Reservation Policies and Equity in National Park Access

Jonathan E. Hughes[1,2*]

October 25, 2025

Abstract

National parks are experiencing unprecedented demand. High use strains infrastructure, damages ecosystems and reduces visitor enjoyment. To sustainably manage visitation, many parks now require reservations, raising concerns about equity. I quantify the effects of two reservation system features, advance purchase windows and competition for permits, on visitor income at seven national parks. Both effects disproportionately favor higher-income users. In the most competitive day-ahead and advance markets, reservation holders come from zip codes with 3–5% higher median household income. Extending the advance purchase window to six months shifts reservations toward users residing in zip codes with 5% higher income. Robustness checks imply individual effects of the same direction. This underscores a key challenge for park managers: designing reservation systems that protect resources while ensuring broad access. Without attention to distributional impacts, efforts to control crowding risk exacerbating income-based disparities in who can visit and enjoy the nation's public lands.

Main

National parks play a crucial role in preserving biodiversity, natural landscapes, historical and cultural heritage. However, the sustainability of the parks themselves is under threat from overuse. In 2024, U.S. national parks saw record use, 331.9 million visits, including 38 parks that experienced levels above their 10-year averages[1]. Many park campgrounds are routinely filled to capacity[2]. Such high use is costly, taxing park resources[3], negatively affecting plants and wildlife[4], and causing congestion that diminishes visitors' experiences[5,6].

In response to these concerns, scholars, users and park managers have, for over 50 years, argued for rationing use to avoid a tragedy of the commons in parks and protected areas[7,8]. Unlike market

*[1]Department of Economics, University of Colorado Boulder. [2]Renewable and Sustainable Energy Institute, University of Colorado Boulder. *email*: jonathan.e.hughes@colorado.edu

goods, price increases are seldom used to ration demand on public lands. This leaves non-market allocation methods such as reservation systems, lotteries, queues (first-come, first-served systems) and merit systems as potential rationing methods. Of these alternatives, reservation systems are the most common, receiving support from users across a range of settings[9–12].

While reservations for campsites and river trips date back to at least the 1970s, several national parks have recently adopted policies to more broadly manage visitation. These systems, implemented nearly entirely online, include vehicle reservation systems (regulating parking at popular destinations or travel on popular corridors), and timed-entry systems (permitting park entry during specific time windows). Initial evidence suggests these systems have helped improve sustainability and are generally supported by the public[13,14]. However, many have expressed concern these systems can have the unintended effect of decreasing access for lower income users[8,12,15]. These concerns echo evidence that lower income individuals have poorer access to urban green spaces[16] and that terrestrial and marine protected areas are located closer to wealthier neighborhoods[17]. More recently, there is growing concern that technology limitations and congestion in online reservation systems such as Recreation.gov, may disadvantage lower income or less technologically-saavy users[18]. This highlights a tension in the dual mission of park managers, to protect natural resources, historical and recreational sites while, at the same time, promoting equitable access– two objectives that can be at odds with one another.

Unfortunately, empirical evidence on the equity effects of reservation systems for public lands is limited[12]. Rice et al.[19] use mobile phone data to study demographics of national park campers who reserve in advance versus those who camp in first-come, first-served sites. They find those who reserve in advance reside in higher income areas compared to those who camp first-come-first-served. However, they are not able to distinguish between the effects of reserving in advance and the effects of the online reservation system itself. Hughes[20] studies the exclusionary effects of competition in congested online reservation systems by comparing river permits allocated by lottery with those obtained during online "buying frenzies." He finds users who obtained their permit during a buying frenzy are from higher income zip codes than those selected at random. This suggests congestion in the online reservation system itself is an important factor in determining the types of users who receive a permit. However, since both lottery and frenzy reservations are made far in advance of the actual trips, we learn little about the effects of advance purchase.

In this paper, I examine how the advance purchase period and competition for reservations (permits) affect the income distribution of visitors at seven national parks. Whereas prior work has studied demographic effects in a single park[13,15], I exploit variation in advance purchase periods and permit competition within and across parks to separately identify the effects of each factor on visitor income. Findings of substantial equity effects may motivate park managers to implement random lotteries to avoid competition effects or to implement additional phasing of on-sales to avoid advance-purchase effects. Therefore, understanding these relationships could improve equity in sustainable management of the national parks.

Results

The analysis focuses on eleven reservation systems at seven national parks from 2021 through 2024. Table 1 summarizes the main features of each park's system. Advance reservation periods range from 30 to 120 days and vary both across parks and within a given park over time. For instance, Yosemite National Park has experimented with advance periods of different lengths while Acadia has maintained a 90-day period throughout. Advance allocations can be block format, whereby reservations for all dates within a period are available at one time (*e.g.* the entire month of July becomes available on March 1), or rolling (*e.g.* a single date 90 days in the future is reservable). Each park also makes a portion of its permits available shortly in advance of the desired visit date to accommodate users who either cannot or prefer not to reserve in advance. In most cases these are day-ahead reservations, but can also be two-day (Acadia and Haleakala) or seven-day ahead (Yosemite).

Table 1: Advance Reservation Windows (Days in Advance) for Reservation Systems, 2021–2024

Park/Region	2021	2022	2023	2024
Rocky Mountain (Bear Lake Rd.)	30-60 (block), 1 (day-ahead)	30-60 (block), 1 (day-ahead)	30-60 (block), 1 (day-ahead)	30-60 (block), 1 (day-ahead)
Rocky Mountain (Rest of Park)	30-60 (block), 1 (day-ahead)	30-60 (block), 1 (day-ahead)	30-60 (block), 1 (day-ahead)	30-60 (block), 1 (day-ahead)
Arches	–	90–120 (block), 1 (day-ahead)	90–120 (block), 1 (day-ahead)	90–120 (block), 1 (day-ahead)
Glacier (Sun Rd)	60 (rolling), 1 (day-ahead)	120 (rolling), 1 (day-ahead)	120–150 (block), 1 (day-ahead)	120 (rolling), 1 (day-ahead)
Glacier (Many Glacier)	–	–	120-150 (block), 1 (day-ahead)	120 (rolling), 1 (day-ahead)
Mount Rainier (Sunrise)	–	–	–	90-120 (block), 2 (day-ahead)
Mount Rainier (Paradise)	–	–	–	90-120 (block), 2 (day-ahead)
Haleakalā (Summit Sunrise)	60 (rolling), 2 (day-ahead)	60 (rolling), 2 (day-ahead)	60 (rolling), 2 (day-ahead)	60 (rolling), 2 (day-ahead)
Acadia (Cadillac Sunrise)	90 (rolling), 2 (day-ahead)	90 (rolling), 2 (day-ahead)	90 (rolling), 2 (day-ahead)	90 (rolling), 2 (day-ahead)
Acadia (Rest of Day)	90 (rolling), 2 (day-ahead)	90 (rolling), 2 (day-ahead)	90 (rolling), 2 (day-ahead)	90 (rolling), 2 (day-ahead)
Yosemite	30-60 (5-blocks), 7 (day-ahead)	60-120 (1-block), 7 (day-ahead)	–	90-240 (block, Apr–Oct), 7 (day-ahead)

Figure 1 illustrates differences in reservation activity, competition and permit allocations for two representative systems, Rocky Mountain National Park (RMNP) - Bear Lake Road permits and sunrise at the summit of Cadillac Mountain in Acadia National Park. Figure 1a shows reservations by order (purchase) date in RMNP. The four spikes in each calendar year correspond to the on-sale dates of the block allocations. This rush to reserve is consistent with reservations for national park campgrounds and is an indicator of the popularity of these permits[2]. Lower levels of advanced purchase continue between each block allocation. Day ahead reservations begin on Memorial Day weekend each year, contributing to reservation totals during the remainder of the year. Figure 1b shows reservations for Acadia, which has a rolling allocation of advance reservations each spring. Reservations increase substantially around Memorial Day weekend when day-ahead allocations begin. Reservation activity drops mid-summer when advance purchases end, leaving only day-ahead reservations for the remainder of the season.

