Appendix to "Welfare Losses from Wildfire Smoke: Evidence from Daily Outdoor Recreation Data"

12 April 2025

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Figure A1: Recreation.gov Web Interface

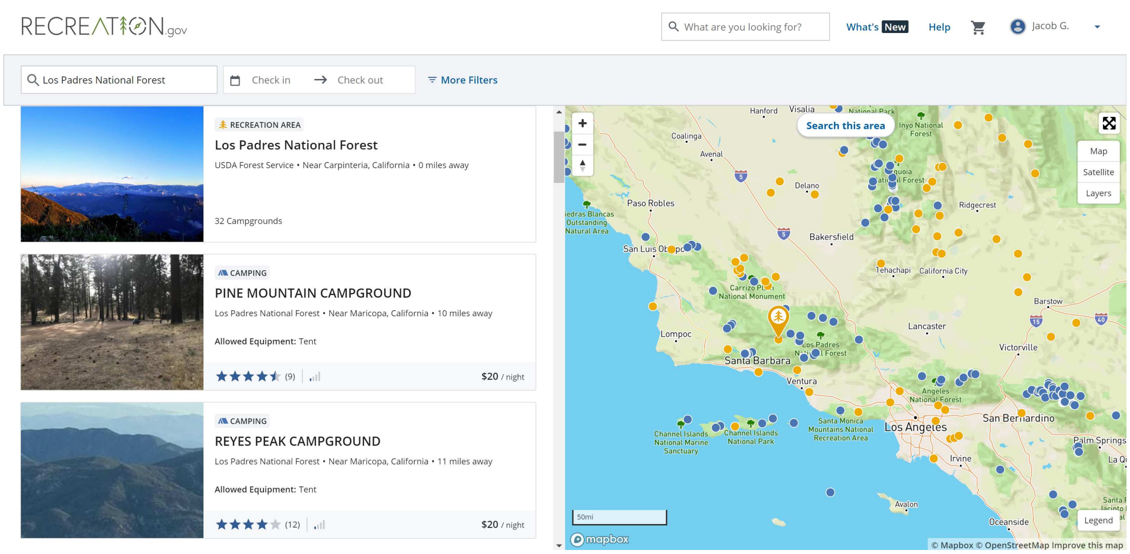


Figure A2: Automobile Route from Santa Barbara, California to Yosemite National Park

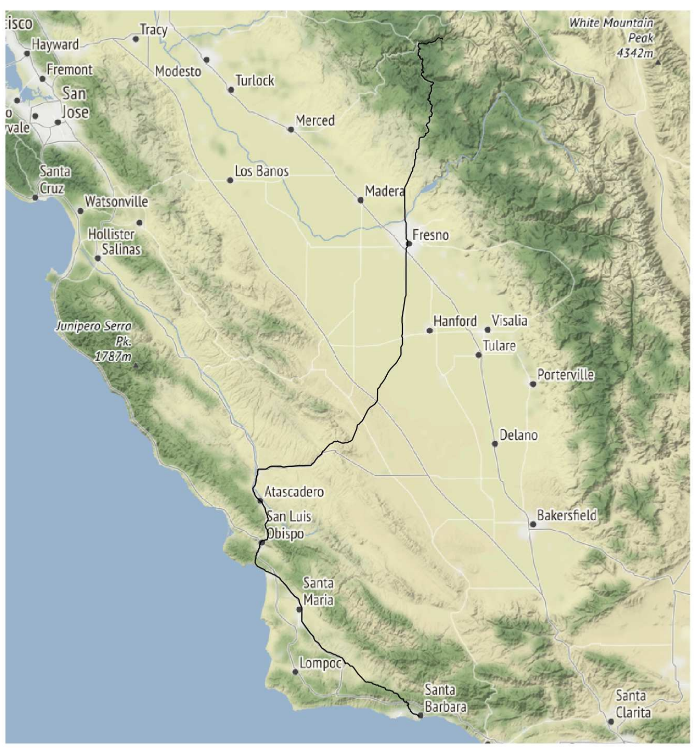
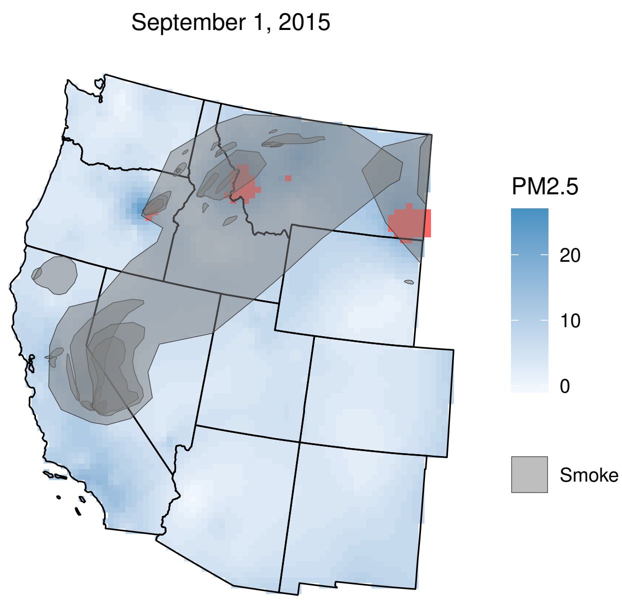


Figure A3: NOAA Smoke Plumes and $PM_{2.5}$



Notes: Red areas are affected by smoke and poor air quality.

Figure A4: Fire Detection Points and Fire Perimeters

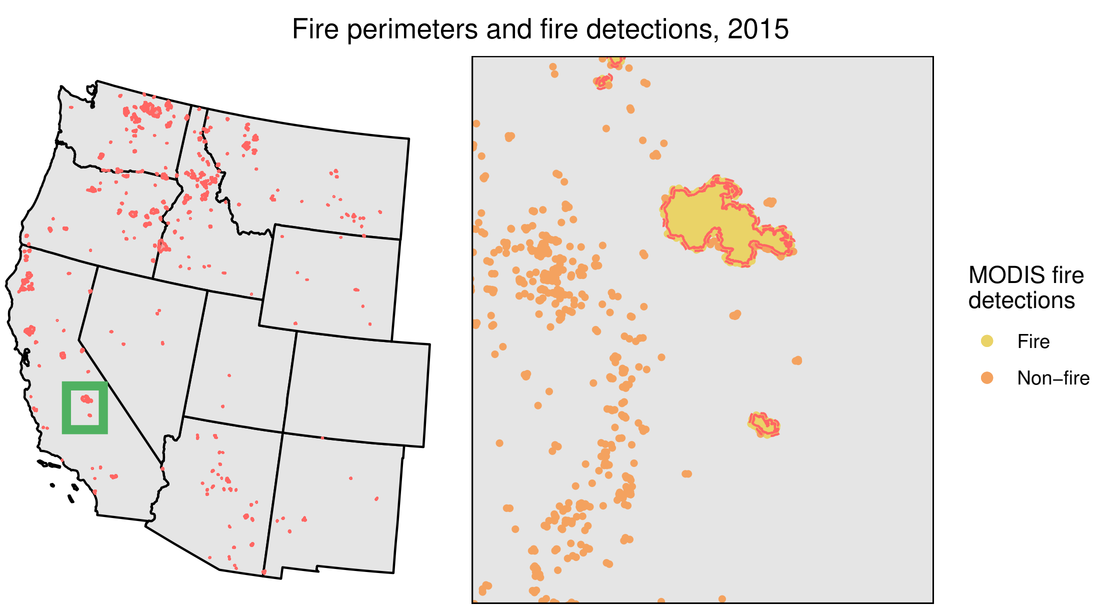


Table A1: Most Visited Federally Managed Campgrounds

Campground	Recreation area	State	Agency	Annual average campers
Upper Pines	Yosemite NP	CA	NPS	99,820
Mather	Grand Canyon NP	AZ	NPS	59,196
Watchman	Zion NP	UT	NPS	49,389
Serrano	Big Bear, San Bernardino NF	CA	USFS	46,610
Pinecrest	Summit RD, Stanislaus NF	CA	USFS	36,576
Fallen Leaf	Lake Tahoe Basin	CA	USFS	32,966
Lodgepole	Sequoia And Kings Canyon NP	CA	NPS	30,634
North Pines	Yosemite NP	CA	NPS	26,883
Moraine Park	Rocky Mountain NP	CO	NPS	25,884
Lower Pines	Yosemite NP	CA	NPS	25,644
Wawona	Yosemite NP	CA	NPS	25,407
Hodgdon Meadow	Yosemite NP	CA	NPS	24,746
Pinnacles	Pinnacles NP	CA	NPS	24,210
Crane Flat	Yosemite NP	CA	NPS	23,844
Indian Cove	Joshua Tree NP	CA	NPS	23,376
Dogwood	Arrow Head, San Bernardino NF	CA	USFS	21,540
Acorn	New Hogan Lake	CA	USACE	21,164
Black Rock	Joshua Tree NP	CA	NPS	19,888
Kalaloch	Olympic NP	WA	NPS	18,105
Dinkey Creek	High Sierra RD, Sierra NF	CA	USFS	16,294
Logger	Truckee RD, Tahoe NF	CA	USFS	16,253
Diamond Lake	Diamond Lake RD, Umpqua NF	OR	USFS	15,683
Kyen	Lake Mendocino	CA	USACE	15,015
Dorst Creek	Sequoia And Kings Canyon NP	CA	NPS	14,435
North Rim	Grand Canyon NP	AZ	NPS	13,898
Ohanapecosh	Mount Rainier NP	WA	NPS	13,889
Devils Garden	Arches NP	UT	NPS	13,138
Oh Ridge	Mono Lake RD, Inyo NF	CA	USFS	13,063
Fish Creek	Glacier NP	MT	NPS	12,434
Manzanita Lake	Lassen Volcanic NP	CA	NPS	12,379

Figure A5: Relationship Between Control Function $\tilde{\varepsilon}_{ijt}$ and Travel Cost Using Model (4) of Table 4 Showing Correlation Between Preferences and Travel Cost in the Selected Sample of Reservers

