also robust to clustering at the start-date level and are available upon request.

5.2 Potential mechanisms

In this section, I present results exploring the potential mechanisms of the observed income effects discussed above. Since these models incorporate supplemental data and require further sample restrictions, to preserve power I focus on the specification in Equation 4. However results based on Equation 5, using the within-trip variation, are qualitatively very similar, though less precisely estimated than those presented here.

[26] Specifications with log income as the dependent variable produce statistically significant and qualitatively similar results. The point estimates for reservations during the buying-frenzy range from 0.046 to 0.048.

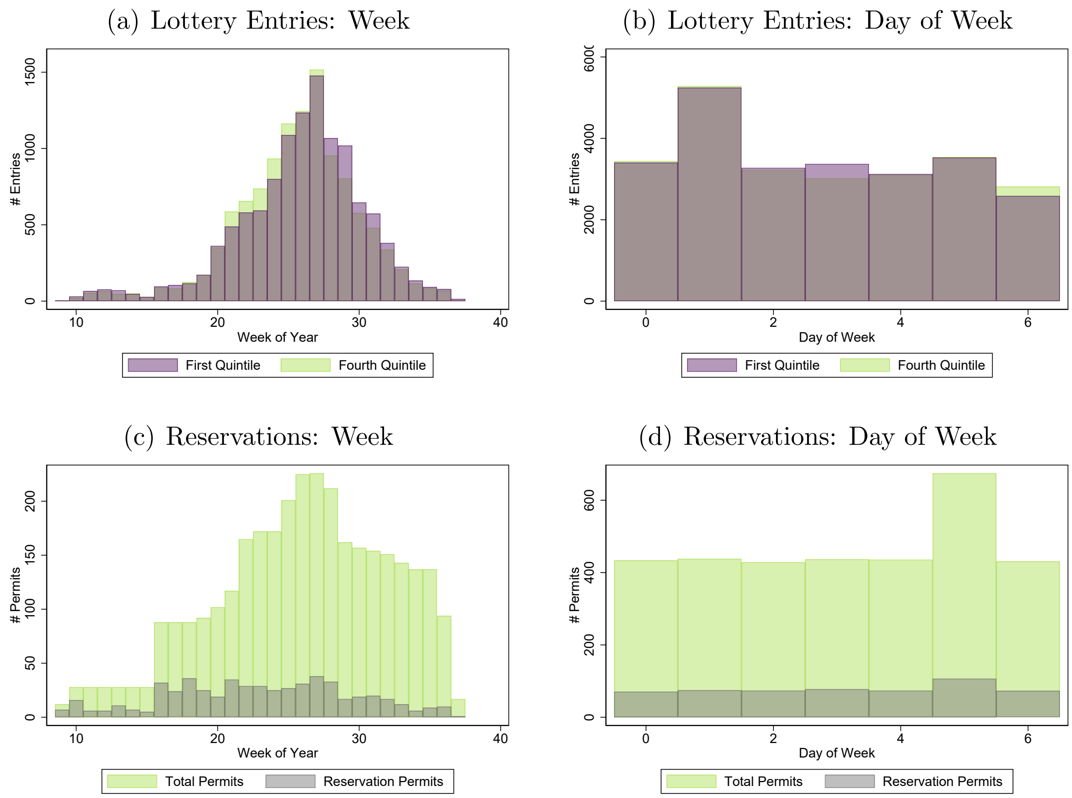


Figure 3: Comparison of preferences for trip start times by income group with permits obtained during the reservation "buying frenzy." Preferences proxied by lottery entries by trip week of season (a) and start day of week (b). Permits obtained during the frenzy by week of season (c) and day of week (d).

Preferred trip availability

Figure 3 explores whether users in different income groups systematically prefer different types of trips and whether the types of trips appearing during the reservation on-sale buying frenzy is non-random. Figures 3a and 3b show trip start week and day of week for lottery entries by income group. Users in the first quartile are somewhat more likely to enter for trips later in the season and for trips beginning on Wednesdays. Users in the fourth quartile are slightly more likely to enter for a Saturday trip start. Figure 3c and Figure 3d compare the total number of permits available during the season with those appearing in the reservation on-sale.[27] Reservation permit availability follows total permit allocations

[27] There is a greater number of permits for Friday trip starts because the Rio Chama only offers permitted trips on weekends.

fairly closely, though a larger proportion of frenzy permits are available earlier in the season compared to peak season. This underscores the importance of controlling for unobserved factors that vary across trip start dates as discussed and implemented in the empirical models above.

Preferences

Systematic differences in preferences could explain the observed income effects if lower income households have lower willingness-to-pay for a permit and therefore choose not to participate in a reservation on-sale buying-frenzy. Of course, individual-level preferences are unobserved. In their place I use two proxies. First, using the sample of lottery entries, I calculate the travel distance between each user's home zip code and the river site. Users who are willing to travel greater distance for river trips also likely have higher willingness-to-pay for those trips. Second, I use the number of river lottery entries on Recreation.gov. Users that are willing to participate in multiple lotteries likely have higher values for river permits.

Figure 4 summaries these two proxies by income quartile. Panel a suggests higher income users are more willing to travel greater distances to a river site. Panel b shows higher income users complete more transactions on Recreation.gov. Higher income households seem more willing to spend time traveling and online, which could indicate a greater willingness to participate in the frenzy.

(a) User Travel Distance (b) Recreation.gov Activity

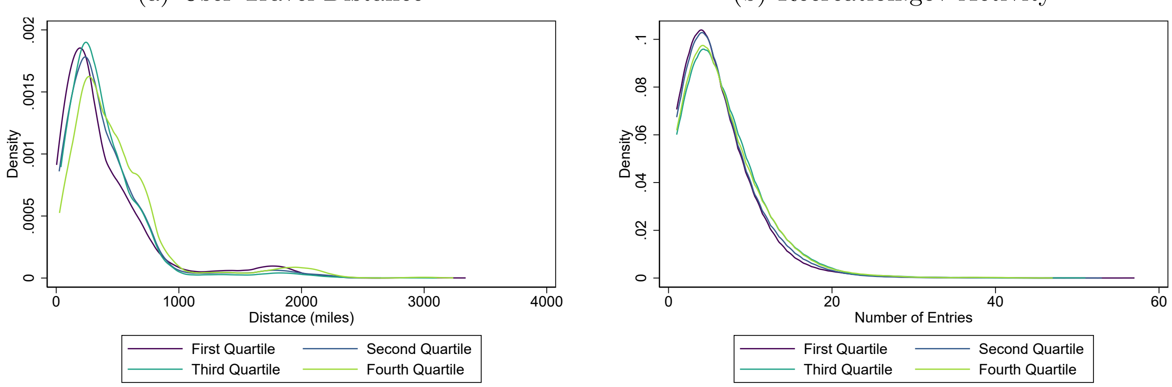


Figure 4: Proxies for user preferences (willingness to pay) (a) the mean travel distance from user's home zip code to the recreation site and (b) the mean number of completed orders on Recreation.gov, by income quartile.

