Chapter 4 The Effects of Public Health Advisories on the Value of Recreational Camping

4.1. Introduction

The year 2020 brought significant economic disruption from the COVID-19 global pandemic and in the U.S. Pacific Northwest (PNW), from a devastating wildfire season. Outdoor recreation was a sector of the economy that was impacted a variety of ways from both shocks. Park managers were initially preparing for a record-breaking year in visitation given recent growth trends (Bergstrom et al. 2020). Instead, National and state parks completely shut down access during the early onset of the pandemic (March-April 2020). Camping and hiking trips were postponed and backcountry permits were canceled. During that same period of shutdowns and stay-at-home (SAH) orders, people, with little other activity options, flocked to outdoor recreational areas that remained open. For example, during the first weekend of SAH orders in Oregon, areas of the Oregon Coast were flooded with visitors (Tobias, 2020). At this point in time, information on how COVID-19 spread and the risk associated with various activities was uncertain and being continually updated via news alerts, the CDC, and White House briefings. When SAH orders eased, outdoor recreation activities remained a relatively safe option to engage in while individuals made decisions based on risk of infection and congestion. Some areas recorded substantial increases in demand for recreation (Shartaj et. al 2022). At Oregon State Parks, once SAH and closures were eased, camping demand quickly returned to levels from prior summers despite the continuing public health crisis of COVID-19. Furthermore, the global pandemic would not be the only public health risk advisory for the PNW that year. In the closing days of summer, the 2020 Labor Day wildfires began to turn the skies apocalyptic red. The air quality index (AQI) alert advised all individuals that health would be impacted by the air quality and that everyone should remain indoors. This level would remain at unhealthy levels for over ten (10) days in much of the PNW.

Prior research examining impacts to outdoor recreation from public health risk have found a variety of different impacts. Initial research into COVID-19 have found welfare losses for recreation attributable to the pandemic and these losses were larger for households with lower risk tolerance (Landry et al. 2020). Other research found increases in demand for outdoor recreation during the summer of height of the pandemic (Volenec et al. 2021; Shartaj et al. 2022). Smoke from wildfires has increased welfare losses to recreators whose choices were impacted by poor air quality (Gellman et al. 2022a, 2022b). The implications of these results suggest public health risks and polices can rapidly change our demand and values for our public lands. The outdoor recreation economy accounts for roughly 1.9% of the United States gross domestic product (Bureau of Economic Analysis 2021) and thus the implications of these demand shifts are crucial for both understanding the benefits associated with conservation efforts and informing our management strategies of public lands. For example, of Oregon's roughly 61.6 million acres of land, 53 percent is federally managed. Oregon State agencies own nearly 1.8 million acres of land with 5.5 percent of managed under the Oregon Parks and Recreation Department (OPRD) (ODSL, 2021). Understanding the economic value recreators derived from visiting public lands can help us understand outdoor recreation's role in public health scares and under changing air quality.

My research explores the benefits and losses associated with camping trips in response to two types of public health advisories. I examine both the impacts of before and during the COVID-19 pandemic as well as how health advisories from air quality influence recreators over a four-year period (2018 - 2021). Whereas previous research in this area often relies on survey approaches to understand recreationalist preferences, I utilize an administrative dataset which observes all recreators deciding to take a trip in my timeframe. The dataset covers four years of all camping reservations made through the administrative reservation system for Oregon State Parks. The increasing access to administrative data from online reservations systems for recreation provides researchers a unique opportunity to explore the revealed preferences of recreators by examining their observed behavior (e.g., Lloyd-Smith et al. 2020; Gellman et al. 2022b). Online reservation systems contain millions of observations of individual recreationalist planning multiple future and present trips throughout various park systems. I observe individual recreators making daily decisions to recreate at locations throughout the park system across many phases of the COVID-19 pandemic and major air quality alerts. This rich daily dataset of revealed preferences of recreators behavior is paired with daily COVID-19 infection rates by county from both the location of the park and the recreators origin. The air quality index (AQI) is linked by the nearest county reporting for each park. These public health advisories capture some of the factors that may impact camping trip decisions and the value of those trips.

This research makes a few contributions to the literature on the value of outdoor recreational activities. First, it is one of the few research papers utilizing the emerging access to administrative data of individuals making multiple recreational choices over many years (Lloyd-Smith et al. 2020, Gellman et al. 2022). Second, the global COVID-19 pandemic impacted all facets of the economy, shifting demand and disrupting supply chains. Public land managers do not have as much flexibility to quickly match these changes with funding or staffing given the budgets are often determined *a priori*. Examining the associated benefits and losses of how public health advisories impact recreational activities can help us understand the overall economic value generated by recreational camping.

The layout of this chapter is as follows. First, I present a general discussion and literature review on the travel cost method and the use of administrative data. Second, I describe the administrative data from OPRD reservation system, *The New York Times* COVID-19 dataset and the daily environmental quality indicators collected for park-specific conditions. Third, I cover the methods and modeling approach utilized for the empirical analysis on public health risk and impacts to camping in Oregon. Fourth, I present results of the analysis and estimate welfare impacts associated with public health advisories. The final section provides a discussion of the implications of this study.

4.2 Travel Cost Method and Administrative Recreation Data

Nonmarket methods are used to value the goods and services which generate positive utility for individuals but have no or low observable monetary value due to the absence of a traditional market. One such approach is the travel cost method, first proposed by Hotelling (1947) and pioneered by Clawson et al. (1966). This method is a primary way economists understand the nonmarket values associated with recreation benefits from the use of natural resources such as public lands. For recreational activities, the implicit price of a recreational trip is estimated as the travel cost of visiting a site. This price includes the round-trip time and monetary cost of traveling to the recreation destination and reveals the recreators willingness to pay for the location they chose. The variation in the environmental quality at the time of the recreation trip allows an analyst to estimate the economic impacts associated with changes to quality, conditions and access to environmental amenities (Lupi et al. 2020). The workhorse of recreational demand modeling, the random utility model, can estimate both site choice and participation dimensions of the recreation decision by assuming over a period of time individual recreators make independent decisions on whether to make a trip and then where to take the trip. The underlying assumption is that the trip decision observed maximizes the utility of the individual. This method accounts for the cross-site substitutability among many sites and has been used to measure impacts from oil spills, environmental policy, threatened species, wildfire, and weather (e.g., Hesseln et al. 2003; Alvarez et al. 2014; English et al. 2018; Dundas et al. 2018; Dundas et al. 2020). In recreational applications, research often relies on intercept surveys of on-site or off-site visitors (Lupi et al. 2020). The ever-increasing reliance on online reservation systems to help manage demand for reservable public land sites provides a new potential dataset of observable recreational activity (Lloyd-Smith et al. 2020, Gellman et al. 2022b). The reservation system provides a set of all reservations made at a park on a given day. The datasets can be computational large depending on the time period and the number of locations selected. This is especially the case if a modeler is allowing for substitutability across sites as supported in the random utility framework. Others utilizing administrative datasets have handled this issue in various was. Lloyd-Smith et al. (2020) modeled camping decisions using a Kuhn-Tucker approach which controlled for substitutability among sites for individuals by reducing the timeframe to a year and a province of reservations. Gellman et al. (2022b) used administrative data covering many years, over various states and utilized a zonal travel cost method, trading off statistical power for substitution to reduce the computational burden. In this chapter. I examine the impacts of COVID over many years and locations and therefore, I will follow Gellman et al. (2022b) and use a zonal approach.

Online reservations systems provide a time series of recreation decisions over many sites over many years. The representative approach removes concerns of response bias and recall error when considering on- and off-site survey data but does introduce other concerns with the assumptions required of individual recreators (Lupi et al. 2020). Demographic information is not reported through the reservation system and therefore some extrapolated assumptions are made via the median or mean demographic information from the recreators zip code (Lloyd-Smith et al 2020; Gellman et al 2022a). Nevertheless, the reservation dataset provides a complete picture of all recreators taking a trip to a park on any given day. Each site/day combination can be associated with specific data on site conditions such as temperature, precipitation and air quality.