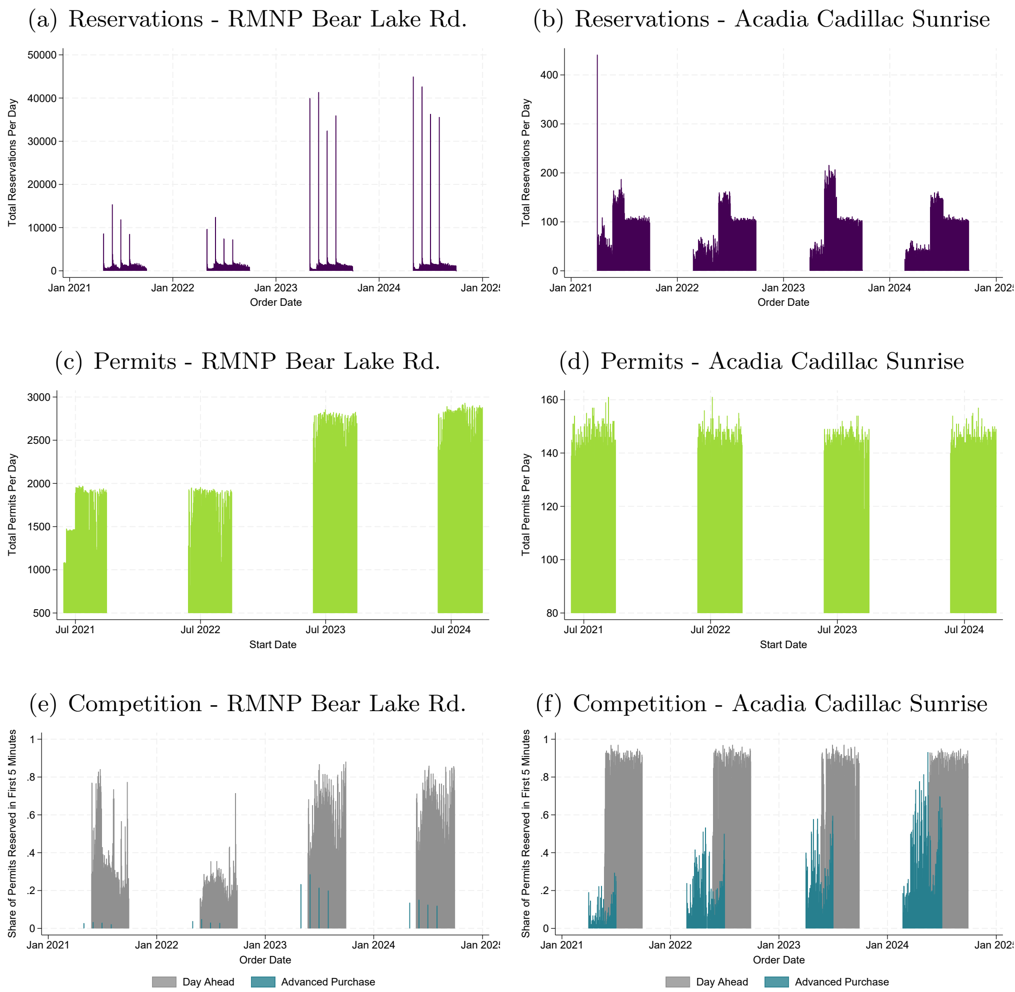


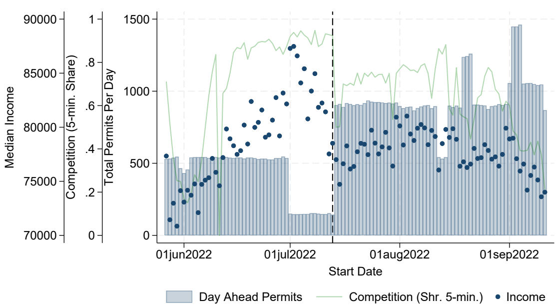
Figure 1: Reservations, competition and permit allocations for Rocky Mountain National Park (Bear Lake Road) and Acadia National Park (Cadillac Mountain Sunrise). Reservations are the total number of reservations made per day. Competition is the share of total day-ahead permits reserved during the first five minutes permits are available. Permits are the total number of permits available by travel date. **a** Spikes in reservations at Rocky Mountain National Park at the beginning of the advanced block distribution period. **b** Acadia reservations reflect the sum of advance purchase and two-day-ahead market. **c** Total permits allocated by Rocky National Park managers vary over the period. **d** The allocation is constant in Acadia, about 150 per day. Competition for day-ahead reservations is intense in both Rocky Mountain National Park **e** and Acadia **f**. In Acadia, over 90% of day-ahead permits are reserved during the first five minutes.

Figure 1c and Figure 1d plot total permits reserved for each day of the permit season. While the data are noisy, we can infer an (approximately) binding permit cap in RMNP during the 2021 through 2024 season. The cap appears to increase from approximately 1,000 permits per day early in the 2021 season, to approximately 1,500, then approximately 2000 permits per day later in the season. The cap is approximately the same throughout the entire 2022 season but increases to somewhat under 3,000 permits per day during the 2023 and 2024 seasons. For sunrise permits to Cadillac Mountain in Acadia, daily permits fluctuate around 150 each year, suggesting an allocation (target) of around 150 per day consistent with anecdotal reports[21]. Figures A1 through A3 of the Extended Data presents summary statistics for all eleven permit systems.

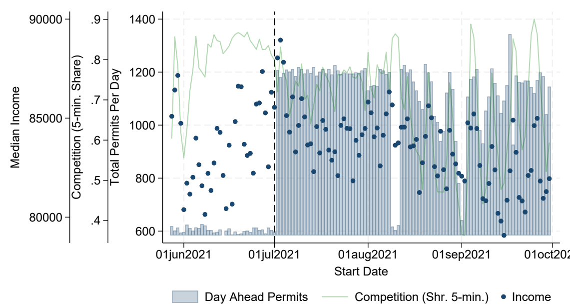
Figure 1e and Figure 1f plot competition for day-ahead and advance purchases in the two systems. I define competition as the share of total permits allocated (for a start date or block) that are reserved during the first five minutes permits are available. During 2021 and 2022, competition for advance purchase permits in RMNP is low, approximately five percent of permits are reserved during the first five minutes of each on-sale event. Competition is moderately higher during the 2023 and 2024 seasons, with between 10 and 20 percent of available permits reserved during the first five minutes. In contrast, day ahead permits are generally more competitive. In 2023 and 2024, 60 to 80 percent of available permits are reserved during the first five minutes. For Acadia, both advance and day ahead reservations are competitive. Advance reservations during the first five minutes increase from approximately 10 to 20 percent in 2021 to over 60 percent on many days during the 2024 season. Over 90 percent of day-ahead permits are reserved during the first five minutes. The Extended Data show similar periods of intense competition for day-ahead permits in each of the other parks.

Differences in reservation system design parameter create variation in competition for permits that I exploit in the regression analysis below. When demand for permits exceeds supply, the permit allocation affects competition for reservations, all else equal. To see this, Figure 2 plots day ahead permit reservations for the Going to the Sun Road in Glacier National Park during the 2022 season (panel a) and RMNP (No Bear Lake Road/rest of park) during the 2021 season (panel b). In Glacier, 500 permits per day were awarded in June 2022. Early season permits are limited to lower elevations as the summit over Logan Pass has not yet been cleared of snow. However, each year additional permits are allocated once the entire road opens. The exact date varies from year to year depending on snowpack and the spring thaw. In 2021, this occurred on July 13th as indicated by the vertical dotted line in Figure 2a, amounting to an (essentially) exogenous increase in the permit allocation on that date. The green line in Figure 2 plots the five minute competition measure. We see competition rises throughout June, presumably due to increasing summer travel during the period, peaking at approximately 90 percent in early July. Competition falls to about 70 percent when additional permits are allocated on July 13th – travelers have already arrived at the park having made plans weeks or months in advance and so, the exogenous increase in permits decreases competition without increasing permit demand, at least in the short-run. Thus, park managers' decisions about the number of permits to award can determine the level of permit competition. Further, we see similar patterns in the average income of permit holders. Income, approximated as the median household income in the zip code where a user resides, increases throughout June. However, immediately after July 13th, both competition and income fall sharply. Income decreases from about \$85,000 in early July, to between \$75,000 and \$80,000 after permits are released. This result is consistent with Hughes[20] who finds income is positively correlated with competition for river permits in the western United States.

(a) Glacier - Going to the Sun Road



(b) RMNP - Rest of Park



(c) Yosemite

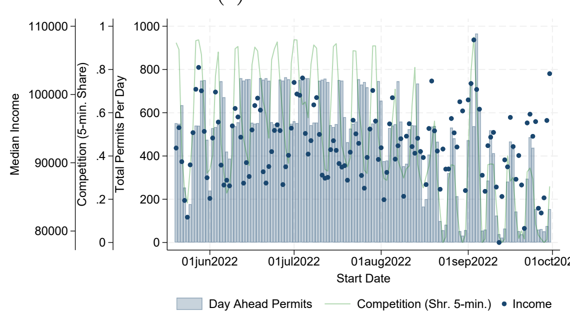


Figure 2: Correlations between day-ahead reservations, competition and visitor income in four reservation systems: **a** Glacier National Park (2022); **b** Rocky Mountain National Park - Rest of Park (2021); and **c** Yosemite (2022). Day-ahead permits are the total number of day ahead permits allocated each period. Competition is the share of total day-ahead permits reserved during the first five minutes permits are available. Income is zip-code level median household income of park visitors, averaged by reservation date.

Figure 2b shows similar trends for RMNP. During the 2021 season, park managers realized approximately one third of reservation holders "no-show," resulting in un-used capacity[22]. As a result, on July 1, 2021 RMNP increased Bear Lake road permits from 600 to 1,200 per day. This reduced the competition measure from approximately 85 percent to approximately 70 percent.

