Online Reservation Systems, Buying Frenzies and Equitable Access to Public Lands

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Abstract

Rationed access is an important tool to promote sustainable use of public lands. However, online reservation systems can lead to "buying frenzies" when low prices create excess demand. Using transaction-level data for river permits in the United States sold both by reservation-system buying frenzy and lottery, I show successful frenzy buyers reside in wealthier zip codes than those selected at random. This effect increases with congestion and leads to an unequal distribution of consumption benefits where high-income zip codes receive 25 percent more recreational trip value. These effects can undermine park managers' efforts to provide equitable access through low fees.

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1 Introduction

The increasing popularity of outdoor recreation has led park managers to restrict use by requiring 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 permit demand vastly exceeds supply. With a lottery system, permits are randomly allocated to users. However with a reservation system, permits are made available during an on-sale event. A "buying frenzy" results when users attempt to access the web page simultaneously. Under these circumstances, the actual allocation of permits could disproportionately fall on groups who have an advantage in navigating, or are more willing to endure, online congestion.

During an online buying frenzy, consumers employ strategies to improve their odds of 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 and familiarity with specific online sales platforms may play important roles in allocating consumption. Importantly, competition for goods creates congestion externalities when one user's participation reduces the likelihood of another user's purchase. Online markets may exacerbate these effects. Further, congestion costs may be disproportionately higher for some households, *e.g.* when on-sale events occur during the workday making it more difficult for working families to participate. The extent to which these factors favor wealthier users and disadvantage or discourage lower income consumers could create an inequitable allocation of consumption. Unfortunately, investigation into these types of effects has been hampered by the lack of examples where outcomes are observed for both online buying frenzies and alternate allocation mechanisms.

I exploit novel features of markets for recreational river permits in the United States to investigate whether online buying frenzies create distributional effects. Using transaction-level data from Recreation.gov, I compare purchases of identical river trips allocated by both lottery and buying frenzy. I show households that successfully purchase in the buying frenzy reside in higher income zip codes compared to those selected at random via lottery.

Specifically, zip-code median household income is $2,856 to $3,027 (4%) higher. The income difference grows in size with the number of page views (refresh activity) during the buying frenzy, suggesting congestion plays a role in access across groups. Although it is impossible to pinpoint the precise mechanism, I rule out several explanations including differences in preferences over trips characteristics, timing differences and willingness to pay. I conclude the most likely explanation is a combination of high transaction costs and congestion effects that discourage lower income users from participating in frenzies and limit their success when they do.

Next, 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 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 allocates a greater share of recreational benefits to higher income zip codes. Specifically, zip codes in the fourth income quartile receive 25 percent *more* recreational trip value compared to zip codes in the first income quartile.

This work is at the intersection of several literatures. First, 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 a 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 allocation 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 during online buying frenzies, decreasing access for lower income users. Since there is no secondary market, these distributional effects are fundamental to the online buying frenzy and not due to subsequent reallocation.

Second, I contribute to the literature on buying frenzies (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 (Becker, 1991; Bulow and Klemperer, 1994; DeGraba, 1995; Denicolo and Garella, 1999; Balachander, Liu, and Stock, 2009; Liu and Schiraldi, 2014; Courty and Nasiry, 2016; Loertscher and Muir, 2022), here I show online buying frenzies can create distributional effects.

Third, 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). Some predicted online sales channels would improve access to goods and services by removing the requirement consumers appear in person (Pozzi, 2013; Goldfarb and Tucker, 2019). However, improving access can also lead to congestion. Here, I show this can lead to a new type of digital divide that shifts consumption benefits toward users from higher-income zip codes.

[1] Compared to new product launches or Black Friday sales, online "on-sale" events may exacerbate buying frenzies because online queuing is less costly than in-person queuing.

[2] The Taylor Swift New Eras tour buying frenzy led to high profile Congressional hearings (Treisman, 2023). Similarly, Sony 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.

Finally, 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.[3] A key theme in this work is that lower income households have poorer access to information technology and this leads to an unequal distribution of benefits. However, I show users in lower-income zip codes are less likely to purchase goods sold in online buying frenzies. Whether these users have a competitive disadvantage in buying frenzies or because they choose not to participate due to large non-pecuniary costs, the existence of these congested online markets creates a digital divide in the allocation of recreational permits.

2 Permits for recreation on public lands

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). If users do not consider the negative effects of their recreation, these externalities justify resource management. Since park managers have largely deemed higher fees undesirable (Walls, 2022), use permits have become the preferred strategy.[4]

Permits are obtained one of three ways: On a walk-up 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. 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). Many park managers have elected

[3] 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).

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

to have their permits administered by Recreation.gov. Recreation.gov 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 administers 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. 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 (trip leaders) submit their lottery entry via Recreation.gov between December 1 and January 31. An entry consists of a specific trip start date. Users may submit only one trip per river each season. Lottery entry fees are low, between $6 and $16 dollars. There is no secondary market for permits. Resales are prevented by verifying the user'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.[5] Winners are notified several days later, typically during the beginning of February and then have several days to confirm (accept) their permit. Permits not accepted during this confirmation

[5] 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 don't allow anyone to predict future or past numbers generated." (https://www.recreation.gov/lottery/how-they-work)

period are made available during a reservation on-sale.[6,7] The on-sale date is well-known to users, as it is listed on each river's Recreation.gov lottery page and publicized in online magazines and forums (Crockett, 2022; Gibbins, 2024). Since the lottery for every site and start date has many entries, whether a trip appears subsequently in the buying frenzy depends on whether the lottery winner claims the permit and not the number of lottery entries.[8]

The sequential structure creates a system that allocates identical goods (river trips for specific dates) by both lottery and buying frenzy at essentially the same moment in time. In other words, permits for the same trip can be offered both by lottery and buying frenzy a few days or weeks apart. I exploit this feature to account for unobserved differences in trip characteristics that could be correlated with user preferences. However in this system, users' decisions to participate in the reservation on-sale could be non-random, *i.e.* there could be selection into the buying frenzy sample. Below I provide suggestive evidence selection effects do not explain the observed income differences and argue selection into the frenzy, to the extent it occurs, can be considered part of the distributional effect of this allocation mechanism. Section 4.2 presents evidence income differences are not due to the short time lag between lotteries and buying frenzies.

3 Data

I obtain transaction-level data on lottery entries and reservations 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, customer state and zip code for the 2019 and 2020 seasons. Note

[6] Online Appendix Table A1 summarizes the relevant dates for 2020. Specific dates vary occasionally from year to year and are announced well in advance on Recreation.gov. On-sales begin at 8 am Mountain Time on the scheduled date.

[7] The two-part permit allocation scheme reallocates permits in a manner that allows sufficient trip planning. Late cancellations would likely go un-used since users would not have sufficient time to plan and organize a trip.