I investigate these potential mechanisms further by including travel distance and entries as additional controls in Equation 4. Column one of Table 5 reproduces the results of the main specification. Columns two and four present results with the additional controls. Unfortunately, the data allowing me to link individual users to past orders are only for the 2020 season and therefore use of these proxies yields a restricted sample. Column three presents results of the base model with this restricted sample. The effects of travel cost and number of lottery entries are statistically significant. However in both cases, the estimated reservation effects are similar to those in the base model, suggesting preference heterogeneity is not a main driver of the observed income differences across allocation mechanisms. Column four also has an alternate interpretation. If lower income households are less-experienced navigating river lotteries on Recreation.gov, as proxied for by their number of entries, they may be less successful during a buying frenzy due to this inexperience. However, a sizable income gap remains even after controlling for this measure of experience.

	Base Model	Travel Distance	Base Model*	Order Activity
Reservation System	3027.47	3217.74	4028.68	2801.18
	(833.59)	(861.07)	(1279.75)	(1021.87)
Travel Distance		6.63		
		(2.30)		
Number of Entries				407.36
				(90.37)
Site by Day-of-Week Effects	Yes	Yes	Yes	Yes
Site by Week-of-Season Effects	Yes	Yes	Yes	Yes
Observations	4126	4046	3832	3686
Adj. R-sq.	0.01	0.02	0.01	0.15

Table 5: Results from several specifications showing the main income effect results are robust to including proxies for user preferences (willingness to pay). The dependent variable is Median Household income by customer zip code. Travel distance is the distance in miles between the user's zip code and the river site. Number of entries is the number of river lottery entries during the 2020 season. Standard errors clustered at the site level. Results are also robust to clustering at the start-date level and are available upon request. *Denotes the base model estimated on the restricted sample of users that can be matched to lottery entries.

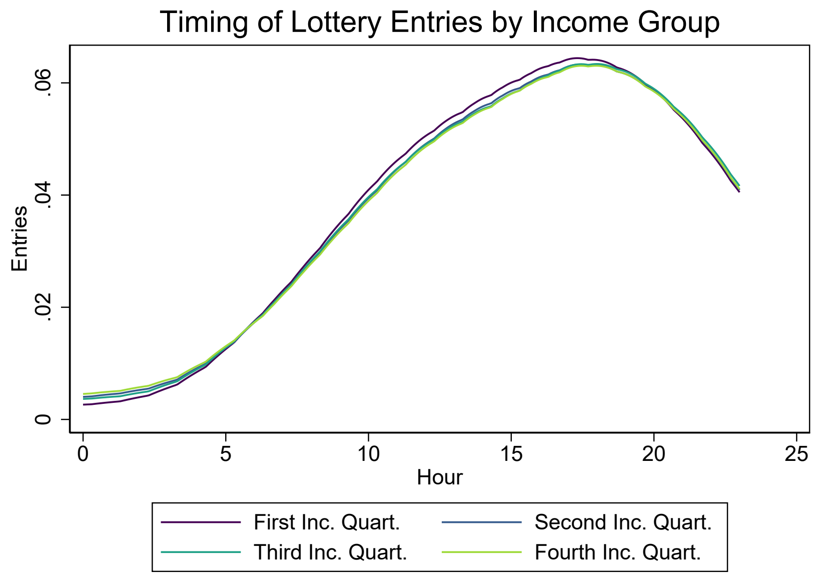


Figure 5: The distribution of lottery entry time by income quartile suggests users have similar preferences for participating in site selection on Recreation.gov when unconstrained by the timing of an on-sale event.

Time and scheduling costs

Time and scheduling costs reflect the ability of individuals to modify work or family schedules to participate in a reservation on-sale buying frenzy. To get a sense of individuals' preferences for accessing Recreation.gov, I first look at lottery participation. Since lottery entries can occur at any time over a number of weeks before the entry deadline, the timing of users' entries provides insight into their preferred times on the site. Figure 5 plots the distributions of lottery entry times (on weekdays) for each quartile of the income distribution. Users across the income distribution prefer to participate during the afternoon and evening and there are no substantial differences across income groups. While income groups have fairly uniform preferences when unconstrained, they may have different costs when constrained to participate in buying frenzy on a specific day and time.

Table 6 shows the results of several specifications exploring the role of these costs. In column one, I include an interaction for whether the reservation on-sale occurs on a weekend. Relative to weekdays, the estimated income effect is approximately $1,000 smaller when the buying frenzy occurs on a weekend. However, this effect is not statistically significant. Next

	Weekend Sales	Local Hours 7am - 10am	Recreation.gov Hour 8am
Reservation System	3537.76		
	(1241.12)		
Reservation*Weekend	-1091.83		
	(1173.78)		
Reservation*7 am Local Time		3433.93	3943.31
		(2338.70)	(3856.32)
Reservation*8 am Local Time		3320.43	3152.13
		(1409.00)	(1258.34)
Reservation*9 am Local Time		4094.42	10062.62
		(2547.72)	(15503.54)
Reservation*10 am Local Time		-1020.12	-5049.88
		(3388.67)	(7810.39)
Site by Day-of-Week Effects	Yes	Yes	Yes
Site by Week-of-Season Effects	Yes	Yes	Yes
Observations	4126	3937	3699
Adj. R-sq.	0.01	0.01	0.01

Table 6: Results showing the differential relationships between income and reservation success by timing of reservation on-sale in user's local time. The dependent variable is Median Household income by customer zip code. Standard errors clustered at the site level. Results are also robust to clustering at the start-date level and are available upon request.

I turn to the on-sale timing in each user's local time zone. I create indicator variables for the hour in local time that the reservation transaction occurs, *i.e.* the indicator variable for 8 am is equal to one for a user located in the mountain time zone and the indicator variable for 7 am is equal to one for a user located in the Pacific time zone. I then estimate the mean reservation effects by time zone by interacting these indicator variables with the reservation indicator. Results of this exercise are presented columns two and three. Column two uses observations from the first four hours of the on-sale event. In column three I limit observations for reservations to those occurring during the first hour of the on-sale. Focusing on column 3, income effects are largest, approximately $10,000, when the on-sale begins at 9am local time, though the estimate is not statistically significant. Taken together, the weekend and "start of the workday" results provide some suggestive evidence scheduling costs may play a role in the observed income effects. However, taking these estimates at face value, a sizable income gap remains even when the buying frenzy occurs at a time when scheduling costs are presumably lowest, *i.e.* on weekends.