Income, which had been increasing throughout the spring, decreases after the shock such that the average reservation holder resides in a zip code with about $2,000 lower median income.

Figure 2c plots day ahead permits, competition and income for Yosemite in 2022. During the peak summer season, permits and competition follow an inverse relationship. It appears that more permits are allocated Sunday through Wednesday each week and fewer on Thursday through Saturday. This pattern could be due to higher weekend camping demand since camp reservations substitute for an entry permit. Nevertheless, on days with fewer day-ahead permits there is intense competition for reservations and income increases. However, behavior is different during the early and late season when permits, competition and income all move together. Here, it appears that competition and potentially income, are driven by recreational demand shocks. This highlights the need to control for time-varying demand shifters that could be correlated with income in the regressions below.

Regression results

I flexibly estimate the relationships between the average income, competition in the advanced and day-ahead permit markets and advanced reservation lead-time using a series of linear regressions. Competition in the advanced and day-ahead permit markets is modeled with sets of indicator variables corresponding to four regular interval bins of the five-minute competition measure. The length of advance purchase is captured by a set of indicator variables corresponding to the number of days before the trip start date permit reservations are first accepted. Lead time of zero days, *i.e.* same day purchases, is the omitted category. Therefore, comparisons are between a given category and reservations made when there is sufficient capacity for same-day entry. These results are presented in Table 3. Column 1 presents results from a base specification that controls for permit fixed-effects. Columns 2 - 4 add controls for demand shifters based on: whether the permit falls on a weekend or federal holiday (column 2); week of year (column 3); and permit-specific week-effects (column 4).

Higher competition, in both the advanced and day-ahead permit markets, is associated with higher average income. During the least competitive advance purchase on-sales, where five minute sales percentages are between zero and 25 percent, reservation holders come from zip codes with median income between $343 and $520 higher than users who reserve same day. However, in the most competitive advance on-sales, with five minute sales percentages between 75 and 100 percent, the average reservation holder resides in a zip code with $3,748 to $4,135 higher median income. Effects are similar for day-ahead reservations. In the most competitive day-ahead on-sales, successful reservation holders come from zip codes where median income is between $2,690 and

Table 2: Reservation Systems and Zip-Code Level User Income

	(1) Base	(2) Weekend Effects	(3) Seasonality	(4) Park Seasonality	(5) Non Parametric
Advance Comp. (0, 0.25)	520.4*	519.7*	479.2	343.4	595.2**
	(288.6)	(296.7)	(300.1)	(273.4)	(271.8)
Advance Comp. [0.25, 0.50)	730.2	693.4	403.8	115.6	1069.0**
	(497.6)	(497.0)	(499.2)	(483.1)	(466.7)
Advance Comp. [0.50, 0.75)	2614.8***	2529.8***	2506.1***	1814.8***	1976.2**
	(509.4)	(584.0)	(522.6)	(515.5)	(736.3)
Advance. Comp. [0.75, 1.00)	4135.1***	3968.8***	4047.7***	3747.7***	3158.8***
	(786.9)	(754.1)	(701.5)	(716.2)	(890.8)
Day-Ahead Comp. (0, 0.25)	-351.0	-271.9	-197.7	-120.8	1866.5***
	(556.3)	(554.2)	(530.5)	(476.9)	(558.5)
Day-Ahead Comp. [0.25, 0.50)	54.57	36.37	59.43	-73.73	2279.2***
	(495.1)	(460.0)	(469.0)	(472.3)	(385.8)
Day-Ahead Comp. [0.75, 1.00)	965.5**	957.1**	658.2	615.4	3232.0***
	(440.2)	(402.3)	(441.9)	(418.5)	(436.3)
Day-Ahead Comp. [0.75, 1.00)	3203.8***	2815.2***	2771.2***	2690.4***	5029.8***
	(549.8)	(551.1)	(575.4)	(554.5)	(502.6)
Lead-Time Days (0, 30)	3702.0***	3631.8***	3456.8***	3313.2***	
	(336.2)	(335.0)	(332.5)	(333.4)	
Lead-Time Days [30, 60)	3641.6***	3533.6***	3333.4***	3254.3***	
	(396.8)	(410.8)	(403.0)	(361.3)	
Lead-Time Days [60, 90)	3830.1***	3722.9***	3378.4***	3256.4***	
	(415.8)	(435.8)	(425.2)	(376.3)	
Lead-Time Days [90, 120)	2586.0***	2480.7***	2455.1***	2466.2***	
	(643.8)	(672.0)	(704.7)	(661.2)	
Lead-Time Days [120, 180)	2022.3**	1922.1**	1707.3**	1614.7**	
	(784.5)	(798.6)	(786.1)	(777.3)	
Lead-Time Days [180, ∞)	2098.5***	1880.5***	1681.1***	2060.3***	
	(577.8)	(595.6)	(495.9)	(541.7)	
Federal Holiday		1952.8***	1722.0***	1655.2***	1621.5***
		(308.9)	(249.5)	(229.7)	(330.2)
Weekend		1520.5***	1539.8***	1527.7***	1506.3***
		(279.2)	(274.5)	(269.9)	(301.3)
Permit Effects	Yes	Yes	Yes	Yes	Yes
Week Effects	No	No	Yes	Yes	No
Permit*Week Effects	No	No	No	Yes	No
Observations	5,279,457	5,279,457	5,279,457	5,279,457	527,512

Table 3: The dependent variable in each regression is median household income by customer zip code. Federal Holiday is a set of indicator variables equal to one if the trip start date is a federal holiday. Weekend is a set of indicator variables equal to one if the trip start date is a Saturday or Sunday. Standard errors clustered at the permit-by-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$3,204 higher compared to those who purchased same day. In all cases, permits falling on federal holidays or weekends are associated with higher incomes. Controlling for holiday, weekend and seasonal effects reduces the estimated effects of competition on income, suggesting controlling for demand related factors is important.

While it is tempting to interpret the estimated effects on zip-code level income as individual effects, this characterization would be misleading due to the "ecological fallacy"[23,24]. Aggregation introduces both zip-code-level selection and within-zip sorting arising from heterogeneous individual treatment effects. I model these effects as selection on unobservables[24,25] and adapt the approach of Oster[26] to demonstrate that, under plausible bounds on residual within-group sorting, the aggregate and average individual-level effects have the same sign. In other words, higher income *individuals* are more likely to reserve during more competitive day-ahead and advance on-sales. These results are presented in Tables A2 and A3 of the Extended Data.

Advance purchase reservations are also associated with higher incomes, consistent with results in Rice et. al.[19] for camping reservations. Relative to same-day reservations, advance reservations made up to 30, 30 to 60, and 60 to 90 days in advance are associated with median zip-code incomes that are $3,254 to $3,830 higher. Longer advance purchases are associated with somewhat smaller income differences, between $2,455 and $2,586 for 90 to 120 days, $1,615 and $2,022 for 120 to 180 days and between $1,681 and $2,099 for greater than 180 days. The pattern of non-linearity of the advanced purchase parameters, suggests a more flexible specification for lead time may be important. Column 5 presents results using Robinson's square of root N-consistent semi-parametric regression[27] that allows for a general functional relationship between advance purchase lead time and income $\lambda(l_i)$. I estimate the model on a random ten percent sample of transactions and without week-effects for computational tractability. The estimated effects of competition in the advance and day-ahead reservation markets are comparable to estimates in columns 1-4. In the most competitive advance purchase on-sales, reservation holders come from zip codes with $3,159 higher median income. The most competitive day-ahead on-sales are associated with $5,030 higher median income.

The relationship between advance purchase lead time and income is plotted in Figure 3. Median income shows a generally upward trend, increasing with advance purchase lead time. Users who reserve 180 days in advance come from zip codes where median income is approximately $10,000 higher than those who reserve same-day, all else equal. However, while visitors from lower income zip-codes appear to prefer short advance purchase windows or day-ahead reservations, congested buying frenzies in the day-ahead markets disadvantage lower income users. Therefore, moving to a day-ahead-only model would not necessarily alleviate the equity problem.

When interpreting the results in Table 3 and Figure 3 it is important to note while higher income users prefer to reserve in advance, this preference only impacts equity if their reservations prevent lower income users from reserving later. Therefore, a better test of the advanced reservation effect would focus on the effective lead time when advanced reservations are sold-out, potentially excluding lower income users.