[8] Unfortunately, the characteristics of users who are awarded a permit through the lottery but choose not to accept are unobserved. While Table A2 in the Appendix suggests acceptance rates vary across rivers, comparisons of outcomes within-trip account for unobserved factors that may be correlated with both users and specific trips.

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 latter, 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. Permits purchased after the first day are mainly cancellations and are likely purchased by a different type of user.[9] Summary statistics for the lottery and reservation systems for each river are presented in Table A2 of the online Appendix.

Unfortunately, user-level demographic information is not available from Recreation.gov. Instead, 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. Additional specifications explore educational attainment and ethnicity as alternate dependent variables. I utilize Google Analytics data on the number of users, sessions and page views for Recreation.gov to measure web congestion.

To better understand these allocation systems, Figure 1a plots the number of completed transactions, either lottery entries or permit purchases, for Green and Yampa River permits in Dinosaur National Monument (CO and UT) during the 2020 season. Several features are worth noting. First, lottery entries greatly outnumber available permits. For instance, there were approximately 8,000 entries for approximately 300 permits. This suggests the permit system substantially curtails river use in the monument. Second, 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. Waiting could reduce uncertainty regarding the most favorable river conditions during the season, for instance as winter snowfall totals are realized. Third, the majority (72%) of successful reservations outside of the initial lottery, occur during the first two hours of the reservation period. This indicates timing is critically important to obtaining a permit during the on-sale period.

[9] For instance those with unusual scheduling flexibility or individuals using subscription services to monitor for cancellations.

Figure 1b investigates congestion using web page traffic data. I plot the number of visitors to the Dinosaur National Monument page on Recreation.gov during the lottery and reservation periods and 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.

Figure 1c plots median income, by zip code, for users with frenzy and lottery permits in Dinosaur National Monument. The distribution of 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 obtained during the buying frenzy. Figure 1d plots the distribution of median household income for permit holders at the nine different river sites. Also plotted is the population-weighted distribution of zip-code level median household income for the US. Again, 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. These results suggest users from higher income zip codes have an advantage in the reservation on-sale. Compared with the U.S. as a whole, permit holders are more likely to live in higher-income zip codes. However, the substantial overlap in the income distributions suggests that the observed effects reflect differences across income groups that broadly mirror the national distribution, rather than differences within a narrowly defined (higher-income) group of river users.

4 Demographic effects

Here I more rigorously compare the demographics of users awarded permits in permit lotteries with those in reservation on-sale buying frenzies. While this empirical setting has many benefits, there are two main identification challenges. First, because trips available during the buying frenzy are a subset of all trips, they could contribute to selection in the types of users who participate in the reservation on-sale if different users value different trip characteristics. I present two different identification strategies for addressing this concern. Second, the population of users participating in the lottery and the reservation on-sale buying frenzy could differ due to the short time lag between the lottery and the frenzy. Below I present evidence against selection into the (slightly later) frenzy as an explanation for the observed income differences.

The first approach to address potential differences in trips offered during the lottery and frenzy uses fixed-effects and parametric controls to account for unobserved factors that may be correlated with demographics and trip characteristics. Specifically, I estimate models of the form:

$$Y_{li} = \delta_r + \Gamma_{it} + \alpha_s + \epsilon_{li} \tag{1}$$

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. Since buying frenzies may select or screen out users from the population of those who wish to obtain a permit, the model is written with allocation mechanism as the independent variable and the demographics of permit holders (*e.g.* income) as dependent variables. Sections A.2 and A.3 of the appendix describe potential mechanisms for the differential effects of buying frenzies on user characteristics.

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. Online Appendix Table A4 presents results that directly control for anticipated river conditions by incorporating historical streamflow and air temperature data. Because users make trip decisions in advance, this specification uses average conditions over the prior ten seasons (2009–2018) to capture expected conditions on a particular trip. The results are very similar to those presented below.

Estimates produced with Equation 1 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. 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 within a particular trip.[10] This approach has the advantage that it 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.[11] 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:

$$Y_{li} = \delta_r + \gamma_{it} + \epsilon_{li} \tag{2}$$

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

4.1 Results

Table 1a presents estimates of Equation 1 for income and several other zip-code characteristics. Users who obtain a permit during a reservation-system buying frenzy are from zip codes with median household incomes approximately $3,027 (4%) higher than those of users obtaining permits through the lottery. Because income is measured at the zip code rather than the household level, it is an imperfect proxy for individual income. Nonetheless, the fact that successful users are disproportionately from wealthier zip codes is consistent with, though not definitive evidence of, higher individual incomes.[12] Column two presents results for educational attainment. Users who obtain 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 In-

[10]For example, trips beginning on July 3, 2020 in Desolation Canyon where one permit was awarded by lottery and two were awarded during the frenzy would be included, but a trip in Desolation Canyon on July 4, 2020 where all three permits were awarded by lottery would be excluded.

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

[12]Online Appendix B and Appendix Table A6 present quantile regression results showing a positive effect for reservation-system buying frenzies across the zip-code income distribution with the largest effects below median income.

ternet penetration, age and percentage of the population that is white are all higher, though these effects are not statistically significant.

Table 1b presents estimates of Equation 2 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. Users who obtain a permit during the reservation on-sale come from zip codes with $2,856 higher median income 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, age and percent white are again statistically insignificant.

Finally, because factors such as income, education, and race may be correlated, I examine their joint relationship with permit outcomes using an auxiliary Logit model. In this model, obtaining a permit during the reservation buying frenzy is the binary dependent variable, and the five characteristics in Table 1 are the independent variables. In this case, the Logit estimates for income and percent white are positive and statistically significant ($p < 0.05$) and the other factors are imprecisely estimated. Below I focus on income as the main demographic difference across zip codes.

4.2 Participation timing assumption

The results in Section 4.1 assume the population of users is constant over the (short) time between the lottery and buying frenzy periods. Put another way, a threat to my interpretation of the results arises if frenzy participants are only those users who can afford to delay their travel plans until the reservation on-sale. Here, I provide evidence on the reasonableness of this assumption. There are at least two concerns. First, information is revealed over the course of the spring leading up to the rafting season. For instance, spring snow pack levels correlate with water levels during the season. Therefore, trip values could change during the period between the lottery and online buying frenzy in ways that are correlated with income. Second, travel may become more expensive as the season approaches such that lower income users are discouraged from reserving a permit several weeks later during the buying frenzy.

While it is impossible to test these hypotheses directly, I provide three pieces of evidence in an attempt to assuage these concerns. First, Column one of Table 2 investigates the mean income during the lottery entry period. There is some evidence more users from lower-income zip codes enter the lottery after the initial ten days. However, there is no evidence of the opposite, *i.e.* users who enter later and therefore closer to the actual trips are higher income. Second, column two of Table 2 investigates income by trip proximity, defined as the difference between the trip start date and the end of the lottery entry period. I divide trip proximity into quintiles. Trips in the first quintile occur approximately 140 days after the lottery entry deadline. Trips in the fifth quintile occur approximately 40 days afterward. I find no evidence users whose trips are closer (further) in time come from higher (lower) income zip codes.