Congestion and on-sale success probability

If congestion is the main driver of the income effects during a buying frenzy we expect a positive relationship between web page activity and the observed income effects. Here, we can think of web traffic as measuring the intensity of competition for permits, rather than some exogenously derived internet congestion. Figure 6a presents three measure of web traffic on the Dinosaur National Monument page of Recreation.gov. During the 2020 Dinosaur National Monument reservation on-sale the number of users spike to approximately 2200 and sessions increase to 1576.[28] However, page views increase from around 2000 per day to over 76,000.[29] To put this number in perspective, the average session consists of nearly *50* page views. This indicates a huge amount of page refresh activity consistent with a congested buying frenzy.

For each site, Figure 6b plots the difference in mean income between permits awarded during the on-sale and the lottery versus page views on the day of the reservation on-sale. There is a strong positive relationship between this measure of web congestion and income effects during the buying frenzy.

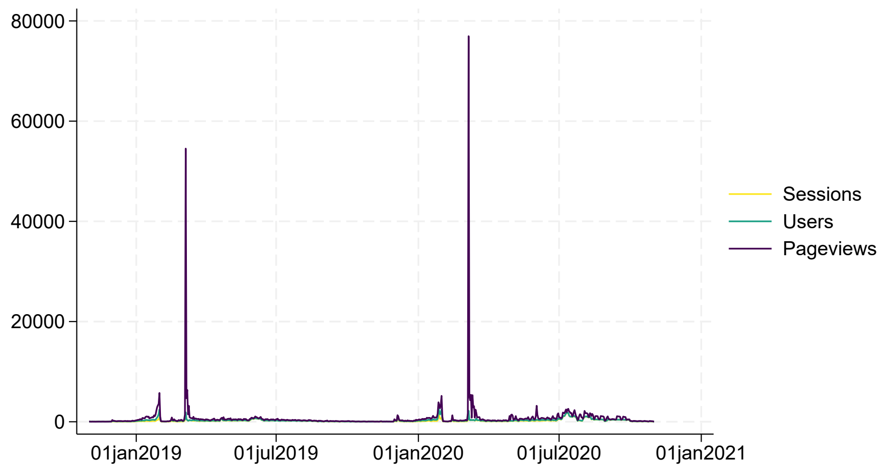
I test this result more formally in Table 7 by interacting page views with the reservation indicator in Equation 4. Results from this specification are shown in column one. I present analogous results using users and sessions as alternate measures of web congestion. An increase of 10,000 page views is associated with a \$1,400 increase in the income effect of the buying frenzy. In column two and column three I estimate positive but statistically insignificant effects for users and sessions.

Finally, I combine these results with those incorporating proxies for heterogeneity in willingness to pay. Column four presents results using page views as a measure of intensity of congestion and using travel distance and number of lottery entries as proxies for preferences. These results support congestion during the buying frenzy as the main mechanism generating

[28]In hourly reports, Google Analytics counts sessions that span hours, *e.g.* 7:55 am to 8:05 am, as one "session." However, when a user's visit spans two hours they are counted as two distinct "users." Therefore, I expect "users" as defined by Google Analytics to be an over-estimate of the actual number of users and instead use sessions as the main measure of site visitors.

[29]There are similar but somewhat smaller increases during 2019.

(a) Dinosaur Web Traffic Spikes During On-Sale Events



(b) Web Traffic Measures and Income

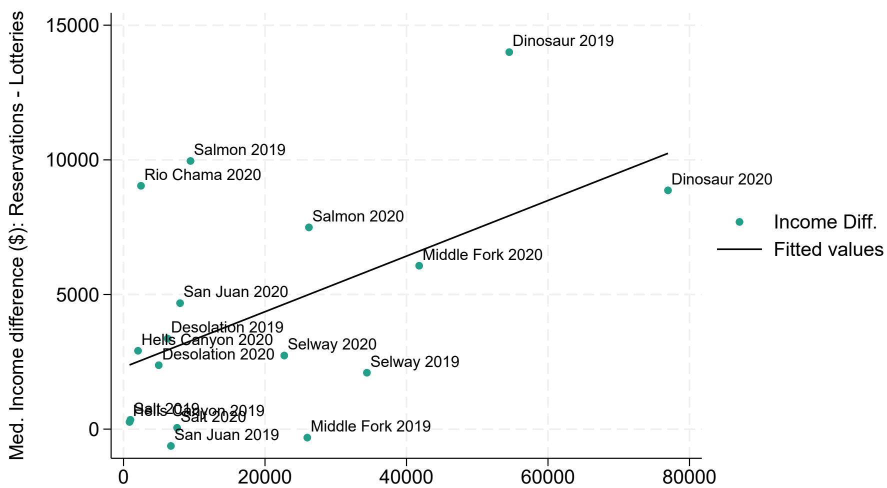


Figure 6: Measures of online congestion (a) increase during the Dinosaur National Monument reservation on-sale (buying frenzy) event. Page views (b), a proxy for web page refreshing activity, are positively correlated with the mean income difference between users who obtain their permit via the online buying-frenzy and the lottery.

the distributional effects. While the proxies for willingness to pay matter, there remains a large and statistically significant relationship between web congestion and the income gap during the online buying-frenzy.

	Page Views	Web Users	Sessions	WTP Proxies
Reservation System	1591.23	438.0	1187.2	1399.4
	(491.56)	(893.66)	(937.57)	(903.83)
Reservation * Page Views	0.14			0.17
	(0.05)			(0.03)
Reservation * Users		3.05		
		(2.08)		
Reservation * Sessions			3.22	
			(2.22)	
Page Views	-0.02			-0.03
	(0.06)			(0.02)
Users		-0.46		
		(2.63)		
Sessions			-0.56	
			(2.58)	
Travel Distance				6.98
				(2.77)
Number of Entries				384.36
				(93.21)
Site by Day-of-Week Effects	Yes	Yes	Yes	Yes
Site by Week-of-Season Effects	Yes	Yes	Yes	Yes
Observations	4126	4126	4126	3006
Adj. R-sq.	0.01	0.01	0.01	0.04

Table 7: Results showing the potential role of online congestion in the observed income effects. The dependent variable is Median Household income by customer zip code. Sessions refer to a group of user interactions on a web page. Users are individuals or devices accessing a web page. Page views count the number of times a page is accessed and capture page refresh activity. Travel distance is the distance in miles between the user's zip code and the river site. Number of entries is the number of river lottery entries during the 2020 season. Standard errors clustered at the site level. Results are also robust to clustering at the start-date level and are available upon request.