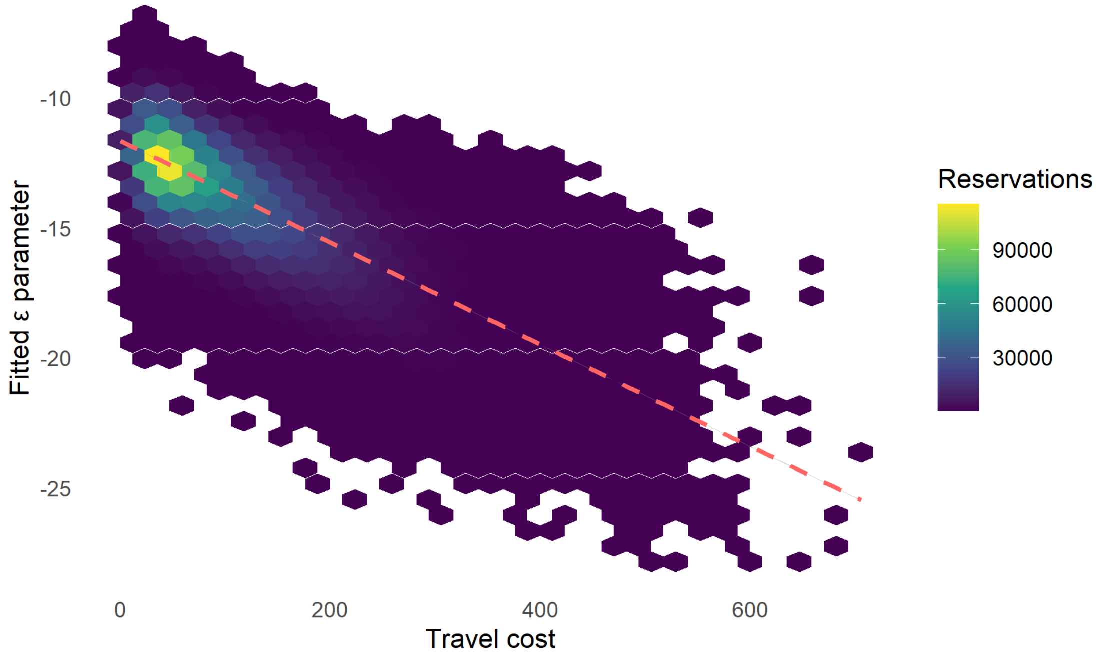


Figure A6: Total Estimated Welfare Losses and Proportion of Visits Affected by Smoke per Year

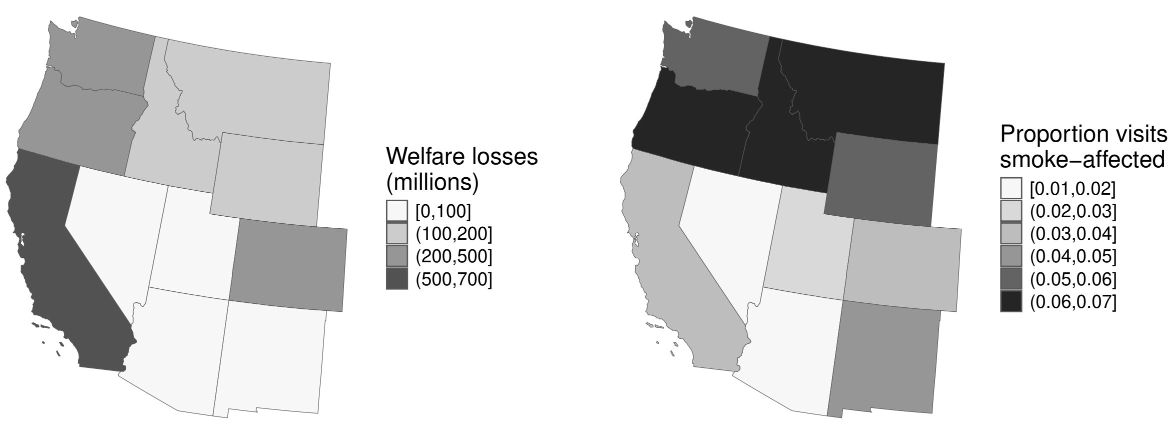


Table A2: Predicted Probability Campground Will Be Smoke-Affected, by Number of Smoke Days in the Preceding Week

	1{Campground is smoke-affected}
Intercept	0.0000
	(0.0001)
1{Smoke days in week of arrival = 1}	0.2013**
	(0.0005)
1{Smoke days in week of arrival = 2}	0.3009**
	(0.0008)
1{Smoke days in week of arrival = 3}	0.3798**
	(0.0010)
1{Smoke days in week of arrival = 4}	0.4850**
	(0.0012)
1{Smoke days in week of arrival = 5}	0.6108**
	(0.0013)
1{Smoke days in week of arrival = 6}	0.7390**
	(0.0016)
1{Smoke days in week of arrival = 7}	1.0000**
	(0.0018)
N	1,528,470

Notes: * $p < 0.05$, ** $p < 0.01$.

Appendix B: Numerical example of sample selection correction

In Section 3.3, we propose a control function approach to account for unobserved preferences $\tilde{\varepsilon}_{ijt}$ that could bias estimation of $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ if omitted. In this appendix, we provide a numerical example to illustrate the source of this bias, its effect on estimation of willingness to pay (WTP), and correction using a control function. We show that WTP is only biased when preferences for the reservation decision influence the cancellation decision (i.e., given selection) and when the counterfactual cancellation decision of non-reservers is unobserved. Furthermore, the bias operates through correlation between preferences and travel cost:

Table A3: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Heterogeneity by Smoke Days in Week Before Arrival

	(1)	(2)	(3)	(4)
Travel cost (dollars)	-0.0025**	-0.0024**	-0.0024**	-0.0024**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-10.5524**	-11.6117**	-11.5449**	-7.4215**
	(0.9020)	(2.3964)	(2.4152)	(0.7843)
High temp. (degrees C)	0.0202**	0.0289**	0.0289**	0.0302**
	(0.0044)	(0.0023)	(0.0023)	(0.0021)
Low temp. (degrees C)	-0.0031	-0.0183**	-0.0189**	-0.0226**
	(0.0057)	(0.0025)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0043**	-0.0060**	-0.0061**	-0.0057**
	(0.0011)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0027	-0.0342**	-0.0352**	-0.0368**
	(0.0255)	(0.0124)	(0.0124)	(0.0126)
Smoke days = 1	0.0158	-0.0718**	-0.0575*	-0.0776**
	(0.0268)	(0.0247)	(0.0246)	(0.0201)
Smoke days = 2	-0.1521**	-0.2164**	-0.1975**	-0.2217**
	(0.0436)	(0.0427)	(0.0416)	(0.0339)
Smoke days = 3	-0.2257**	-0.3050**	-0.2862**	-0.3182**
	(0.0410)	(0.0441)	(0.0437)	(0.0357)
Smoke days = 4	-0.4418**	-0.4792**	-0.4506**	-0.5066**
	(0.0472)	(0.0511)	(0.0502)	(0.0447)
Smoke days = 5	-0.5737**	-0.6032**	-0.5779**	-0.6583**
	(0.0448)	(0.0560)	(0.0551)	(0.0488)
Smoke days = 6	-0.7121**	-0.7612**	-0.7444**	-0.8348**
	(0.0603)	(0.0669)	(0.0669)	(0.0637)
Smoke days = 7	-1.0022**	-1.0065**	-0.9868**	-1.0481**
	(0.0660)	(0.0939)	(0.0922)	(0.0908)
WTP: 1 smoke day	-6.31	30.11*	23.87*	31.96**
	(10.45)	(11.92)	(11.38)	(9.66)
WTP: 2 smoke days	60.79**	90.8**	82.03**	91.32**
	(21.15)	(24.32)	(22.91)	(20.36)
WTP: 3 smoke days	90.26**	127.98**	118.9**	131.09**
	(22.07)	(27.66)	(26.04)	(23.07)
WTP: 4 smoke days	176.63**	201.07**	187.15**	208.68**
	(31.73)	(33.26)	(31.01)	(29.87)
WTP: 5 smoke days	229.38**	253.09**	240.06**	271.19**
	(38.74)	(39.86)	(36.75)	(34.92)
WTP: 6 smoke days	284.7**	319.4**	309.19**	343.87**
	(46.09)	(50.3)	(47.28)	(47.41)
WTP: 7 smoke days	400.7**	422.33**	409.86**	431.74**
	(59.86)	(73.41)	(68.21)	(68.64)
N	2,723,034	2,691,655	2,691,655	2,688,739
Campground x week-of-year FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

among the selected sample of reservers, those with a high travel cost tend to have had a high taste for the site. This relationship downward biases estimates of the travel cost parameter in the cancellation decision, inflating WTP estimates. Finally, we demonstrate bias correction using the control function for $\tilde{\varepsilon}_{ijt}$ given in Equation 10.

In this numerical example, we simulate the two-stage reservation and cancellation decision using a Monte Carlo of 10,000 random draws. For every iteration, we generate $N = 100,000$ users i, each with a spatial coordinate $(x, y) \in [0, 1] \times [0, 1]$, where x and y are distributed uniformly. In addition, we generate a single site j at a random coordinate $(x, y) \in [0, 1] \times [0, 1]$, where x and y are again distributed uniformly. User i's travel cost c_{ij} is given by the Euclidean distance from i to j.

Users who reserve far in advance maximize utility based on expected smoke conditions. Define the utility from the reservation as $U^R_{ij} = \alpha_j + \delta c_{ij} + \phi \mathbb{E}[s_j] + \varepsilon_{ij}$, where α_j is an intercept, c_{ij} is the travel cost, s_j denotes smoke conditions at the site, and ε_{ij} is the individual's preferences from reservation. We will assert arbitrarily that $\alpha_j = 1$, $\delta = -0.8$, and $\phi = -1.6$. Therefore, the true WTP is $\phi/\delta = 2$. Each user's site-specific preference values of ε_{i0} and ε_{ij} are drawn from a type I extreme value distribution. Based on the "time of visitation," expected smoke conditions $\mathbb{E}[s_j]$ are drawn for each user from $\{0.1, 0.2, 0.4\}$ with equal probability. Users will choose to reserve $R_{ij} = 1 \iff U^R_{ij} \geq U^R_{i0}$.