Third, additional evidence supporting the timing assumption, and against differential selections, comes from another river system. During the 2021 season, the John Day River (OR) allocated permits in two blocks. Fifty percent of the permits were offered on March 4, 2021. The remaining permits were offered on May 1, 2021. This setting is advantageous since it deals with actual permit purchases and not lottery entries. The timing is notable as the two offerings overlap the lottery confirmation and frenzy periods in my main results. Each reservation phase covers the entire John Day River season, which also coincides with the rivers in my sample. As such, timing variation comes from the different reservation periods and not from user choices or trip start dates, as in the two previous examples. Online Appendix Figure A1 plots the number of permits reserved on each day during the spring of 2021 and shows behavior consistent with a buying frenzy each period. Column three of Table 2 tests whether average income during the later frenzy is systematically different. Again, there is no evidence later timing is associated with higher income. Overall, these results cast doubt on the timing difference between lotteries and online buying-frenzies as an explanation for the observed income differences.

4.3 Suggestive evidence for potential mechanisms

Online Appendix A presents a simple theoretical framework for users' decisions to participate in the lottery or reservation on-sale buying frenzy, highlighting potential mechanisms for the observed demographic effects. In this section, I present empirical results exploring several potential mechanisms.

Congestion

If congestion is the main driver of the income differences during a buying frenzy we expect a positive relationship between web page activity and the observed income differences. Here, we can think of web traffic as capturing the intensity of competition for permits that leads to congestion externalities. Congestion effects could be direct technological effects (*e.g.* slower internet speeds that limit refresh rates) or behavioral adaptations (*e.g.* employing bots or multiple devices). Figure 2a presents three measures 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. However, page views increase from around 2000 per day to over 76,000.[13] 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.

Figure 2b 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 for each site. There is a strong positive relationship between page views and zip code income during the buying frenzy. I test this result more formally in column one of Table 3 by interacting page views with the reservation indicator in Equation 1. An increase of 10,000 page views is associated with a $1,400 increase in income. In online Appendix Table A7 I present analogous results using users and sessions as alternate measures of web congestion and find qualitatively similar positive, but statistically insignificant, effects. Further, while observations for Dinosaur National Monument stand out from other observations in Figure 2b, the results in Table 3 do not depend on this river. When Dinosaur National Monument is excluded from the sample, the effect of page views is somewhat smaller, but still large, approximately $1,000

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

for an additional 10,000 page views.[14]

Selection

What remaining mechanisms could explain the observed differences between lotteries and online buying-frenzies? Direct technological constraints, of the types considered in the extant digital divide literature (*e.g.* lower broadband connectivity and mobile phone based internet), are one explanation. An alternate explanation is that lower income households simply choose not to participate in the frenzy either due to lower willingness to pay for river trips or because they face larger costs of participating in the frenzy.

Of course while systematic differences in preferences could explain the observed income differences, individual-level willingness to pay is unobserved. In its place I use two proxies. First, I calculate the travel distance between each user's zip code and the river site. Users who are willing to travel a 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. I include travel distance and entries as additional controls in Equation 1. Column two of Table 3 shows that while the proxies for willingness to pay matter, there remains a large and statistically significant relationship between congestion and the income gap during the online buying frenzy. To the extent these proxies capture differences in preferences, this result suggests the observed effects cannot be fully explained by differences in willingness-to-pay between higher and lower income users.

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. Table 4 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, 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

[14] Results available upon request.

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 effect by time zone by interacting these indicator variables with the reservation indicator. Results of this exercise are presented in 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 three, the income differences 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 suggest scheduling costs may play a role in the observed income differences. However, suppose lower income households systematically choose not to participate in the buying frenzy, due to higher scheduling costs (or lower willingness to pay), this selection effect *can be considered part of the distributional effect of the online allocation mechanism* since it is generated by the frenzy itself. Lower income households would have had better access to permits under a random allocation scheme.

5 Distribution of recreational benefits

To understand the incidence of buying frenzies I estimate the distribution of 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 report trip benefits, rather than benefits normalized by income, to be more consistent with park managers' goals of providing equitable access to recreational opportunities. Further, I focus on the distribution of benefits *across* income groups, *i.e.* vertical equity, rather than the distribution of benefits *within* income groups, *i.e.* horizontal equity (Fischer and Pizer, 2019). This choice reflects limitations of the data that allows assignment of users to zip-code income groups but does not provide insight into the characteristics or preferences of users within income groups.[15]

I first estimate willingness to pay for different trips by adapting the lottery choice model of Yoder, Ohler, and Chouinard (2014). This methodology uses the probabilities of winning each lottery, defined by the number of entries, as a measure of the relative willingness to pay for each trip. Intuitively, users trade off the odds of winning against trip characteristics, *i.e.* one would be willing to enter a low odds lottery if the trip were more desirable. As such, the odds of winning is inversely related to willingness to pay and the number of entries can be used to estimate relative trip values. I describe this methodology in more detail in online Appendix C.[16]

Because lottery odds only reveal *relative* willingness to pay across trips, I use prices for commercial trips on each river to scale relative willingness to pay and recover an estimate of absolute trip values. Commercial trip values are an imperfect measure of preferences. 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 prices do not vary to reflect river conditions and therefore may underestimate the value of the most preferred trip. 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 river, but whether the difference in commercial and private trip values is constant across sites. That said, I provide evidence below the distributional results do not (qualitatively) rely on the use of commercial trip values.

Next, I estimate the likelihood users in different zip code income groups are awarded permits in the lottery and reservation systems using the observed permit market outcomes. I take a reduced form approach grouping lottery entrants into quartiles of the income distribution pooling across all trip start dates for that site. Using data from only the reservation on-sale buying frenzies, I estimate a series of multinomial logit models, to predict the likelihood users in different parts of the income distribution receive a permit. This procedure,

[15]However, the potential mechanisms discussed in Section 4.3 likely also create horizontal equity effects worthy of future study with more suitable data.

[16]Trip values vary substantially by river, week of season and start day-of-week each as shown in online Appendix Figure A3.

as well as the specific success probability estimates, are described in more detail in the Appendix.

Finally, I combine the two sets of estimates, values and success probabilities, 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 by reservation, 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 as are the administrative costs of park managers. Rather, the goal is to understand how benefits accrue to different income groups under the two allocation schemes. To this end, the approach outlined here 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.

Figure 3a shows the distribution of benefits under a pure lottery allocation. The shares of recreational benefits across incomes are quite flat, with the first, third and fourth quartiles receiving approximately $10.5 million/year in total benefits. Quartile 2 receives slightly less, approximately $9.7 million per year. In contrast, Figure 3b shows the distribution of recreational benefits for a reservation system with a buying frenzy. Zip codes in the first and second income quartiles receive $9.9 and $9.0 million in recreational value, respectively. However, users from zip codes in the third and fourth income quartiles receive $11.8 and $12.4 million in trip value. Compared to the first quartile, users in the fourth quartile receive 25 percent more recreational value.