Current research utilizing recreational administrative data to measure the economic value of access and condition of natural resources is limited (Lloyd-Smith et al 2020; Lupi et al. 2020; Gellman et al 2022). Lloyd-Smith et al. (2020) use administrative data to estimate the economic value of park-level amenities and closure impacts. Gellman et al. (2022) construct a zonal travel cost model to estimate the welfare loss from wildfire through cancellation of trips. Our data is similar in structure as both of these previous endeavors. A zonal travel cost approach would lose some off the individual detail by averaging out the travel cost information to an aggregated level corresponding zones around each park (Loomis et al. 2009; Gellman et al. 2022). However, if I maintain the level of observation from the origin zip code and daily scale it aligns more with the theory of individuals maximizing their own utility. This is especially important given I can observe individuals making decisions over long periods of time within our dataset. A hybrid individual-zonal travel cost method provides us a potential solution for our individual specific analysis (Brown et al 1983; Loomis et al. 2009). In the hybrid individual-zonal approach, the individual trip is weighted by the share of population of the recreators participating from the corresponding zip code and the population of individuals who did not make a trip. Following Loomis et al. (2009) the dependent variable in the hybrid model can be estimated as follows:

$$\frac{Trips_i}{Population_i} = \left(\frac{Trips_i}{Participations_i}\right) * \left(\frac{Participations_i}{Population_i}\right) \tag{4.1}$$

The intensive margin $\frac{Trips_i}{Participations_i}$ defines the change in level to which the existing activity is undertaken. My dataset allows for the tracking of individuals through time by observing them making multiple trip occasions. On a given day for a specific trip, I know whether it is the individual's first trip (or tenth) in our sample timeframe. I also observe participants on each trip occasion at all parks from a given population. Therefore, I observe the intensive and the extensive margins of individual trips and can control for the participation of each reservation by counting the number of trips made to Oregon State Parks by an individual through time.

4.3. Data

4.3.1 OPRD Reservation Data

OPRD uses the third-party reservation system *ReserveAmerica*, a product that provides online campsite reservations processing for various state, provincial, private, and local government parks, campgrounds, and conservation agencies in North America. The reservation system provides a rich set of information on a population of recreators at a location through time and requires recreators to make an account before they reserve a campsite. This unique account id is what allows observation of individuals making multiple decisions on whether to make a trip through time. I obtained use of the *ReserveAmerica* data for OPRD sites through a public records request for all reservations which occurred from 2018 to 2021. The dataset provides information on which park was reserved, the individual id, the zip code of the individual making the reservation, the order date, the status of the reservations (cancelled, arrived, or no show), the arrival and departure dates, what type of site was reserved (tent, cabin, RV site, etc.), the number of visitors at each site and the full price paid.

Thirty-five (35) of the parks with reservable campsites were observable over the complete time period. These parks are shown on a map of Oregon in Figure 4.1. The dataset provides a full population of recreators who decided to make a reservation for a camping trip to these sites. Figure 4.2 provides four maps of all observed reservations by zip code for each year from 2018 to 2021. Figure 4.2 highlights the demand for camping at Oregon State Parks is not limited to local residents but is national in scope. Each reservation in the figure is classified as either active, cancelled or no-show. As expected, cancellations did increase substantially during 2020. Due to the pandemic, SAH orders and very active wildfire season in 2020, there were disruptions to park service across all parks. OPRD closed its campgrounds from March 23rd to June 8th due to COVID-19. After the reopening of parks on June 9th, recreators who made their reservation prior to SAH orders for June to August 2020 were honored while other recreators resumed the process of deciding to make a camping reservation. During this period, the reservation window was shortened from 9 months to 30 days which likely had a large impact in reservation patterns. Furthermore, there were also fewer sites to choose from due to numerous factors. OPRD was not fully staffed due to a revenue fall. Park managers may have used their discretion to make decisions on various park-specific closures. Some parks remained closed for longer periods, some closed entire camping loops, while cabins and yurts remained closed at others. These impacts can be controlled for to some degree such as an indicator for the mandatory period of closures and the park-specific fixed effects. However, the exact restriction of the supply of sites and timing is less known. Nevertheless, recreators from all across the country continued to make trips to Oregon during 2020. For our main analysis, I examine the set of recreators who made a reservation and fulfilled that reservation by traveling to the park and checking in.

4.3.2 Travel Cost

The cost of travel is the key component to estimating welfare associated with a recreational trip. The sample contains recreators from across the United States planning to recreate at Oregon State Parks. Given this national population, driving may not be a realistic assumption under this condition given a share of recreators may have flown to the nearest airport and rented a vehicle to travel to their recreation destination, assuming the probability of flying to the recreation site increases the further away the recreator has to travel. The main analysis therefore restricts the set of potential recreators to individuals living within 800 miles of their park destination. This assumption follows from English et al. (2018) which found recreators located within 500 miles of a recreation site almost always drove and those over a distances of 1500 miles almost always flew, and the convergence point of the switch between the two modes occurred at roughly 800 miles. This assumption reduces our dataset size to 1.02 million observations but still retains 80 percent of the entire sample of individuals camping at Oregon State Parks from 2018 to 2021.

I calculate travel costs using the distance and travel time between the origin zip code and the destination of each campground. For each individual zip code, I identify and match to a Census Zip Code Tabulation Areas (ZCTAs) using the centroid of each ZCTA.[43] I calculate the travel distance and time from each origin to each park destination using Google's Distance Matrix API. The distance and travel time are based on the best estimates of what is known about both current and historical traffic conditions between two points using the road network of Google Maps.

For gasoline cost, I link individual Petroleum Administration for Defense Districts (PADD) from the Energy Information Administration (EIA) to each recreators origin. Given our 800-mile distance restriction, the set of recreators contained two PADD regions, west coast (PADD 5) and the Rocky Mountains (PADD 4). The arrival date was linked to the weekly prices reported by the EIA PADD origin, linking the closest measure of gasoline prices in the region on the day the individual made the trip to the park. For the departure date, all recreators were assume to face prices of the park's region, PADD 5. For average fuel economy, I assume various vehicles based on the site type reserved for that trip. RV sites are assumed to accommodate a light-duty long vehicle and thus the average fuel economy and operational cost of light-duty long vehicles where used. For all tent, cabin, walk-to, primitive or yurts sites, I assume light duty small vehicle average fuel economy and their associated operational cost. Average fuel economy by year were collected from the U.S. Department of Transportation Office of Highway Policy Information by vehicle type.[44] Operational cost by year were collected from the Triple AAA reports on average Driving Cost by vehicle type.[45]

[43] ZCTA centroids are not always located near a road. For the few ZCTA which returned NULL values, I manual directed the centroid to the nearest road.
[44] https://highways.dot.gov/
[45] https://exchange.aaa.com/

For the value of time, we assume the individual is constrained by their labor/leisure trade-off (Lupi et al. 2020). The appropriate value of the opportunity cost of travel has long been researched and is often extrapolated from the reported individual's average income level (Shaw 1992; Fezzi et al 2014; Lloyd-Smith et al. 2019; Lupi et al. 2020). I employ a lower wage rate of 1/3 the average household income as per other research in field (Fezzi et al 2014; English et al 2018; Gellman et al. 2022b). The administration data does not provide individual demographic information on income and therefore I link each recreationalist's reservation to the median household income at the census ZIP Code Tabulation Areas (ZCTAs) for each year using U.S. Census Bureau. I then calculate the wage rate by dividing the household income by 2,080 which assume full-time employment to calculate the per hour wage rate following previous research (English et al. 2018).

I assume a per trip travel cost function as follows:

$$TC_{ipjt} = \frac{[C_{rpjt} * D_{ipt}] + Fee_{ipjt}}{n} + VTT_{it} * c \tag{4.2}$$

Where D_{ipt} represents the distance traveled between ZTCA to and from park p for individual i at time t. Roundtrip distance cost are represented by C_{rpjt} which sums the out-of-pocket driving cost of gasoline given departure PADD region r and per-mile maintenance and per-mile depreciation for an average vehicle based on park and campsite j in time t. Fee_{ipjt} is the reported fees for the campsite j reserved for individual i at time t. The sum of the costs is then divided by the number of visitors in the party reported in the reservation (n). VTT_{it} is the value of time for the individual who reserved the site and $T_{ijt}$is the time spent traveling to the location. All associated cost are adjusted for inflation and are reported in 2018 US dollars.