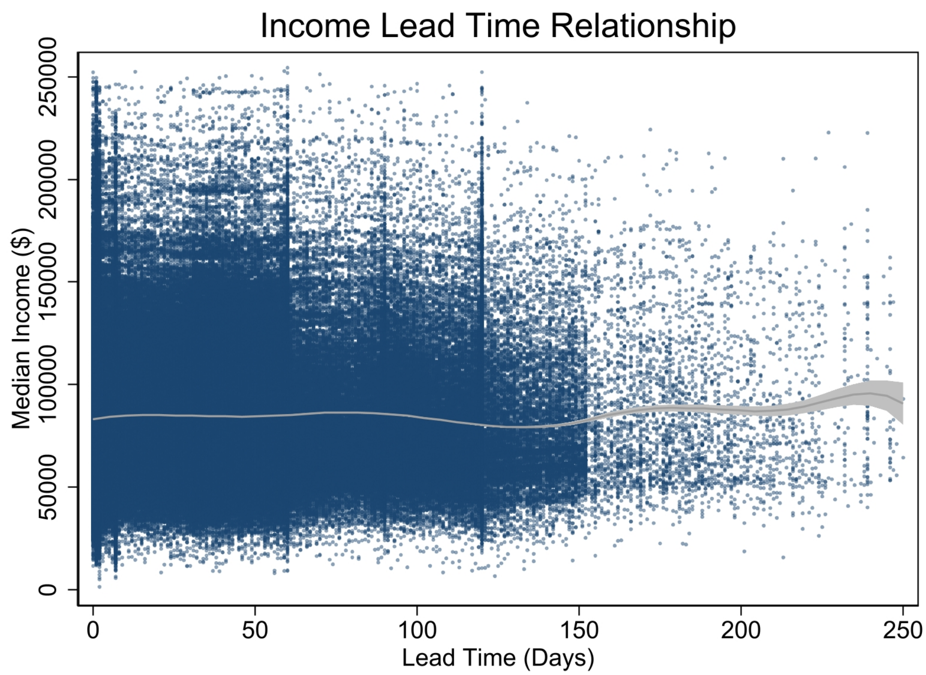


Figure 3: Relationship between advance purchase reservation lead time and visitor income. Non-parametric relationship estimated using Robinson's square of root N-consistent semi-parametric regression. Data are a 10 percent sample of all reservations. Model specification includes permit-specific mean effects.

Because parks' advance purchase period may reflect differences in demand and tend not to vary during this period, it is difficult to separate out the effect of the effective lead time from differences in park characteristics that may be correlated with user incomes. However Yosemite, did experiment with different advance reservation periods. In 2021, the park operated five advanced purchase block allocations approximately 30 to 60 days in advance of trip start dates. In 2022, the separate periods were eliminated in favor of a single block allocation (March 23, 2022) with lead time between 60 and 120 days depending on trip date. Finally, in 2024 the single block allocation was moved back three months (January 5, 2024) increasing lead time to between 90 and 240 days. These changes altered the effective date of the advanced purchase.

Figure 4 plots the booking curves for Yosemite permits for July 4 in 2021, 2022 and 2024.

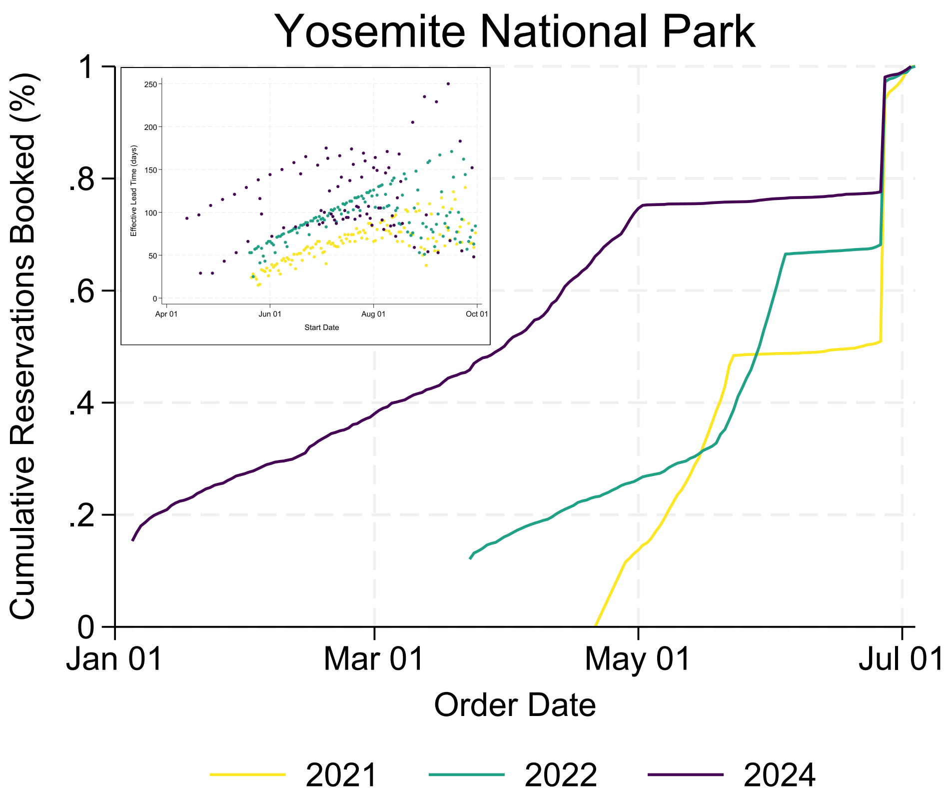


Figure 4: Booking curves for Yosemite National Park ticketed entry permits for July 4 in 2021, 2022 and 2024. Changes in the duration of the reservation period and total permit allocation each year lead to different effective lead times (inset), defined as the date advanced reservations are sold-out.

Cumulative reservations are the share of total permits booked by any given order date. The plateau in each curve occurs when advance reservations are completely booked, *i.e.* the effective lead time for making an advance reservation. The jump in each curve in late June marks the seven day-ahead on-sale. For 2024, we see that opening reservations earlier extends the reservation period and shifts the effective lead time from the end of May in 2021 to the beginning of May in 2024. In 2022, the larger allocation to advanced reservations, about 70% versus 50% in 2021, shifts lead time to early June. However in 2024, the longer advance reservation period extends lead time back to May 1. Figure 4 (inset) shows these changes in the Yosemite reservation system affect reservation lead time throughout the season, increasing average times from 2021 to 2022 and from 2022 to 2024. Regression results using this variation in effective lead time are presented in Table A4 of the extended data. In Yosemite, increasing lead time is correlated with a shift toward reservation holders residing in higher-income areas. Each additional day of lead time corresponds to \$21–\$24 higher median zip-code income; thus, extending the lead time from 30 to 180 days implies a difference of approximately \$3,150 to \$3,600 in median zip-code income. This result is broadly consistent with results for all seven parks above, and suggests exclusionary effects and not simply differences in preferences, explain the observed advanced purchase effects.

Discussion

While evidence suggests that reservation systems can be effective at protecting national park resources and visitor experience, I show that these systems can also have equity effects. In the most competitive advance reservation on-sales, reservation holders reside in zip codes with median incomes between \$3,200 and \$4,200 (4 to 5 percent) higher. In the most competitive day-ahead on-sales, reservation holders come from zip codes with incomes \$2,700 to \$5,000 (3 to 6 percent) higher. Longer advance reservation periods also favor higher-income users: increasing the effective lead time from 30 to 180 days is associated with \$1,500 to \$3,500 higher zip-code income. These trends are consistent with Miller et al.[13] who surveyed users before and after the implementation of the timed-entry system in Arches National Park. During the timed-entry period visitors planned further in advance. Visitor incomes were higher than during the pre-period, though a joint test of income differences across eight categories was not statistically significant. While the authors conclude there are no statistically significant exclusionary effects during the timed-entry pilot, their results suggest timed-entry reservation systems can impact visitor incomes, consistent with the results presented here.

So what is a park manager to do if equitable access is a concern? Because reservation systems are designed to ration use, some level of competition is unavoidable. However, active monitoring and management of competition in advance and day-ahead reservation systems could partially mitigate competition effects. For instance, changes to the share of permits offered in the advance versus day-ahead markets could lower competition in some cases. Admittedly, this may not always be possible. For instance, sunrise permits for Acadia and Haleakala are extremely competitive in both the day ahead and advance markets (see Figure A in the Extended Data). However, the Rocky Mountain National Park and Yosemite systems would seem to benefit from a rebalancing of permits toward the day/week-ahead markets.

In terms of advanced reservation periods, the evidence presented here suggests higher income users do preferentially reserve in advance, consistent with evidence from related markets[19]. This leads to equity effects when permits are fully reserved months in advance. Therefore, additional phasing of permit on-sales could help alleviate advanced reservation effects. This strategy has been pursued by a number of public campgrounds. While shorter lead times would allow users with scheduling constraints the chance to compete for permits, competition effects may still favor higher income users, even with staggered allocations. These competition effects could increase when the total permit allocation is further subdivided into sequential allocations, highlighting a potential trade-off in equity effects. In some cases random allocation via lotteries, such as those used in many river systems some popular hiking destinations, may be required to ensure equitable allocation of permits.

Methods

Data

Transaction-level data on reservations (permits) are from the Recreation Information Database (RIDB)[28]. The sample runs from 2021 through 2024, covering the first post-COVID year of reservation systems through the most recent year data are available. Median household income data are from the American Community Survey (ACS)[29]. I match zip-code-level income with each user's zip code as reported in RIDB. I collect detailed historical data on the design of each park's permit system from the corresponding product pages on Recreation.gov and use the Internet Archive Wayback Machine[30] to access prior years' data. Additional information on each park's reservation system is presented in Table A1 of the Extended Data.

