Journal of Forest Economics, 2023, 38: 293–316

The Effect of the COVID-19 Pandemic on the Willingness-to-pay for Outdoor Recreation in Wilderness Areas

Matthew R. Sloggy[1*], Dede Long[2,3] and José J. Sánchez[1]

[1] *USDA Forest Service, Pacific Southwest Research Station, Riverside, CA, USA*

[2] *California State University, Long Beach, Long Beach, CA, USA*

[3] *Harvey Mudd College, Claremont, CA, USA*

ABSTRACT

Understanding behavioral changes in the usage of outdoor recreational resources is important for the management of landholding agencies and organizations like the US Forest Service or Bureau of Land Management. Although the costs of operating these resources are often contrasted with the values they offer, little is known about how the values of benefits change in times of crisis. This work investigates the effect of a public health crisis – the COVID-19 pandemic – on recreation patterns and economic values for two wilderness areas in California: Desolation Wilderness and the Inyo Wilderness Area. The effects of the pandemic are estimated using a set of count data models with a robust set of controls. Results show that the value of recreating in wilderness areas increased during the pandemic, albeit temporarily. Further, we find that the group size and duration are important factors that determine the value of forest recreation.

Keywords: Outdoor recreation, non-market valuation, pandemic, permit data, travel cost model

JEL Codes: Q26, Q23, L83

*Corresponding author: Matthew R. Sloggy, matthew.sloggy@usda.gov. We would like to thank Thomas Holmes, Forest Service Southern Research Station, for providing wilderness permit data as well as the participants of the W4133 working group meeting in Hood River, Oregon in April of 2022 for their useful and helpful comments. We also thank the anonymous reviewers and editor for their input in improving the manuscript.

ISSN 1104-6899; DOI 10.1561/112.00000566

1 Introduction

Participation in outdoor recreation in the United States of America (USA) reached a historic high in 2020 prior to the COVID-19 pandemic, with 53% of Americans ages six and over participating in outdoor activities at least once in 2020 (Outdoor Foundation, 2021). However, operation and maintenance budgets for public lands remained stagnant in 2020, which led to deferred maintenance backlogs on recreational infrastructure on public lands (Selin *et al.*, 2020). The COVID-19 pandemic drastically affected visitation to recreational sites and remains a salient public health threat (Rice *et al.*, 2020; Spennemann and Whitsed, 2021). When stay-at-home orders and physical distancing measures severely limited travel and recreational opportunities during the pandemic, certain types of outdoor recreation become safer options for people seeking to connect with nature and to socialize with small groups of friends and family, improving mental and physical health (Jackson *et al.*, 2021). As a result, the use of public lands for recreation increased during the pandemic (Shartaj *et al.*, 2022). For example, several news media outlets and non-profit organizations cited the COVID-19 pandemic as the main driver of an observed increase in the use of national parks (Outdoor Foundation, 2021; Forbes, 2021).

Despite media coverage, results in the literature are mixed with respect to the impact of the pandemic on recreation patterns. Findings differ based on site location, available amenities, and landscape attributes. For example, Landry *et al.* (2021) found that overall recreation levels declined during the pandemic. One possible explanation is that many recreation options are social in nature (e.g., football games; Lim and Pranata, 2021). This decline has had large economic impacts, as Spennemann and Whitsed (2021) found that changes in recreation patterns led to severe declines in economic activity. Contrarily, other studies concluded that the pandemic led to visitor booms within forests (Derks *et al.*, 2020a).

The changes in recreation patterns from the pandemic pose additional challenges as well as opportunities for federal agencies such as the National Park Service, the US Forest Service (FS), and the Bureau of Land Management (BLM), along with state, regional, and municipal entities that manage large quantities of land that provide recreation opportunities. Specifically, increases in visitation raise the risk of damage and also increase management costs (Buckley, 1991), as higher visitation levels might strain key ecosystem services, such as water resources, and increase wildfire risks (Derks *et al.*, 2020a). This is especially true for the western United States with a more arid climate (Osterkamp and Friedman, 2000) and a greater amount of public land (Leonard *et al.*, 2021) than the eastern states. Moreover, it is important for land holding agencies to understand the benefits of providing recreational activities to the public. As such, changes in resource values due to the pandemic, if permanent, justify additional investments to prevent degradation in ecosystem services due to overuse and deferred maintenance. Better information regarding these changes may help coordinate investments and make efficient management decisions.

Though many recreation studies focus on the frequency of visitation, the pandemic has impacted several other aspects of recreational patterns. For instance, some individuals feel less inclined to recreate in large groups (Rice *et al.*, 2020; Landry *et al.*, 2021) and have more flexible schedules (Spurk and Straub, 2020). Previous work in recreation demand typically ignores the impacts of group size, as well as the effect of additional time spent recreating. To fill gaps in the literature and provide key information that guides policies, we investigate how the COVID-19 pandemic has changed visitation, and thus valuation, of recreating in two wilderness areas in California, Desolation Wilderness and the Inyo Wilderness Area. We construct a dataset derived from a time series of visitation to wilderness areas from wilderness permit data, merged with weather and socioeconomic data to estimate a zonal travel cost model. The empirical model facilitates us to quantify the change in visitation and valuation occurring before and after the USA instituted a national emergency order. In addition, we investigate how group size and time spent affect individuals' valuation of recreational resources. A unique aspect of the study is its treatment of the pandemic. Many recreation demand studies examining the pandemic do not compare different representations of the pandemic, whereas this study does. This is also the first study to examine how the pandemic has impacted wilderness recreation, including overnight recreation.

Our study makes several contributions to the literature. First, we evaluate changes in the recreational value of wilderness areas due to the pandemic, measured by people's willingness-to-pay (WTP). To our knowledge, we are the first to do so for wilderness areas, which differ from other recreation areas considered in past research because the recreation activities in wilderness areas allow for easier social distancing. The changes in visitation have critical impacts on the ecosystem of the recreation sites, and the WTP for these resources is important for guiding future policies aimed at maintaining the environmental sustainability of outdoor recreational resources and the ecosystems they inhabit. By measuring the monetary-equivalent public benefit, that is, WTP, of wilderness areas and how it changes as a result of the pandemic, our results may be used to quantify the return of investments that maintain the natural capitals in wilderness areas and as inputs to evaluate the benefits and costs of alternative management strategies.