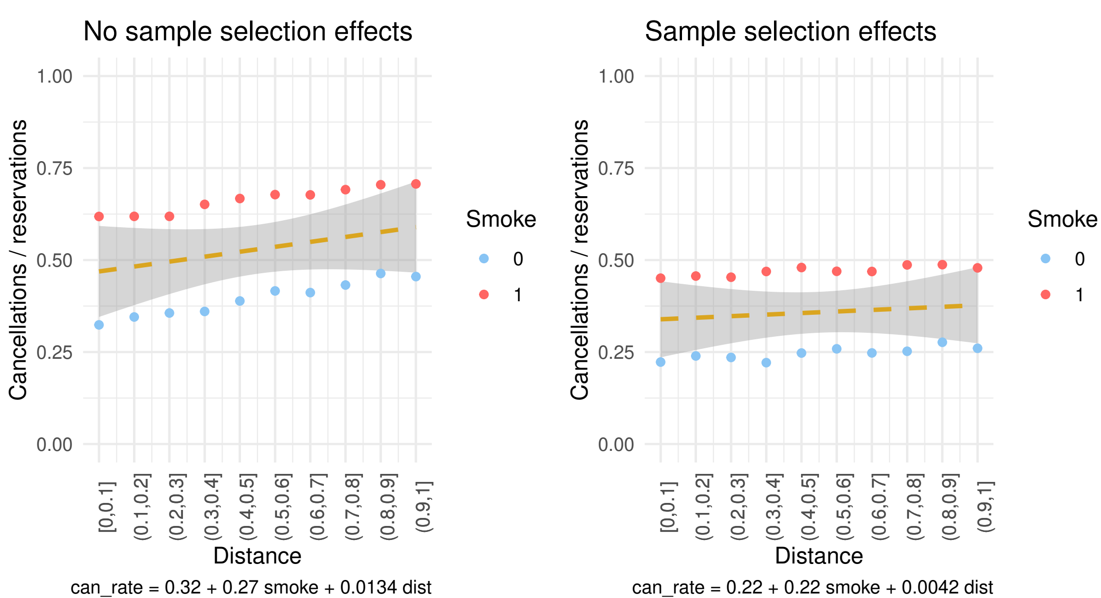
For the cancellation decision, the user decides based on realized smoke conditions. Let the utility from cancellation be $U^C_{ij} = \alpha_j + \delta c_{ij} + \phi s_j + \upsilon_{ij}$. Realized smoke s_j is drawn from $\{0, 1\}$ with $\mathbb{P}(s_j = 1) = 0.25$ for each user to create variation based on the "time of visitation."

We consider two types of error structures υ_{ij} in the cancellation decision. The first is an independent error, $\upsilon^{ind}_{ij} = \frac{1}{\rho}\eta_{ij}$, where $\eta_{ij} \sim$ type I extreme value, which assumes that the user's preferences in the decision are completely unrelated to their choice to have reserved. The second is a dependent error, $\upsilon^{dep}_{ij} = \varepsilon_{ij} + \frac{1}{\rho}\eta_{ij}$, which allows preferences at the time of reservation to affect the decision. We assume $\eta_{ij} \sim$ type I extreme value and arbitrarily set $\rho = 0.7$. Users will cancel $C_{ij} = 1 \iff U^C_{ij} \leq U^C_{i0}$. Because of the differing error structures, we consider two decisions under both υ^{ind}_{ij} and υ^{dep}_{ij}, which we denote as C^{ind}_{ij} and C^{dep}_{ij}, respectively.

The selection issue in the real recreation data arises because we can only observe the cancellation decision for reservers. However, under the Monte Carlo simulation, we can also examine the counterfactual decision of the non-reservers to see if they "would have" cancelled. We show that, even with a dependent error v_{ij}^{dep}, estimation of $\mathbb{P}(C_{ij} = 0)$ on the full sample (reservers and non-reservers) without observing ε_{ij} will still recover the true WTP because no selection effect exists. That is, the biased estimation of $\mathbb{P}(C_{ij} = 0|R_{ij} = 1)$ is because ε_{ij} and c_{ij} are correlated in the selected sample, not the full sample.

Figure B1 illustrates the effects of selection by contrasting cancellation rates with and without selection effects, illustrating several key points. First, the overall cancellation rate is lower in the presence of selection, as indicated by the intercept of the fitted gold line. Users who made a reservation had a high initial preference for the site, so they are less likely overall to cancel. Second, the average effect of smoke, which is the distance between the red and blue points, is similar both with and without sample selection effects. Third, the effect of travel cost, which is the slope of the gold fitted line, is attenuated when preferences at the time of reservation affect the cancellation decision. This attenuation illustrates that the selection effect likely operates through positive correlation between ε_{ij} and travel cost.

Figure B1: Example Cancellation Rate to Illustrate the Effects of Selection



Next, we show that WTP estimates are only biased under a selected sample and when preferences at the time of reservation affect the cancellation decision. We estimate a logit regression for the reservation and cancellation decisions, varying whether we use the full sample or selected sample of reservers and the dependent error υ_{ij}^{dep} or the independent error υ_{ij}^{ind} for the cancellation decision.

Table B1 shows results from 10,000 draws. In Column 1, we use the full sample for the reservation decision. In Columns 2 and 3, we estimate the cancellation decision with both errors υ_{ij}^{ind} and υ_{ij}^{dep} but with the full sample. These regressions show that the selection effects would not cause biased estimation if the counterfactual cancellation decision of the non-reservers were known. In Column 4, we estimate the cancellation decision among only the selected sample but with an independent error υ_{ij}^{ind} (i.e., assuming no selection effects). Regression 4 demonstrates that sample selection is not an issue if the user's preferences at the time of reservation are unrelated to their cancellation decision. Biased estimation arises in Column 5 when there is both sample selection and when the reservation preferences affect the cancellation decision. Finally, Column 6 shows that inclusion of a control function corrects for the bias of Column 5. This result lends support to the use of this bias corrector in the empirical dataset.

Table B1: Monte Carlo 10,000 Simulated Regressions of Reservation and Cancellation Decisions

	(1)	(2)	(3)	(4)	(5)	(6)
WTP	2.00**	2.01**	2.01**	2.01**	6.70	2.00**
	(0.10)	(0.11)	(0.14)	(0.15)	(8.52)	(0.25)
Dep. var.	R_{ij}	C_{ij}	C_{ij}	C_{ij}	C_{ij}	C_{ij}
Users	All users	All users	All users	Reservers	Reservers	Reservers
Error	ε_{ij}	υ_{ij}^{ind}	υ_{ij}^{dep}	υ_{ij}^{ind}	υ_{ij}^{dep}	υ_{ij}^{dep}
Control function		No	No	No	No	Yes

Notes: True WTP = 2. * $p < 0.05$, ** $p < 0.01$.

Appendix C: Bootstrapped standard errors for $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$

In Section 4, we used a two-stage sample selection correction to estimate $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$. Wooldridge (2015) recommends that researchers bootstrap standard errors when estimating two-stage control functions. Because we cluster standard errors at the campground level, our bootstrap follows the process outlined by Cameron and Miller (2015) in a methods guide for clustered standard errors: for B bootstraps and G clusters, (1) sample with replacement G times from the original sample of clusters, and (2) compute parameter estimates. The estimating dataset contains $G = 999$ clusters. The resampling occurs over entire clusters; in some bootstraps, some clusters will not be represented, whereas some clusters will have all of their observations appear multiple times in the estimating dataset. Cameron and Miller (2015) note that $B = 400$ should be "more than adequate" in most settings.

In this section, we test that the bootstrapped coefficients follow a normal distribution, assessing whether $B = 400$ is adequate. Table C1 reports W statistics from Shapiro-Wilk tests of normality for the smoke and travel cost coefficients from the main estimation of Table 4. We fail to reject the null hypothesis that the bootstrapped smoke and travel cost coefficients follow a normal distribution. These tests imply that 400 bootstraps are adequate for the analysis. Figures C1 and C2 plot the bootstrapped coefficients visually.[34]

[34] One single iteration of the bootstrap produced abnormally large coefficient estimates, where, for example, the travel cost coefficient was estimated as -23 trillion. Still, that iteration produced a WTP in line with the other iterations; the WTP was equal to $74, suggesting that despite the abnormal magnitude of the coefficients, the ratios of coefficients to one another were proper. Nevertheless, we remove this single outlier from Figures C1 and C2, and from the analysis in the main text.

Table C1: W Statistics from Shapiro-Wilk Test of Normality for Bootstrapped Coefficients of $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ with Sample Selection Correction (parentheses indicate p values; the null hypothesis is that the coefficients are normally distributed)

	(1)	(2)	(3)	(4)
Smoke in week of arrival	0.996	0.998	0.998	0.994
	(0.450)	(0.979)	(0.852)	(0.084)
Travel cost (dollars)	0.990	0.996	0.995	0.995
	(0.006)	(0.343)	(0.291)	(0.255)
Campground x week-of-year FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Figure C1: Distribution of Estimated Smoke Coefficient from Models (1) to (4) in Bootstrapped Estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ with Sample Selection Correction (red line indicates mean)