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.

These distributional effects do not depend on willingness-to-pay estimated using commercial trip values. To illustrate this I calculate the share of *relative* trip value for each site by income quartile and then average across sites.[17] As in the main estimates, lotteries yield a flat distribution of trip value across the income distribution. Users from zip codes in the first and fourth income quartiles each receive about 25 percent of the trip value for each site. However under reservation systems, users in the fourth income quartile receive about a third more trip value than users in the first quartile, 29 percent compared to 20 percent.

6 Discussion and conclusions

Rationing plays an increasingly important role in the sustainable management of public lands. I exploit novel features of the market for river permits to compare outcomes for buyers of the *same trips* allocated randomly via lottery and through online reservation-system buying-frenzies. Users successful in the buying frenzy reside in wealthier zip codes than those selected at random. This result is especially surprising in a setting where secondary markets are absent. The income gap grows with congestion and suggests online reservation systems that create buying frenzies disproportionately benefit higher income users.

There are several policy implications. First, park managers, policy makers or users concerned about equity in the non-market allocation of recreational permits 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, the results suggest potentially important efficiency effects. On the spectrum of mechanisms, efficient auctions allocate permits to those with the highest willingness to pay but are inequitable if only the wealthy purchase. On the other end of the spectrum, random lotteries are perfectly equitable but likely highly inefficient. Buying frenzies occupy an important middle ground. While I find substantial equity effects, these

[17] Trip values for each site are normalized by the most-preferred option, *i.e.* $\hat{U}(x_1) = 1$.

effects are almost certainly smaller than those in an auction. Further, congestion imposes non-pecuniary costs that can take the place of absent scarcity prices (Bucovetsky, 1984) improving efficiency over a random allocation. Therefore, a full accounting of the equity and efficiency trade-offs of different permit markets seems an important area for further study.

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7 Tables

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 1: 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.

Validity of Lottery and Frenzy Timing Assumption

Lottery Period		Proximity to Trip		John Day Frenzies	
Day 10 to 20	-1,395.57	Prox. Q2	-191.10	Late Frenzy	-378.1
	(488.72)		(600.99)		(1120.05)
Day 20 to 30	-394.30	Prox. Q3	350.35		
	(646.97)		(682.87)		
Day 30 to 40	-503.27	Prox. Q4	234.60		
	(525.45)		(866.59)		
Day 40 to 50	-294.13	Prox. Q5	-1433.08		
	(501.50)		(1664.19)		
Day 50 though 61	-557.22				
	(444.92)				
Site by Day-of-Week Effects	No		Yes		Yes
Site by Week-of-Season Effects	No		Yes		Yes
Site by Start Date Effects	Yes		No		No
Observations	98099		98099		1294
Adj. R-sq.	0.01		0.01		0.01

Table 2: Results showing the robustness to timing of lottery participation. The dependent variable is Median Household income by customer zip code. Under "Lottery Period," day 10 to 20 is an indicator equal to 1 if the entry occurs during the first 10 days entries are accepted. Under "Proximity to Trip" Prox. Q2 refers to the second quartile of proximity of permit purchase to trip start in days. Prox. Q5 trips are nearest, purchased approximately 60 days before the trip start. Under "John Day Frenzies" Late Frenzy is an indicator equal to one if the permit was reserved during the late period, May 1, 2021. Standard errors clustered at the site level.

Web Congestion and Willingness to Pay Proxies

	Page Views	WTP Proxies
Reservation System	1591.23	1399.4
	(491.56)	(903.83)
Reservation * Page Views	0.14	0.17
	(0.05)	(0.03)
Page Views	-0.02	-0.03
	(0.06)	(0.02)
Travel Distance		6.98
		(2.77)
Number of Entries		384.36
		(93.21)
Site by Day-of-Week Effects	Yes	Yes
Site by Week-of-Season Effects	Yes	Yes
Site by Start Date Effects	No	No
Observations	4126	3006
Adj. R-sq.	0.01	0.04

Table 3: Results showing the role of proxies for willingness to pay. The dependent variable is Median Household income by customer zip code. Under "Page Views," page views count the number of times a page is accessed and thus captures page refresh activity. Under "WTP Proxies" 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.

	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 4: 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.