Importantly, we test whether the changes in valuation vary with the time since the pandemic emergency order. We find that given enough time, the recreational patterns observed after the pandemic will regress to the pre-pandemic level. This result is consistent with the outdoor recreation literature, where visitation increases immediately following a disturbance (e.g., wildfire), but returns to pre-disturbance levels after a certain amount of time (Sánchez *et al.*, 2016; Boxall and Englin, 2008; Englin *et al.*, 2001). Lastly, we investigate how group size and time spent affect individuals' valuation of recreational resources. Though past research has examined visitor permit data (e.g., Mendes and Proença, 2011; Baerenklau, 2010; Englin *et al.*, 2008), this is the first that focuses on COVID-19 impact of outdoor recreation in wilderness areas. Our unique data source also differentiates us from other studies using cell phone derived visitation data to investigate how the pandemic affects recreation (e.g., Kupfer *et al.*, 2021).

2 Data

Our study considered two wilderness areas in the state of California: Desolation Wilderness (DW; USDA FS, 1998) and the Inyo Wilderness Area (IWA; USDA FS, 2022). Their locations within the boundaries of California are shown in Figure 1. The US FS administers the DW and co-manages the IWA with BLM, which represent complex, multi-benefit resources that control the amount of human involvement in the landscape (Saarinen, 2019). This feature made them an attractive outdoor recreation option, particularly during the pandemic. To access the outdoor recreation opportunities the wilderness areas offer, individuals were required to fill out a permit that provides information such as group size, the site or trailhead they access, home address, and in the case of multi-day permits, the length of their stay in the wilderness area. Several trails in both sites have a limited number of permits or quotas (USDA FS, 2022; Recreation.gov, n.d.). The amount of visitation has been simultaneously tied to the level of deterioration of the trail systems, but also to funding provided to them (Daniels, 2009). With respect to acreage, IWA is larger, with 80,616.6 hectares, whereas DW contains 25,883.7 hectares. Both wilderness areas offer considerable recreation opportunities including hiking, backpacking, and wildlife viewing. These sites were selected for two main reasons. First, they are two of the most frequently visited sites within the US FS system, with DW being close to scenic Lake Tahoe, and the IWA being the main access point for Mount Whitney, the tallest mountain in the continental US. Second, the wilderness areas are located in different parts of the state, making our sample more representative.

The visitation dataset is constructed from US FS wilderness permit data for 2019 and 2020, which contains a total of 49,843 wilderness permits across both sites. For the year 2019, there were 6,812 and 14,985 permits for DW and the IWA, respectively. Both areas had a higher number of permits in 2020 (during the pandemic), with 11,579 permits for DW and 16,107 permits for the IWA. Though occasionally the number of available permits changes

Figure 1: Map of the study area – the Desolation Wilderness and Inyo Wilderness Area within the state of California.

year to year, this is not the case for the two wilderness areas we examine, and so the change in visitation is driven by changes in demand alone, rather than supply. Note that permits are collected for groups entering the areas, rather than individuals. A maximum of 12 individuals for DW (USDA FS, 1996) and 15 individuals for IWA (USDA FS, 2022) are allowed per permit. From both the group size and the number of permits, total visitation can be calculated by adding the group sizes across all permits. The total visitation in our sample was 61,865 in 2019 and 81,621 in 2020. The average group size remained constant across the two years (2.9 persons per permit).

The permit data was merged with the zip-code level income data from the American Community Survey (US Census Bureau, 2020), together with data on precipitation and temperature from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset (Daly and Bryant, 2013). It is important to note that we capture changes in income between the two years, using two different US Census datasets for 2020 and 2021. Thus, we have both spatial variations, as well as temporal variation, in income. The temperature data was reported weekly in degrees Celsius (C), while the precipitation data is reported in millimeters (mm) per week. We calculate weather variables (mean temperature and precipitation) for each wilderness area as well as the average for the five largest urban areas in California (Los Angeles, San Diego, San Bernardino, San Francisco, and Sacramento). More specifically, these values were weighted average temperatures and precipitations, using the land area of each urban area as weights.

We estimate an approximate per-person, per-day travel cost, referred to as the price of a visit. The price calculation is given in Equation (1) below:

$$\text{price} = \left[\frac{\text{c} * \text{distance}}{\text{group size}} + \frac{1}{3}\frac{\text{income}}{2080} * \text{hours}\right]\frac{1}{\text{days}} \tag{1}$$

In Equation (1), the distance refers to the round-trip travel distance between the entry point of a wilderness area and the centroid of the visitor's zip code in kilometers, which is calculated using Google Maps API (Google, n.d.)[1]. The parameter c is the per-mile travel cost reported by the American Automobile Association (AAA; AAA [American Automobile Association], 2018) of \$0.1103 per kilometer (\$0.1776 per mile).[2] The total travel cost was then divided by group size to obtain the per-person cost. The second additive component measured the traveler's value of time. We converted individuals' annual household income to an hourly wage by dividing household income by the number of working hours in a year (2080).[3] Previous work in the travel cost literature highlights that the opportunity cost of time is not equivalent to the visitor's income level (Champ *et al.*, 2003), the value of time must be converted from the visitor's income using a factor between 0 and 1 (McKean *et al.*, 1995). Though there is not a strong consensus over which factor to use, a large collection of papers (e.g., Parson, 2017; English *et al.*, 2018) recommend using one-third. We follow the instructions outlined in the majority of studies and use one-third as our conversion factor. The value of time metric was then multiplied by the hours spent in the wilderness area plus the round-trip hours spent driving, which captured the opportunity cost. Finally, we calculated the per-day cost by dividing the total cost by the number of days the individual spent in the wilderness area.

To estimate a zonal travel cost model, the daily permit data was aggregated to the month-wilderness area-zip-code level, which included all visits to a specific wilderness area from each zip code in a given month. This aggregation also allowed us to use a comprehensive set of fixed effects, including month, wilderness area, and zip code fixed effects, to control for unobservable variables.

[1]The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Department of Agriculture of any product or service.

[2]This cost includes gasoline, as well as maintenance costs on the vehicle.

[3]The income data, discussed in a later paragraph, is mapped to the individual from census block level median income reported in the American Community Survey (US Census Bureau, 2020).

Our final dataset contains 16,480 observations.[4] In addition, we calculate two different measurements of the pandemic. First, we construct a dummy variable indicating whether the national emergency order has been put into place or not.[5] Second, we construct a "weeks since" metric, which corresponds to the number of weeks since the pandemic national emergency order in the USA (March 13, 2020). Our summary statistics of the variables used in the empirical models can be found in Table 1.