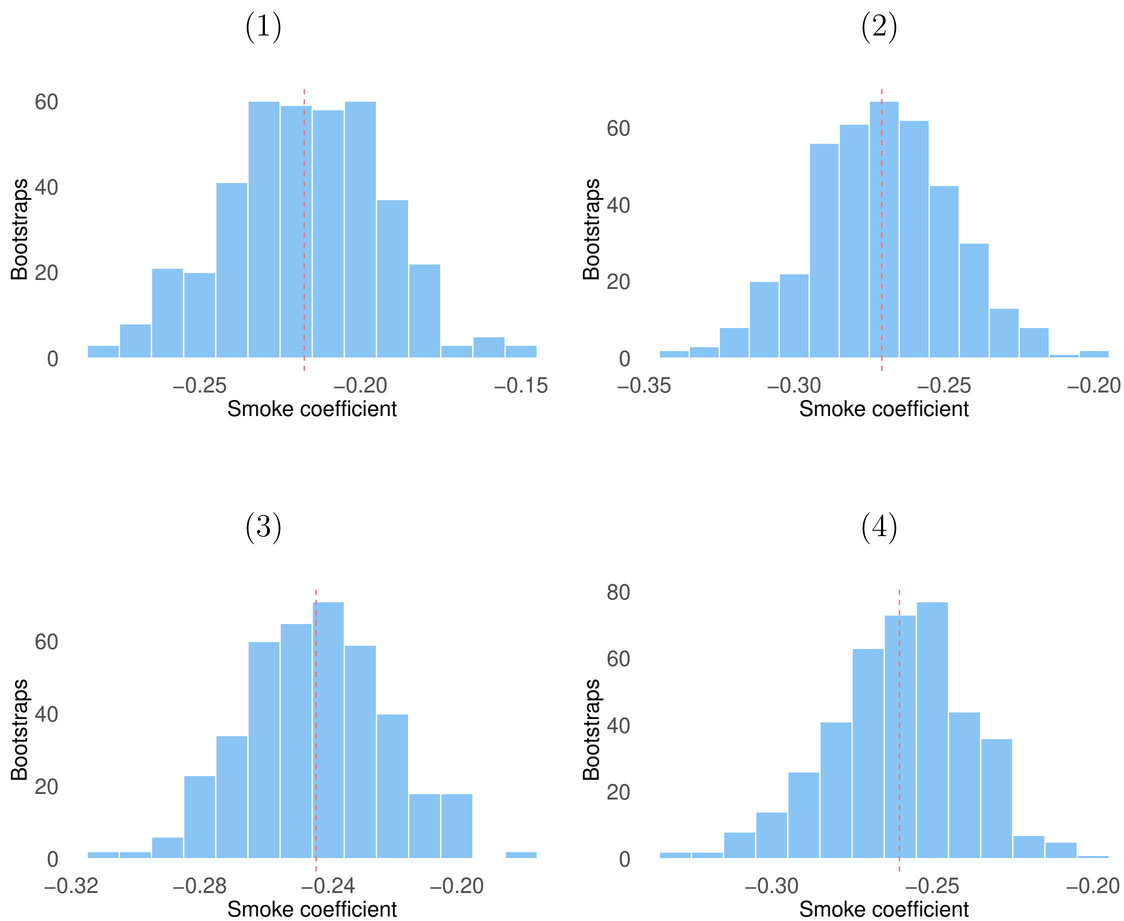
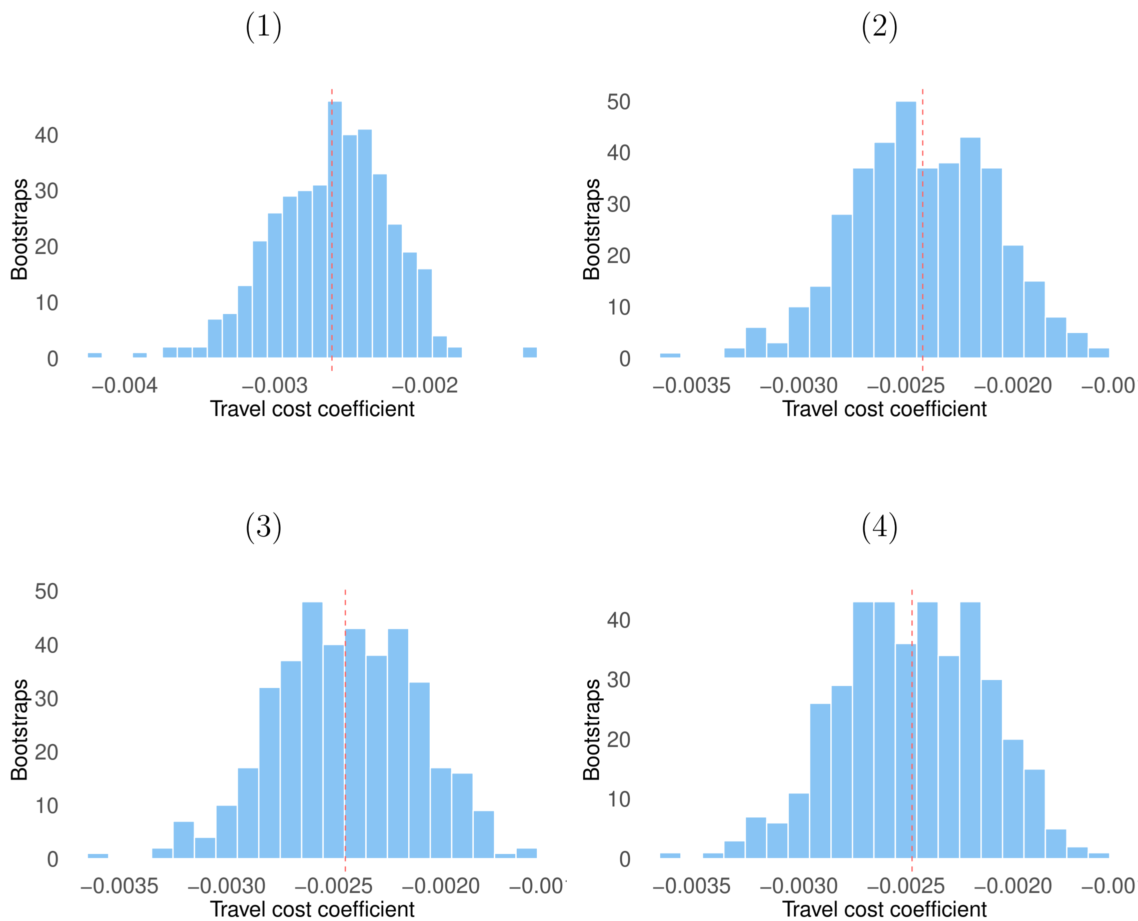


Figure C2: Distribution of Estimated Travel Cost Coefficient from Models (1) to (4) in Bootstrapped Estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ with Sample Selection Correction (red line indicates mean)



Appendix D: Heterogeneity and robustness by campground characteristics

In this section we explore a series of robustness checks and heterogeneity analyses. These include a test of the influence of no-shows on cancellation estimates. We also provide results by various campground characteristics, including visitation levels, region, managing agency, and site amenities. Lastly, we explore temporal aspects of demand, including heterogeneity by time of booking and by holiday weekend.

D1 Testing the influence of no-shows in cancellations

One may be concerned that recreationists do not formally cancel their reservation when they decide not to complete a trip. Unreported no-shows threaten the identification of any willingness to pay (WTP) that is based on cancellations, as it could underestimate them. Although most of the campgrounds in the Recreation.gov dataset do not report check-ins or no-shows, a subset do. Just 36 out of 999 campgrounds (3.6 percent) report no-shows, but they represent 19.7 percent of the reservations used in the cancellation estimation. Overall, no-shows represent approximately 14.1 percent of all cancellations at the campgrounds which report no-shows.

As a robustness check, we recode no-shows at the reporting campgrounds to arrivals, which would reflect what the data would show at non-reporting campgrounds. If there is no difference in WTP when recoding no-shows, then it suggests that no-shows do not threaten the results of the main analysis.

Table D1 tests two models. Column 1 allows smoke and travel cost to respond differentially for no-show and non-no-show campgrounds. This model shows that no-show and non-no-show campgrounds have different overall measures of WTP. In Column 2 we recode no-shows as arrivals for the campgrounds that report no-shows. Comparing the WTP of no-show campgrounds with and without recoding (\$116.66 and \$118.44), WTP is virtually unchanged and is not statistically different. This analysis should alleviate concerns that no-shows influence the estimate of WTP in the full sample.

Table D1: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Testing Effect of No-Shows on Cancellation by Recoding No-Shows as Arrivals

	(1)	(2)
Smoke x 1(Non-no-show campground)	-0.2608**	-0.2605**
	(0.0188)	(0.0188)
Smoke x 1(No-show campground)	-0.2628**	-0.2786**
	(0.0689)	(0.0730)
Travel cost x 1(Non-no-show campground)	-0.0025**	-0.0025**
	(0.0004)	(0.0004)
Travel cost x 1(No-show campground)	-0.0023**	-0.0024**
	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-7.8180**	-7.9904**
	(0.8223)	(0.8606)
High temp. (degrees C)	0.0306**	0.0306**
	(0.0022)	(0.0022)
Low temp. (degrees C)	-0.0252**	-0.0253**
	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0057**	-0.0058**
	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0376**	-0.0368**
	(0.0134)	(0.0136)
WTP, non-no-show campgrounds	103.82**	104.32**
	(17.39)	(17.8)
WTP, no-show campgrounds	116.66**	118.44**
	(32.1)	(33.75)
No-shows recoded as arrivals?	No	Yes
N	2,688,739	2,688,582
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$

D2 Campground popularity

This section explores heterogeneous welfare damages based on the popularity of a campground. We define popularity based on the average number of visitors per year for years in which it was open. For reference, Table A1 shows the most-visited campgrounds, many of which belong to high-profile national parks, such as Yosemite, Grand Canyon, and Rocky Mountain. The least popular tend to be small, local, or regional US Forest Service campgrounds. We rerun the main estimation but allow the smoke and travel cost coefficients to vary by the quartile of popularity. Given 999 campgrounds, each quartile contains approximately 250 locations.

Table D2 displays full results, including point estimates for smoke responses, travel cost responses, and WTP. Across specifications, the magnitude for both the smoke and travel cost coefficients are lower at more popular campgrounds. These results suggest visitors are more willing to incur both higher travel costs and some environmental disamenity for highly desirable locations.

The translation of these responses to welfare impacts is less clear. WTP is estimated as the ratio of marginal disutility in smoke to that in expenditure (the smoke coefficient divided by the travel cost coefficient). Because WTP is a ratio, it could be either higher or lower given reductions in both the smoke parameter (the numerator) and the travel cost parameter (the denominator). Table D2 shows that the reduction in the smoke parameter dominates, resulting in lower WTP at popular campgrounds. In general, welfare damages tend to be largest for the middle two quartiles of popularity.

D3 Campground characteristics and amenities

In this section, we consider heterogeneous responses by campground characteristics. First, we test for heterogeneous responses by managing agency. We run separate regressions only on the set of campgrounds managed by each agency. Table D3 displays results. This analysis suggests that the welfare costs of smoke are higher for National Park Service locations and lower for US Forest Service locations. We do not obtain statistically significant results for the US Army Corps of Engineers, Bureau of Land Management, or Bureau of Reclamation locations, likely due to being statistically underpowered. As noted in Section 2.6, the data feature 908 US Forest Service campgrounds and 50 National Park Service campgrounds, but only 31 US Army Corps of Engineers, 5 Bureau of Land Management, and 5 Bureau of

Table D2: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Heterogeneity by Campground Popularity