4.3.3 Covid-19 New York Times Data

COVID-19 infection rates are collected from *The New York Times* database on GitHub.[46] This database provides daily case counts, case averages, case rates per 100k, death counts, death averages, and death counts per 100k. Individual recreationists are linked to their respective COVID rates by county of origin and park by date of arrival on the park reservation. Linking the date of arrival provides a direct representation of the current COVID condition at the time of the recreators travel to the park. Rates are separated into the county where the recreators are coming from

[46] https://github.com/nytimes/covid-19-data

(Recreator Rate, RR) and the county of where the parks are located (Park Rate, PR). Table 4.2 provides averages of various COVID indicators from RR and PR.

The New York Times also reported on COVID-19 by assessing five different risk levels. Low risk is defined as a per capita case rate of 1 or below per 100,000 people. A moderate risk is defined with an per capita case rate of above 1 and less than 3 cases. A high-risk case level is defined of a per capita case rate above 3 but below 11 cases. A very high-risk level per capita risk is higher than 11 cases but below 45 cases. Lastly, extremely high risk is a per capita rate of above 45 cases per 100,000.[47] This risk assessment allows me to pursue a binning method to see how risk levels impacted recreational behavior by linking the risk assessment to the county of origin and park the day of arrival. Figure 4.3 shows the average and maximum per capita rate within our study range.

The impact from COVID-19 could have many effects on a decision-making process. Resident levels or the infection rate of the destination could induce recreators to cancel planned trips, not show up or induce them to leave. It could induce some recreators to flee high case count areas to ones with lower case counts as found by Volenec et al. (2021). On the other hand, people in high case count locations may stay home given the increased risk of spreading the infection more. Coupled with the relatively safer option of camping outdoors compares to staying in hotels, COVID-19 also had the potential to make camping more attractive to individuals who are not normally participating in this type of outdoor recreation, introducing a new population to the benefits of participating in the great outdoors. The assumption behind the impact of COVID-19 risk assessment is likely impacted by the individuals risk aversion level as found in other research (Landry et al. 2020). Though our analysis does not observe the individual risk aversion, our dataset can observe how risk information impacted overall visitation levels.

To identify the varying impacts the public risk advisories can have on a recreators decision to take a trip, I create two indicators on whether at the time of arrival the county level of the recreator was between moderate and high risk or if the county was at very high and extreme risk. For the impact of whether the park counties risk rate had an impact, I create an indicator determining if the recreators' county was higher than the park county on the day of the trip.

[47] Low risk was defined by counties reporting an average daily rate of less than 1 case per 100,000. Moderate risk reported about 2 cases per 100,000. High risk of about 3 or more cases per 100,000. Very high risk reported a average daily case of more than 11 cases per 100,000. Extremely high risk was when the daily rate case was more than 45 cases per 100,000. Reported: https://www.nytimes.com/interactive/2021/us/covid-risk-map.html

4.3.4 Park Air Quality Data

The availability of park-specific environmental quality data such as weather have increasingly been added to models of recreation behavior (Mendelsohn et al 1999; Loomis et al. 1999; Dundas and von Haefen 2020, 2021, Chan et al. 2020; Gellman et al. 2022b). Oregon State University's PRISM database allows for the ease of collection of park-specific weather variables such as temperature (minimum, average, maximum) and precipitation.[48] Our previous findings in chapter 2 and 3 suggest weather variables do influence visitation to public land. Here I control for the realized condition at a park by collecting the actual temperatures observed on the day of the reservation arrival date. Daily temperature variables at each park can control for park conditions which may influence the decision to make a camping trip. The mean temperature in Fahrenheit is included and I hypothesize the relationship should have a positive impact as temperatures warm throughout the year. Daily precipitation for each park (inches) is also included and I hypothesize the relationship should have a negative impact on participation.

Air quality is another environmental factor that may impact recreation choices. In 2020 there were massive wildfires in Oregon in late summer burning nearly 2 million acres of land (NWCC, 2021). A total of 32 parks experienced very high levels of AQI for 10 straight days in 2020. There was also significant fire activity in 2018 and 2021, which burned 1.3 million and 1.5 million acres, respectively. 2019 was relatively moderate for Oregon's wildfire season with an estimated 249,000 acres burned (Williams, 2019; NWCC, 2021). Figure 4.4 illustrates the variation of high AQI days during the four-year study period.

AQI is a health warning advisory system connected to risks associated with the level of pollutants in the air. The scale of runs from 0 to 500 and is based on 6 different categories. The higher the value, the greater the air pollution and health concern. A level of Good (0 to 50 AQI) suggest the air quality is satisfactory. A Moderate level (51 to 100 AQI) suggest the air quality is acceptable but there might be some risk to a few individuals. Unhealthy for sensitive groups (101 to 150 AQI) suggest members of sensitive groups may experience health impacts and the general public is less effected but still may endure some health impacts. Unhealthy levels (151 to 200) suggest members of the general public may experience health impacts and those who are sensitive will likely experience more serious impacts. Very unhealthy levels (201 to 300) ensure the risk is raised for everyone and all individuals are impacted by the health advisory. Hazardous levels (301>) impact all individuals and is considered an emergency condition. Many of the

[48] https://prism.oregonstate.edu/

recommendations of higher AQI limit the advised amount of time spent outdoors and therefore can negatively impact the decision to make a camping trip (Gellman et al. 2022a; Gellman et al. 2022b).

Daily AQI data is available in geographical areas with monitoring stations. The Environmental Protection Agency provides information at the daily level where available.[49] All daily estimates from Oregon's monitoring system were collected and averaged to the county level. In Oregon, not every county had a monitoring system nor did every county have a full set of observed days. I interpolate between missing daily AQI values and match each park county to the nearest reporting AQI county on the day of arrival for each reservation. Using the AQI risk rating system, the rating is incorporated into a binary indicator to capture two impacts. First, an indicator is defined for whether or not the AQI is between 101 >200, which corresponds to impacts to health for sensitive groups and some reported negative impacts to of the general public. The other indicator determines if the AQI was above 200, which captures both very unhealthy and extremely unhealthy air quality. The second group captures the impacts of a health risk advisory that applies to *all* individuals. Both bins of sensitive/unhealthy and very unhealthy/extremely are relative to days which have AQIs of good or moderate advisories.

4.4 Methodology

The goal of this analysis is to estimate the welfare changes from observed individual decisions to camp at an Oregon State Park in two distinct periods, i.e., pre- and during COVID-19. I am both interested in the yearly variation during the two time periods and how overall health risk advisories impacted welfare during this time. I focus our analysis on a hybrid individual-zonal travel cost method following Loomis et al (2009). This method allows me to estimate these effects by examining the rate of individual trips per capita. This method is similar to the zonal travel cost model. However, in our method we maintain individual data associated with each of our observations within our dataset. The per capita rate is calculated by the population of the ZCTAs minus the observed individuals reserving a site at any other Oregon State Park on the day of arrival. I then identify the daily reservation rate from each location to find the participation level of the given population, identifying the share of campers from each ZCTA. Next, I determine how many trips each individual took in a given year which calculates our participation rate. I lastly convert