6 Incidence of recreational benefits

To understand the incidence of recreational benefits I estimate the expected recreational benefits to different income groups under two counterfactual scenarios. The counterfactual exercise imagines replacing the hybrid lottery and reservation system with either a pure lottery or a pure reservation system. I first estimate willingness to pay for different sites and trip start dates. Then, I estimate the likelihood users in different income groups are awarded permits. In the lottery and reservation systems, I estimate the empirical probabilities for each user and trip using the observed permit market outcomes. I combine these two sets of estimates to calculate the expected benefits for different portions of the user income distribution for every possible trip. Comparing the outcomes under each counterfactual yields an estimate of the incidence of allocating permits using only a reservation system. This estimate is likely a lower bound of the true distributional effect since allocating all permits, rather than only a portion of permits, would likely intensify the buying frenzy.

The goal of this exercise is not to conduct a full welfare analysis of these competing systems. For instance, the private costs to users of participating in the buying frenzy are unobserved. Rather, the goal is to understand how benefits may accrue to different groups of users under the two allocation schemes. To this end, the approach outlined below is suitable for estimating the price in each permit market, but not the full schedule of willingness to pay. If users have heterogenous trip values, these estimates will be a lower bound on the surplus each user receives. The distribution of benefits across the income distribution will be unbiased if willingness to pay does not systematically vary across users with different incomes. However, if high income users have systematically higher willingness to pay, as suggested at least anecdotally by Figure 4, then the estimates will be conservative in the sense high income, high value users would receive an even larger share of the benefits than estimated here.

Trip utility

A number of authors have investigated the allocation of recreational permits by lottery (Scrogin and Berrens, 2003; Scrogin, 2005; Yoder, Ohler, and Chouinard, 2014). These papers model lottery participation using an expected utility framework and estimate demand for different recreational trips. I extend this approach to estimate the share of recreational value allocated to different income groups during a buying frenzy. To estimate willingness to pay for different trips I adapt the model of lottery choice developed by Yoder, Ohler, and Chouinard (2014). Here, the choices of all users to either enter the lottery or choose the outside option determine equilibrium outcomes. This approach is preferable to a more standard discrete choice framework because the large number of possible trips (site and trip start date) each user faces, makes estimation of a choice model extremely challenging.

I model lottery participation as a non-cooperative simultaneous game with a rational expectations Nash Equilibrium solution. As in Section 3.1 above, each user chooses $\mathbf{x}_i$ from among the available alternatives in $\mathbf{X}$ to maximize their expected utility $EU_l[\mathbf{X}]$. To capture differences across individuals it is convenient to think of utility in terms of individual-specific and common factors. Specifically, divide individual l's utility $U_l(\mathbf{x}_i)$ into factors common to all users, $U(\mathbf{x}_i)$ and idiosyncratic factors unique to each user ν_{li}, such that:

$$U_l(\mathbf{x}_i) = U(\mathbf{x}_i)\nu_{li}, \tag{6}$$

where $\nu_{li} \sim_{iid} (1, \sigma^2)$. Users know their own preferences as well as the distribution of ν_{li}. This has the benefit of a representative agent interpretation where $E[U_l(\mathbf{x}_i)] = U(\mathbf{x}_i)$. To see how equilibrium choices of the representative agent are related to lottery entries, note the expected utility from choosing the lottery for good $\mathbf{x}_i$ is:

$$E_l[\widehat{EU}_l(\mathbf{x}_i)] = \widehat{EU}(\mathbf{x}_i) = \frac{Q_i}{\hat{A}_i}U(\mathbf{x}_i), \tag{7}$$

which is the representative consumer's expected utility in the lottery for good $\mathbf{x}_i$. Here, the hat notation denotes the fact users must form predictions about the probability of success in each lottery *ex ante* but the actual probabilities depend on the number of entries are are realized *ex post*. Rearranging this expression yields the predicted number of entries for good $\mathbf{x}_i$:

$$\hat{A}_i = \frac{Q_i U(\mathbf{x}_i)}{\widehat{EU}(\mathbf{x}_i)} \tag{8}$$

Under the assumptions above, $U(\mathbf{x})$ can be interpreted as a von Neumann-Morganstern utility index. The utility of the most preferred alternative can normalized to one and the outside option normalized to zero, *i.e.* $U(\mathbf{x}_1) = 1$ and $U(\mathbf{x}_0) = 0$. Yoder, Ohler, and Chouinard (2014) show that in equilibrium, $\widehat{EU}(\mathbf{x}_i) = \widehat{EU}(\mathbf{x}_j) = C \ \ \forall\ i \neq j$, when the number of entrants is sufficiently large.[30] Intuitively, if the number of entrants were zero, entrants would

[30]The expected utilities are approximately equal when the number of entrants is small.

apply for their most preferred trip. However, the probability of winning decreases as the number of applicants increases. Entries are split across trips until the expected utilities are equal. Since no user would participate in the lottery if the cost of entering exceeded the expected utility, entries occur until expected utility equals cost. Therefore, in equilibrium the expected utility for any good $\mathbf{x}_i$ can be related to the most preferred option $\mathbf{x}_1$ by: $\pi(\mathbf{x}_1) \times 1 = \pi(\mathbf{x}_i) \times U(\mathbf{x}_i)$ and the von Neumann-Morganstern utility index for good $\mathbf{x}_i$ is:

$$U(\mathbf{x}_i) = \frac{\pi(\mathbf{x}_1)}{\pi(\mathbf{x}_i)} = \frac{A(\mathbf{x}_i)Q_1}{A(\mathbf{x}_1)Q_i} \tag{9}$$

In other words, the relative utilities of goods are defined by the relative probabilities of winning the lottery.

To estimate utility indices for the lottery goods in $\mathbf{X}$ note that the expected utility of user l can be written as:

$$\widehat{EU}_l(\mathbf{x}_i) = \hat{\pi}_i U_l(\mathbf{x}_i) = \hat{\pi}_i U(\mathbf{x}_i)\nu_{li} = \widehat{EU}(\mathbf{x}_i)\nu_{li} = C\nu_{li}. \tag{10}$$

Although the representative agent chooses $\mathbf{x}$ such that expected utilities are equal across goods, idiosynchratic tastes represented by ν_{li} mean individual's expected utility varies across goods. As a result, observed lottery entries for each good differ from the predicted values such that the probability that user l chooses $\mathbf{x}_i$ over $\mathbf{x}_j$ is:

$$Prob[EU_l(\mathbf{x}_i) > EU_l(\mathbf{x}_j)] = Prob[C\nu_{li} > C\nu_{lj}] = Prob[\nu_{li} > \nu_{lj}] \tag{11}$$

Define the indicator function I_{li} that is equal to one if $\widehat{EU}_l(\mathbf{x}_i) > \widehat{EU}_l(\mathbf{x}_j) > C \ \forall l \in L$ and $j \neq i \ \in \ N+1$ and is zero otherwise. The total number of lottery entries for good $\mathbf{x}_i$ is the sum of all entries for which $I_{li} = 1$, $i.e$ $A_i = \sum_{l=1}^{L} I_{li}$. Therefore, the expected number of lottery entries can be written in terms of the probability an individual l chooses good $\mathbf{x}_i$ as:

$$E[A_i|\mathbf{X}] = \hat{A}(\mathbf{x}_i) = \sum_{l=1}^{L} I_{li} \cdot \prod_{j\neq i} Prob[\nu_{li} > \nu_{lj}] \tag{12}$$