I collect data on eleven permits at the seven national parks currently employing general reservation systems: Acadia, Arches, Glacier, Haleakala, Mount Rainier, Rocky Mountain and Yosemite. Reservations may permit access to specific locations, *e.g.* Cadillac Mountain (Acadia) or the Bear Lake Road corridor (RMNP), or to large areas of the park such as in Arches or Yosemite. Permits may also pertain to a specific time of day, *e.g.* sunrise (Acadia or Haleakala) or hourly blocks when park entry is permitted (RMNP). These eleven systems are general in the sense they do not pertain to a specific activity and can encompass hiking, car touring, wildlife viewing, etcetera. I exclude reservation systems at two parks for activities requiring advanced or technical skills (Old Rag in Shenandoah and Angels Landing, the Subway and the Narrows in Zion).

The RIDB data record the exact time and date of each transaction. I calculate reservation lead times as trip start-date minus order-date. From historical product pages I note the on-sale date as the first day permits are available for each period. I then classify individual transactions as "advance-purchase" or "day-ahead" reservation if the transaction falls on the on-sale date, for either type, and record whether the purchase occurred during the first five minutes of the on-sale period.

Regression model

The empirical model separately estimates the effects of advanced reservation lead time and competition for permits on the average incomes of permit holders. To do this requires controlling for factors related to the time-varying demand for particular permits that could also be correlated with the incomes of permit holders. The main specification is:

$$\text{Income}_{it} = \alpha A_{pt} + \delta D_{pt} + \lambda L_{ipt} + \epsilon_p + \epsilon_t + \epsilon_{it}, \tag{1}$$

where Income_{it} is the average median household income (zip-code level) of user holding permit i purchased at time t. Competition for advanced purchase permits is flexibly modeled as a vector of indicator variables A_{pt}, defined by the ranges for the share of available permits that are purchased during the first five minutes permits are for sale. The specification uses four intervals: $(0, 0.25)$; $[0.25, 0.50)$; $[0.50, 0.75)$; and $[0.75, 1.00]$. Similarly, D_{pt} is a vector of indicator variables defined by analogous intervals of competition during day-ahead on-sale events. To flexibly capture advance purchase, L_{ipt} is a vector of indicator variables corresponding to different lead time intervals. Specifically, I use six bins: $(0, 30)$; $[30, 60)$; $[60, 90)$; $[90, 120)$; $[120, 180)$; and $[180, \infty)$. Day-of purchase, *i.e.* zero lead time, are the omitted category serving both as the reference for advanced and day-ahead on-sales, but also purchases at other times during the season captured by the lead time categorical variables.

I control for permit-specific factors using mean-effects ϵ_p. Here, I distinguish between permit types for parks that have multiple timed-entry permits, for example Bear Lake Road and the rest of the park in RMNP. I control for time-varying demand factors that may be correlated with user characteristics with ϵ_t, a set of time or time-by-permit fixed-effects and ϵ_{it} is the error term.

Signs of individual-level effects

The results above rely on zip-code-level proxies for individual incomes. In general, results from aggregate regressions cannot be interpreted as individual effects, a result broadly known as the ecological fallacy[23,24]. Here, I develop robustness checks to determine the likely sign of individual effects based on the aggregate results. The use of zip-code-level income data creates two potential problems. First, aggregation can lead to omitted variable bias due to zip-code-level selection into different reservation types (e.g. more versus less competitive parks or periods). Second, when individual treatment effects are heterogeneous, aggregation induces compositional bias whenever the distribution of individuals (or their potential outcomes) co-varies with group composition.

I model these concerns as selection on unobservables and estimate two auxiliary regressions. First, I estimate a specification that accounts for baseline compositional differences across zip-codes that could drive reservation selection[25]. Specifically, I include zip-code-level proxies for income distribution (Gini coefficient), travel costs (the distance between each zip code centroid and each national park) and affinity for outdoor recreation (purchases on Recreation.gov per capita). Second, to account the possibility of slope heterogeneity, I create proxies for missing cross-moments by interacting the zip code controls with the reservation system competition and lead time dummies[24]. In the latter, I calculate the marginal effects of the main effects at the means of distance, Gini coefficient and Recreation.gov purchases. While it is impossible to identify individual-level treatment effects using aggregate zip-code data, I use the approach developed by Oster[26] to construct bounds on the average individual-level effects at typical zip compositions, which allows me to determine the likely *sign* of those effects under reasonable assumptions about residual within-zip sorting.

These results are presented as Table A2 of the Extended Data. I choose the specification with permit and week effects to account for park-specific preferences and seasonality (column 3 in Table 3) but not the fully interacted model (column 4 in Table 3) to simplify calculation of the marginal effects when the seasonal categorical variables are unbalanced across parks. Because the zip code controls are not available for all observations, column 1 presents results for the base model estimated on the restricted sample. Column 2 adds controls for income distribution, travel costs and affinity for outdoor recreation. Column 3 adds interaction terms proxying for the missing cross-moments and reports marginal effects evaluated at the means of zip-code Gini, travel distance and recreation.gov activity. The coefficient stability tests outlined in Oster[26] assess robustness to omitted variable bias by comparing changes in coefficient estimates and r-squared values between regressions with and without control variables that account for selection on observables.

Comparing columns 1 and 2, adding zip-code characteristics generally increases the magnitudes of the estimated effects of lead-time and competition in advance and day-ahead reservations. R-squared increases from approximately 0.0244 to 0.0456. Column 2 of Table A3 reports the proportional selection parameter necessary to reduce the estimated effect to zero (δ_0)[26]. Values are all either much larger than one or negative, indicating the selection on unobservables would have to be either substantially stronger than selection on observables *or* act in the opposite direction to eliminate the estimated effects, or change their sign.

Comparing columns 1 and 2 with column 3, adding proxies for missing treatment heterogeneity, we see the estimated marginal effect for the most competitive advance on-sales is smaller in magnitude compared to the parameter estimates in columns 1 and 2. The estimated marginal effect for the most competitive day-ahead on-sales are larger in magnitude. The marginal effects of lead time are generally smaller in magnitude and the r-squared value increases slightly to 0.0503. While the δ_0 values reported in Table A3 are generally smaller in magnitude than those in column 1, they all exceed the threshold of $\delta = 1$ or are negative. Therefore, while the individual-level average treatment effect cannot be identified from aggregate data, the results above suggest the individual level effects are unlikely to have a different sign than the estimates presented in Table 3. In other words, individuals who obtain their permit in a competitive advanced or day-ahead on-sale or those who reserve weeks or months in advance are likely higher income than other users.

Data availability

Transaction level reservation data are available from the Recreation Information Database (`https://ridb.recreation.gov/`). Zip-code level income data are available from the American Community Survey (`https://www.census.gov/programs-surveys/acs.html`). Replication data for this paper are available via Zenodo at (`https://zenodo.org/records/17186257`).

Code availability

Replication code for the analysis is available at `https://github.com/jonathan-e-hughes/Park-Reservations`.

References

[1] National Park Service. Visitor use statistics dashboard, 2024. URL `https://www.nps.gov/subjects/socialscience/visitor-use-statistics-dashboard.htm`. Accessed: 2025-07-21.

[2] Margaret Walls, Casey Wichman, and Kevin Ankney. Nature-based recreation: Understanding campsite reservations in national parks. *Washington, DC: Resources for the Future*, 2018.

[3] William L Rice, Oakes Spivey, Peter Newman, and B Derrick Taff. “On the staff of the Grand Canyon”: Assessing manager and stakeholder perspectives on sustainable wilderness visitor use management. *International Journal of Wilderness*, 27(1):54, 2021.

[4] Jeremy S Dertien, Courtney L Larson, and Sarah E Reed. Recreation effects on wildlife: A review of potential quantitative thresholds. *Nature Conservation*, 44:51–68, 2021.

[5] A Myrick Freeman III and Robert M Haveman. Congestion, quality deterioration, and heterogeneous tastes. *Journal of Public Economics*, 8(2):225–232, 1977.

[6] David N Cole, Raymond J Hoff, and Stephen C Bunting. *Managing wilderness recreation use: common problems and potential solutions*. Number 230-232. US Department of Agriculture, Forest Service, Intermountain Research Station, 1987.

[7] Garrett Hardin. The tragedy of the commons: the population problem has no technical solution; it requires a fundamental extension in morality. *Science*, 162(3859):1243–1248, 1968.

[8] George H Stankey and John Baden. *Rationing wilderness use: Methods, problems, and guidelines*, volume 192. Intermountain Forest and Range Experiment Station, U.S. Forest Service, 1977.

[9] Christopher M Fleming and Matthew Manning. Rationing access to protected natural areas: an Australian case study. *Tourism Economics*, 21(5):995–1014, 2015.