[49] https://www.epa.gov/outdoor-air-quality-data/download-daily-data

my final participation rate in per capita terms (Loomis et al 2009; Gellman et al 2022b). The estimating equation for the hybrid individual/zonal travel costs model is specified as follows:

$$\frac{Trip_{zipt}}{(\frac{(Pop_{zy}-R_{z_{p-1}}t)}{R_{pzt}})} = \beta_0 + \beta_1 TC_{zipt} + \beta_2 T_{pt} + \beta_3 Prec_{pt} + \beta_4 AQI_{c_p t} + \beta_4 COVIDRiskl_{p_c\, z_c t}$$

$$+\beta_5 OPRD_t + \beta_6 Days_{it} + \rho_t + w_t + z_i + \varepsilon_{ct} \quad , \qquad (4.3)$$

where $Trip_{zipt}$ is the number of trips per year taken by individual i in zip code z to park p on the day of arrival t. We include the number of trips per year to control for the intensive margin of the individual decision to take trips in a given year. The extensive margin is represented by the population, $Pop,$ of zip code z in the corresponding year y minus all other campers making a reservation (R) at a different park on the arrival day from the corresponding zip code. This is all over the number of campers reserved in zip code visiting a park on the arrival day. $TC_{zipt}$is the individual travel cost for each trip in zip code *z* to park *p* on arrival day *t.* The TC varies over time with gasoline prices and site type j. T_{pt} and $Prec_{pt}$ is the mean temperature in Fahrenheit and precipitation in inches for each park on the arrival day, respectively. AQI_{ct} is a binary indicator for whether the AQI was between unhealthy for sensitive groups and unhealthy or the AQI is between unhealthy to hazardous risk advisory. The AQI is linked to the closest county, $c,$ for park at time of arrival, t. $RiskLevel_{p_c\, z_c t}$ are binary indicators of per capita risk level defined by *The New York Times* for the county where the park resides and the county of origin of where the individual is departing from on the arrival day. $OPRD_t$ is a binary indicator for when Oregon Parks and Recreation Department cancelled reservations from March 23rd to June 8th. $Days_i$ controls for the number of days stayed at the campsite for the reservation of individual i. Fixed effects control for park-specific characteristics γ_p, day-of-week w_t, and zipcode z_i. I cluster the standard errors across county of reservation origin to control for heteroskedasticity of our observations within each county. I use a natural log transformation of the dependent variable allowing for a simplified calculation of the consumer surplus as the reciprocal of the travel cost coefficient and following previous research in the field (Haab et al. 2002; Loomis et al. 2009).

The main interests are in the marginal utility and disutility of various conditional factors at a given park on a given reservation day. I calculate this by taking the ratio of the coefficient of the conditional public health advisory indicators $(AQI, RiskLevel)$ and coefficient on travel cost.

Thus, the primary model focuses on the population of recreators who reserved and made a trip during the sample timeframe.

4.5 Results

Table 4.3 columns 1-4 are annual model estimates from estimating eq. (4.3) using individual trips per capita as the dependent variable. The travel costs coefficients are inflation adjusted to January 2018 US dollars and thus can be compared across years. The reciprocal of the travel cost coefficients provides the consumer surplus per day of camping at Oregon State Parks, reported in the table in the row labeled willingness to pay (WTP). In 2018 and 2019, the travel cost coefficients are negative and significant and translate to daily consumer surplus values of \$179 and \$186, respectively. Comparing this to other estimates using similar administrative data, our measurements are on the higher end of Lloyd-Smith et al. (2020) which estimated a range of \$81-\$178 per person for overnight camping in Alberta, Canada. However, our estimates are much lower than Gellman et al. (2022b) which find consistent estimates around \$400 per trip. Given the total number of fulfilled reservations for years 2018 and 2019, the net economic value of camping at Oregon State Parks was \$62.6 and \$64.7 million, respectively, suggesting a 3.2 percent growth in economic value in the 2 years pre-COVID. The park-specific quality parameters on temperature and precipitation reflect intuitive demand impacts, suggesting rising temperatures increase demand and more rainy days decrease overall demand. Campers in 2018 experienced high levels of wildfire activity and the coefficients on AQI alert days are negative and significant. By taking the ratio of travel cost coefficient and the disutility of a high AQI indicates a welfare loss of \$50 due to very unhealthy or hazardous air quality conditions. Our findings are within range of those calculated by Gellman et al. (2022b) of \$62/day. Gellman et al. (2022b) further controlled for the substitution effect as well as cancellations which increased the welfare loses per person to \$107.

The following year (2020) marked the start of the COVID-19 pandemic. Overall, SAH orders and park closures reduced the number of total reservations fulfilled in 2020. The number of reservations fulfilled fell by 35 percent from the previous year. During this same period, the daily consumer surplus increased by \$20 dollars (\$206) while the annual economic value dropped substantially to \$46.6 million. This suggest that although the willingness to pay grew by 9.7 percent, the annual economic value fell by 27.9 percent from the previous year. Long closures, lower staff and decreases in availability of sites served far fewer individuals overall. This is supported by the negative coefficient on the indicator for park closures during March 23rd and June

8th where OPRD unilaterally halted reservations. Nevertheless, our public risk indicators suggest a welfare benefit during the 2020 pandemic year for individuals coming from counties where the per capita county COVID rates were medium to high risk and very high to extreme risk. On average, the daily consumer surplus rose about $76 to $91 on days where the recreator is experiencing elevated risk of COVID-19 in their home county. For health advisory risk from AQI levels, there were daily welfare losses similar to that of 2018. Very unhealthy and above AQI caused roughly $38 in losses to daily consumer surplus.

The year following the pandemic, 2021, saw a 13 percent rise in daily consumer surplus - an increase of $32 ($238).[50] This year did not entail unilateral closures, however, though disruptions and pandemic precautions where still occurring, a national rollout of vaccines likely impacted the risk perceptions of public health advisories of COVID-19. Reservations during this period surpassed pre-pandemic levels and by the end of the year, the annual economic value generated by camping at Oregon Parks in 2021 was around $85.7 million or nearly 34.7 percent more than estimated levels pre-pandemic levels. The public risk indicators differ during this period as well. In 2021, the findings suggest the county level of risk played no significant role in the decision to make a trip.

As for the health risk advisories, AQI also did not appear to impact decisions during 2021. Each AQI category had no significant impact on welfare. This could be due to the relatively lower levels of days where parks where consistently exposed to bad air quality. The year was an active wildfire year but only three (3) parks experienced very high AQIs for 2 consecutive days. However, this assumption would then suggest 2018 would have behaved similarly. Other explanations could be that by 2021 there was enough pent-up demand from the previous year through SAH orders, closures and general disruption that public health advisories did not impact individuals risk assessment in a traditional way.

The full model results are presented in column 5. This model pools all the years together and uses yearly indicators to control for yearly variation. Our findings from the annual model hold in our pooled model. The average daily consumer surplus value of Oregon camping is estimated to be roughly $205. When examining the public health risk of air quality, we find a negative impact suggesting a welfare loss of on average $37 during this time period with the presence of very unhealthy AQI and above across all years. Public health risk indicators suggest that when

[50] A cross model test finds the travel cost coefficient across 2019 and 2021 are statistically different. In fact, travel cost coefficient across 2020 and 2021 or 2020 and 2018 are all statistically different across models at the 1% level. Whereas we reject the null at the 5% level for a statistical difference between 2018 and 2019 travel cost coefficient.

recreators were experiencing elevated levels of COVID-19 risk in their county, the value of a camping trip increased $31 per day.

A key finding is highlighted in the full model. When I control for the pre- and during COVID-19 time periods, the indicator reveals substantial welfare benefits to during COVID camping trips ($62 per day). This is not to say the impacts of COVID-19 increased overall welfare but that during a global pandemic access to recreational spaces such as camping increased in economic value generating welfare benefits for those participating in recreation. The mechanism is likely a combination of the reduction of access as well as the risk associated with other substitutes such as international and domestic air travel, hotels, indoor activity venues and other activities which involve close proximity making social distancing difficult. These make the relative low risk of outdoor activities such as camping more attractive.

4.5.1 Robustness

Table 4.4 illustrates how the various fixed effects improve the fit of model specifications. I begin with only yearly fixed effects, Table 4.4 col. 1, and add a different fixed effect in each successive column. Col. 2 includes zip code level effects, followed by park level controls, weekday indicators and finally the number of nights stayed during the reservation. Each inclusion of these controls improves the fit of the model with the greatest improvement of the zip code level controls. Lastly, I include the results from robust standard error versus clustering on county and the results are stable.