The observed entry counts are related to expected counts by the idiosyncratic utility. Specifically, I assume $A_i(\mathbf{x}_i) = (\nu_i|\mathbf{X})\hat{A}(\mathbf{x}_i)$. Taking logs we have:

$$lnA(\mathbf{x}_i) = ln\hat{A}(\mathbf{x}_i) + \epsilon_i \tag{13}$$

where ϵ_i=ln (v_{li}). Substituting for $\hat{A}$ using (8) and $\widehat{EU} = C$ yields:

$$lnA(\mathbf{x}_i) = lnU(\mathbf{x}_i) - lnC + lnQ_i + \epsilon_i, \tag{14}$$

which, combined with assumptions on the functional form of $lnU(\mathbf{x}_i)$ and the distribution of ϵ_i provides and estimable equation. In the empirical model below I flexibly capture $lnU(\mathbf{x}_i) - lnC + lnQ_i$ with mean effects for the trip start week-of-season and day-of-week effects. I assume ϵ_i follows a gamma distribution and estimate (14) as a negative binomial regression.

Finally, estimates from (14) can be combined with (9) to estimate the utility index for any good $\mathbf{x}_i$. Specifically, the estimated von Neumann-Morgenstern utility index $\hat{U}(\mathbf{x}_i)$ is:

$$\hat{U}(\mathbf{x}_i) = \frac{\hat{\pi}(\mathbf{x}_1)}{\hat{\pi}(\mathbf{x}_i)} = \frac{\hat{A}(\mathbf{x}_i, Q_i)}{\hat{A}(\mathbf{x}_1, Q_1)}\frac{Q_1}{Q_i}, \tag{15}$$

where $\hat{A}(\mathbf{x}_i, Q_i)$ are the (exponentiated) predicted values from (14) and values for $\hat{A}(\mathbf{x}_1, Q_1)$ correspond to the trip with the lowest lottery probability, *i.e.* the most desirable trip. Using this procedure I recover estimates for the *relative utilities* for every trip in the sample.

To compare across sites, for which users likely have very different willingness to pay, I must estimate the *utilities* of each trip not simply the relative utilities for different start dates at a particular site. To do this, I assume the utility of the *most preferred* trip $\hat{U}(\mathbf{x}_1)$ is equal to the price for a commercially guided trip on each river during the 2020 season.[31] The values are collected from OARS and other commercial guides using the Internet Wayback Machine. Under this assumption, the value of trip $\mathbf{x}_i$ is just $\hat{U}(\mathbf{x}_1) \times \frac{\hat{\pi}(\mathbf{x}_1)}{\hat{\pi}(\mathbf{x}_i)}$.

Commercial trip values are an imperfect measure of preferences for those who take pri-

[31] Unfortunately, while whitewater river recreation has been a popular topic in the non-market valuation literature, willingness to pay estimates for the sites I study here are unavailable.

vate trips. Commercial values may be higher than private values if users are willing to pay a premium for a guided trip. On the other hand, commercial trip operators post a single price for an entire season. Since prices do not vary to reflect river conditions, the posted price may underestimate the value of the *most preferred* trip. However, since I am most interested in comparing the share of trip value received by users in different parts of the income distribution, what matters is not whether commercial trip values equal the marginal private trip value for each site, but whether the difference in commercial and private trip values is constant across sites.

On-sale success probability

I estimate the probabilities users in different parts of the income distribution are successful in obtaining a permit during a reservation on-sale buying frenzy using a reduced form approach. I assume the population of potential users is captured by the population of lottery entrants. This assumption is consistent with the assumption of negligible lottery transaction cost. For each site, I group lottery entrants into quartiles of the income distribution pooling across all trip start dates for that site.

To simulate the creation of a pure reservation on-sale system it is necessary to estimate the probabilities for any trip start date, not only those start dates that appeared in prior Recreation.gov on sale events.[32] I assume user preferences vary by trip start-week and day-of-week. Using data from only the reservation on-sale buying frenzies, I estimate a series of multinomial logit models, one for each site. In these models, the dependent variables are indicators corresponding to the quartiles of the site-specific income distributions, again based on the income distribution of lottery entrants. The independent variables are fixed-effects for trip start week-of-season and day-of-week. I use these parameter estimates to predict the probability that an individual user, from a given income group, is successful in obtaining a permit for a particular trip start date during the frenzy.

[32]Under a pure reservation system $p_{a,i} = 1$ for all sites and start dates.

6.1 Trip value estimates

Trip values vary substantially depending on the day of week and the week of season the trip begins. Figure 7a presents willingness to pay estimates for each river and start date during the 2020 season. Willingness to pay for most sites peaks several weeks into the season then gradually tails off into the late season. Values are highest for the Selway and Middle Fork of the Salmon river, peaking at over $3,000 per person. Willingness to pay values for each river also display daily variation that indicate strong preferences for start dates on certain days of the week. Figure 7b presents average willingness to pay by trip start day of week for each river.[33] Mondays are the preferred start day for every river. Thursdays and Fridays are the second-most preferred days for each river.

Given the substantial variation in values for different trip start dates, any distributional effects will depend on both an individual's probability of securing a permit and also upon the specific trip that is obtained. Appendix Table A3 summarizes the estimated reservation success probabilities for different trip start day-of-week by quartile of the user income distribution. The Selway River is omitted here because there are too few reservation permits to estimate the multinomial logit model in this sample. Users in the first income quartile are disadvantaged relative to all other users for all days of the week except Thursday. For Monday trip starts, the mean success probability across all sites for users in the first income quartile is 15 percent, compared with 32 and 33 percent for users in the third and fourth quartiles. Overall there is a substantial difference in the probability of successfully obtaining a permit across the income distribution. Users in the first income quartile are successful approximately 20 percent of the time compared to 29 percent for users in the fourth income quartile. The equates to a 32 percent lower likelihood of obtaining a permit during the frenzy.

Similarly, Table A4 summarizes average success probabilities across all sites by start week. To compare across sites that begin at different times of the year, start weeks are shifted to "week of season" before averaging. Success probabilities tend to be higher for users in the fourth income quartile during the middle of the season. The lower probabilities for reserving

[33] Here, the Rio Chama is omitted since permitted trips are limited to Friday and Saturday start days.