8 Figures

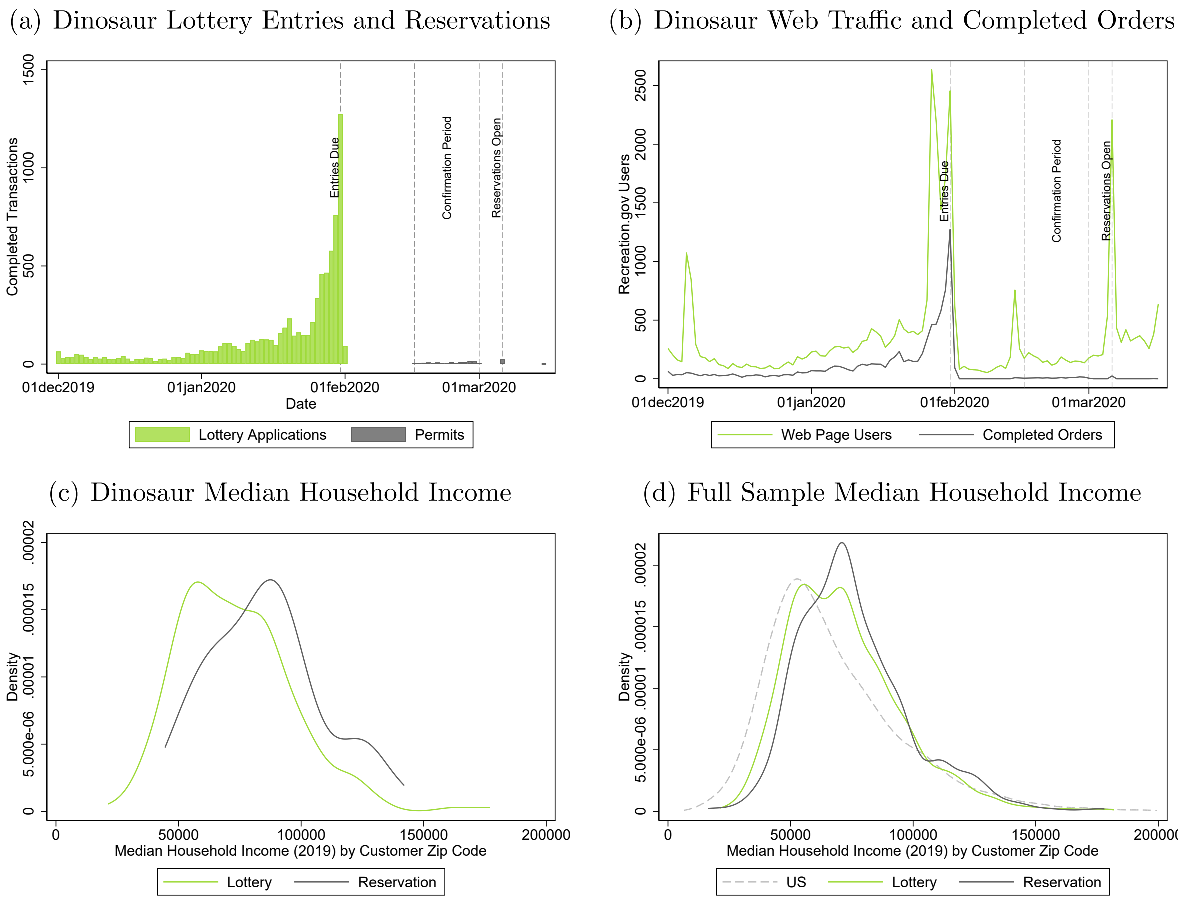


Figure 1: (a) Lottery entries and online reservation activity for Green and Yampa River permits in Dinosaur National Monument (CO and UT). Lottery entries are accepted from December 1 through January 31. Lottery winners must confirm their permits between February 16 and March 1. The "on-sale" reservation period for unclaimed permits begins at 8am MST on March 6. (b) Web traffic on the Dinosaur National Monument Recreation.gov page and completed orders for lottery entries and on-sale reservations. (c) Median household income by zip code for Dinosaur National Monument users who were awarded permits by lottery and reservation on-sale buying frenzy. (d) Median household income by zip code for the U.S. (population weighted) and the full sample of users at all nine rivers who were awarded permits by lottery and reservation on-sale buying frenzy.

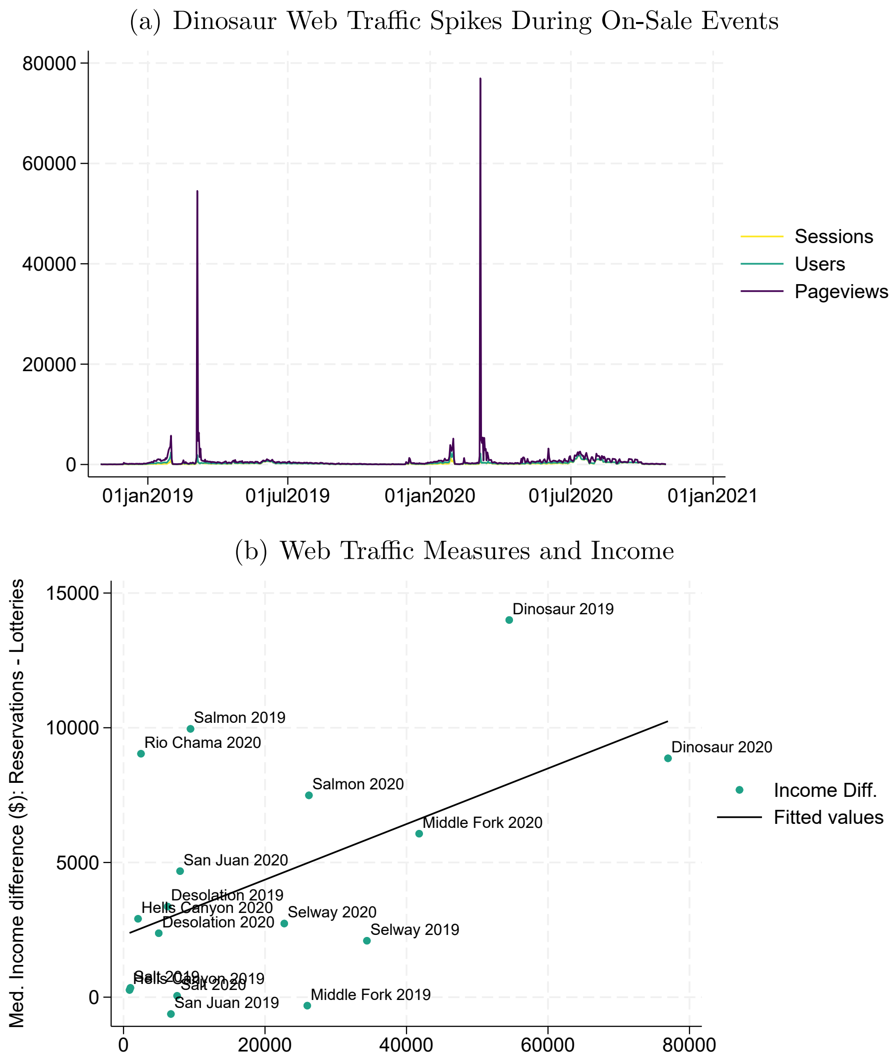
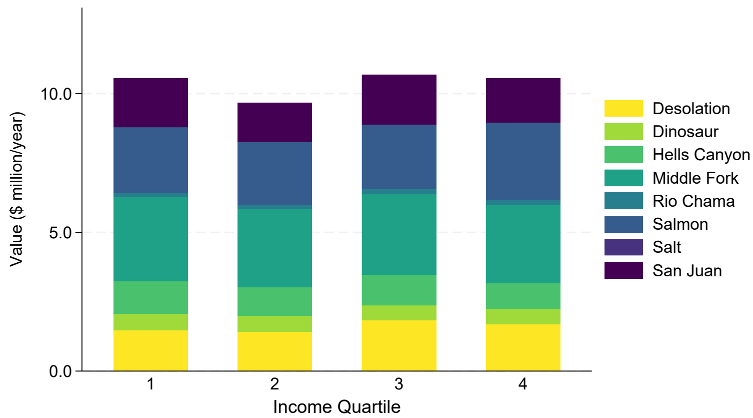


Figure 2: Measures of online congestion (a) increase during the Dinosaur National Monument reservation on-sale (buying frenzy) event. Page views (b), a proxy for web page refresh activity, are positively correlated with the mean income difference between users who obtain their permit via the online buying frenzy and the lottery.