4.6 Discussion

This analysis examines the welfare impacts of how public health risk advisories have impacted the consumer surplus of camping to Oregon State Parks over the years of 2018 to 2021. The public health risk included COVID-19 risk levels and air quality health advisories. Counties with high risk of COVID-19 infection rates experienced positive welfare benefits through camping at Oregon State Parks. The overall economic value generated also increased from pre- to during COVID-19. This highlights the crucial role recreational spaces had during the pandemic. During COVID-19, the economic value associated with Oregon Parks camping increased by $5 million even with the large economic value losses in the first year. The investments in public parks provided extensive economic value during the global pandemic and provides insight into the benefits we gain by conserving and maintaining our public parks. These findings support other research which show public lands play a vital role in public health and welfare (Loomis et al. 2009; Landry et al. 2020; Volenec et al. 2021; Shartaj et al. 2022). I also find supporting evidence of the welfare losses associated with AQI health advisory warnings. These impacts create significant welfare losses to outdoor recreation camping for the years which experienced days of degraded air quality. AQI impacts are likely to increase given wildfires in the PNW occur under warm and dry conditions which are projected to occur more frequently under current warming trends in the region (Halofsky et al. 2020).

In future work, I plan on expanding this research to allow for the substitution of sites among recreators and explore the impacts of cancellations. Currently, the hybrid individual-zonal travel cost is limited in controlling for each site. The participation rate does not control for individuals choosing a different site given the conditions of the preferred site. This, of course, is important given the focus of AQI at the park specific location. Recreators may shift their destination from one park to the other given the parks realized AQI on the day of the trip. This is likely biasing the estimates found in this analysis for certain years, though virtually all parks were impacted by the wildfires in late summer of 2020. Therefore, expanding the model to a discrete choice framework such as a random utility model, would expand on the validity of the estimates found here by flexibly allowing for substitution among sites in response to changing conditions.

Another research path would be to utilize cancellation within the dataset. In this analysis, the set of recreators were reduced to those that made a trip. However, all reservations, no shows and cancellations are observable and linked to a given recreator. Therefore, I can uniquely observe a group of individuals who may actively have substituted amongst parks given park quality by cancelling and reserving elsewhere. The cancellations data could also provide even further insights into welfare impacts of public health advisories following other emerging research in recreational cancellation impacts (Gellman et al. 2022b). Lastly, this research focused on the two years before and the two years during the pandemic. Inclusion of more years, such as 2022 and 2023, could explore how the economic value of camping faired after other substitutes began to return to the market.

The timing of future public health risk such as a global pandemic and air quality advisories are unknown and uncertain. However, both of these public risks are projected to increase in future modeling scenarios (Halofsky et al. 2020; Marani et al. 2021). Understanding the role public land and outdoor recreation play in public health scenarios is helpful in framing the true value of the benefits generated.

4.7 List of Figures

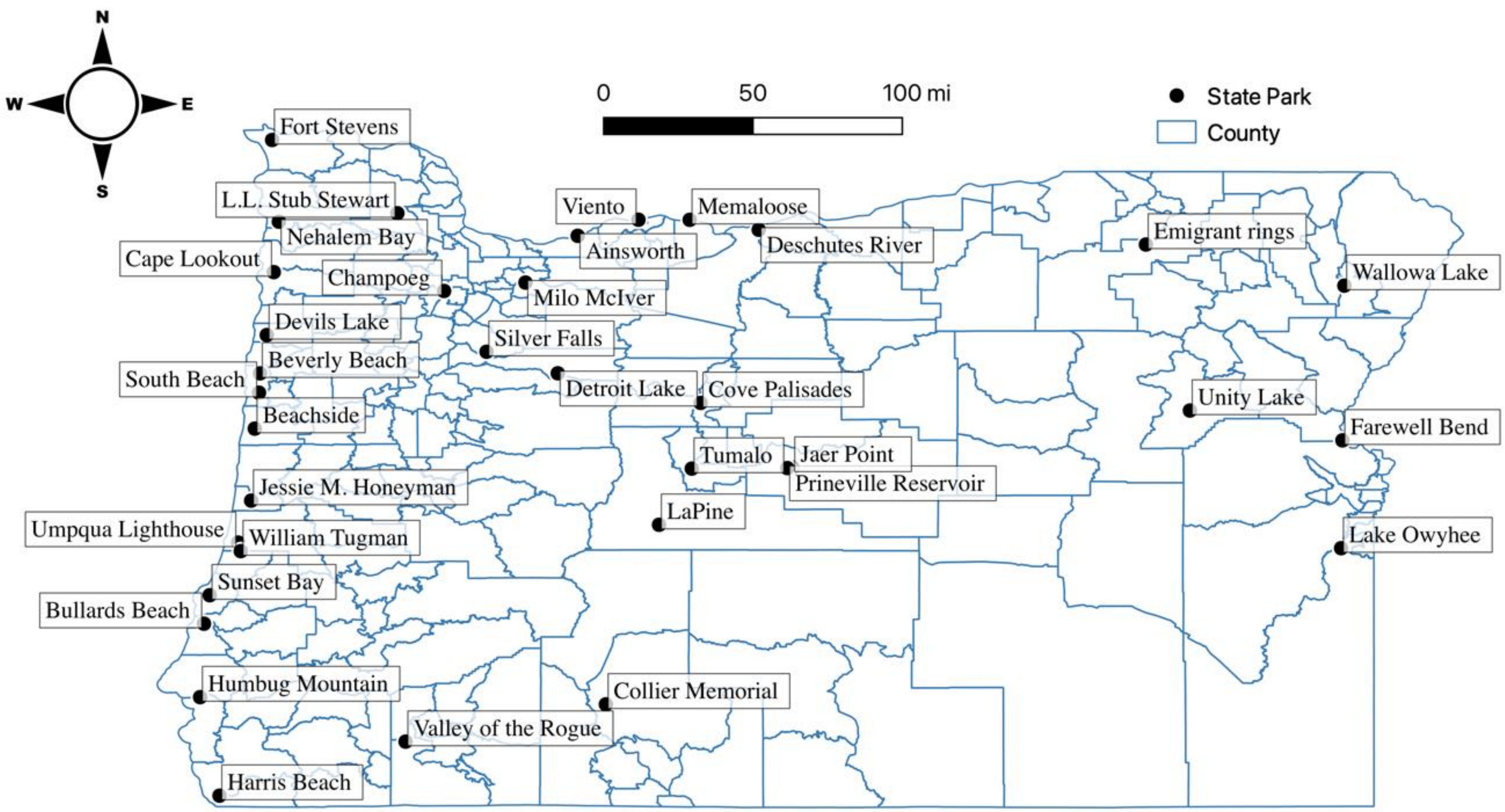
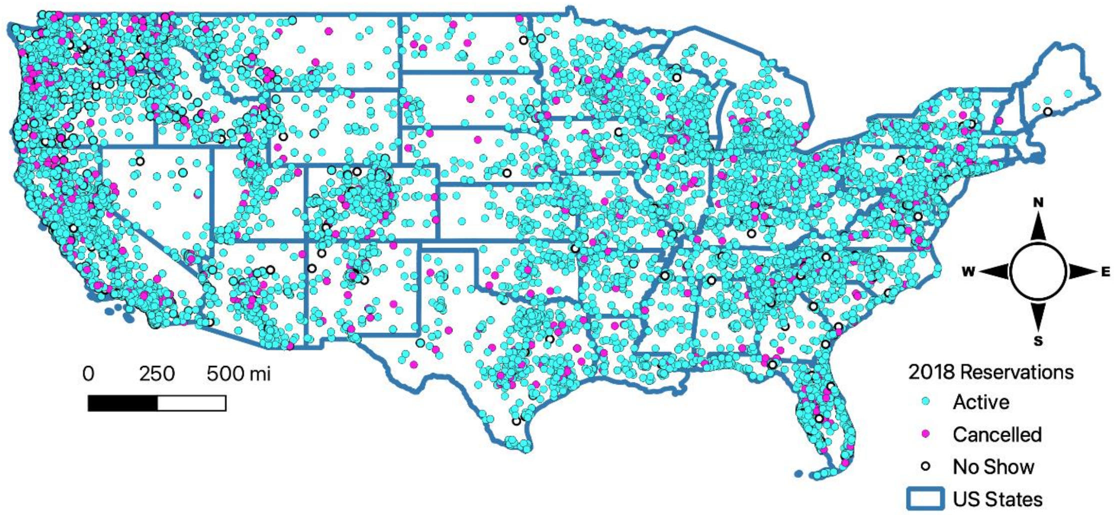
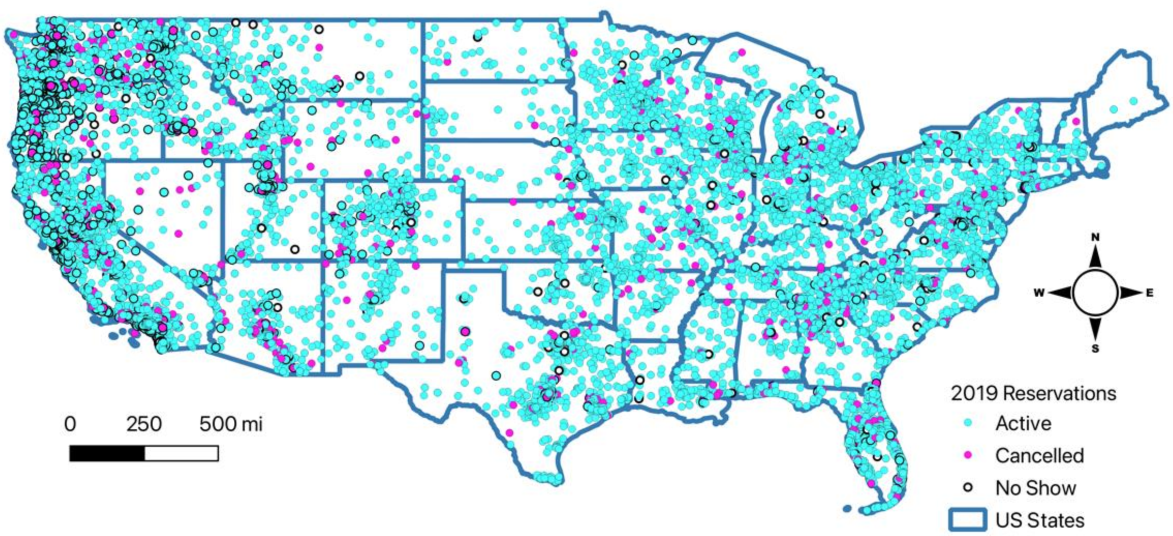