	(1)	(2)	(3)	(4)
Inv. distance to wildfire (km^{-1})	-11.0284**	-12.0844**	-11.9595**	-7.8196**
	(0.9225)	(2.4306)	(2.4448)	(0.8254)
High temp. (degrees C)	0.0187**	0.0289**	0.0293**	0.0307**
	(0.0044)	(0.0023)	(0.0023)	(0.0022)
Low temp. (degrees C)	-0.0012	-0.0204**	-0.0213**	-0.0252**
	(0.0055)	(0.0025)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0046**	-0.0059**	-0.0061**	-0.0057**
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0037	-0.0377**	-0.0387**	-0.0402**
	(0.0256)	(0.0120)	(0.0120)	(0.0122)
Smoke x first quartile (most popular)	-0.2208**	-0.2297**	-0.2035**	-0.2446**
	(0.0320)	(0.0345)	(0.0338)	(0.0286)
Smoke x second quartile	-0.2563**	-0.3296**	-0.3007**	-0.2915**
	(0.0425)	(0.0417)	(0.0407)	(0.0335)
Smoke x third quartile	-0.2364**	-0.3161**	-0.2889**	-0.3301**
	(0.0462)	(0.0482)	(0.0482)	(0.0482)
Smoke x fourth quartile (least popular)	-0.2488**	-0.3577**	-0.3457**	-0.2781**
	(0.0576)	(0.0673)	(0.0681)	(0.0743)
Travel cost x first quartile (most popular)	-0.0028**	-0.0023**	-0.0024**	-0.0024**
	(0.0004)	(0.0003)	(0.0003)	(0.0004)
Travel cost x second quartile	-0.0010*	-0.0027**	-0.0027**	-0.0026**
	(0.0005)	(0.0003)	(0.0003)	(0.0003)
Travel cost x third quartile	-0.0009	-0.0030**	-0.0030**	-0.0030**
	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Travel cost x fourth quartile (least popular)	-0.0009	-0.0031**	-0.0031**	-0.0032**
	(0.0006)	(0.0005)	(0.0005)	(0.0005)
WTP: first quartile (most popular)	79.36**	98.63**	86.49**	102.87**
	(17.55)	(21.64)	(20.09)	(18.25)
WTP: second quartile	249.52	123.65**	112.36**	110.23**
	(136.76)	(22.99)	(21.6)	(19.31)
WTP: third quartile	253.55	106.16**	96.52**	108.62**
	(169.66)	(22.64)	(21.48)	(20.82)
WTP: fourth quartile (least popular)	272.18	116.18**	110.39**	87.8**
	(195.78)	(29.58)	(28.58)	(27.56)
N	2,723,034	2,691,655	2,691,655	2,688,739
Campground x week-of-year FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Reclamation campgrounds.

Next, we assess regional heterogeneity. Two components are important to understand regional differences in smoke impacts. One component is how the frequency of smoke differs, which is in part addressed in the total welfare analysis in Table 6 and Figure A6. A second component of regional heterogeneity is the potentially differential responses to smoke by region. We run separate regressions by region to explore these responses. Table D4 shows that per-trip welfare losses are highest for California, the Pacific Northwest, and the Great Basin; they are lowest for the Rocky Mountains and Northern Rocky Mountains.

We also investigate heterogeneity by campground characteristics. The Recreation.gov data report the site type that individuals have reserved, where a site is a reservable location within a campground. These site types include RV sites, "standard" sites, tent-only sites, and "walk to/hike to" sites, the last of which are accessible only by hiking in. Ex-ante, responses to smoke could differ for RV users because they are arguably less exposed to smoke than tent-only or walk to/hike to sites; on the other hand, RV users could be older and more health-sensitive. Results are reported in Table D5. We find that RV users have the strongest responses to smoke, resulting in higher welfare losses for these individuals. According to the RV Industry Association, about 66 percent of RV owners are aged 55 or older, so these results could reflect health-related sensitivity to wildfire smoke.[35] The other site types, such as tent-only or walk to/hike to, might be visited most by users who are younger or more able-bodied. Separately, in Column 2, we find no differences by electric or non-electric sites.

Lastly, we test the influence of desirable environmental amenities. We collect water body data from the USGS National Hydrography Dataset and elevation data from the USGS National Elevation Dataset. We draw 1 km boundaries around campground centroids and measure heterogeneity by the proportion of area that is a water body, the maximum elevation, and the range in elevation (maximum minus minimum), the last of which is a measure of terrain diversity. Column 1 of Table D6 shows that people are more tolerant of smoke if there are water bodies nearby, which is an element of campground desirability. Column 2

[35] RV Industry Association. Go RVing RV Owner Demographic Profile: Class A Motorhomes. https://www.rvia.org/news-insights/go-rving-rv-owner-demographic-profile-class-motorhomes.

shows that people are more tolerant of smoke at higher elevations, which could correspond to mountainous locations. Column 3, which reports responses by terrain diversity, shows no clear trend.

Table D3: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Results by Managing Agency

	(1)	(2)	(3)	(4)	(5)
Smoke in week of arrival	-0.300**	-0.177**	-0.105*	0.121	-0.129
	(0.0250)	(0.0410)	(0.041)	(0.238)	(0.125)
Travel cost (dollars)	-0.003**	-0.001**	-0.007**	-0.001	-0.004
	(0.0003)	(0.0004)	(0.002)	(0.003)	(0.002)
Inv. distance to wildfire (km^{-1})	-9.835**	-4.990**	-11.551**	-2.243	-32.845**
	(0.905)	(1.090)	(4.291)	(1.914)	(6.836)
High temp. (degrees C)	0.033**	0.033**	0.005	0.034**	0.038
	(0.003)	(0.004)	(0.006)	(0.011)	(0.035)
Low temp. (degrees C)	-0.026**	-0.029**	-0.011	-0.056**	-0.033
	(0.003)	(0.005)	(0.011)	(0.015)	(0.029)
Precip. in week of arrival (mm)	-0.005**	-0.007**	-0.005**	-0.001	-0.001
	(0.001)	(0.003)	(0.002)	(0.001)	(0.006)
$\tilde{\varepsilon}_{ijt}$	-0.049**	-0.094*	-0.143**	-0.007	-0.040
	(0.009)	(0.040)	(0.036)	(0.071)	(0.100)
Agency	USFS	NPS	USACE	BLM	BOR
WTP	91.24**	119.12**	14.03	-112.82	35.85
	(10.32)	(42.02)	(7.64)	(477.86)	(49.65)
N	2,017,300	507,282	128,772	17,155	18,230
Campground x week-of-year FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Table D4: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Results by Region

	(1)	(2)	(3)	(4)	(5)	(6)
Smoke in week of arrival	-0.276**	-0.222*	-0.138**	-0.378**	-0.177**	-0.195*
	(0.0360)	(0.090)	(0.041)	(0.044)	(0.041)	(0.077)
Travel cost (dollars)	-0.002**	-0.003**	-0.004**	-0.005**	-0.003**	-0.002**
	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Inv. distance to wildfire (km^{-1})	-7.837**	-2.934	-14.647**	-5.331**	-17.844**	-7.643**
	(1.0130)	(5.243)	(1.439)	(1.806)	(4.670)	(1.841)
High temp. (degrees C)	0.039**	0.026**	0.035**	0.020**	0.020**	0.022*
	(0.0030)	(0.008)	(0.004)	(0.003)	(0.006)	(0.010)
Low temp. (degrees C)	-0.029**	-0.015	-0.032**	-0.017**	-0.037**	-0.017*
	(0.0040)	(0.009)	(0.006)	(0.004)	(0.006)	(0.009)
Precip. in week of arrival (mm)	-0.003*	-0.006**	-0.008**	-0.004**	-0.013**	-0.002
	(0.0010)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$\tilde{\varepsilon}_{ijt}$	-0.025	-0.033	-0.076*	-0.106**	-0.053*	-0.039
	(0.0170)	(0.020)	(0.037)	(0.018)	(0.022)	(0.023)
Region	California	Great Basin	Northern Rockies	Pacific Northwest	Rocky Mountains	Southwest
	CA	NV, UT	ID, MT	OR, WA	CO, WY	AZ, NM
WTP	129.2**	78.3*	38.35*	83.17**	53.39**	79.44
	(25.84)	(35.93)	(17.04)	(12.73)	(11.71)	(41.72)
N	1,213,510	212,033	182,722	548,514	388,211	143,749
Campground x week-of-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Table D5: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Results by Site Type

	(1)	(2)
Travel cost (dollars)	-0.002**	-0.002**
	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-7.824**	-7.818**
	(0.8240)	(0.8240)
High temp. (degrees C)	0.031**	0.031**
	(0.0020)	(0.0020)
Low temp. (degrees C)	-0.025**	-0.025**
	(0.0020)	(0.0020)
Precip. in week of arrival (mm)	-0.006**	-0.006**
	(0.0010)	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037**	-0.037**
	(0.0130)	(0.0130)
Smoke x RV Site	-0.347**	
	(0.0510)	
Smoke x Standard Site	-0.264**	
	(0.0220)	
Smoke x Tent Only Site	-0.237**	
	(0.0410)	
Smoke x Walk To/Hike To Site	-0.215**	
	(0.0550)	
Smoke x Electric Site		-0.251**
		(0.0470)
Smoke x Nonelectric Site		-0.262**
		(0.0220)
WTP: RV Site	143.26**	
	(28.01)	
WTP: Standard Site	108.99**	
	(16.64)	
WTP: Tent Site	98**	
	(22.64)	
WTP: Walk To/Hike To Site	88.86**	
	(26.31)	
WTP: Electric Site		103.72**
		(24.53)
WTP: Nonelectric Site		108.24**
		(17.26)
N	2,688,739	2,688,739
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Table D6: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Results by Terrain Within 1 km: Proportion of Area that is Water, Max Elevation, and Max Elevation Minus Min Elevation

	(1)	(2)	(3)
Travel cost (dollars)	-0.002**	-0.002**	-0.002**
	(0.0003)	(0.0004)	(0.0004)
Inv. distance to wildfire (km^{-1})	-7.813**	-7.841**	-7.853**
	(0.8250)	(0.8400)	(0.8350)
High temp. (degrees C)	0.031**	0.030**	0.030**
	(0.0020)	(0.0020)	(0.0020)
Low temp. (degrees C)	-0.025**	-0.024**	-0.024**
	(0.0020)	(0.0020)	(0.0020)
Precip. in week of arrival (mm)	-0.006**	-0.006**	-0.006**
	(0.0010)	(0.0010)	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037**	-0.038**	-0.038**
	(0.0130)	(0.0130)	(0.0130)
Smoke x Prop. Water = 0	-0.287**		
	(0.0280)		
Smoke x Prop. Water in 0-0.01	-0.183		
	(0.1000)		
Smoke x Prop. Water in 0.01-0.02	-0.260**		
	(0.0730)		
Smoke x Prop. Water in 0.02-0.03	-0.234**		
	(0.0490)		
Smoke x Prop. Water in 0.03-1	-0.215**		
	(0.0480)		
Smoke x Max Elev. in -10-1000 m		-0.289**	
		(0.0460)	
Smoke x Max Elev. in 1000-2000 m		-0.329**	
		(0.0410)	
Smoke x Max Elev. in 2000-3000 m		-0.207**	
		(0.0340)	
Smoke x Max Elev. in 3000-4000 m		-0.262**	
		(0.0410)	
Smoke x Elev. Diff. in 0-150 m			-0.199**
			(0.0330)
Smoke x Elev. Diff. in 150-300 m			-0.286**
			(0.0430)
Smoke x Elev. Diff. in 300-400 m			-0.365**
			(0.0770)
Smoke x Elev. Diff. in 400-1200 m			-0.241**
			(0.0340)
WTP: Lowest bin	118.58**	118.69**	81.65**
	(21.88)	(26.96)	(26.96)
WTP: Second bin	75.77	134.78**	117.12**
	(42.74)	(26.42)	(26.42)
WTP: Third bin	107.44**	84.82**	149.48**
	(33.92)	(18.09)	(18.09)
WTP: Highest bin	96.59**	107.4**	98.84**
	(18.96)	(23.65)	(23.65)
N	2,688,739	2,654,110	2,654,110
Campground x week-of-year FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

D4 Time of booking, choice set, and campground quality

One consequence of campground quality, whether measured by popularity as in Appendix D2 or by physical amenities as in Appendix D3, is that some desirable campgrounds may get completely booked and become unavailable for visitors who reserved at a later time. The model of Figure 3 implies a one-stage choice for the reservation decision. The assumption of this model is that the window of opportunity to book at a location is between one week and six months in advance; someone who booked only one month in advance could have booked at an alternative site earlier, but chose not to. This choice is endogenous.