3 Empirical Model

There are several hypotheses that we test in order to determine the effects of the pandemic on visitation and valuation of wilderness areas. We implemented a travel cost model in which the effect of price is interacted with the pandemic indicator, similar to previous work (Englin and Shonkwiler, 1995). Specifically, we estimated a non-linear, negative binomial regression to capture the effects of the pandemic on visitation counts. The estimation is performed using maximum likelihood via gradient optimization, as described in Bergé (2018). The negative binomial model has a long history in the travel cost literature, and is used frequently (e.g., Hellerstein, 1991; Grilli *et al.*, 2018). It fits a set of data to the mean of the binomial distribution (Hilbe, 2011). The scale parameter is also estimated based on the likelihood function. First, we hypothesize that the pandemic affected visitation, and thus valuation, of wilderness areas. Our first model which tests this hypothesis is specified as follows:

$$
\begin{aligned}
v_{jti} = \exp(&B_1 pandemic_t * price_{jti} + B_2 price_{jti} + B_3 income_{it} + B_4 precip_{jt} \\
&+ B_5 temp_{jt} + B_6 urban\,precip_t + B_7 urban\,temp_t + \alpha_j + \gamma_t \\
&+ z_i + \varepsilon_{jti})
\end{aligned} \tag{2}
$$

where v_{jti} is the number of visits to wilderness area j (i.e., DW or IWA) from zip code i in month t. $price_{jti}$ is the price of travel to wilderness area j in month t from zip code i, calculated using Equation (1). The pandemic dummy variable $pandemic_t$ captures the start of the pandemic, which equals 1 when the lockdown measure had officially been implemented in the USA, 0 otherwise. We only include the pandemic dummy variable as an interaction with the price variable, and not as a standalone variable. This is to prevent the intercept of the demand curve from shifting and hindering the calculation of WTP. We

[4] The aggregation results in 16,520 observations. Forty (0.2%) observations do not match to a zip code, likely due to individuals not filling out the permit correctly.

[5] The national emergency order, which went in effect March 13$^{\text{th}}$ of 2020, was in response to the rapid spread of COVID-19 in the US. This was a turning point in the early pandemic, resulting in massive closures of private business and public buildings.

Table 1: Descriptive statistics of variables used in models.

Variable	Description	Mean	St. Dev.	Min	Max
Visits	Visits to wilderness areas per week	9.05	19.36	1.00	694.00
Group size	Number of people per permit	2.77	1.62	1.00	15.00
Time (days)	Amount of time spent in wilderness area	4.53	3.52	1.00	55.00
Per-day price (2019 USD)	The travel cost divided by the number of days in wilderness area	119.70	68.32	24.11	3437.99
Distance (km)	The distance from the zip code centroid and wilderness entrance for a given permit	525.21	808.33	0.00	5134.00
Pandemic dummy	National emergency order; post emergency order = 1; else = 0.	0.47	0.50	0.00	1.00
Household income (2019 USD)	The median household income from a permit's census block group	87,188.08	54,374.11	18,12	2,917,083.00
Mean temp (Celsius)	Weekly mean temperature within a wilderness area	14.07	4.24	−5.68	18.53
City mean temp (Celsius)	Weekly mean temperature in the urban areas of California	27.87	2.25	14.09	30.17
Precipitation (mm per week)	Weekly mean precipitation within a wilderness area	8.89	18.32	0.00	381.34
City precipitation (mm per week)	The mean precipitation in the urban areas of California for a given week	3.70	13.94	0.01	218.09

include a variable on annual median household income, $income_{it}$, reported at the zip code level and mapped to the individual using their zip code of origin. We also control for variations in weather with the inclusion of $precip_{jt}$ and $temp_{jt}$, which is the daily precipitation and temperature for a given month and wilderness. In addition, we include the average monthly precipitation and temperature in urban areas across California, labeled as $urban\ precip_t$ and $urban\ temp_t$. The site, week, and zip code fixed effects, α_j, γ_t, z_i are included to capture time-invariant unobservables, and time variant unobservables that are common across wilderness areas, and zip codes, respectively. In order to evaluate whether the pandemic affected visitation and valuation, we tested the null hypothesis that $\mathbf{B_1}$ is equal to zero. Rejecting the null hypothesis would indicate that the pandemic changed visitation to the wilderness areas in our sample. A positive coefficient would indicate that visitation and valuation both increased.

Next, we hypothesize that the pandemic has a dynamic effect on visitation and valuation, meaning that both the visitation and valuation of wilderness areas changes as more time passes after the start of the pandemic. In the second model, we represent the pandemic emergency order differently by using a continuous variable w_t which measures the weeks since the national pandemic emergency order was announced. We also include the quadratic term, w_t^2 to capture any non-linear effect. For example, if the coefficient on w_t is positive, but w_t^2 is negative, it indicates that although visitation increases after the national emergency declaration, it would regress to the pre-pandemic level over time. In other words, it can show whether we should expect the changes in recreation at these two sites to be permanent or return to pre-pandemic levels. The quadratic representation has enough flexibility to capture non-linear trends in time, but is also parsimonious and can be easily interpreted within a regression framework. We report this model specification in Equation (3).

$$\begin{aligned} v_{jti} = \exp(&B_1 w_t * price_{jti} + B_2 w_t^2 * price_{jti} + B_3 price_{jti} + B_4 income_{it} \\ &+ B_5 precip_{jt} + B_6 temp_{jt} + B_7 urban\ precip_t + B_8 urban\ temp_t \\ &+ \alpha_j + \gamma_t + z_i + \varepsilon_{jti}) \end{aligned} \tag{3}$$

Furthermore, by interacting the pandemic dummy variable, as well as the weeks with price in Equations (2) and (3) without including the pandemic dummy or the weeks since as a separate variable, we are ensuring that the intercept of the demand curve stays the same. The null hypotheses tested in this model are that $\mathbf{B_1}$ and $\mathbf{B_2}$ are equal to zero. Rejection of the null hypothesis indicates that the effects of the pandemic on visitation and valuation vary over time. The actual direction of the change would vary based on the coefficient values.

It is important to note that because Equations (2) and (3) both utilize the negative binomial distribution, their coefficients are comparable across models. However, caution must be applied when comparing the pandemic dummy in

Equation (2) to the weeks since variables in Equation (3). Both the pandemic dummy and weeks since variables can be understood as changing the coefficient on the price variable. A change in the price variable can be interpreted as follows: a change in the differences in logged visitation is expected to change by the price coefficient assuming a marginal change in price. Thus, both the pandemic dummy and weeks since variables change the magnitude of this effect, though their units are different.