Figure 4.1: Map of 35 OPRD Parks with Camping Facilities

Note: Map shows the state of Oregon with white outlines denoting counties and white dots showing OPRD units with camping reservation data for this analysis



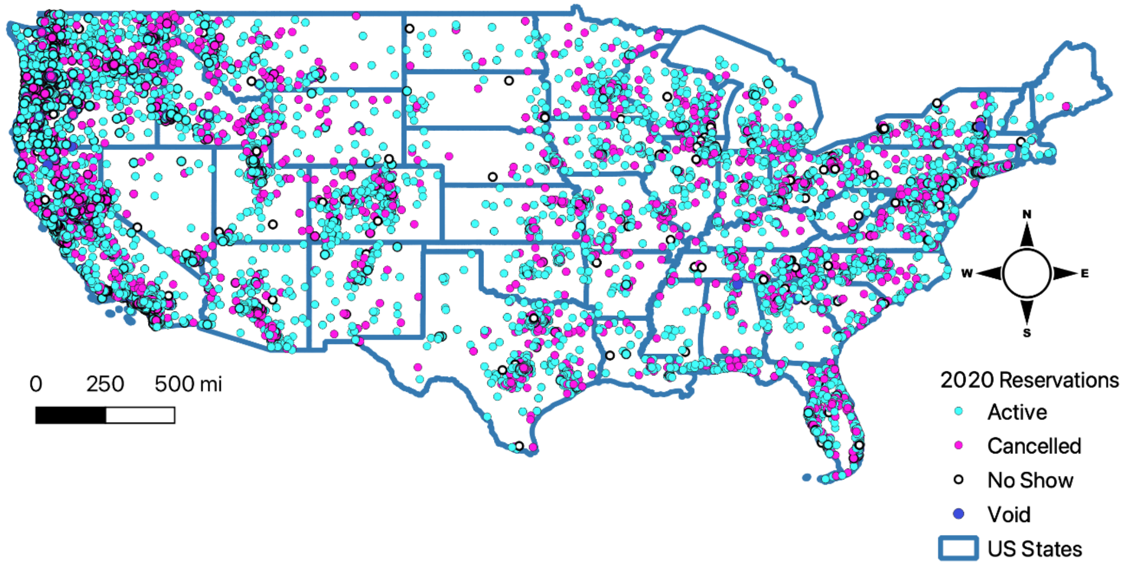
MAP 1: Recreators Origins for OSP Reservations in 2018



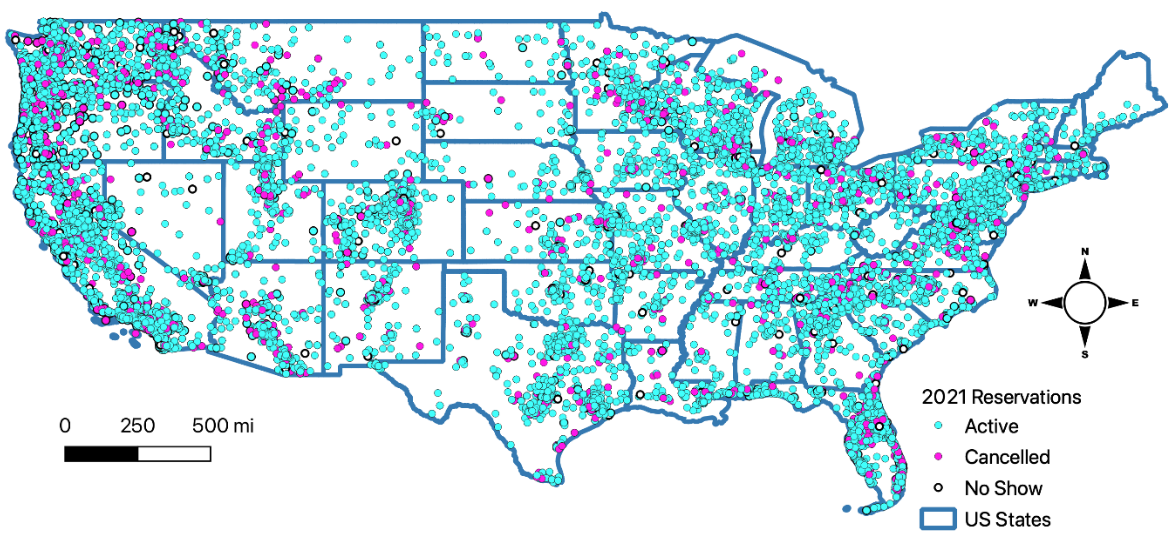
MAP 2: Recreators Origins for OSP Reservations in 2019

Figure 4.2: Location of Recreators Camping at OPRD Park

Note: Map shows the United States with blue outlines denoting states. Blue reservation is active meaning the reservation was fulfilled. Pink is cancelled reservations. Black outline dots are reservations where the recreators did not show.



MAP 3: Recreators Origins for OSP Reservations in 2020



MAP 4: Recreators Origins for OSP Reservations in 2021.

Figure 4.2: Location of Recreators Camping at OPRD Park (Continued)

Note: Map shows the United States with blue outlines denoting states. Blue reservation is active meaning the reservation was fulfilled. Pink is cancelled reservations. Black outline dots are reservations where the recreators did not show.