[10] David P Carter and Juniper Katz. Land management policy tools and institutionally contingent types of goods: Understanding rock climbers' resistance to and desire for public lands fees and quotas. *Journal of Environmental Policy & Planning*, 26(3):264–278, 2024.

[11] William L Rice, B Derrick Taff, Sophie A Morris, Bing Pan, Colby Parkinson, and Peter Newman. Explorations of preferred and maximum booking windows among us national park campers: Implications for improved fairness. *Tourism and Hospitality Research*, page 14673584241237442, 2024.

[12] William L Rice, Kelsey E Phillips, Christopher A Armatas, Nicholas A Pitas, Suiwen Sharon Zou, and Abigail Fuesler. A systematic review of visitor preferences concerning recreation allocation. *Socio-Ecological Practice Research*, pages 1–13, 2025.

[13] Zachary D Miller, Amy Tendick, Caleb Meyer, David Pettebone, Bret Meldrum, and Steve Lawson. Comparing visitor perceptions, characteristics, and support for management actions before and during a pilot timed entry system at arches national park. *Sustainability*, 15(13): 10035, 2023.

[14] Noah Creany, Christopher A Monz, and Scott M Esser. Understanding visitor attitudes towards the timed-entry reservation system in rocky mountain national park: Contemporary

managed access as a social-ecological system. *Journal of Outdoor Recreation and Tourism*, 45: 100736, 2024.

[15] Zvi Schwartz, William Stewart, and Erik A Backlund. Visitation at capacity-constrained tourism destinations: Exploring revenue management at a national park. *Tourism Management*, 33(3):500–508, 2012.

[16] Erica N Spotswood, Matthew Benjamin, Lauren Stoneburner, Megan M Wheeler, Erin E Beller, Deborah Balk, Timon McPhearson, Ming Kuo, and Robert I McDonald. Nature inequity and higher COVID-19 case rates in less-green neighbourhoods in the United States. *Nature Sustainability*, 4(12):1092–1098, 2021.

[17] Anna Lou Abatayo, Madelon van Adrichem, and John Lynham. Comparing access to us marine and terrestrial protected areas. *Nature Sustainability*, 7(3):255–259, 2024.

[18] Kelsey E Philips and William L Rice. Visitor sentiment concerning changes in backcountry permit allocation at Glacier National Park, Montana, USA. *Journal on Protected Mountain Areas Research and Management*, 16:30–37, 2024.

[19] William L Rice, Jaclyn R Rushing, Jennifer M Thomsen, and Peter Whitney. Exclusionary effects of campsite allocation through reservations in us national parks: Evidence from mobile device location data. *Journal of Park and Recreation Administration*, 40(4):45, 2022.

[20] Jonathan E. Hughes. Are "buying frenzies" equitable? distributional effects of congested online markets. *Working Paper*, 2025.

[21] Average Wild Experience. Cadillac mountain sunrise reservations 2025: Everything you need to know, 2024. URL `https://averagewildexperience.com/cadillac-mountain-sunrise-2025/`. Accessed: 2025-07-09.

[22] Amy Golden. Reservation system will return to rocky mountain national park in 2022, 2021. URL `https://www.skyhinews.com/news/reservation-system-will-return-to-rocky-\protect\penalty\z@mountain-national-park-in-2022/`. Accessed: 2025-07-21.

[23] W. S. Robinson. Ecological correlations and the behavior of individuals. *American Sociological Review*, 15(3):351–357, 1950. URL `https://www.jstor.org/stable/2087176`. Accessed: 2025-10-21 18:10 UTC.

[24] Leo A. Goodman. Some alternatives to ecological correlation. *American Journal of Sociology*, 64(6):610–625, 1959. URL `http://www.jstor.com/stable/2774045`.

[25] Yair Mundlak. On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society*, pages 69–85, 1978.

[26] Emily Oster. Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204, 2019. doi: 10.1080/07350015.2016.1227711. URL `https://doi.org/10.1080/07350015.2016.1227711`. Published online: June 1, 2017.

[27] Peter M Robinson. Root-n-consistent semiparametric regression. *Econometrica: Journal of the Econometric Society*, pages 931–954, 1988.

[28] Recreation.gov. Recreation Information Database, 2025. URL `https://ridb.recreation.gov/download`. Accessed June 10, 2025.

[29] U.S. Census Bureau. American Community Survey, 2021. URL `https://www.census.gov/programs-surveys/acs`. Accessed November 8, 2021.

[30] Internet Archive. Internet archive: Wayback machine, 2024. URL `https://web.archive.org/`. Accessed: 2025-07-09.

Online Appendix

A Extended data

Table A1: Timed Entry Reservation Periods for Selected National Parks, 2021–2024

Park / Region	**2021**	**2022**	**2023**	**2024**	**Release Time (Adv.|Day-Ahead)**
Rocky Mountain (Bear Lake/Rest of Park)	5/28–10/11	5/27–10/10	5/26–10/22	5/24–10/20	8am,10am MDT | 5pm/7pm MDT
Arches	4/3–10/3	4/1–10/31	4/1–10/31	4/1–10/31	8am MDT | 6pm/7pm MDT
Glacier (Sun Road)	5/28–9/6	5/27–9/11	5/26–9/10	5/24–9/8	8am MDT | 8am/7pm MDT
Glacier (Many Glacier)	–	–	7/1–9/10	7/1–9/8	8am MDT | 8am/7pm MDT
Mount Rainier (Sunrise/Paradise)	–	–	–	5/24–9/2	8am PT | 7pm PST
Haleakalā (Summit Sunrise)	Year-round	Year-round	Year-round	Year-round	7am HST
Acadia (Sunrise/Rest of Day)	5/26–10/19	5/25–10/22	5/24–10/22	5/22–10/27	10am ET
Yosemite	5/21–9/30	5/20–9/30	–	4/13–10/27	8am PST

Table A2: Robustness to selection on unobservables

	(1) Base Model b/se	(2) Mundlak b/se	(3) Interactions b/se
Advance Comp. (0, 0.25)	505.568	743.435	927.862
	(296.510)	(326.090)	(324.339)
Advance Comp. [0.25, 0.50)	394.276	730.272	626.440
	(504.070)	(444.210)	(619.885)
Advance Comp. [0.50, 0.75)	2549.774	2580.916	1247.629
	(523.808)	(517.157)	(482.515)
Advance. Comp. [0.75, 1.00)	4064.044	3949.032	1845.641
	(693.541)	(639.148)	(646.012)
Day-Ahead Comp. (0, 0.25)	-190.752	-164.850	-145.967
	(528.739)	(511.502)	(498.874)
Day-Ahead Comp. [0.25, 0.50)	38.745	57.866	235.590
	(463.857)	(436.537)	(508.937)
Day-Ahead Comp. [0.75, 1.00)	641.965	702.997	1018.080
	(439.658)	(408.147)	(477.037)
Day-Ahead Comp. [0.75, 1.00)	2774.404	2972.047	3087.836
	(586.719)	(542.674)	(625.150)
Lead-Time Days (0, 30)	3439.621	3469.592	3069.527
	(330.375)	(316.099)	(359.333)
Lead-Time Days [30, 60)	3336.790	3406.809	3229.327
	(397.361)	(394.876)	(308.420)
Lead-Time Days [60, 90)	3404.646	3441.446	2936.309
	(423.183)	(414.411)	(400.028)
Lead-Time Days [90, 120)	2466.230	2410.337	1819.969
	(708.505)	(610.762)	(504.557)
Lead-Time Days [120, 180)	1715.562	1689.119	1238.116
	(777.852)	(690.396)	(629.794)
Lead-Time Days [180, ∞)	1606.460	1881.282	687.177
	(485.422)	(439.075)	(373.497)
Federal Holiday	1701.732	1746.530	1756.118
	(243.159)	(212.763)	(216.496)
Weekend	1480.314	1563.064	1560.229
	(273.142)	(208.121)	(214.716)
Permit Effects	Yes	Yes	Yes
Week effects	Yes	Yes	Yes
Park*Week	Yes	Yes	Yes
Observations	5126717	5126717	5126717
R-squared	0.0244	0.0456	0.0503

Table A3: Oster Robustness Parameters ($R_{\max} = 1.3 \times R_c$)

	$\delta_0^{\text{Mundlak}}$	δ_0^{Full}
A1 = 1	−4.983	−3.829
A2 = 1	−3.465	−4.703
A3 = 1	−132.121	1.670
A4 = 1	54.738	1.450
D1 = 1	10.146	5.681
D2 = 1	−4.825	−2.086
D3 = 1	−18.363	−4.718
D4 = 1	−23.973	−17.170
L1 = 1	−184.553	14.455
L2 = 1	−77.567	52.374
L3 = 1	−149.086	10.927
L4 = 1	68.749	4.908
L5 = 1	101.834	4.520
L6 = 1	−10.913	1.303

Table A4: Effects of Timed-Entry Systems on User Income

	(1) YoseBase	(2) YoseWeekendEff	(3) YoseSeasons
AdvSoldOut	21.49***	27.84***	24.13***
	(1.354)	(1.496)	(1.516)
Permit Effects	Yes	Yes	Yes
Week effects	No	Yes	Yes
Weekend Effects	No	No	Yes
Observations	495594	495594	495594