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



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

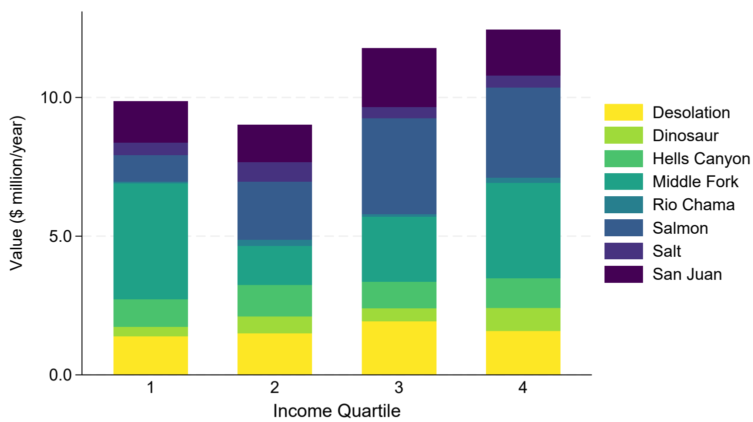


Figure 3: Estimate trip values by recreational user income quartile (1-4) assuming (a) all trips are allocated using lotteries or (b) all trips are allocated using a reservation system. Zip code income quartiles are calculated from the population of lottery entrants. There are insufficient observations to estimate reservation success probabilities for Selway River trips.

Online appendix

A User participation in lotteries and reservation systems

This section presents a simple framework to motivate the empirical work in the main text. 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.

A.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 $x \in X$, where $X = [x_0 \ x_1 \ x_2 \ldots x_N]'$ and the goods x are trips at a given site defined by different start dates, *e.g.* day-of-week and week-of-season. Good 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.[1] Lottery entries for good 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 determined *ex post*, users must make their entry decisions *ex ante* before the final number of entries is realized. I assume users' predictions about the number of entries for each lottery are *ex post* correct such that $E[\pi_i] = \pi_i = \frac{Q_i}{A_i}$. This simplifications seems reasonable since park managers publish detailed reports on prior years' lottery results.

[1] 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.

Individuals have preferences over the goods defined by the utility function $U(x)$.[2] I denote the utility individual l gains from consuming good x_i as $U_l(x_i)$. 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.[3] Each user solves:

$$max\ (\pi_i U_l(x_i) - C, U(x_0)) \tag{3}$$

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 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 x such that:

$$\pi_i U_l(x_i) > \pi_j U_l(x_j)\ \forall\ j \neq i \tag{4}$$

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.

A.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 $U_l(x_0)$. In the second stage,

[2]Utility for the outside option can be normalized to zero such $U(x_0)$ is the utility gained from winning a lottery trip.

[3]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.

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 $\pi_{a,i}$.[4] 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 by individual user l. As before, the 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:

$$max\ (\pi_{a,i}\pi_{r,li}U_l(x_i) - T_l, U_l(x_0)) \tag{5}$$

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, congestion (rivalry) 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: $U_l(x_i) > U_l(x_0)$.[5]

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

[5] 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.

A.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 congestion that affects success during the buying frenzy.

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 (5) 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).

Congestion

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 ($\pi_{r,ijt}$) in Equation 5. 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.[6]

B Additional robustness checks on the main specifications

In this section I investigate the robustness of the main income results to several alternate specifications. Results are shown in online Appendix Table A4. 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 differences 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 1 using site by week and site by day-of-week effects. Column five replaces site-specific time-effects with predicted temperatures and stream flows, by week-of-year and day-of-week, based on the prior ten seasons (2009-2018) on each river. 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 2 using within-trip variation in allocation mechanism.[7] Overall, these results support the conclusion users who are successful in navigating

[6]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.

[7]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.

congestion in the buying frenzy reside in higher income zip codes compared to those selected at random via permit lottery.

Systematic differences in preferences for river trips (preference) could explain the observed differences in income. Because individual preferences are unobserved, I collect data on two proxies, each user's travel distances to the river site and a count of all order activity on Recreation.gov. Online Appendix Table A5 explores the robustness of the main income result to including these proxies as additional control variables. Column one of Table A5 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.

Finally, Online Appendix Table A6 presents quantile regression results for the 10th, 25th, 50th, 75th and 90th percentiles of the zip code income distribution. Across the income distribution, users who are successful in obtaining a permit in the reservation buying frenzy tend to reside in higher income zip codes. However, compared with the average effect ($3,027) reported in Table 1, we see relatively large effects at the lower end of the income distribution. The effects are smaller, and not statistically significant, at the 75th and 90th percentiles. This suggests a robust effect, though one that generates the largest shifts in lower income zip codes. These results are consistent with Figure 1d that shows both a rightward shift in the income distribution for users who obtained their permit during the buying frenzy, but also a compression coming from a larger increase in income in the left tail.

C Methodology for estimating recreational trip values

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, limited data on individual characteristics and lack of repeated choice data make 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 A.1 above, each user chooses x_i from among the available alternatives in X to maximize their expected utility $EU_l[X]$. 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 $U_l(x_i)$ into factors common to all users, $U(x_i)$ and idiosyncratic factors unique to each user ν_{li}, such that:

$$U_l(x_i) = U(x_i)\nu_{li}, \tag{6}$$

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 $E[U_l(x_i)] = U(x_i)$. To see how equilibrium choices of the representative agent are related to lottery entries, note the expected utility from choosing the lottery for good x_i is:

$$E_l[EU_l(x_i)] = EU(x_i) = \frac{Q_i}{A_i}U(x_i), \tag{7}$$

which is the representative consumer's expected utility in the lottery for good x_i. Here, as before, I assume users make predictions about the probability of success in each lottery based on the number of entrants that are *ex post* correct. Rearranging this expression yields the number of entries for good x_i:

$$A_i = \frac{Q_i U(x_i)}{EU(x_i)} \tag{8}$$

Under the assumptions above, $U(x)$ 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.* $U(x_1) = 1$ and $U(x_0) = 0$. Yoder, Ohler, and Chouinard (2014) show that in equilibrium, $EU(x_i) = EU(x_j) = C \;\; \forall \, i \neq j$, when the number of entrants is sufficiently large.[8] Intuitively, if the number of entrants were zero, entrants would 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 x_i can be related to the most preferred option x_1 by: $\pi(x_1) \times 1 = \pi(x_i) \times U(x_i)$ and the von Neumann-Morganstern utility index for good x_i is:

$$U(x_i) = \frac{\pi(x_1)}{\pi(x_i)} = \frac{A(x_i)Q_1}{A(x_1)Q_i} \tag{9}$$

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 X note that the expected utility of user l can be written as:

$$EU_l(x_i) = \pi_i U_l(x_i) = \pi_i U(x_i)\nu_{li} = EU(x_i)\nu_{li} = C\nu_{li}. \tag{10}$$

Although the representative agent chooses x such that expected utilities are equal across goods, idiosyncratic 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

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

such that the probability that user l chooses x_i over x_j is:

$$Prob[EU_l(x_i) > EU_l(x_j)] = Prob[C\nu_{li} > C\nu_{lj}] = Prob[\nu_{li} > \nu_{lj}] \tag{11}$$

Define the indicator function I_{li} that is equal to one if $EU_l(x_i) > EU_l(x_j) > C\ \forall l \in L$ and $j \neq i \ \in \ N+1$ and is zero otherwise. The total number of lottery entries for good 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 number of lottery entries can be written in terms of the probability an individual l chooses good x_i as:

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

In reality, the observed entry counts are related to expected counts by the idiosyncratic utility such that trip characteristics, mean utility and costs predict the number of lottery entries, on average, the the actual counts differ due to idiosyncratic utility shocks. Specifically, I assume $A_i(x_i) = (\nu_i|X)\hat{A}(x_i)$. Taking logs we have:

$$lnA(x_i) = ln\hat{A}(x_i) + \epsilon_i \tag{13}$$

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

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

which, combined with assumptions on the functional form of $lnU(x_i)$ and the distribution of ϵ_i provides and estimable equation. In the empirical model below I flexibly capture $lnU(x_i) - lnC + lnQ_i$ 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 x_i. Specifically, the estimated von Neumann-Morgenstern utility index $\hat{U}(x_i)$ is:

$$\hat{U}(x_i) = \frac{\hat{\pi}(x_1)}{\hat{\pi}(x_i)} = \frac{\hat{A}(x_i, Q_i)}{\hat{A}(x_1, Q_1)} \frac{Q_1}{Q_i}, \tag{15}$$

where $\hat{A}(x_i, Q_i)$ are the (exponentiated) predicted values from (14) and values for $\hat{A}(x_1, Q_1)$ 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 $\hat{U}(x_1)$ is equal to the price for a commercially guided trip on each river during the 2020 season.[9] The values are collected from OARS and other commercial guides using the Internet Wayback Machine. Under this assumption, the value of trip x_i is just $\hat{U}(x_1) \times \frac{\hat{\pi}(x_1)}{\hat{\pi}(x_i)}$.

C.1 Trip value estimates

Trip values vary substantially depending on the day of week and the week of season the trip begins. Figure A3a 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 A3b presents average willingness to pay by trip start day of week for each river.[10] Mondays are the preferred start day for every river. Thursdays and Fridays are the second-most preferred days for each river.

On-sale success probability

[9] 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.

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

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.[11] 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.

Online Appendix Table A8 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 A9 summarizes average success probabilities across all sites by start week.

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

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 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.

D External validity

Here I present evidence to support the claim the distributional effects observed for users of Recreation.gov may extend to other online settings. The main external validity concern is one of selection. Users of Recreation.gov may be systematically different from other online consumers in ways that affect their participation in, and success during, buying-frenzies. While it is impossible to completely alleviate this concern, I compare the characteristics of visitors to Recreation.gov with those of other major e-commerce sites using web page user demographic data from semrush.com. Semrush uses individual-level web search and click history data to infer the demographics characteristics of web page visitors. I collect data from spring 2024 to be comparable to the lottery and buying frenzy periods for the rivers in my sample. If other online consumers are similar to Recreation.gov users, it seems reasonable to conclude they may behave similarly during an online buying frenzy.

I first investigate the age distribution of users to Recreation.gov and two major events industry sites, ticketmaster.com and axs.com. Since, the events industries are a major source of online buying-frenzies, the ability to generalize my results to these setting seems particularly valuable. For additional context, I also present data on two major e-commerce sites, amazon.com and ebay.com. Figure A2 presents the distribution of users ages for these sites. The age distribution for Recreation.gov closely follows those of other sites. The majority of site visitors fall between the ages of 25-34, 35-44 and 45-54. To the extent the distributional effects I observe during buying frenzies are driven by the distribution of users' ages, the similarity of age patterns suggests my results may generalize to other online settings.

Next, I compare demographics of sex, income, education and employment across site visitors. These data are shown in Table A10. Here, the users of Recreation.gov appear quite similar to the events industry sites, ticketmaster.com and axs.com, but diverge somewhat from the larger e-commerce sites, amazon.com and ebay.com. For Recreation.gov and the events industry sites, 42 to 44 percent of visitors are middle to high income compared with 35 to 36 percent for the more general e-commerce sites. Recreation.gov and events industry site users also have similar levels of educational attainment and employment. Approximately 53 percent of Recreation.gov visitors have a university or post-graduate education compared with 51 to 52 percent for the events industry sites. Approximately 59 percent of Recreation.gov users are engaged in full-time work or as a homemaker compared to 60 percent for ticketmaster.com and axs.com. About 48 percent of amazon.com and ebay.com users have a university or postgraduate education and approximately 54 to 56 percent are fully employed or work as a homemaker. A larger share of site users are women in every case except amazon.com.

Overall, the demographics of Recreation.gov users are very similar to users of other online web sites, in particular the events industries. To the extent users who are similar in terms of age, income, eduction and sex, behave similarly in a buying frenzy, the comparisons presented here suggest my results may extend to a variety of online settings.

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.

Site	Lottery Entries	Number Orders Lottery Permits	Reservation Permits	Fees Paid 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 A2: 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. 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 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-columns summarize 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.

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 A3: 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.

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 A4: 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.

	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 Orders				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 A5: 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.

Quantile Regression - Income

	$Q_{0.10}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
Reservation	$ 4,072.00	$ 5,130.00	$ 2,122.00	$ 1,741.00	$ 1,376.50
	(953.25)	(979.01)	(1003.70)	(1436.32)	(2425.85)
Percentile of Income	$ 47,823	$ 56,085	$ 70,275	$ 85,007	$ 102,500
Site by Day-of-Week Effects	Yes	Yes	Yes	Yes	Yes
Site by Week-of-Season Effects	Yes	Yes	Yes	Yes	Yes
Observations	4126	4126	4126	4126	4126
Pseudo R-sq.	0.05	0.04	0.04	0.05	0.09

Table A6: Dependent variable is Median Household income by customer zip code. Q_x corresponds to quantile regression estimate for the x-th quantile. Standard errors in parentheses.

	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 A7: Results showing the potential role of online congestion in the observed income differences. 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.

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 A8: 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 A9: Predicted probabilities from multinomial logistic regression of trip start timing on indicator variables corresponding to quartiles of zip code level median household income.

	Web Site Visitor Demographics				
	recreation.gov	ticketmaster.com	axs.com	amazon.com	ebay.com
Female	53%	51%	56%	46%	52%
Male	47%	49%	44%	54%	48%
Low	56%	58%	59%	65%	64%
Middle	33%	31%	31%	26%	27%
High	11%	11%	10%	9%	9%
None completed	2%	2%	2%	3%	3%
High school	45%	46%	47%	49%	49%
University	47%	45%	45%	42%	42%
Postgraduate	6%	7%	6%	6%	6%
Unemployed	12%	11%	11%	15%	14%
Parental leave	0%	0%	0%	0%	0%
Leave of absence	1%	1%	1%	1%	1%
Student	4%	5%	6%	7%	6%
Part-time work	10%	11%	12%	12%	11%
Full-time work	48%	51%	52%	43%	45%
Homemaker	11%	9%	8%	11%	11%
Business owner	6%	5%	5%	5%	5%
Retired	7%	6%	5%	6%	6%

Table A10: Comparison of demographic characteristics for visitors to Recreation.gov and other major e-commerce sites. Demographic data are for spring 2024 and are estimated by semrush.com. The income, education and employment characteristics of Recreation.gov users are quite similar to those of visitors to ticketmaster.com and axs.com, suggesting the buying frenzy results presented here may extend to the events industries such as sporting events, concerts and the theatre. Recreation.gov and events industry users are higher income and more highly educated than the average visitor to major e-commerce sites, amazon.com and ebay.com, suggesting future work is needed to determine whether buying frenzies yield similar distributional effects in other online settings.