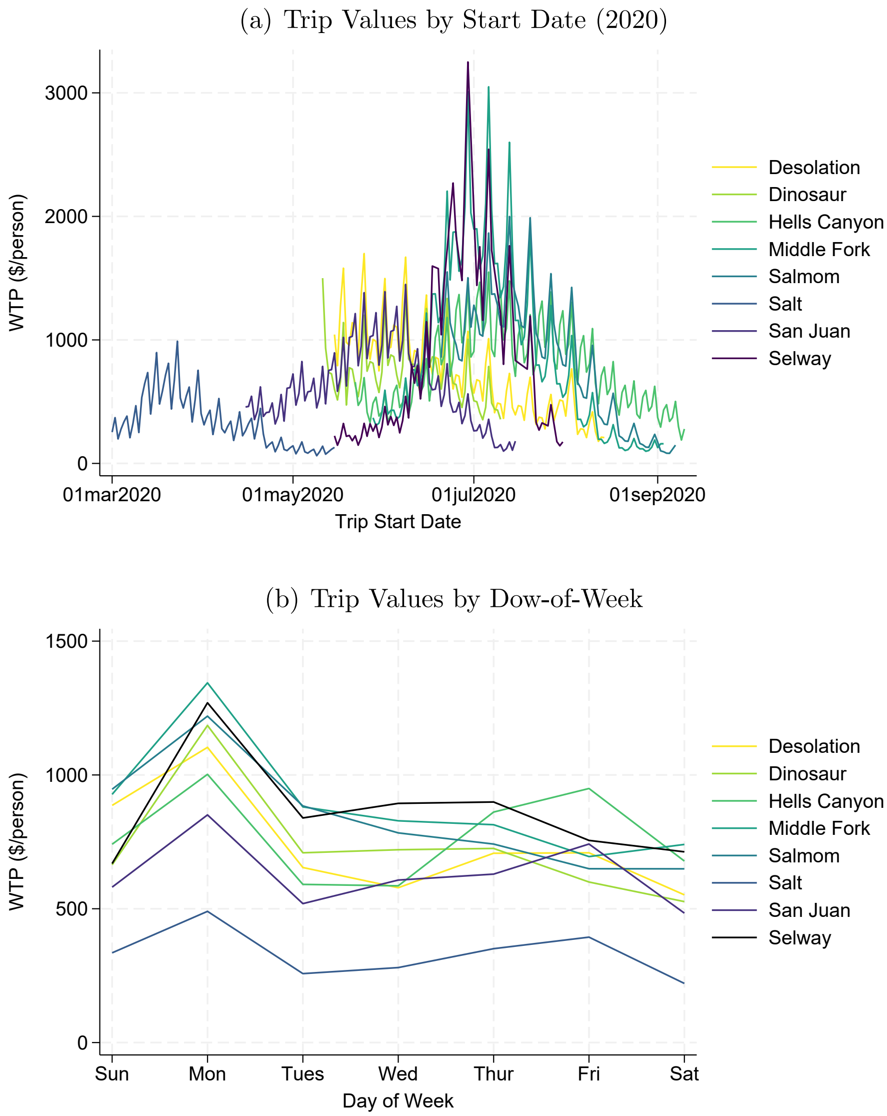
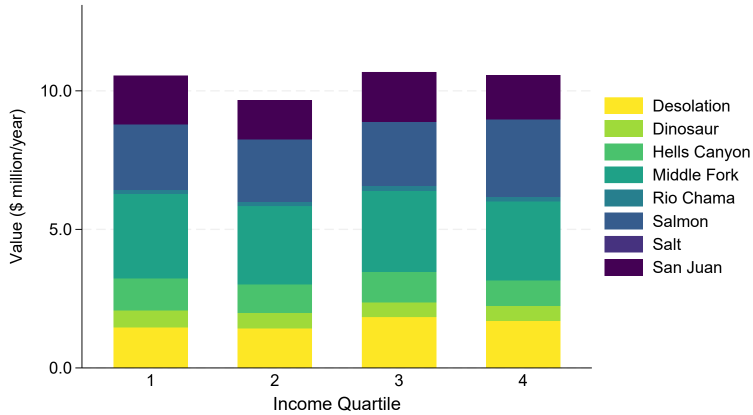


Figure 7: Estimated willingness to pay in dollars per person for river trips by (a) date of the 2020 season and (b) day of week averaged over the 2019 and 2020 seasons. Rio Chama values are omitted because permitted launches are limited to Fridays and Saturdays.

more valuable start dates combined with the overall lower success probability suggest lower income users are likely allocated a substantially lower share of recreational trip value.

Figure 8 summarizes the estimated expected recreational values by income quartile and confirms this intuition. Figure 8a shows the distribution of benefits under a pure lottery allocation. The share of recreational benefits to each group are quite flat, with the first, third and fourth quartiles receiving approximately \$10.5 million/year in total benefits. Quartile

(a) Distribution of annual trip value under universal lottery system.



(b) Distribution of annual trip value under universal reservation system.

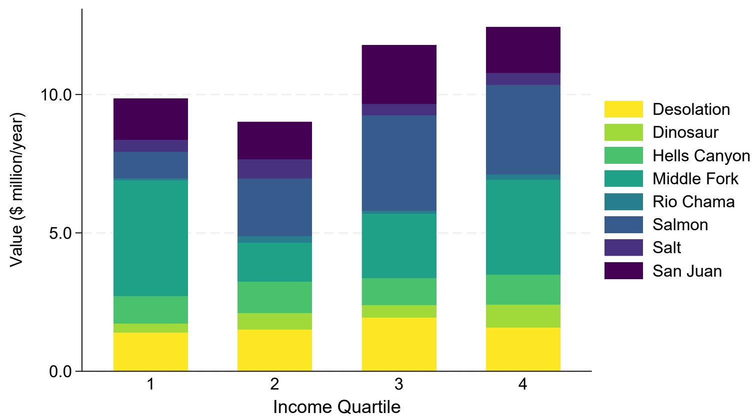


Figure 8: Estimate trip values by recreational user income quartile (1-4) assuming (a) all trips are allocated using lotteries or (b) all trips are allocated using a reservation system. Income quartiles are calculate from the population of lottery entrants. There are insufficient observations to estimate reservation success probabilities for Selway River trips.

2 receives slightly less, approximately $9.7 million per year.[34] In contrast, Figure 8b shows the distribution of recreational benefits for a reservation system with a buying frenzy. Users in the first and second income quartiles receive $9.9 and $9.0 million in recreational value, respectively. However, users in the third and fourth income quartiles receive $11.8 and $12.4 million in trip value. Compared to users in the first quartile, users in the fourth quartile receive 25 percent more recreational value.

[34]Though permits in each lottery are allocated at random, users in each income quartile can have slightly different preferences over trips. The distribution of trip benefits in 8a is not perfectly flat because some trips are more valuable than others.