The third hypothesis tested is whether there are returns to scale for recreation. In other words, we want to see how the time spent recreating or the group size impact visitation and valuation. We estimate two additional equations that capture the effects of time spent in the wilderness area (Equation (4)) and the group size (Equation (5)). As shown in Equations (4) and (5), instead of interacting price with the time since the pandemic emergency order, we interact price with the time spent in the wilderness ($time_i$) and the size of the group recreating ($group\,size_i$). This provides a way to test whether the value of the wilderness area changes as recreationists spend more time at the site, and as the size of their groups increases.

$$\begin{aligned} v_{jti} &= \exp(B_1 time_i * price_{jti} + B_2 price_{jti} + B_3 income_{it} + B_4 precip_{jt} \\ &\quad + B_5 temp_{jt} + B_6 urban\,precip_t + B_7 urban\,temp_t + \alpha_j + \gamma_t \\ &\quad + z_i + \varepsilon_{jti}) \qquad (4) \\ v_{jti} &= \exp(B_1 group\,size_i * price_{jti} + B_2 price_{jti} + B_3 income_{it} + B_4 precip_{jt} \\ &\quad + B_5 temp_{jt} + B_6 urban\,precip_t + B_7 urban\,temp_t + \alpha_j + \gamma_t \\ &\quad + z_i + \varepsilon_{jti}) \qquad (5) \end{aligned}$$

The null hypothesis in this case is that $\mathbf{B_1}$ is equal to zero in both Equations (4) and (5). Rejecting the null hypothesis in both cases would indicate that time spent recreating and size of the group recreating impact visitation and group size.

4 Results

In this section, we present the results from estimating Equations (2)–(5). For all models, we vary the model specification to observe how sensitive the results are to the inclusion or exclusion of additional controls. Results from Equations (2) and (3) are presented in Tables 2 and 3. Both Equations (2) and (3) are count data models with comparable coefficient interpretations, which can be interpreted as the percent change in visitation for a single unit increase in the variable of interest (Allison and Waterman, 2002). As a robustness check, we estimate the model with three specifications. Column (1) presents the results without the weather controls or month-year fixed effects. Column (2) adds the month-year fixed effects, whereas column (3) contains both weather controls and month-year fixed effects.

4.1 Does the Pandemic Impact Visitation?

For all model estimations of Equation (2) reported in Table 2, the pseudo-R^2 vary between approximately 0.15 and 0.20. For context, the pseudo-R^2 is used for ordinal or categorical models when a traditional R^2 cannot be calculated (Cohen *et al.*, 2014). Because this is a negative binomial regression, we also report the over-dispersion statistic. The over-dispersion statistic measures the extent to which the variance of the count data, in our case visitation, is higher in the observed data or the predicted data. If it is higher than 1 in the predicted model, it is over-dispersed, and a negative binomial model is better suited to capture the variation in the data (Payne *et al.*, 2018). The Bayesian Information Criterion (BIC) and the Akaike Information Criteria (AIC) statistics are both the smallest in column (3), which indicates that adding weather controls improves the predictive power of the model.

The coefficient on the per-day per-visitor price is significant at the 1% level ($p < 0.01$) and has a negative sign in all three specifications. Importantly, the interaction between the per-day per-visitor price and the pandemic dummy variable is statistically significant at the 1% level and positive, which shows that after the pandemic, the slope of the demand curve became less elastic with respect to price. The inclusion of month-year dummies substantially reduces the magnitudes of the coefficients, implying that time controls are important for controlling for unobserved factors that are varying through time but are spatially fixed, such as seasonal closures.

The functional form of Equation (2) restricts changes in visitation (and thus, changes in WTP) to be discrete. Following the standard practice in the recreation literature, we calculate traveler's WTP as the inverse of the absolute value of the per-day per-visitor price coefficient. This yields the per-person per-day WTP averaged across both wilderness areas. We find that the WTP for recreating in wilderness areas predicted by Equation (2) is \$38.3 prior to the pandemic emergency order, with a 95% confidence interval of \$27.01 to \$65.97. Following the pandemic emergency order, the point estimate of the WTP grew to \$40.3 per person per trip, with a 95% confidence interval of \$26.99 to \$79.47.

4.2 Is the Impact of the Pandemic on Visitation Dynamic?

The results obtained from estimating Equation (3) are reported in Table 3. The pseudo-R^2 and over-dispersion statistics follow a similar pattern as in Table 2. The coefficient on the per-day per-visitor price (not including any interaction term) is nearly identical in magnitude to that reported in Table 2, indicating

Table 2: Regression results for estimating Equation (2) with a negative binomial distribution.

Dependent Variable:	Visits		
Model:	(1)	(2)	(3)
Variable			
Price	-0.0334^{***}	-0.0261^{***}	-0.0261^{***}
	(0.009)	(0.0058)	(0.0059)
Income	0.0439^{***}	0.0339^{**}	0.0338^{***}
	(0.0096)	(0.0071)	(0.0067)
Price $\times$ pandemic dummy	0.0021^{***}	0.0013^{**}	0.0013^{**}
	(0.0008)	(0.0007)	(0.0007)
Additional Controls			
Temperature	No	No	Yes
Precipitation	No	No	Yes
Fixed Effects			
Site	Yes	Yes	Yes
Zip code	Yes	Yes	Yes
Month-year	No	Yes	Yes
Observations	16,480	16,480	16,480
Squared Correlation	0.0294	0.0392	0.0394
Pseudo R^2	0.1535	0.1977	0.2007
BIC	130,493.70	126,247.30	125,962.40
AIC	98,960.16	94,320.59	94,005.65
Over-dispersion	2.5855	3.9668	4.0948

Clustered (site) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05

that different representations of the pandemic still produce consistent results. The coefficient on income is higher in Table 3 than in Table 2.

The results from Table 3 provide insight into the time-pattern of post-pandemic changes in recreation and show that there is a positive relationship between the per-day per-visitor price and "weeks since", but a negative relationship between the interaction of per-day per-visitor price and the quadratic term of "weeks since". This implies that immediately following the national emergency order, the effect of price on visitation falls significantly (i.e., a more elastic demand curve); however, the effect of price will return to its pre-pandemic level over time.

