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# Supplementary Materials for

## **Air pollution and visitation at U.S. national parks**

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### **Supplementary Text**

#### **Ozone Trends**

A sparse model of annual ozone trends is also estimated. The estimated regression equation is:

$$
Y_{it} = \sum_{\tau=1990}^{2014} \alpha_{\tau} \mathbf{1}[t_t = \tau] + \sum_{\tau=1990}^{2014} \gamma_{\tau} \mathbf{1}[t_t = \tau] \Theta_i + \epsilon_{it}. \quad (S.1)
$$

 $Y_{it}$  is either the maximum 8-hour pollution reading from any monitor in park/city  $i$  on day  $t$  or an indicator for whether any monitor in park/city  $i$  on day  $t$  exceeded 70 parts per billion (ppb).  $\mathbf{1}[t_t = \tau]$  is an indicator variable for whether date t is in year  $\tau$ , and  $\Theta_i$ is an indicator variable for whether location  $i$  is a national park. The variable  $\alpha_{\tau}$  is the (unconditional) average annual ozone concentration in U.S. metropolitan areas in year  $\tau$ , and  $\alpha_{\tau} + \gamma_{\tau}$  is the (unconditional) average annual ozone concentration in national parks in year  $\tau$ . Bootstrapped standard errors are robust to heteroscedasticity and clustered at the park/metropolitan area to correct for autocorrelation in the error term, and are computed using a bootstrap procedure with 500 repetitions.

Figure S1 presents the unconditional annual ozone trends in U.S. cities and national parks from 1990 to 2014. Results are broadly similar to the estimates trends in Fig. 1. Trends in average ozone concentrations were largely flat for U.S. metropolitan areas until the mid-2000s, after which they have declined steadily. In contrast, average ozone concentrations have increased steadily in almost all years in parks (fig. S1A). Metropolitan areas had much higher summertime ozone in 1990 compared to parks. Cities mostly saw improvements in summertime ozone concentrations. Average ozone concentrations in parks increased through the mid-2000s, and returned to 1990 levels at the end of our sample (fig. S1B). Similarly, metropolitan areas have seen large decreases in the average number of exceedance days while parks saw little progress until the mid-2000s (fig. S1C). Parks have nearly identical ozone concentrations by all three measures by 2014.

#### **Non-Parametric Impacts of Ozone on Visitation**

A flexible model of pollution and weather impacts on log visitation is estimated to explore the potential role of nonlinear impacts of each on visitation. We estimate the following model:

$$
Y_{pym} = f(X_{pym}; \boldsymbol{\beta}) + g(W_{pym}; \boldsymbol{\alpha}) + \theta_{py} + \gamma_m + \epsilon_{pym}.
$$
 (S. 2)

All variables are the same as in equation (2). Maximum ozone  $(X_{vvm})$  and all weather variables ( $\boldsymbol{W}_{pym}$ ) are replaced with a set of ventile, or five-percentile, indicator variables. For example, the maximum ozone function is given by:

$$
f(X_{pym}; \beta) = \begin{bmatrix} \beta_{0,5} \cdot \mathbf{1}(X_{pym} < X_{0,5}) \\ \beta_{5,10} \cdot \mathbf{1}(X_{pym} < X_{5,10}) \\ \vdots \\ \beta_{95,100} \cdot \mathbf{1}(X_{pym} < X_{95,100}) \end{bmatrix}
$$

where  $\mathbf{1}(\cdot)$  is an indicator function that equals one if maximum ozone concentrations at park  $p$  in month  $m$  of year  $y$  lies in the specified ventile of observed ozone concentrations. Equation (S.2) allows for flexible, non-linear impacts of ozone and weather on visitation, imposing only that the impact of each variable is constant within a given ventile. Bootstrapped standard errors are robust to heteroscedasticity and clustered at the park to correct for autocorrelation in the error term, and are computed using a bootstrap procedure with 500 repetitions.

Figure S2 graphs the results from estimating equation (S.2), the non-parametric estimates of maximum ozone and weather on visitation. The estimates are interpreted as the impact on visitation of every ventile of each variable relative to the omitted lowest ventile group. Figure S2A displays the results for maximum ozone, which shows a roughly linear, decreasing relationship of maximum ozone on visitation. The average slope over all ventiles is approximately -0.01 log(visits)/ppb. figs. S2B to S2E present the weather results. Temperature (fig. S2B) has a highly non-linear impact on visitation, exhibiting an inverted-U shape. Precipitation (fig. S2C) and humidity (fig. S2D) have imprecisely estimated associations with visitation except for the highest ventiles of each where visitation decreases sharply. Visitation increases in wind speed after the  $20<sup>th</sup>$ percentile (fig. S2E); however, the results are imprecisely estimated. The results motivate our empirical strategy in equation (2). Maximum ozone is restricted to have a linear impact on log visitation. We include a three-knot linear spline in temperature to control for the non-linear impact of weather on visitation, and use monthly average values for wind, precipitation and humidity since their marginal effects do not show high degrees of non-linearity.

#### **Seasonal Trends in Ozone, Visitation, and Weather**

We explore seasonality in each variable by estimating the following regression for ozone, visitation, visibility, and weather:

$$
V_{pym} = \gamma_0 + \theta_y + \gamma_m + \eta_p + \epsilon_{pym}.\quad (S.3)
$$

 $V_{\text{pvm}}$  is either maximum ozone, the exceedance fraction, visitation, visibility, or one of the weather variables. Equation (S.3) estimates average month-of-year effects for each variable controlling for time-invariant park fixed effects  $(\eta_p)$  and year fixed effects  $(\theta_v)$ . All estimates are relative to January, the omitted month category. Bootstrapped standard errors are robust to heteroscedasticity and clustered at the park to correct for

autocorrelation in the error term, and are computed using a bootstrap procedure with 500 repetitions.