Nevertheless, it is reasonable to wonder if congestion at desirable sites might distort welfare estimates for late reservers whose first choice was not available. A check on this possibility is to estimate welfare differentially according to how far in advance an individual reserved. Six months ahead of time, an individual should have a full choice set. Figure D1 displays welfare estimates from such an exercise, allowing smoke and travel cost coefficients to vary with 30 day bins that group the time of reservation. Full results are listed in Table D7.

Figure D1: Welfare Estimates by Time of Reservation

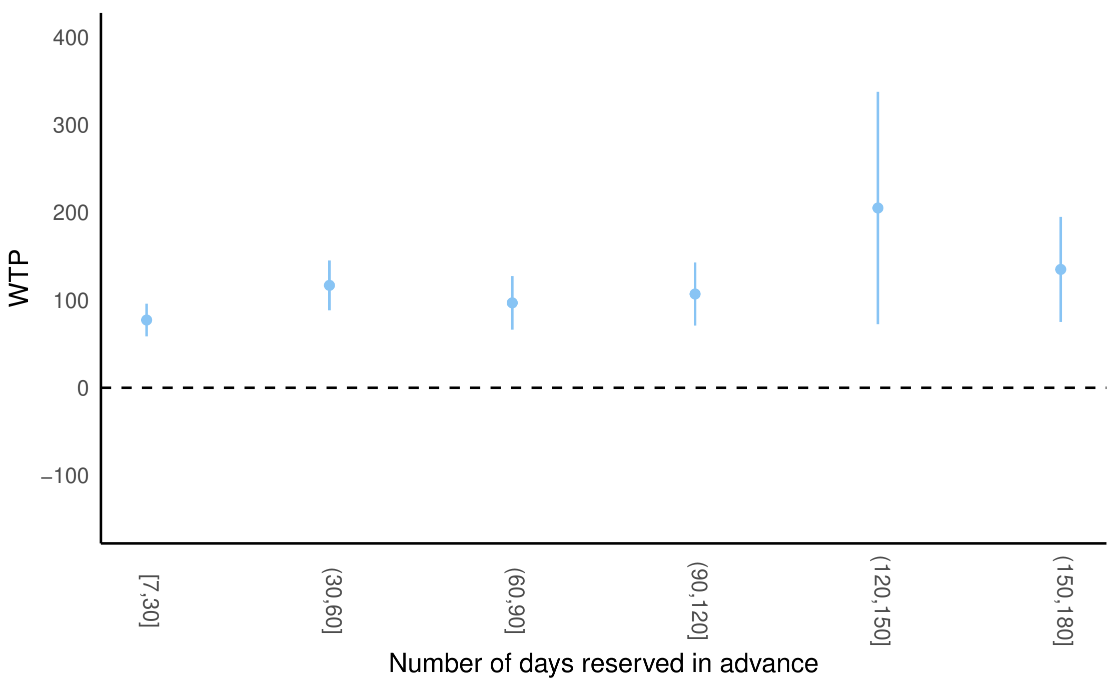


Table D7: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Heterogeneity by Time of Reservation

	(1)
Inv. distance to wildfire (km^{-1})	-7.619**
	(0.822)
High temp. (degrees C)	0.032**
	(0.002)
Low temp. (degrees C)	-0.026**
	(0.003)
Precip. in week of arrival (mm)	-0.006**
	(0.001)
$\tilde{\varepsilon}_{ijt}$	-0.037**
	(0.010)
Smoke x [7,30] days ahead	-0.229**
	(0.024)
Smoke x (30,60] days ahead	-0.324**
	(0.028)
Smoke x (60,90] days ahead	-0.262**
	(0.034)
Smoke x (90,120] days ahead	-0.280**
	(0.037)
Smoke x (120,150] days ahead	-0.294**
	(0.029)
Smoke x (150,180] days ahead	-0.216**
	(0.032)
Travel cost x [7,30] days ahead	-0.0030**
	(0.0002)
Travel cost x (30,60] days ahead	-0.0028**
	(0.0002)
Travel cost x (60,90] days ahead	-0.0027**
	(0.0003)
Travel cost x (90,120] days ahead	-0.0026**
	(0.0003)
Travel cost x (120,150] days ahead	-0.0014**
	(0.0005)
Travel cost x (150,180] days ahead	-0.0016**
	(0.0003)
N	2,417,246
Campground x week-of-year FE	Yes
Day-of-week FE	Yes
Campground x year FE	Yes

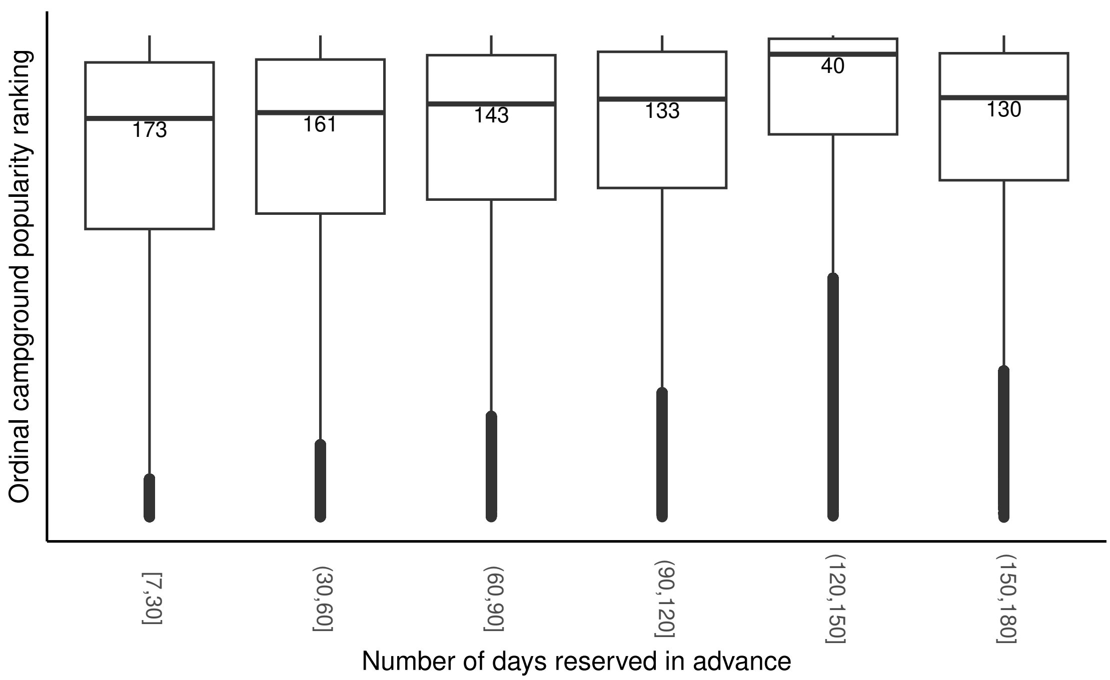
Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

The welfare values of Figure D1 include the main estimate of $107 in their confidence intervals, mitigating concerns for the estimates in the main text. However, one feature of Figure D1 is that welfare damages are somewhat higher for the two earliest bandwidths, at

$205.02 ([72.50, 337.54]) and $134.98 ([75.06, 194.90]). This relationship could be driven by unobservable differences in preferences for early planners. It could also be due to differences in the quality of the campgrounds that are reserved ahead of time, since Appendix D2 and Appendix D3 showed that quality is consequential for welfare estimates. In particular, Table D2 showed lower welfare values for the least popular locations. In addition, Table D2 and Table D7 showed lower magnitude travel cost coefficients for popular campgrounds and earlier reservers, respectively, which is suggestive of composition effects.

Figure D2 shows the distribution of campground popularity by time of reservation using the ordinal rankings developed in Appendix D2. According to this figure, while popular campgrounds are still selected in later months, the distribution of reservations in earlier months includes fewer low-popularity sites. These composition effects could help explain the patterns observed in Figure D1 and Table D7.

Figure D2: Earlier Reservations For More Popular Campgrounds, With Median Popularity Rank Denoted



D5 Temporal demand and holiday weekends

Demand to camp varies temporally. For instance, holiday weekends are known to be popular times to visit national parks.[36] The heterogeneity analyses of Appendix D have found that welfare estimates can differ by the desirability of a location; this relationship may also hold for desirable arrival times.

To explore this issue, we test for heterogeneity on holiday weekends. We define days of arrival as falling on a holiday weekend if the weekend, including Friday and Monday, includes the US federal holidays of Memorial Day, Independence Day, or Labor Day. Table D8 displays results from this estimation. We find that welfare losses are larger on federal holiday weekends, both due to increased sensitivity to smoke and decreased sensitivity to travel cost. These results add to the evidence on the upper-bound welfare losses from wildfire smoke.

Table D8: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Heterogeneity by Holiday Weekend

	(1)
Inv. distance to wildfire (km^{-1})	-7.812**
	(0.8250)
High temp. (degrees C)	0.031**
	(0.0020)
Low temp. (degrees C)	-0.025**
	(0.0020)
Precip. in week of arrival (mm)	-0.006**
	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037**
	(0.0130)
Travel cost x Holiday weekend = 0	-0.0025**
	(0.0003)
Travel cost x Holiday weekend = 1	-0.0020**
	(0.0004)
Smoke x Holiday weekend = 0	-0.256**
	(0.0210)
Smoke x Holiday weekend = 1	-0.310**
	(0.0580)
WTP: Non-holiday weekend	103.12**
	(16)
WTP: Holiday weekend	152.86**
	(44.13)
N	2,688,739
Campground x week-of-year FE	Yes
Day-of-week FE	Yes
Campground x year FE	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

[36] National Park Service. Visiting During the Busy Season. `https://www.nps.gov/jotr/planyourvisit/visiting-during-the-busy-season.htm`.