These effects vary across river sites. For Desolation Canyon, Dinosaur National Monument, Hells Canyon, the Rio Chama, the Salmon and the San Juan, the share of recreational benefits allocated to the fourth income quartile exceeds benefits to the first quartile, sometimes by a large margin. However, for the Salt River the share of benefits for the highest and lowest quartiles is quite similar and users in the second quartile receive the largest share of benefits. For the Middle Fork of the Salmon, the first quartile is allocated substantially more of the benefits than the fourth quartile.

7 Discussion and conclusions

Buying frenzies, particularly in online settings are common and occur in a wide range of markets. Here I provide, to my knowledge, the first empirical evidence buying frenzies create distributional effects. I exploit novel features of the market for recreational permits on public lands to compare outcomes for buyers of the *same goods* allocated randomly via lottery and through online buying frenzies. I find evidence users successful in the buying frenzy are, on average, wealthier and more highly educated than those selected at random. This result is especially surprising in settings where secondary markets are absent. In addition to a regressive distribution of consumption, I show the income gap grows with online congestion. This result suggests a new type of digital divide, where online sales channels disproportionately benefit higher income users. There is no reason to expect a priori that this effect is limited to recreational permit markets.

There are several policy implications. First, resource managers, policy makers or firms concerned about equity in the non-market allocation of scarce goods may prefer lotteries to on-sale events that lead to buying frenzies. Second, policies to prevent re-sale may not alleviate equity concerns since it appears something fundamental to congested online environments favors wealthier consumers. Third, while quantifying welfare is beyond the scope of the present paper, the results suggest potentially important efficiency effects. On the spectrum of mechanisms, auctions are viewed as efficient in that they allocate goods to those with the highest willingness to pay but are inequitable if only higher income consumers receive the good. On the other end of the spectrum, lotteries are viewed as perfectly equitable since allocations are random. However, lotteries are likely highly inefficient. The work presented here suggests buying frenzies occupy an important middle ground. While I find substantial equity effects, these effects are almost certainly smaller than those in a full auction allocation. In terms of efficiency, I document substantial online congestion during on-sale events. To the extent this congestion imposes non-pecuniary costs that take the place of absent prices (Bucovetsky, 1984), buying frenzies could also occupy a middle ground on the efficiency spectrum. Therefore, a full accounting of the equity and efficiency trade-offs of online buying frenzies seems an important area for further study.

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A Appendix

A.1 Validity of lottery and frenzy timing assumption

The main identifying assumption underlying the results in Table 3 is that the value users assign each good is constant over time such that the observed differences in user characteristics are driven entirely by the allocation mechanism. This assumption seems reasonable since the river permit lotteries and online buying-frenzies occur at essentially the same time. However while the timing is close in the context of users' overall trip planning period, there is a three to four-week gap between when lottery results are announced and when the frenzy occurs. Further, Figure 1 suggests lottery entrants value waiting until the submission deadline to make their trip selection, potentially because information on expected river conditions improves over time. Therefore, timing between the lottery and frenzy could matter if trip preferences evolve *differently* for different types of users during this time.

Unfortunately, it is impossible to test the identifying assumption directly because while the population of lottery entrants is known, the population of buying-frenzy participants is unobserved (since only those users who successfully purchase a permit appear in the data). Indeed, potential mechanisms of the observed effects could be due to users' decisions not to participate in the frenzy at all (*e.g.* due to scheduling or time costs). However, it is important to show the observed differences in income are not due to the timing difference alone. I provide several pieces of information in support of the assumption that timing does not drive the observed effects.

Figure A1 plots lottery entries and median household income during the 2020 season for the rivers in my sample. While most users wait until the end of the lottery period to make their trip selection, the average income of lottery entrants appears constant over the period. I verify the later empirically by regressing the income of lottery entrants on a set of indicators for 10-day blocks of days during the entry period. The reference period (omitted period) is the first 10-day period. I include a full set of park by trip-start-date fixed-effects. Results of this exercise are shown in the first column of Table A2. Apart from days 10 through 20, none of the point estimates are statistically significant. Further, we see that the point estimates are all negative, suggesting users who enter the lottery later in the period are lower income. This trend is inconsistent with the hypothesis that higher incomes during the buying-frenzy are due to systematic differences in the value households derive from a later permit allocation. In other words, while users may value waiting to decide on trip details, higher and lower income do not appear different in this regard.

Because one may worry the types of information users collect during the lottery entry period may differ from the types of information collected during the period between the lottery announcement and buying frenzy, I provide evidence from a closely related setting that addresses this period. During the 2021 season, the John Day River in Oregon allocated permits in two different block offerings. Fifty percent of the permits were offered on March 4, 2021.[35] The remaining permits were offered on May 1, 2021. The timing is notable as the two offerings overlap the period of interest in the main results. Figure A2 plots the number of permits reserved on each day during the spring of 2021 and shows the vast majority of permits were obtained on the first day of each offering, consistent with a buying-frenzy during each period. Figure A2 also plots average income on each day of the period, which is relatively constant. I test whether the average income of users who successfully obtain a permit during the early and late frenzies is different by regressing income on an indicator for whether the permit was obtained on a May 1, 2021. I include a full set of start-date fixed-effects and drop observations from days other than the two frenzies. These results are shown in column two of Table A2. We see the point estimate for the later frenzy is negative, small and not statistically significant. Again, these results do not support the hypothesis that the higher incomes observed during frenzies (in the main results) are driven by the timing difference between allocations.

[35]While the John Day used a similar allocation strategy during 2020, effects of the COVID-19 pandemic make analysis of these data problematic. Allocations in later years were made on a rolling basis.

B Appendix figures

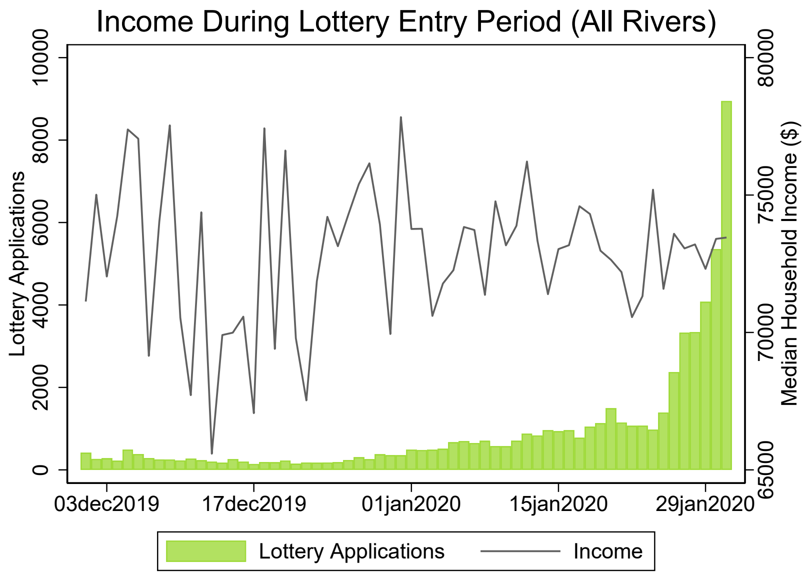

Figure A1: Median household income averaged to the day during the lottery entry period showing that although users overall may value waiting to enter the lottery, this preference does not appear to systematically vary by income.