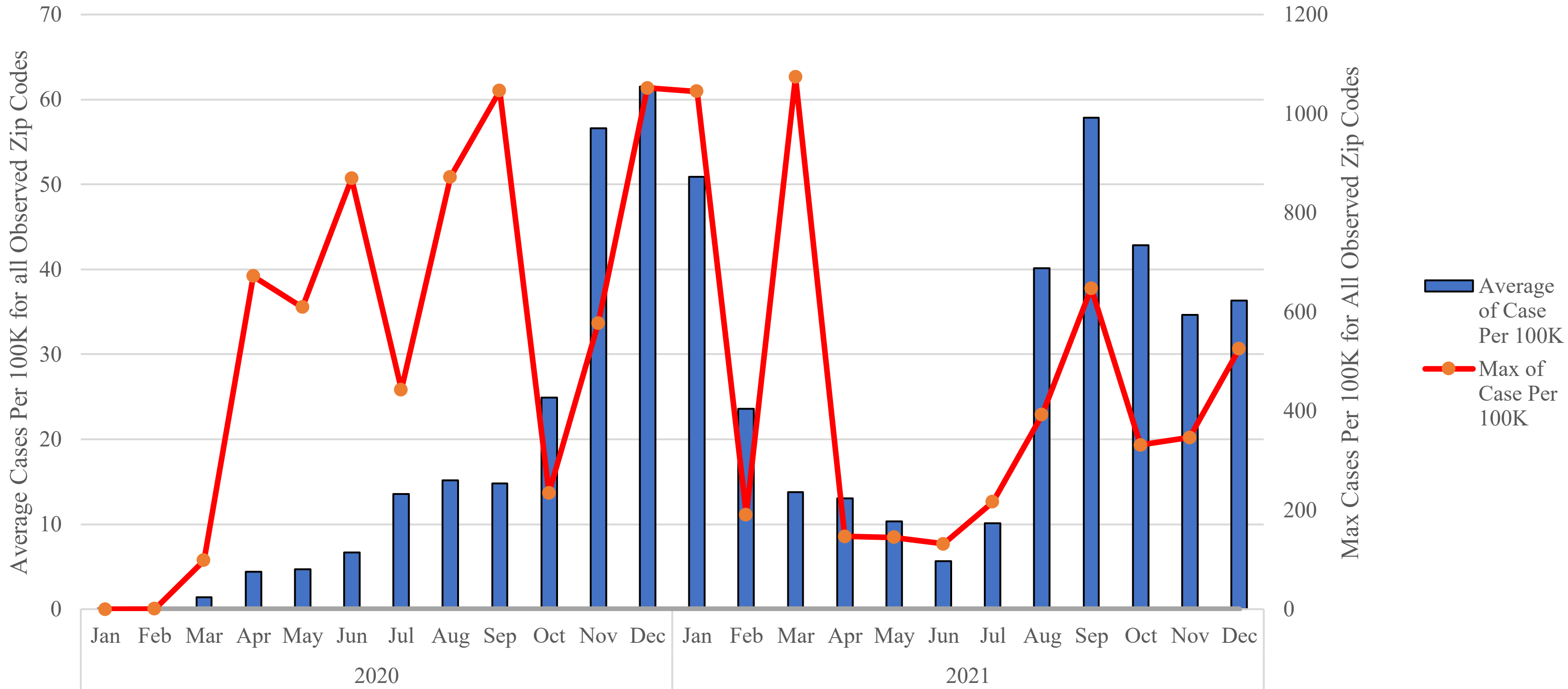


Figure 4.3: Average and Max Cases per 100K Observable in All Zip Codes

Note: The left-hand scale is the average cases per 100k people of all counties observed in the analysis over the two years during the study timeframe. The right-hand scale is the max cases per 100k people in the observed counties in the study.

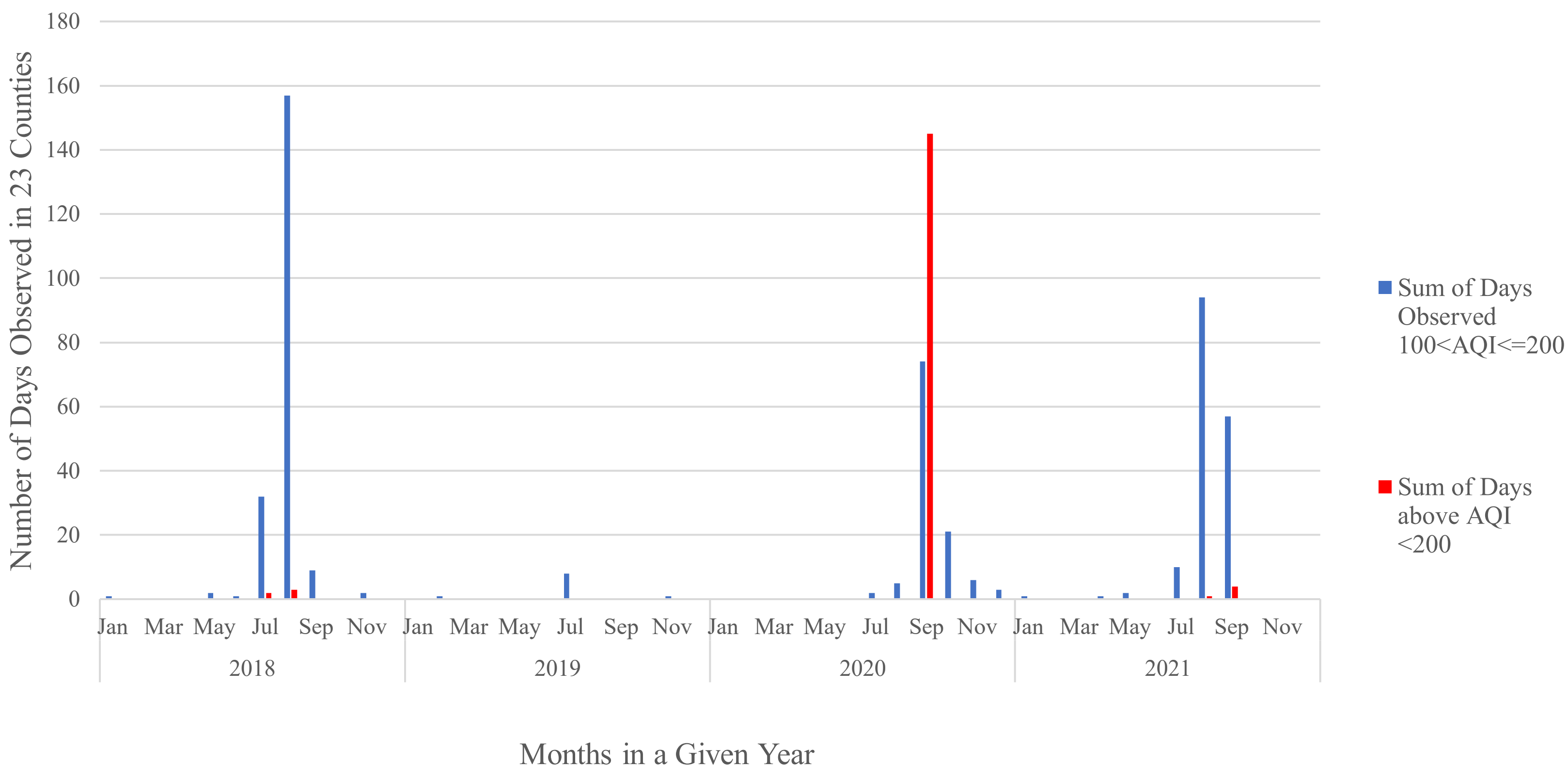


Figure 4.4: Number of Air Quality Advisory Days Observed in the 23 Counties where Park are Located

Note: The graph presents the number of days observed in all counties with state parks at two levels of unhealthy AQI over the four years. 100<AQI<=200 is a health advisory of unhealthy to sensitive groups and some of the general public. An AQI above 200 is unhealthy for all individuals.