Appendix E: Alternative thresholds for sample restriction

We make two sample restrictions in the main text. First, we restrict attention to individuals within 650 km (400 miles) of one-way driving distance, which is meant to reduce the possibility of chained trips or air travel (English et al. 2018). We also define cancellations close to the arrival date as those made within seven days. In this section we provide sensitivity analyses for these threshold definitions.

E1 Distance restrictions

The main estimates of this paper restrict the estimating sample to reservations from origins within driving distance of a site, which we define as 650 km of one-way driving distance, or approximately 400 miles. Figure 2 shows that this threshold admits approximately 85 percent of the total reservations into the estimation. In this section, we show results from the main estimation using alternative distance thresholds of 350 km (approximately 217 miles) and 950 km (approximately 590 miles).

Table E1 illustrates how willingness to pay (WTP) estimates increase as the distance threshold is relaxed. Using a restrictive threshold of 350 km, WTP is estimated to be \$79 per person per trip; with a wider threshold of 950 km, WTP is estimated to be \$140 per person per trip. Column 2 reports the main estimates, identical to Table 4. The main estimate of \$107 is included in the confidence interval of the 950 km estimate ([90.30, 189.36]), and falls narrowly outside the confidence interval for the more restrictive 350 km estimate ([51.26, 106.22]).

As the distance threshold is relaxed, the increasing WTP estimates are driven by a decline in the magnitude of the travel cost coefficient. In other words, increasing the pool of potential reservers decreases the estimated response to travel cost. This phenomenon could result from including visitors at greater distances who chose not to cancel their reservations. An additional difference across estimations is the magnitude of the coefficient for the $\tilde{\varepsilon}_{ijt}$ preference parameter. The magnitude is likely smaller at lower thresholds due to the correlation of preferences with travel cost; removing reservations from larger distances eliminates some visitors with both high travel costs and high tastes for the chosen site.

Table E1: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Restricting Sample Distance to Within 350 km (217 miles), 650 km (404 miles), or 950 km (590 miles) of Site

	350 km	650 km	950 km
Smoke in week of arrival	-0.2651**	-0.2603**	-0.2589**
	(0.0241)	(0.0218)	(0.0206)
Travel cost (dollars)	-0.0034**	-0.0025**	-0.0019**
	(0.0005)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-8.9377**	-7.8141**	-7.5899**
	(0.8670)	(0.7920)	(0.8101)
High temp. (degrees C)	0.0331**	0.0306**	0.0300**
	(0.0025)	(0.0023)	(0.0021)
Low temp. (degrees C)	-0.0248**	-0.0252**	-0.0249**
	(0.0028)	(0.0025)	(0.0024)
Precip. in week of arrival (mm)	-0.0061**	-0.0057**	-0.0056**
	(0.0010)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0240	-0.0385**	-0.0390**
	(0.0165)	(0.0106)	(0.0128)
N	2,044,062	2,688,739	2,851,414
WTP	78.74**	107.14**	139.83**
	(14.02)	(16.33)	(25.27)
Campground x week-of-year FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

E2 Heterogeneous results within τ days of arrival

The main estimation considers the cancellation decisions of users within $\tau = 7$ days of arrival, where τ is defined in Figure 3. In this section, we explore heterogeneous results for alternative temporal thresholds. We reconstruct the dataset to estimate visitors' probability of cancellation within $\tau = 3$, 5, 7, and 9 days of arrival. The variable of interest is an indicator equal to 1 if a smoke-affected day occurred within the τ day threshold. We consider only standing, uncancelled reservations as of τ days before arrival.

Table E2 reports these results.[37] For $\tau = 3$, 5, 7, and 9 days, we find welfare damages of \$137, \$129, \$107, and \$92 per person per trip, respectively. These results are consistent with an information mechanism, which was explored in Section 4.3. For smaller values of τ, the occurrence of one smoke day corresponds to a greater likelihood of smoke on the actual day of arrival. Visitors may have a greater propensity to cancel when observing smoke closer to the date of arrival. The travel cost coefficient is largely stable as τ decreases; greater WTP is driven by a growth in the magnitude of the smoke coefficient. Overall, however, the main estimate of \$107 is included in the confidence interval of the estimates from each model.

Table E2: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within τ Days of Arrival

τ	3 days	5 days	7 days	9 days
Smoke	-0.2961**	-0.2929**	-0.2603**	-0.2281**
	(0.0536)	(0.0241)	(0.0218)	(0.0207)
Travel cost (dollars)	-0.0022**	-0.0023**	-0.0025**	-0.0025**
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^-1)	-12.2894*	-7.9469**	-7.8141**	-7.7057**
	(4.9610)	(0.8285)	(0.7920)	(0.8411)
High temp. (degrees C)	0.0384**	0.0343**	0.0306**	0.0284**
	(0.0026)	(0.0023)	(0.0023)	(0.0020)
Low temp. (degrees C)	-0.0310**	-0.0279**	-0.0252**	-0.0235**
	(0.0029)	(0.0026)	(0.0025)	(0.0023)
Precip. (mm)	-0.0052**	-0.0054**	-0.0057**	-0.0055**
	(0.0009)	(0.0008)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0291*	-0.0353**	-0.0385**	-0.0380**
	(0.0147)	(0.0136)	(0.0106)	(0.0126)
N	2,917,431	2,783,520	2,688,739	2,602,897
WTP	136.73**	128.9**	107.14**	91.69**
	(37.43)	(22.22)	(16.33)	(15.03)
Campground x week-of-year FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

[37] In addition, refer to Table 4 in the main text for results when $\tau = 7$.

Appendix F: Smoke and air pollution sensitivity analysis

This section provides several sensitivity analyses related to the measurement of smoke and air pollution. These include an exploration of smoke at the home zip code, alternative definitions of the smoke indicator variable, and heterogeneous responses by smoke-induced $PM_{2.5}$ levels.

A natural question in travel cost models concerns the outside option $j = 0$. Smoke in the week of arrival could make alternative activities more or less desirable, which would threaten the stable unit treatment value assumption (SUTVA). We note in Section 3.2 that it is uncommon for individuals to cancel and rebook at other sites in the dataset, but we cannot observe activities in the $j = 0$ choice. Since the $j = 0$ choice is generally treated as a "stay-at-home" option, an empirical test to explore possible SUTVA violations is the presence of smoke at the home zip code.

In Table F1 we test two definitions of "smoke at the home zip code" using either the week of arrival or the day of arrival. The weekly definition of the variable in Column 1 yields insignificant coefficients. Using a daily definition in Column 2, we find that smoke at the home zip code has no effect on cancellation if the destination is unaffected; however, when both the home and destination are affected, visitors are more likely to cancel their reservation. This effect could be due to either greater information about or salience of smoke on days when it is also smoky at the visitor's home zip code. Alternatively, the result could be driven by correlation between the intensity of smoke and the likelihood that both the destination site and the home location are affected. However, the result goes against the initial SUTVA concern, since we would have expected that smoke at the home location would decrease, rather than increase, the likelihood of cancellation by reducing the quality of the $j = 0$ option.

Next, we test alternative $PM_{2.5}$ cutoffs to define a day as smoke-affected. As noted in Section 2.3, we count days as smoke-affected if there is an observed smoke plume and $PM_{2.5}$ levels are greater than 1.64 standard deviations above the location-specific seasonal mean for days without smoke, following Burkhardt et al. (2019). The goal of this measure is to ensure that smoke plumes observed using satellite photography reflect on-the-ground conditions. This exercise is similar in spirit to continuous measures for smoke-specific $PM_{2.5}$ by Childs et al. (2022). Still, we explore sensitivity to this definition. Table F2 varies the threshold to qualify as a smoke-affected day. Column 1 displays results using only observed smoke plumes irrespective of $PM_{2.5}$, which includes observations where smoke may have been high in the air column. Columns 2 through 4 use threshold cutoffs of the 90th percentile, the 95th percentile, and the 97.5th percentile for on-the-ground $PM_{2.5}$. The strength of the smoke coefficient grows as the cutoff becomes more restrictive, resulting in higher willingness to pay (WTP) estimates.

Elaborating on this analysis, we test a binned $PM_{2.5}$ approach. We develop a continuous measure of smoke-specific $PM_{2.5}$ following a similar method to Childs et al. (2022). For every campground, we define smoke-specific $PM_{2.5}$ as:

$$\mathrm{PM}^S_{jt} = \max\left\{\ 0\ ,\ \mathbb{1}\{\text{smoke\_plume}\}_{jt} \times (\mathrm{PM}_{jt} - \overline{\mathrm{PM}}_{j,m(t)})\ \right\}, \tag{12}$$

where $\mathbb{1}\{\text{smoke\_plume}\}_{jt}$ is an indicator variable if any smoke plume covered campground j on day t, PM_{jt} is the overall $PM_{2.5}$ level on day t, and $\overline{\mathrm{PM}}_{j,m(t)}$ is the campground-specific seasonal mean $PM_{2.5}$ on non-smoke days.[38]

Table F3 tests two binned approaches to explore how welfare estimates vary with smoke-specific $PM_{2.5}$. We define the bin cutoffs as 0, 9, and 35 $\mu g/m^3$, levels which roughly correspond to EPA Air Quality Index thresholds for “Good,” “Moderate,” and “Unhealthy for Sensitive Groups” or “Unhealthy.” The 35 $\mu g/m^3$ level is also the EPA 24-hour standard for fine particulate matter pollution. Column 1 interacts the main smoke indicator, i.e. smoke in the arrival week as defined in Section 2.3, with weekly mean smoke $PM_{2.5}$. Column 2 instead takes the weekly maximum smoke $PM_{2.5}$, since peaks in pollution could be as important as the mean in this context. In both cases we find evidence of increasing welfare losses with greater $PM_{2.5}$ pollution.

[38] For additional discussion of data, refer to Section 2.3.