We calculate the time over which the results predict a return to pre-pandemic recreation levels. After taking the partial derivative of Equation (3) with respect to price $(B_1 w_t + B_2 w_t^2 + B_3)$, we can solve for the number of weeks until the effect of price is equal to the pre-pandemic level (B_3). This

Table 3: Regression results from estimating Equation (3) with a negative binomial distribution

Dependent Variable:	Visits		
Model:	(1)	(2)	(3)
Variable			
Price	-0.0329^{***}	-0.0263^{***}	-0.0259^{***}
	(0.0074)	(0.0059)	(0.0055)
Price × weeks since	0.0006^{***}	0.0004^{***}	0.0003^{***}
	(8.7×10^{-5})	(0.0001)	(0.0001)
Price × weeks since^2	$-2.21\times10^{-5\,***}$	$-1.52 \times 10^{-5\,***}$	$-1.33\times10^{-5\,***}$
	(2.75×10^{-6})	(3.95×10^{-6})	(4.46×10^{-6})
Income	0.0431^{***}	0.0341^{***}	0.0335^{***}
	(0.0089)	(0.0072)	(0.0066)
Additional Controls			
Temperature	No	No	Yes
Precipitation	No	No	Yes
Fixed Effects			
Site	Yes	Yes	Yes
Zip-code	Yes	Yes	Yes
Month	No	Yes	Yes
Observations	16,480	16,480	16,480
Squared Correlation	0.0467	0.05649	0.06856
Pseudo R^2	0.1601	0.1996	0.2020
BIC	129,797.60	126,053.80	125,831.4
AIC	98,256.35	94,119.41	93,866.15
Over-dispersion	2.7394	4.0538	4.1624

Clustered (site) standard-errors in parentheses.
Signif. Codes: ***: 0.01

shows the amount of time in which recreation returns to the level prior to the emergency order. The derivation is shown in Equation (6).

$$B_1 w_t + B_2 w_t^2 + B_3 = B_3 \rightarrow B_1 + B_2 w_t = 0 \rightarrow w_t^* = \frac{-B_1}{B_2} \tag{6}$$

Solving Equation (6) using the coefficient estimates in Table 3, column 3 yields a result of 22.56 weeks, which is between 5 and 6 months.

Results presented in both Tables 2 and 3 indicate that the WTP of the wilderness areas increases because of the pandemic. This is because the effect of the per-day per-person price becoming closer to 0, indicating that price has a weaker effect on behavior due to the price elasticity of demand being

Table 4: The average per-day per-visitor WTP across DW and IWA based on the estimation results reported in Tables 2 and 3 (confidence intervals are in the parenthesis).

Model	WTP (pre-pandemic)	Peak WTP (post- pandemic)	Average WTP (post-pandemic)
Equation (2)	\$38.3 (27.01, 65.97)	\$40.3 (26.99, 79.47)	\$40.3 (26.99, 79.47)
Equation (3)	\$38.7 (27.27, 66.39)	\$41.54 (28.68, 75.33)	\$40.68 (28.27, 72.59)

lower. We calculate two measures of WTP with respect to Equation (3): the peak WTP and the average WTP. The peak WTP is the highest WTP value predicted by estimating Equation (3) (occurring 11 weeks after the emergency order).[6] The average WTP is calculated by averaging weekly calculations of WTP across the first 22 weeks following the pandemic. For comparison, we also report the WTP obtained from estimating Equation (2) in Table 4. Note that the peak WTP and the average WTP values are the same here because Equation (2) does not allow WTP to change over time.

The per-person per-day WTP of recreation across both wilderness areas increased by either \$2 (Table 4; row 1) or \$1.8 on average (Table 4; row 2) based on the average WTP and peak WTP estimates obtained from Equation (2). When the difference in visitation WTP was at its peak (11 weeks following the emergency order), the WTP for wilderness areas increased by \$2.8 per-person per-day (Table 3; row 2). The total number of person-days reported in the permit data is 749,905, multiplying the changes in per-person per-day WTP with the total number of person-days leads to a total change in recreation WTP value of \$1,499,810, \$1,349,829, and \$2,099,734, respectively.

As a robustness check, we also estimate versions of Equations (2) and (3) following a Poisson distribution. These results can be found in Appendix A.1. The Poisson model estimations show that signs of the effects are consistent across model choices. However, the coefficients are typically smaller in magnitude, and importantly are not statistically significant. This indicates that the distributional assumptions behind the Poisson model make it more difficult to detect an effect, and that the more flexible negative binomial specification is better suited to model visitation in our case, as demonstrated by an overdispersion coefficient greater than 4.

[6]The peak WTP is calculated as half of the 22 weeks over which the effects of the pandemic emergency order are greater than 0. This must be the case due to the functional form of Equation (4), since we estimate a parabolic relationship between visitation and weeks since the pandemic emergency order.

Table 5: Results of estimating alternative model specifications where the price is interacted with the days spent in the wilderness area (Column 2), and the group size (Column 3), compared to a zonal travel cost model with no interactions (Column 1).

Dependent variable:	Visits		
Model:	(1)	(2)	(3)
Variable			
Price	-0.0257^{***}	-0.0306^{***}	-0.0121^{***}
	(0.0059)	(0.0066)	(0.0046)
Price × days in wilderness		-0.0005^{***}	
		(0.0001)	
Price × group size			0.0017^{***}
			(0.0001)
Income	0.0336^{***}	0.0431^{***}	0.0072
	(0.0069)	(0.0071)	(0.0060)
Additional Controls			
Temperature	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes
Fixed Effects			
Site	Yes	Yes	Yes
Zip-code	Yes	Yes	Yes
Month	Yes	Yes	Yes
Observations	16,480	16,480	16,480
Squared Correlation	0.36317	0.473	0.06440
Pseudo R^2	0.19956	0.20315	0.22453
BIC	126,078.40	125,703.40	123,410.4
AIC	94,128.60	93,745.87	91,452.81
Over-dispersion	4.0459	4.2133	4.8830

Clustered (site) standard-errors in parentheses.
Signif. Codes: ***: 0.01

4.3 Does Time Spent Recreating and Group Size Impact Visitation?

In Table 5 below, we present the results of estimating Equations (4) and (5), respectively. For comparison and robustness, in Table 5, column 1, we include a version of the model with no interaction.

The price coefficients in these alternative models are similar to those reported earlier in the paper. The coefficient on income is statistically significant at 1% level in all models except for Equation (4), which contains an interaction term with group size. This could indicate multi-collinearity between income and group size, as households with larger incomes might also recreate in larger groups.