4.8 List of Tables

Table 4.1: Summary statistics Reservation 2018-2021 All & Reservations within 800 miles

Year	Full Set of Recreators	<800 miles	Fee Paid	Days Stayed	# of Visitors	Gas Price	Distance Miles	Mean Temp (°F)	Precipitation (Inches)	AQI	RR Cases avg. per 100k	PR Cases avg. per 100k
All	1,284,662	1,025,323	$74	2	3	$3.27	191	57	.09	27	8	8
2018	349,718	268,944	$70	2	3	$3.34	186	57	.07	27	0	0
2019	348,176	268,679	$71	2	3	$3.36	187	57	.08	20	0	0
2020	226,275	193,307	$78	2	3	$2.81	191	58	.08	33	8	6.5
2021	360,260	294,393	$78	2	3	$3.76	194	57	.09	25	20.6	24

Note:

RR is the COVID rates from the location the recreator is coming from PR is the rates of the county where the park unit is

Table 4.2: Summary statistics of COVID Rates for Reservation Data

Status	RR Case	RR Cases avg. per 100k	RR Deaths per 100k	PR Cases	PR Cases avg. per 100K	PR Death Avg. per 100K
2020						
All	42.7	7.45	0.09	8.2	5.8	0.08
Active	47.8	8.44	0.1	9.5	8.4	0.12
Cancelled	32.4	5.6	0.09	7.4	5.1	0.07
No Show	59.1	8.44	0.1	9.8	8.2	0.11
2021						
All	86.2	20.9	0.21	28	24.6	0.3
Active	84.6	20.6	0.22	27	24.1	0.3
Cancelled	90.8	21.6	0.21	31.3	26.3	0.31
No Show	96.2	20.9	0.2	29.6	26.5	0.31

Note: RR is the COVID rates from the location the recreator is coming from PR is the rates of the county where the park unit is located.

Table 4.3: Hybrid Individual Zonal Travel Cost Model Results

VARIABLES	(1) 2018	(2) 2019	(3) 2020	(4) 2021	(5) All years
TC Inflation Adjusted	-0.006***	-0.005***	-0.005***	-0.004***	-0.005***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
101>AQI > 200	-0.081***	-0.246**	-0.108**	-0.076	-0.086***
	(0.025)	(0.105)	(0.044)	(0.053)	(0.022)
AQI > 201	-0.278**		-0.188***	-0.0683	-0.181***
	(0.118)		(0.045)	(0.115)	(0.038)
2020 Closure			-0.297**		-0.397***
			(0.131)		(0.111)
Extremely-Very High in Origin			0.368***	-0.039	0.158***
			(0.045)	(0.081)	(0.036)
High-Medium in Origin			0.443***	-0.067	0.151***
			(0.051)	(0.080)	(0.034)
Origin Covid Rates > Park Covid Rates			0.027	-0.099***	-0.055***
			(0.021)	(0.026)	(0.016)
Post-Covid					0.303***
					(0.037)
Mean Temp F	0.022***	0.023***	0.011***	0.022***	0.020***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
PPT Inches	-0.316***	-0.111***	-0.173***	-0.159***	-0.182***
	(0.033)	(0.021)	(0.022)	(0.013)	(0.016)
Constant	1.987***	1.801***	-0.538	1.455**	2.133***
	(0.097)	(0.148)	(0.621)	(0.604)	(0.334)
WTP per day	$179	$186	$206	$238	$205
Observations	264,993	265,245	191,662	291,353	1,013,253
R-squared	0.553	0.522	0.510	0.496	0.513
Zip FE	YES	YES	YES	YES	YES
Park FE	YES	YES	YES	YES	YES
Weekday FE	YES	YES	YES	YES	YES
Days Stayed	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	YES
SE Cluster	County	County	County	County	County

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.4: Robustness Checks on Fixed Effects Controls

Robustness Checks on Fixed Effects Controls

VARIABLES	(1) Only Year FE	(2) Zip & Year Only	(3) Park, Zip and Year	(4) Park, Zip, Year, Day	(5) All years	(6) Robust Std. Errors
TC Inflation Adjusted	-0.004***	-0.004***	-0.005***	-0.004***	-0.005***	-0.005***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(1.44e-05)
101>AQI > 200	-0.123***	-0.125***	-0.116***	-0.096***	-0.086***	-0.086***
	(0.032)	(0.022)	(0.024)	(0.022)	(0.022)	(0.008)
AQI > 201	-0.075	-0.204***	-0.207***	-0.194***	-0.181***	-0.181***
	(0.053)	(0.051)	(0.043)	(0.042)	(0.038)	(0.016)
2020 OPRD Closure	-0.424***	-0.459***	-0.341***	-0.377***	-0.397***	-0.397***
	(0.153)	(0.113)	(0.102)	(0.108)	(0.111)	(0.069)
Extremely-Very High in RR	-0.272*	0.0809**	0.125***	0.120***	0.158***	0.158***
	(0.163)	(0.035)	(0.035)	(0.035)	(0.036)	(0.011)
High-Medium in RR	-0.270	0.109***	0.124***	0.124***	0.151***	0.151***
	(0.171)	(0.035)	(0.034)	(0.034)	(0.034)	(0.011)
RR > PR	-0.018	0.027	-0.047***	-0.055***	-0.055***	-0.055***
	(0.026)	(0.018)	(0.015)	(0.016)	(0.016)	(0.003)
Post-Covid	0.659***	0.413***	0.351***	0.388***	0.303***	0.303***
	(0.16)	(0.04)	(0.038)	(0.038)	(0.037)	(0.013)
Mean Temp F	0.014***	0.016***	0.021***	0.022***	0.020***	0.020***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0001)
PPT Inches	-0.127***	-0.154***	-0.180***	-0.185***	-0.182***	-0.182***
	(0.025)	(0.014)	(0.015)	(0.016)	(0.016)	(0.004)
WTP	$287	$237	$213	$227	$205	$205
Observations	1,013,253	1,013,253	1,013,253	1,013,253	1,013,253	1,013,253
R-squared	0.098	0.447	0.469	0.484	0.513	0.513
Zip FE	N	Y	Y	Y	Y	Y
Park FE	N	N	Y	Y	Y	Y
Weekday FE	N	N	N	Y	Y	Y
Days Stayed	N	N	N	N	Y	Y
Year	Y	Y	Y	Y	Y	Y
Cluster	County	County	County	County	County	No

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Chapter 5 Conclusion

Outdoor recreation is one of the main leisure activities in which we derive economic value from conservation efforts of public lands. This dissertation examines emerging issues surrounding outdoor recreation and public lands by using methods from the field of environmental economics and recreational ecology.

Chapter 2 examines the question posed by many journalists during the late 2010s: Is social media influencing our visitation to public lands? During the 2010s, public lands experienced a rapid increase in visitation. Many journalists claimed the rise in visitation and overcrowding was attributable to the social media and in particular Instagram. Instagram, a photo-sharing app, provided their users a virtual social network to share photos with their caption and the geolocation of the photo. It also gave users the ability to "go viral" with engaging content. Coupled with the location information, the mechanism of engagement and the emergence of influencers, many claims began to suggest the visitation increases and overcrowding at parks was due to Instagram. I began my investigation to check the validity to these claims by examining the regional impacts to Oregon State Parks. I identified four parks which had experienced high engagement from in-app users determined by their highest liked photo. Using a quasi-experimental difference-in-differences approach, I identified systematic difference between the high engagement parks from low engagement parks once Instagram had gained influence. Furthermore, when including Instagram data into our modeling framework the cumulative effect of highly engaging post led to an increase in visitation by 4 to 4.2% per month from all current and past influential photos. These results suggest the impact of Instagram was not felt by every park but by certain parks which generated high engagement with users within Instagram.

In Chapter 3, I expanded the scope of the analysis to National Parks in three steps. The first step, I replicated previous visitation modeling using National Park visitation data. The process helped develop my preferred model, which included a monthly panel structure and park-specific weather controls. I find the inclusion of park-specific weather quality improves the overall fit of the model while the price elasticity of gasoline does not significantly impact visitation as other research has found. In the second step, I explore Instagram's influence at National Parks using the methods developed in chapter 2. The results differed from our state-level analysis, finding across all National Parks there was a significant visitation growth once Instagram gained influence through a sustained user base in May 2012. However, when grouping parks based off user activity levels, only high engagement parks were impacted by the cumulative effect from all past and