Standard errors in parentheses

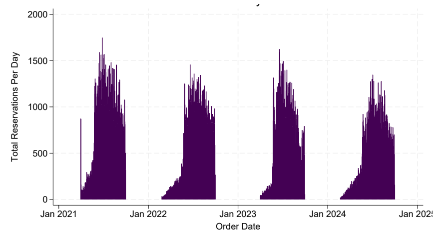
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Robustness to Excluding Potentially Influential Parks

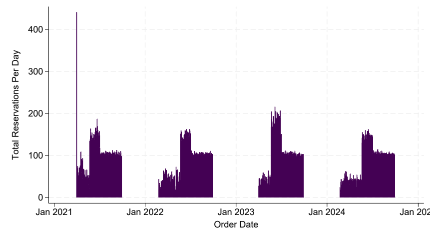
	(1) Acadia	(2) Arches	(3) Glacier	(4) Haleakala	(5) Rainier	(6) Rocky	(7) Yosemite
Advance Comp. (0, 0.25)	325.4	444.7	95.30	345.0	383.5	1396.8***	46.19
	(276.0)	(275.0)	(263.6)	(281.9)	(277.0)	(316.2)	(259.0)
Advance Comp. [0.25, 0.50)	86.28	336.9	516.5**	84.46	156.7	167.5	-182.2
	(502.0)	(465.3)	(224.7)	(503.5)	(486.2)	(909.9)	(459.8)
Advance Comp. [0.50, 0.75)	1867.6***	2076.4***	642.7	1846.6***	1844.7***	2340.6***	1481.5***
	(544.3)	(503.9)	(848.1)	(586.2)	(514.5)	(469.9)	(535.0)
Advance. Comp. [0.75, 1.00)	3700.1***	3943.7***	2197.7	3739.8***	3768.3***	4630.7***	3378.9***
	(725.9)	(727.6)	(2366.8)	(749.2)	(738.5)	(697.4)	(913.6)
Day-Ahead Comp. (0, 0.25)	-1085.1**	376.4	-46.81	-103.7	-30.77	192.8	-372.8
	(462.0)	(431.9)	(502.4)	(478.1)	(474.4)	(601.4)	(528.1)
Day-Ahead Comp. [0.25, 0.50)	-300.7	403.3	-92.85	-64.33	7.000	487.2	-837.9***
	(512.7)	(509.5)	(501.7)	(475.4)	(495.3)	(703.9)	(247.3)
Day-Ahead Comp. [0.75, 1.00)	403.4	739.4	634.8	621.3	718.5	1471.0*	-58.76
	(454.4)	(460.7)	(432.4)	(422.6)	(442.5)	(830.4)	(197.0)
Day-Ahead Comp. [0.75, 1.00)	2439.3***	2693.3***	2539.2***	2642.2***	2736.8***	4374.6***	1909.8***
	(597.3)	(608.8)	(628.5)	(579.8)	(573.6)	(662.2)	(317.1)
Lead-Time Days (0, 30)	3622.1***	2791.3***	3389.3***	3304.0***	3233.9***	3267.3***	3577.8***
	(412.1)	(289.2)	(326.2)	(334.3)	(340.4)	(421.6)	(316.4)
Lead-Time Days [30, 60)	3352.4***	2637.4***	3386.9***	3265.0***	3184.0***	3945.8***	3296.6***
	(424.8)	(301.1)	(360.0)	(363.9)	(366.5)	(421.6)	(377.4)
Lead-Time Days [60, 90)	3463.5***	2531.6***	3384.0***	3283.2***	3229.9***	3565.9***	3284.4***
	(442.7)	(300.6)	(375.0)	(372.5)	(392.0)	(407.0)	(418.8)
Lead-Time Days [90, 120)	2584.4***	1349.6*	3221.9***	2464.6***	2464.2***	2489.5***	2365.7***
	(753.7)	(698.9)	(417.1)	(663.6)	(713.0)	(644.4)	(856.2)
Lead-Time Days [120, 180)	1729.2**	996.4	1987.6***	1620.2**	1564.9*	1893.4**	1548.3
	(810.3)	(798.9)	(407.7)	(778.5)	(798.5)	(702.0)	(1067.2)
Lead-Time Days [180, ∞)	2214.4***	1383.8**	2329.6***	2062.0***	1951.7***	1857.2***	10869.3***
	(590.2)	(503.5)	(513.8)	(545.0)	(562.0)	(599.6)	(3555.3)
Federal Holiday	1647.3***	1727.7***	1870.7***	1668.0***	1570.3***	1678.7***	1432.1***
	(259.6)	(255.7)	(238.8)	(233.3)	(223.2)	(338.9)	(201.4)
Weekend	1544.5***	1781.0***	1826.1***	1525.0***	1345.7***	1375.6***	1294.7***
	(306.7)	(270.2)	(262.1)	(275.5)	(234.0)	(420.1)	(288.2)
Permit Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Permit*Week Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,666,138	4,551,252	4,542,176	5,178,170	5,078,320	3,173,445	4,487,241

Table A6: The dependent variable in each regression is median household income by customer zip code. Each column excludes from the sample observations for the park indicated. The similarity of estimates across samples suggests the results do not rely on any particular park's reservation system. Federal Holiday is a set of indicator variables equal to one if the trip start date is a federal holiday. Weekend is a set of indicator variables equal to one if the trip start date is a Saturday or Sunday. Standard errors clustered at the permit-by-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

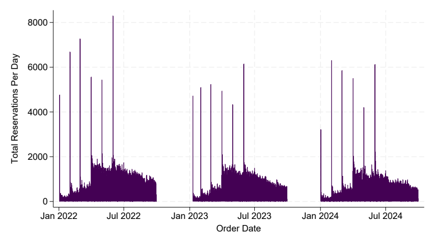
(a) Reservations - Acadia Cadillac Daytime



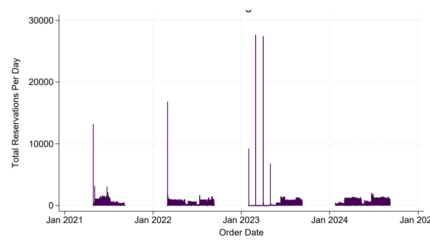
(b) Reservations - Acadia Cadillac Sunrise



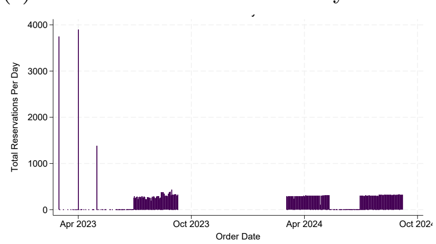
(c) Reservations - Arches



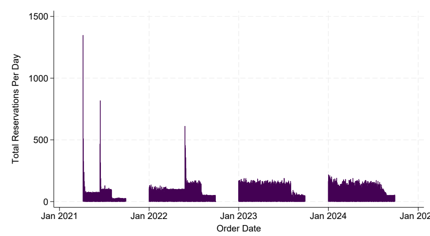
(d) Reservations - Glacier Sun Road



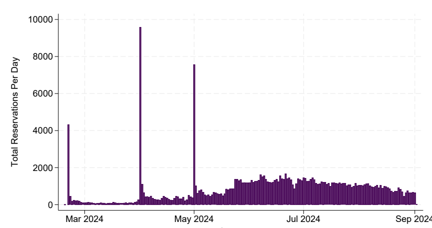
(e) Reservations - Glacier Many Glacier



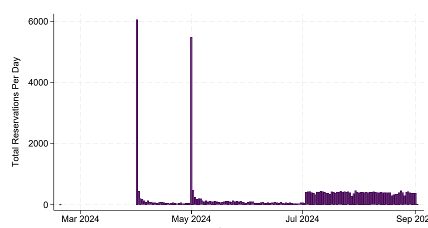
(f) Reservations - Haleakala



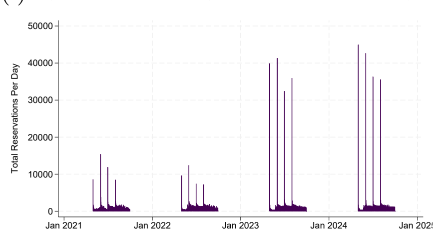
(g) Reservations - Rainier Paradise



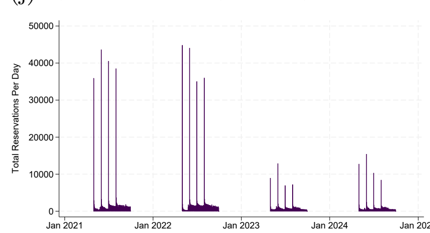
(h) Reservations - Rainier Sunrise



(i) Reservations - RMNP Bear Lake Rd.