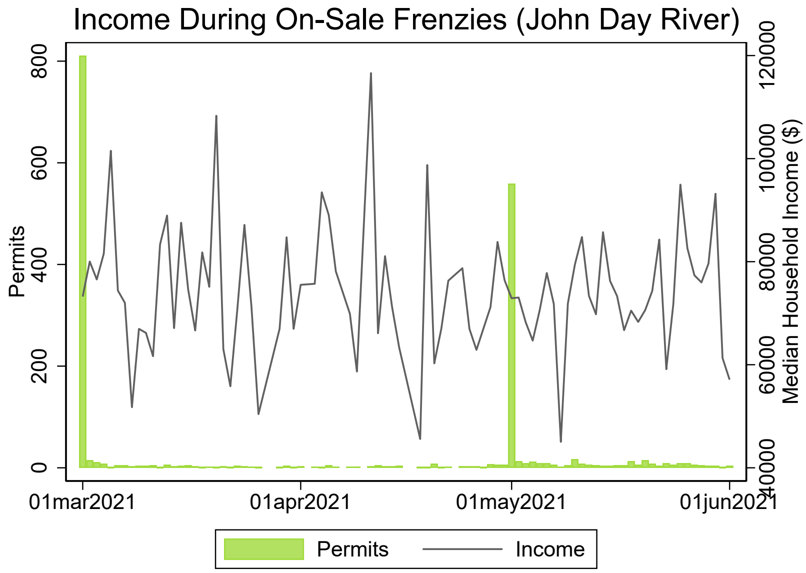

Figure A2: Income and the two buying-frenzies for John Day River permits during the 2021 season. The frenzies, on March 4, 2021 and May 1, 2021 overlap the time between lottery announcements and buying frenzies in the main results. The flat income trend suggests the values users assign trips over the course of the spring permit season does not systematically differ by income group.

C Appendix tables

Site Description	Lottery Entry Period	Confirmation Period	Reservation On-Sale Start
Desolation Gray - Green River	12/1/19 to 1/31/20	2/15/20 to 3/14/20	3/15/20
Dinosaur - Green & Yampa River	12/1/19 to 1/31/20	2/16/20 to 3/1/20	3/6/20
Hells Canyon - Snake River	12/1/19 to 1/31/20	2/14/20 3/15/20	3/16/20
Middle Fork of The Salmon	12/1/19 to 1/31/20	2/14/20 to 3/15/20	3/16/20
Rio Chama Wild and Scenic River	12/1/19 to 1/31/20	2/14/20 to 3/15/20	4/1/20
Salmon River	12/1/19 to 1/31/20	2/14/20 3/15/20	3/16/20
Salt River Canyon Wilderness	12/1/19 to 1/31/20	2/10/20 to 2/20/20	2/24/20
Selway River (4 Rivers)	12/1/19 to 1/31/20	2/14/20 to 3/15/20	3/16/20
San Juan River	12/1/19 to 1/31/20	2/14/20 to 3/15/20	3/16/20

Table A1: Timing of the lottery reservation and on-sale periods for the 2020 season. Dates for the 2019 season are similar and available from the author upon request.

Lottery and Reservation Timing Effects	Lottery Period (All Rivers)	John Day River On-Sales
Day 10 to 20	-1,395.57	
	(488.72)	
Day 20 to 30	-394.30	
	(646.97)	
Day 30 to 40	-503.27	
	(525.45)	
Day 40 to 50	-294.13	
	(501.50)	
Day 50 though 61	-557.22	
	(444.92)	
Late Frenzy		-378.05
		(1120.05)
Constant	73,431.32	
	(429.09)	
Site by Start Date Effects	Yes	Yes
Observations	98099	1294
Adj. R-sq.	0.01	0.01

Table A2: In column one, median household income of lottery entrants varies little during the lottery entry period. In column two, during the John Day River 2021 allocation, user income differs little during the early (March 4, 2021) and late (May 1, 2021) online buying-frenzies. Table shows results of OLS regressions where the dependent variable is median household income by customer zip code. Main explanatory variables in the first column are dummies for 10-day blocks of the lottery entry period. In the second column, the main explanatory variable is an indicator for the second frenzy period on May 1, 2021. Permits obtained on non-frenzy days are omitted. The reference category is the first frenzy period, March 4, 2021. Standard errors clustered at the site level.

Average Predicted Reservation Success Probabilities (All Sites)	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
Sunday	0.22	0.28	0.24	0.27
Monday	0.15	0.21	0.32	0.33
Tuesday	0.23	0.25	0.26	0.26
Wednseday	0.14	0.28	0.27	0.31
Thursday	0.30	0.24	0.20	0.26
Friday	0.18	0.33	0.20	0.29
Saturday	0.17	0.26	0.24	0.33
Overall	0.20	0.27	0.25	0.29

Table A3: Average predicted probabilities from multinomial logistic regression of indicator variables corresponding to quartiles of zip code level median household income on trip start timing.

Predicted Reservation On-Sale Success Probabilities

	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
Week of Season				
1	0.16	0.30	0.18	0.36
2	0.20	0.29	0.29	0.21
3	0.22	0.34	0.29	0.15
4	0.27	0.21	0.24	0.28
5	0.21	0.26	0.23	0.30
6	0.21	0.24	0.25	0.30
7	0.16	0.24	0.26	0.34
8	0.18	0.32	0.23	0.28
9	0.16	0.31	0.24	0.28
10	0.16	0.25	0.28	0.31
11	0.20	0.26	0.25	0.29
12	0.17	0.30	0.22	0.31
13	0.14	0.35	0.29	0.23
14	0.11	0.29	0.24	0.36
15	0.30	0.23	0.31	0.16
16	0.23	0.23	0.24	0.30
17	0.18	0.21	0.15	0.46
18	0.26	0.13	0.22	0.39
19	0.29	0.18	0.32	0.21
20	0.16	0.25	0.29	0.31
21	0.15	0.24	0.32	0.28
22	0.29	0.18	0.26	0.26
23	0.20	0.38	0.15	0.27
24	0.13	0.39	0.16	0.32
25	0.14	0.16	0.25	0.45
26	0.31	0.31	0.17	0.21
27	0.44	0.38	0.01	0.17

Table A4: Predicted probabilities from multinomial logistic regression of trip start timing on indicator variables corresponding to quartiles of zip code level median household income.