Appendix figures

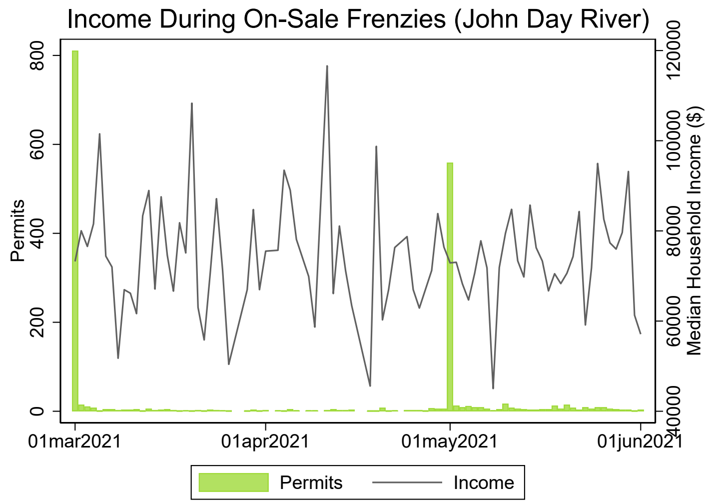


Figure A1: Income and the two buying-frenzies for John Day River permits during the 2021 season. The frenzies, on March 4, 2021 and May 1, 2021 overlap the time between lottery announcements and buying frenzies in the main results. The flat income trend suggests the values users assign trips over the course of the spring permit season does not systematically differ by income group.

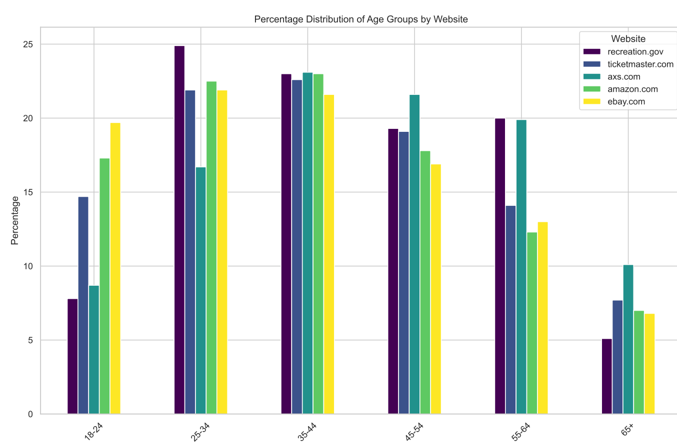


Figure A2: Age distribution of visitors to Recreation.gov showing users' ages are similar to two major events industries sites, ticketmaster.com and axs.com, and two major e-commerce sites, amazon.com and ebay.com. Visitor ages are estimated data from Semrush.com during spring 2024. The overall similarity of the age distributions suggests results for users of Recreation.gov may generalize to other online settings.

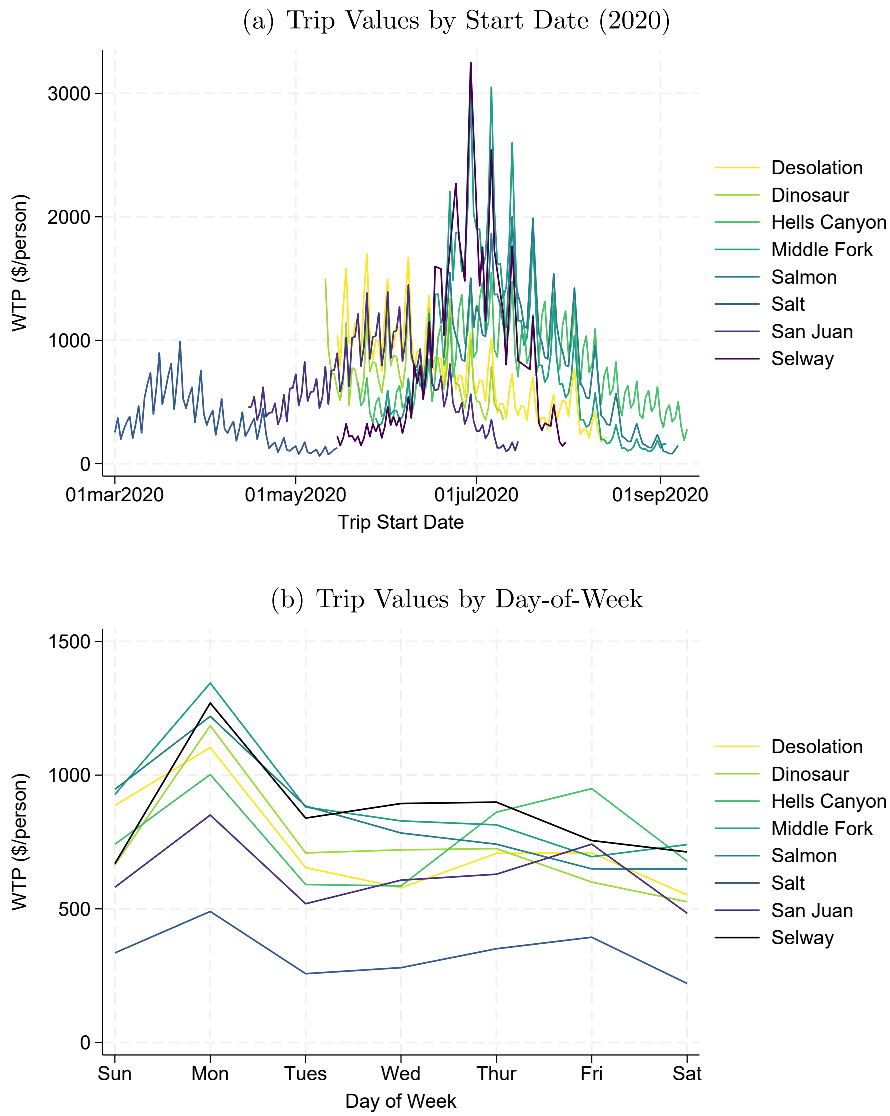


Figure A3: Estimated willingness to pay in dollars per person for river trips by (a) date of the 2020 season and (b) day of week averaged over the 2019 and 2020 seasons. Rio Chama values are omitted because permitted launches are limited to Fridays and Saturdays.