(j) Reservations - RMNP Rest of Park



(k) Reservations - Yosemite

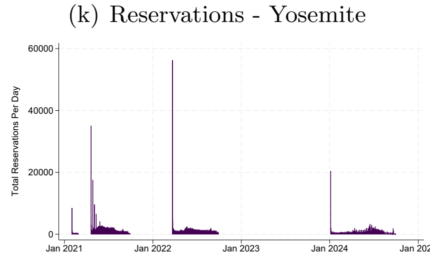
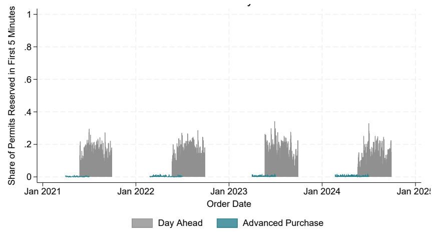
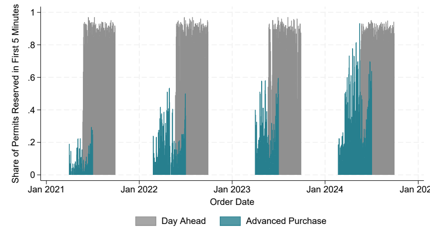


Figure A1: Permit reservation activity at seven national parks, eleven reservation systems.

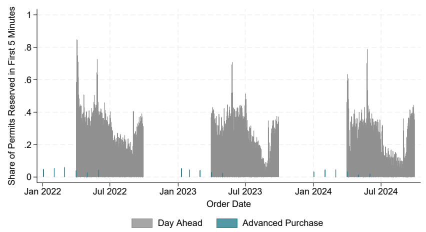
(a) Competition - Acadia Cadillac Daytime



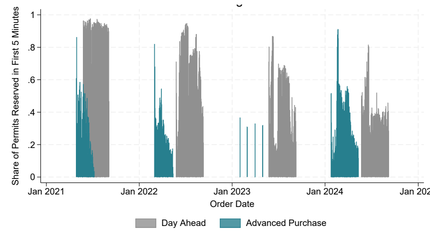
(b) Competition - Acadia Cadillac Sunrise



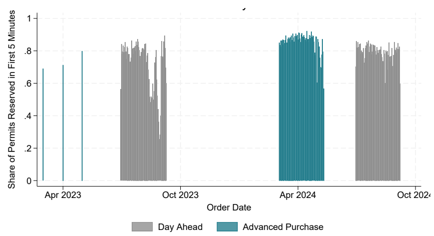
(c) Competition - Arches



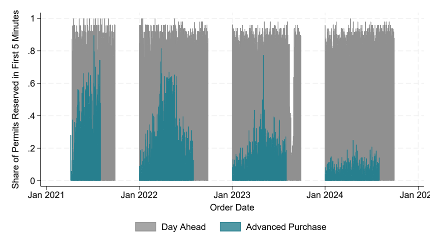
(d) Competition - Glacier Sun Road



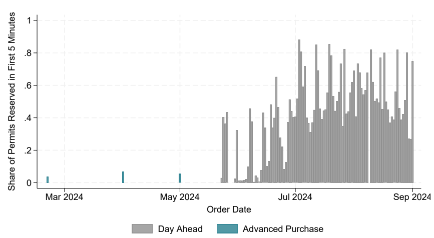
(e) Competition - Glacier Many Glacier



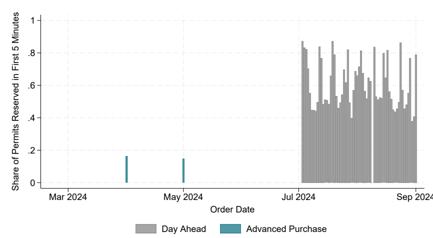
(f) Competition - Haleakala



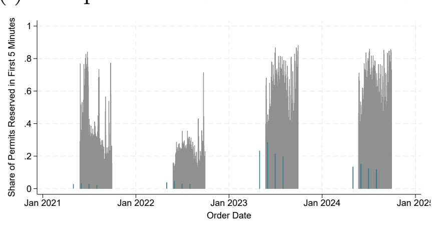
(g) Competition - Rainier Paradise



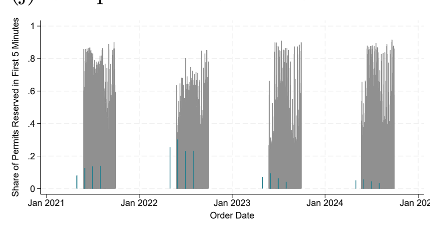
(h) Competition - Rainier Sunrise



(i) Competition - RMNP Bear Lake Rd.



(j) Competition - RMNP Rest of Park



(k) Competition - Yosemite

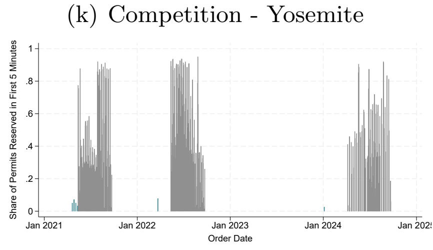


Figure A2: The share of available permits reserved during the first five minutes of the on-sale event.

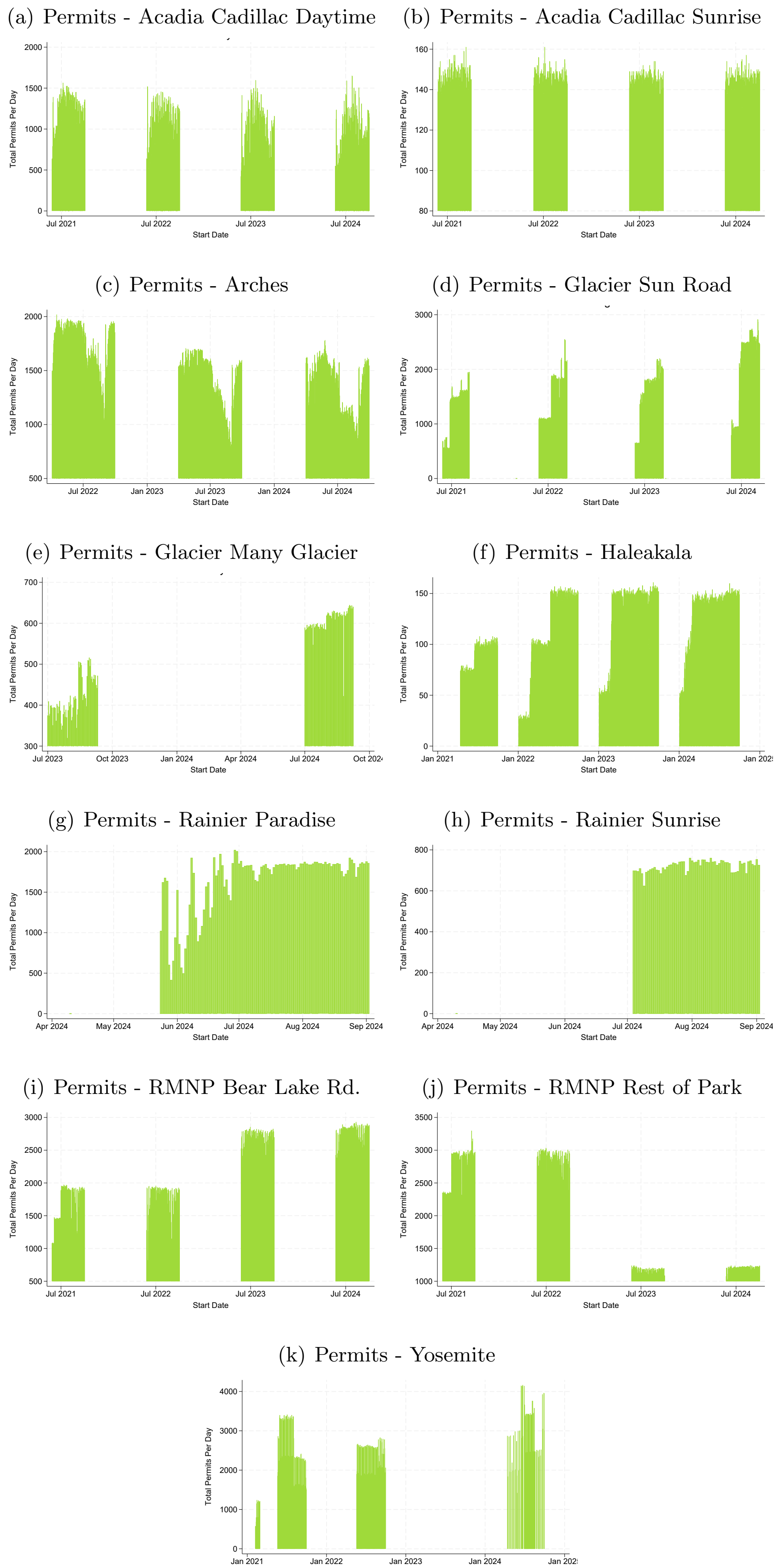


Figure A3: Total permits reserved/allocated by trip date at seven national parks, eleven reservation systems.