Table F1: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Effects of Smoke at Home Zip Code

	(1)	(2)
Smoke at site, week of arrival	-0.211**	-0.237**
	(0.0300)	(0.0230)
Smoke at home zip, week of arrival	-0.035	
	(0.0220)	
Smoke at site x smoke at home zip (week of arrival)	-0.072	
	(0.0440)	
Smoke at home zip, day of arrival		-0.024
		(0.0450)
Smoke at site x smoke at home zip (day of arrival)		-0.127*
		(0.0520)
Travel cost (dollars)	-0.002**	-0.002**
	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-7.845**	-7.809**
	(0.8280)	(0.8240)
High temp. (degrees C)	0.031**	0.031**
	(0.0020)	(0.0020)
Low temp. (degrees C)	-0.025**	-0.025**
	(0.0020)	(0.0020)
Precip. in week of arrival (mm)	-0.006**	-0.006**
	(0.0010)	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.036**	-0.036**
	(0.0130)	(0.0130)
N	2,688,739	2,688,739
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Table F2: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Alternative $PM_{2.5}$ Cutoffs for Smoke

	Smoke plume	Smoke x 90th pctl PM	Smoke x 95th pctl PM	Smoke x 97.5th pctl PM
Smoke in week of arrival	-0.062**	-0.211**	-0.261**	-0.310**
	(0.0120)	(0.0180)	(0.0210)	(0.0250)
Travel cost (dollars)	-0.002**	-0.002**	-0.002**	-0.002**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-8.646**	-7.907**	-7.819**	-7.720**
	(0.9250)	(0.8400)	(0.8240)	(0.8160)
High temp. (degrees C)	0.033**	0.031**	0.031**	0.030**
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Low temp. (degrees C)	-0.027**	-0.025**	-0.025**	-0.025**
	(0.0030)	(0.0020)	(0.0020)	(0.0020)
Precip. in week of arrival (mm)	-0.006**	-0.006**	-0.006**	-0.006**
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037**	-0.037**	-0.037**	-0.037**
	(0.0120)	(0.0130)	(0.0130)	(0.0130)
N	2,518,859	2,688,739	2,688,739	2,688,739
WTP	25.45**	87.13**	107.95**	127.84**
	(6.29)	(14.8)	(17.14)	(19.79)
Campground x week-of-year FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Table F3: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Binned $PM_{2.5}$ Due to Smoke

	Weekly mean smoke $PM_{2.5}$	Weekly max smoke $PM_{2.5}$
Travel cost (dollars)	-0.002**	-0.002**
	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-7.820**	-7.819**
	(0.8240)	(0.8250)
High temp. (degrees C)	0.031**	0.031**
	(0.0020)	(0.0020)
Low temp. (degrees C)	-0.025**	-0.025**
	(0.0020)	(0.0020)
Precip. in week of arrival (mm)	-0.006**	-0.006**
	(0.0010)	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037**	-0.037**
	(0.0130)	(0.0130)
Smoke x Weekly mean smoke $PM_{2.5} \leq 9$ μg/m^3	-0.260**	
	(0.0220)	
Smoke x Weekly mean smoke $PM_{2.5} \in (9{,}35]$ μg/m^3	-0.290**	
	(0.0890)	
Smoke x Weekly mean smoke $PM_{2.5} > 35$ μg/m^3	-0.308	
	(0.1740)	
Smoke x Weekly max smoke $PM_{2.5} \leq 9$ μg/m^3		-0.261**
		(0.0240)
Smoke x Weekly max smoke $PM_{2.5} \in (9{,}35]$ μg/m^3		-0.255**
		(0.0530)
Smoke x Weekly max smoke $PM_{2.5} > 35$ μg/m^3		-0.287**
		(0.0910)
WTP: Smoke $PM_{2.5} \leq 9$ μg/m^3	107.32**	107.68**
	(17.27)	(16.56)
WTP: Smoke $PM_{2.5} \in (9{,}35]$ μg/m^3	119.95**	105.3**
	(39.3)	(31.6)
WTP: Smoke $PM_{2.5} > 35$ μg/m^3	127.29	118.39**
	(67.91)	(40.2)
N	2,688,739	2,688,739
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Appendix G: Total welfare estimate data construction

In Section 5, we report estimates for the total annual number of recreation visits affected by smoke in the West; we combine the Recreation.gov data with overall visitation data from various federal and state agencies. In particular, we use total visitation numbers from the National Park Service, US Forest Service, Bureau of Land Management, US Army Corps of Engineers, and National Association of State Park Directors. Each agency reports visitation at varying spatial and temporal levels. For example, the National Park Service reports visitation at a park by month level; the US Forest Service reports at a forest by year level; and the state parks report at a state by year level. For each data source, we aggregate the daily Recreation.gov data to the most relevant spatial and temporal scale to determine the proportion of visits affected by smoke. Because we have visitors' exacts dates of arrival and length of stay, we can link this visitation to daily smoke conditions at each campground. We can therefore estimate, for example, the proportion of visitation that occurred under smoke conditions at a particular National Park in a given month, a proportion which accounts for temporal substitution within the month. We then multiply this proportion by the total visitation data from each relevant agency to predict the number of visits that took place under smoke conditions.[39] In this section, we detail this process for each data source.

For the National Park Service, we use the agency's Annual Summary Reports.[40] This dataset reports total monthly visitation at all national parks, national monuments, national recreation areas, and other lands that the agency manages. In the western states, 27 national parks are included in the Recreation.gov dataset, and 82 are not.[41] For the 27 parks in the Recreation.gov dataset, we determine each park's monthly proportion of campers that were smoke-affected. We then multiply this proportion by each park's monthly visitation from the Annual Summary Reports to infer the total number of smoke-affected visits. For the 82 parks not in the Recreation.gov dataset, we calculate a statewide proportion of smoke-affected campers in the data. We multiply these state by month proportions by each park's visitation levels in the Annual Summary Reports based on its location.

To estimate smoke-affected visits at national forests, we use the US Forest Service's National Visitor Use Monitoring (NVUM) Program.[42] These data report visitation at all national forests at an annual level. In the West, 70 forests are included in the Recreation.gov dataset, and 8 are not.[43] For the 70 forests in the Recreation.gov data, we calculate each forest's annual proportion of campers affected by smoke and multiply it by the corresponding annual visitation totals in the NVUM data. For the 8 forests not in the Recreation.gov

[39] A smoke day is defined in Section 2.3.

[40] National Park Service. Annual Summary Report. `https://irma.nps.gov/STATS`.

[41] For example, Yellowstone National Park is managed by an alternative reservation system.

[42] US Forest Service. National Visitor Use Monitoring Program. `https://www.fs.usda.gov/about-agency/nvum`.

[43] Campgrounds at some forests are only available on a first come, first serve basis. One example is the Umatilla National Forest in Oregon and Washington, which did not have reservable campsites until 2021.

dataset, we use a statewide annual proportion of smoke-affected campers.

The Bureau of Land Management records visitation statistics as part of its Recreation Management Information System (RMIS).[44] We contacted the program administrator and received data on site by year visitation for all BLM sites.[45] Most visitation is not reservable, and a large portion is considered backcountry. Therefore, the Recreation.gov dataset contains very few BLM campgrounds. We thus combine annual state level proportions of smoke-affected campers from the Recreation.gov data with annual site visitation from the RMIS.

For sites managed by the US Army Corps of Engineers, we use data from its Value to the Nation (VTN) reports.[46] For the study period of 2008 to 2017, the agency only has one year of recreation data, which is for the year 2016. We treat this year as representative of typical annual visitation over the study period. For each site, we multiply the total number of visitors by the state level average of smoke-affected campers from the Recreation.gov data over all years.

Lastly, we estimate smoke impacts at state parks. We use visitation data from the National Association of State Park Directors, which was compiled by Smith et al. (2019). For these data, the unit of observation is a state by year. We again use annual state level proportions of smoke-affected campers from the Recreation.gov data multiplied by the NASPD data.

Having approximated total visitation, we multiply each agency's annual smoke-affected visits by the empirical estimate of losses due to wildfire smoke, valued at $107 per trip. We estimate that more than 21.5 million recreation visits per year are affected by smoke in the West, with annual losses of $2.3 billion. These damages apply to inframarginal visitors who do not cancel their trip.

To generate estimates for lost visitation we follow Dundas and von Haefen (2020), who calculate the welfare loss from reduced recreational fishing due to extreme temperatures. They multiply the predicted number of lost trips by the value of a trip, which they note is

[44] Bureau of Land Management. Public Land Statistics. `https://www.blm.gov/about/data/public-land-statistics`.

[45] Ridenhour, L. and Leitzinger, K. Bureau of Land Management. Personal correspondence.

[46] US Army Corps of Engineers. Value to the Nation. `https://www.iwr.usace.army.mil/Missions/Value-to-the-Nation`.

one over the travel cost coefficient.[47] From Table 3 we can compute that the average value of a trip over the population, including those who do not visit, is $1/0.0244 = \$41$. To predict the number of lost trips, we can use the empirical estimates to calculate the cancellation rate due to smoke. This value is equal to:

$$\begin{aligned}
&\hat{\mathbb{P}}(C_{ijt} = 0 | R_{ijt} = 1, s_{jt} = 1) - \hat{\mathbb{P}}(C_{ijt} = 0 | R_{ijt} = 1, s_{jt} = 0) \\
&= \frac{1}{1 + \exp(\hat{\delta} c_{ijt} + \hat{\phi} + X'_{jt}\hat{\gamma} + \hat{\psi}_{jt})^{-1}} - \frac{1}{1 + \exp(\hat{\delta} c_{ijt} + X'_{jt}\hat{\gamma} + \hat{\psi}_{jt})^{-1}} \\
&= 0.022, \qquad (13)
\end{aligned}$$

where the values for covariates are set to their predicted average and $\hat{\phi}$ is set to the coefficient of -0.2603 from Table 4. Notably, the cancellation rate of 0.022 is very close to the estimated cancellation rate of 0.023 from Gellman et al. (2022), which used a simpler linear probability model. As a back-of-the-envelope estimate, one can infer that lost visitation is approximately equal to $\frac{0.022}{1-0.022}$ times the number of smoke-affected visits. Table 6 reports these estimates of lost visitation. We find that welfare losses from lost visitation are much lower than from trips taken in spite of smoke, in line with earlier descriptive work from Gellman et al. (2022). For further discussion, see Section 5.

[47] The value of a cancelled trip will necessarily be lower than the welfare damage of smoke, or the individual would not have cancelled. For example, if an individual values a trip at \$57 without smoke, then they value the trip at $\$57 - \$107 =$ -\$50 with smoke, so they would prefer to cancel the trip and take the $j = 0$ option of \$0, for a net loss of \$57, i.e. the value of the trip.