The coefficient on the interaction term between price and time spent in the wilderness is negative (Table 5; column 1). This indicates that there are diminishing returns to the utility of recreating. There are several reasons for this, including logistical issues involved in long camping trips, as well as recreational preferences. The interaction between price and group size (Table 5; column 3) has a positive coefficient. This implies that the more people recreating in groups, the higher the WTP of the resource. As a robustness check, we ran an additional version of this model that includes both group size and time spent in the wilderness, along with their interaction, simultaneously. This model shows that the effects observed here are robust to including both group size and time simultaneously. It also shows that the more time spent in the wilderness, the larger the change in WTP from increasing group size. Finally, it shows that as group size increases, the decline in WTP from recreating an additional day becomes smaller in magnitude. These results can be found in Appendix A.2.

5 Discussion

The results of this paper demonstrate that the pandemic changed recreation behavior in wilderness areas. This is consistent with other studies that have documented pandemic-induced changes in recreation behavior, either negatively (e.g., Landry *et al.*, 2021) or positively (e.g., Derks *et al.*, 2020b). The results also support previous findings that recreational activity has increased in remote, forested areas (Derks *et al.*, 2020a), which might be due to the ability to socially distance in these locations. This paper extends the work examining recreation during the COVID-19 pandemic by showing that the increased visitation has led to a change in the valuation of recreational amenities.

A small collection of past studies has examined the time pattern of behavioral changes following the pandemic and found conflicting results. For instance, Bulchand-Gidumal and Melián-González (2021) claim that air travel will likely not return to pre-pandemic levels. On the other hand, Lefferts *et al.* (2022) find that activity levels of older adults likely returned to pre-pandemic levels a year after the pandemic began. Our results show that the pattern of visitations following the national emergency order has returned to pre-pandemic levels in just over 22 weeks. The question of whether or how behavior, especially recreational or tourist activity, will return to the pre-pandemic levels depends on specific characteristics of that activity and site amenities. Visitation may revert back to pre-pandemic levels quickly and in this study may be because recreating in wilderness areas typically allows one to socially distance much more effectively than other outdoor recreation activities (Rice *et al.*, 2019).

The COVID-19 pandemic is one example of possible crisis that can lead to impermanent changes in outdoor recreation activities. Natural disasters such as fires (Englin *et al.*, 2008), and hurricanes (Buerger *et al.*, 2003), can also disrupt recreation activity patterns. As the pattern of these events changes due to climate change (Van Aalst, 2006), examining changes in visitation and valuation is important. To that end, this study has explored the empirical methodology that quantifies the impacts of crises such as the COVID-19 pandemic on outdoor recreation. Though other studies have estimated the effects of the pandemic (Landry *et al.*, 2020), few have looked at the time flow of valuations following such an event. Our results demonstrate that the WTP for recreation is more fluid than is commonly represented in other studies (Rolfe and Dyack, 2019).

There are several additional results that are useful to outdoor recreation and tourism research in general. Our study finds that the per-day WTP of outdoor recreation decreases as the recreational period increases. This is evidence of diminishing marginal returns, which is found in other forms of consumption and investment (e.g., Faff *et al.*, 2013) including outdoor recreation (Beardmore *et al.*, 2015). Our finding complements the literature documenting that this is also a feature of outdoor recreation behavior. In addition, we demonstrate group size has a significant impact on the per-day per-visitor WTP of a recreational amenity, which is consistent with other studies reporting that part of the WTP of outdoor recreation is socialization (Jackson *et al.*, 2021).

6 Conclusion

This study investigates the effects of the pandemic on visitation and WTP to two wilderness areas in California. We find that, in general, after the national emergency order was issued, the demand curve for outdoor recreation at these two sites became less elastic, which led to an increase in willingness to pay. Furthermore, we find evidence of decreasing returns to scale with respect to time spent recreating, and the value of recreating in wilderness areas increases with group size.

There are several limitations to this study. Though the study region contained two different recreational sites, we did not include a comprehensive set of alternative sites to visit. Future work could consider examining outdoor recreation demand using a random utility model to include substitute sites (Lupi *et al.*, 2020). Furthermore, there are additional topics and areas that might be interesting to explore with respect to the demand for outdoor recreation. For example, exploring how disadvantaged communities' recreational behavior is impacted by the pandemic and climate change is of interest to land management agencies given the Biden administration's Executive Orders on improving recreational access and environmental justice (The White House, 2021). In addition, analyzing other factors such as smoke from wildfires, water quality, weather, and expected foot traffic to outdoor recreation sites may be considered. Though these represent interesting opportunities for advances, they are beyond the scope of this current work.

As society struggles to adapt to the continuously shifting world that the COVID-19 pandemic has produced, it is important that we evaluate outdoor recreation behavioral changes and shifts in public preferences. Outdoor recreational amenities have assumed the role of safe havens throughout the pandemic, and the ability to properly manage and maintain them is paramount to the continued provision of their benefits to society. This study provides insights that may help forest and land managers better manage these valuable natural resources moving forward. Overall, we show that in times of crisis, the value of accessible outdoor recreational amenities increases as options for recreators decreases overall. Increases in the economic value of these amenities might justify additional investments in the provision of these natural resources in times of crisis, such as the COVID-19 pandemic or other natural disasters.

Appendices

Appendix A.1 Poisson Models

Although the over-dispersion coefficient in all models reported in Tables 2 and 3 are greater than zero (Section 4.1.), we still test our distributional assumption by running a Poisson model as a robustness check. Table A.1. reports the results of estimating Equations (2) and (3) (with a complete set of controls) with a Poisson distribution instead of a negative binomial distribution.

The coefficient estimates in Table A.1. have the same sign as the main specification reported in Tables 2 and 3 (Sections 4.1 and 4.2). The coefficient on the per-day per-person price is more elastic than in the negative binomial models, meaning that individuals are more responsive to changes in the price of accessing this recreational amenity. More elastic demand results in lower visitation for recreational amenities, indicating that the Poisson model predicts lower visitation for the wilderness areas in the study area, overall. This further suggests a lower WTP for the wilderness areas. Furthermore, the coefficient on income is larger than in any of the negative binomial models reported in Tables 2 and 3 (Sections 4.1 and 4.2).

A key distinction between the results in Table A.1, and the results in Tables 3 and 4 (Sections 4.1 and 4.2), is that when using the Poisson distribution, the coefficients on all of the pandemic terms (including the pandemic dummy variable, and all “weeks since” variables) are statistically insignificant. However,

Table A.1: Results from estimating the Poisson model version of Equations (2) and (3).

Dependent Variable:	Visits	
Model:	(1)	(2)
Variable		
Price	-0.0337^{***}	-0.0336^{***}
	(0.0053)	(0.0054)
Price × pandemic dummy	3.39×10^{-5}	
	(0.0001)	
Price * weeks since		0.0001
		(8.11×10^{-5})
Price * weeks since^2		-5.43×10^{-6}
		$(4.17 \times 10^{-6}$
Income	0.0429^{***}	0.0429^{***}
	(0.0067)	(0.0066)
Additional Controls		
Temperature	Yes	Yes
Precipitation	Yes	Yes
Fixed Effects		
Site	Yes	Yes
Zipcode	Yes	Yes
Month	Yes	Yes
Observations	16,480	16,480
Squared Correlation	0.68834	0.67929
Pseudo R^2	0.60623	0.60808
BIC	153,569.40	153,047.0
AIC	121,611.80	121,081.70

Clustered (site) standard-errors in parentheses.
Signif. Codes: ***: 0.01

this is likely due to the distributional assumptions within the Poisson model, namely that the mean and variance are equal. Furthermore, the magnitudes on both the pandemic dummy and the weeks since variables are smaller as well.

Appendix A.2 Additional Group Size and Recreation Time Results

As a robustness check, we estimated a version of Equations (4) and (5) where the interactions between price and group size, and price and time spent recreating, were included in the regression simultaneously. In addition, we

Table A.2: Results of a robustness check that includes both the time and group interaction terms in the regression at the same time (column 1) compared with a model that includes no interaction terms (column 2).

Dependent variable:	Visits	
Model:	(1)	(2)
Variable		
Price per day	-0.0146^{***}	-0.0257^{***}
	(0.0049)	(0.0059)
Price × group	0.0014^{***}	
	(0.0002)	
Price × time	-0.0004^{***}	
	(0.0001)	
Price × time × group	$4.1 \times 10^{-5***}$	
	(9.43×10^{-6})	
Income	0.0132^{**}	0.0336^{***}
	(0.0058)	(.0069)
Additional controls		
Temperature	Yes	Yes
Precipitation	Yes	Yes
Fixed Effects		
Site	Yes	Yes
Zipcode	Yes	Yes
Month	Yes	Yes
Observations	16,480	16,480
Squared correlation	0.0537	0.36317
Pseudo R^2	0.22578	0.19956
BIC	123,296.10	126,078.40
Over-dispersion	4.9534	4.0459

also included a triple interaction between price, group size, and time spent recreating. We present the results in Table A.2.

We see that our result is robust to the inclusion of the double interaction term. As visitors spend more time in the wilderness, their per-day WTP still declines, and as more people join their group, their per-day WTP still increases. The double interaction group shows that as group size increases, the decline in WTP as time increases becomes less pronounced. Additionally, as time spent recreating increases, the increase in WTP from group size becomes larger.

References

AAA [American Automobile Association]. 2018. "Your driving costs". Accessed May 15, 2019. URL: https://publicaffairsresources.%20aaa.biz/download/11896/.

Allison, P. D. and R. P. Waterman. 2002. "Fixed–effects negative binomial regression models". *Sociological Methodology*. 32(1): 247–265.

Baerenklau, K. A. 2010. "A latent class approach to modeling endogenous spatial sorting in zonal recreation demand models". *Land Economics*. 86(4): 800–816.

Beardmore, B., L. M. Hunt, W. Haider, M. Dorow, and R. Arlinghaus. 2015. "Effectively managing angler satisfaction in recreational fisheries requires understanding the fish species and the anglers". *Canadian Journal of Fisheries and Aquatic Sciences*. 72(4): 500–513.

Bergé, L. 2018. *Efficient estimation of maximum likelihood models with multiple fixed-effects: the R package FENmlm (No. 18-13)*. Department of Economics at the University of Luxembourg.

Boxall, P. C. and J. E. Englin. 2008. "Fire and recreation values in fire-prone forests: exploring an intertemporal amenity function using pooled RP-SP data". *Journal of Agricultural Resource Economics*. 33(1): 19–33.

Buckley, R. 1991. "Environmental impacts of recreation in parks and reserves". In: *Perspectives in Environmental Management*. Berlin, Heidelberg: Springer. 243–258.

Buerger, R., J. Hill, J. Herstine, D. Auger, and J. Taggart. 2003. "Reemerging recreational use patterns on an undeveloped barrier island following the impact of hurricanes: A North Carolina case study". *Society &Natural Resources*. 16(6): 527–539.

Bulchand-Gidumal, J. and S. Melián-González. 2021. "Post-COVID-19 behavior change in purchase of air tickets". *Annals of Tourism Research*. 87: 103129.

Champ, P. A., K. J. Boyle, and T. C. Brown. 2003. *A primer on nonmarket valuation*. Vol. 3. Dordrecht: Kluwer Academic Publishers. 72–82.

Cohen, P., S. G. West, and L. S. Aiken. 2014. *Applied Multiple Regression/-Correlation Analysis for the Behavioral Sciences*. Psychology Press.

Daniels, T. L. 2009. "A trail across time: American environmental planning from city beautiful to sustainability". *Journal of the American Planning Association*. 75(2): 178–192.

Derks, J., L. Giessen, and G. Winkel. 2020a. "COVID-19-induced visitor boom reveals the importance of forests as critical infrastructure". *Forest Policy and Economics*. 118: 102253.

Derks, J., L. Giessen, and G. Winkel. 2020b. "COVID-19-induced visitor boom reveals the importance of forests as critical infrastructure". *Forest Policy and Economics*. 118: 102253. DOI: https://doi.org/10.1016/j.forpol.2020.102253.

Englin, J., T. P. Holmes, and J. Lutz. 2008. "Wildfire and the economic value of wilderness recreation". In: *The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species*. Ed. by T. P. Holmes, J. P. Prestemon, and K. L. Abt. Dordrecht, Netherlands: Springer. Chap. 10. 191–208.

Englin, J., J. Loomis, and A. González-Cabán. 2001. "The dynamic path of recreational values following a forest fire: a comparative analysis of states in the intermountain west". *Canadian Journal of Forest Research*. 31: 1837–1844.

English, E., R. H. von Haefen, J. Herriges, C. Leggett, F. Lupi, K. McConnell, and N. Meade. 2018. "Estimating the value of lost recreation days from the Deepwater Horizon oil spill". *Journal of Environmental Economics and Management*. 91: 26–45.

Faff, R., Y. K. Ho, W. Lin, and C. M. Yap. 2013. "Diminishing marginal returns from R&D investment: Evidence from manufacturing firms". *Applied Economics*. 45(5): 611–622.

Grilli, G., G. Landgraf, J. Curtis, and S. Hynes. 2018. "A travel cost evaluation of the benefits of two destination salmon rivers in Ireland". *Journal of Outdoor Recreation and Tourism*. 23: 1–7.

Hellerstein, D. M. 1991. "Using count data models in travel cost analysis with aggregate data". *American Journal of Agricultural Economics*. 73(3): 860–866.

Hilbe, J. M. 2011. *Negative binomial regression*. Cambridge University Press.

Jackson, S. B., K. T. Stevenson, L. R. Larson, M. N. Peterson, and E. Seekamp. 2021. "Outdoor activity participation improves adolescents' mental health and well-being during the COVID-19 pandemic". *International Journal of Environmental Research and Public Health*. 18(5): 2506.

Kupfer, J. A., Z. Li, H. Ning, and X. Huang. 2021. "Using mobile device data to track the effects of the COVID-19 Pandemic on spatiotemporal patterns of national park visitation". *Sustainability*. 13(16): 9366.

Landry, C. E., J. Bergstrom, J. Salazar, and D. Turner. 2021. "How Has the COVID-19 Pandemic Affected Outdoor Recreation in the U.S.? A Revealed Preference Approach". *Applied Economic Perspectives and Policy*. 43(1): 443–457. DOI: https://doi.org/10.1002/aepp.13119.

Lefferts, E. C., J. M. Saavedra, B. K. Song, and D. C. Lee. 2022. "Effect of the COVID-19 pandemic on physical activity and sedentary behavior in older adults". *Journal of Clinical Medicine*. 11(6): 1568.

Leonard, B., A. J. Plantinga, and M. Wibbenmeyer. 2021. "Stranded land constrains public land management and contributes to larger fires". *Environmental Research Letters*. 16(11): 114014.

Lim, M. A. and R. Pranata. 2021. "Sports activities during any pandemic lockdown". *Irish Journal of Medical Science (1971)*. 190(1): 447–451.

Lupi, F., D. J. Phaneuf, and R. H. von Haefen. 2020. "Best practices for implementing recreation demand models". *Review of Environmental Economics and Policy*. 14(2).

McKean, J. R., D. M. Johnson, and R. G. Walsh. 1995. "Valuing time in travel cost demand analysis: An empirical investigation". *Land Economics*: 96–105.

Mendes, I. and I. Proença. 2011. "Measuring the social recreation per-day net benefit of the wildlife amenities of a national park: a count-data travel-cost approach". *Environmental Management*. 48(5): 920–932.

Osterkamp, W. R. and J. M. Friedman. 2000. "The disparity between extreme rainfall events and rare floods—With emphasis on the semi-arid American West". *Hydrological Processes*. 14(16–17): 2817–2829.

Parson, G. R. 2017. "Travel cost models". In: *A Primer on Nonmarket Valuation*. Ed. by P. A. Champ, K. J. Boyle, and T. C. Brown. 2nd. Dordrecht, Netherlands: Springer. Chap. 6. 187–234.

Payne, E. H., M. Gebregziabher, J. W. Hardin, V. Ramakrishnan, and L. E. Egede. 2018. "An empirical approach to determine a threshold for assessing overdispersion in Poisson and negative binomial models for count data". *Communications in Statistics-Simulation and Computation*. 47(6): 1722–1738.

Recreation.gov. 2022. "Desolation Wilderness Permit". Accessed May 2022. URL: https://www.recreation.gov/permits/233261.

Rice, W. L., T. J. Mateer, N. Reigner, P. Newman, B. Lawhon, and B. D. Taff. 2020. "Changes in recreational behaviors of outdoor enthusiasts during the COVID-19 pandemic: Analysis across urban and rural communities". *Journal of Urban Ecology*. 6(1).

Rolfe, J. and B. Dyack. 2019. "Testing temporal stability of recreation values". *Ecological Economics*. 159: 75–83.

Saarinen, J. 2019. "What are wilderness areas for? Tourism and political ecologies of wilderness uses and management in the Anthropocene". *Journal of Sustainable Tourism*. 27(4): 472–487.

Sánchez, J. J., K. Baerenklau, and A. González-Cabán. 2016. "Valuing hypothetical wildfire impacts with a Kuhn-Tucker model of recreation demand". *Forest Policy and Economics*. 71: 63–70.

Selin, S., L. K. Cerveny, D. J. Blahna, and A. B. Miller. 2020. "Igniting research for outdoor recreation: Linking science, policy, and action". *Gen. Tech. Rep. PNW-GTR-987. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station*. 257: 987. DOI: https://doi.org/10.2737/PNW-GTR-98.

Shartaj, M., J. F. Suter, and T. Warziniack. 2022. "Summer crowds: An analysis of USFS campground reservations during the COVID-19 pandemic". *PloS One*. 17(1): e0261833.

Spennemann, D. H. and R. Whitsed. 2021. "The impact of COVID-19 on the Australian outdoor recreation industry from the perspective of practitioners". *Journal of Outdoor Recreation and Tourism*: 100445.

Spurk, D. and C. Straub. 2020. "Flexible employment relationships and careers in times of the COVID-19 pandemic". *Journal of Vocational Behavior*. 119: 103435.

The White House. 2021. "Fact sheet: President Biden takes executive actions to tackle the climate crisis at home and abroad, create jobs, and restore scientific integrity across federal government". Accessed August 19, 2022. URL: https://www.whitehouse.gov/briefing-room/statements-releases/2021/01/27/fact-sheet-president-biden-takes-executive-actions-to-tackle-the-climate-crisis-at-home-and-abroad-create-jobs-and-restore-scientific-integrity-across-federal-government/.

USDA Forest Service [USDA FS]. 1998. "Desolation Wilderness Management Guide: Land Management Plan Amendment". URL: https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fsm9_045945.pdf.

USDA Forest Service [USDA FS]. 2022. "Inyo National Forest Visitor's Guide". URL: https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fseprd904026.pdf.

Van Aalst, M. K. 2006. "The impacts of climate change on the risk of natural disasters". *Disasters*. 30(1): 5–18.