Figure S3 results from estimating equation (S.3) for maximum ozone, exceedance day fraction, visitation, visibility, and weather. The graphs represent seasonal patterns in each variable relative to January. The results motivate our inclusion of seasonality controls in equation (2).

Maximum ozone and ozone exceedance day fraction (figs. S3A to S3B) are lowest in November to February, and peak between April and September. Similar patterns emerge for visitation (fig. S3C), which peaks in the summertime, consistent with the positive correlation estimated between ozone and park visitation using our naïve ordinary least squares (OLS) model (table S4). Visibility (fig. S3D) shows the opposite pattern, peaking in the wintertime and is at its lowest on average in the late summer. Temperature (fig. S3E) displays another inverse-U shape, peaking in July at nearly  $20^{\circ}C$ higher than in January, on average. Humidity (fig. S3F) typically is lowest in summer months, while wind and precipitation (figs. S3G and S3H) don't display as strong a seasonal trend as the other variables.

#### **Mechanisms for a Negative Ozone-Visitation Association: Robustness**

Defining exceedance day fraction as the number of days in a park-month where maximum ozone exceeded 70 ppb may mask meaningful variation in visitation responses to especially high pollution events. We explore this by regressing log visitation on the fraction of days in a month in the following AQI categories: (i) moderate; (ii) unhealthy for sensitive groups; (iii) unhealthy; and (iv) very unhealthy. The reference group (omitted category) are the fraction of days in a month with ozone concentrations that are in the 'good' category.

Figure S4 presents the results. All elevated AQI levels are associated with decreased visitation. The point estimate generally increases as the AQI warnings become more severe. However, the estimates are only statistically significant at the 1% level for 'Unhealthy for Sensitive Groups' days, and at the 10% level for 'Very Unhealthy' days. These estimates correspond to mean visitation reductions of 3% and 6% respectively. The results suggest that visitation responses increase as the severity of AQI warnings increases, though we are unable to reject the hypothesis that the estimated impacts are uniform across warning categories.

### **Supplementary Tables**

### **Park and Metropolitan Area Monitor Data**

Table S1 summarizes all pollution, visitation, and weather data used in the analysis. Values in parentheses are the average number of pollution monitors over the observation period. Parks included in the table include all national parks with any ozone monitoring data between 1990 and 2014. Bolded and italicized rows are parks included in the final analysis. Parks in S1 were excluded from the final analysis if we had insufficient ozone or weather observations, or if we were unable to construct a measure of upwind ozone for our instrumental variables estimation. The latter restriction limited our analysis to parks in the continental United States and excluded remote parks such as Everglades and Great Sand Dunes National Park.

Table S2 lists the estimated 2010 populations for the top 20 metropolitan areas included in our analysis, the counties from which we drew ozone monitor data, and the years and average monitors in the sample from 1990 to 2014. Monitor data are drawn from counties in which the cities are located to allow a broader representation of ozone trends over time in each city and their surrounding area.

#### **Ozone and Visitation and National Parks: Supplementary Results**

Table S3 contains results for the same specifications used to produce Table 1, but with different controls variables and fixed effects specifications. Columns 1 and 5 present results from a naïve OLS model with no controls. Results show a positive association between ozone concentrations in national parks and visitation. OLS estimates are confounded by a number of factors, including seasonal correlations as shown in fig. S3, and reverse causation because increased visitation increasing ozone precursors through vehicle emissions.

The fixed effects strategies attempt to overcome the empirical challenges from the OLS model by, for example, controlling for unobserved invariant characteristics of individual parks in each year (park-by-year fixed effects), unobserved seasonal factors that are common across all parks (month-of-year fixed effects), and observable differences in weather across park-month observations. Park-by-year fixed effects control, for example, for concerns related to parks' proximity to large urban centers. Parks that are closer to larger metropolitan areas may have higher visitation due to their lower travel costs for many people. However, these parks may also have higher pollution that varies over time due to their proximity to cities (Fig. 1). Park-by-year fixed effects control for such park-specific factors and allows them to change from year to year due to population growth or other phenomena.

Estimates from the fixed effects model show a negative relationship between ozone and park visitation (Columns 2, 3). Column 3 finds that a 1 ppb increase in maximum ozone is associated with a 2.6% decrease in monthly park visitation on average. Controlling for contemporaneous weather reduces the estimate to 1.6%. We find similar results when we decompose the impacts by season, where a 1 ppb increase in average maximum ozone concentrations decreases summertime and fall visitation by 2% and 1.5%,

respectively, and has no statistically discernable impact on spring and wintertime visitation. All year-round estimates are statistically significantly different from zero at conventional levels, as are the estimated summertime and fall ozone impacts.

The instrumental variables strategy isolates changes in visitation from within-park variation in ozone that is due to ozone changes in counties that are upwind of every park. The maintained identification assumption is that changes in upwind ozone concentrations are both correlated with in-park ozone concentations and uncorrelated with omitted factors that may bias the OLS estimates. The IV estimate (column 4) is larger than the fixed effects model. The estimate suggests that a 1 ppb increase in average maximum ozone concentrations reduces average monthly visitation by approximately 4%. The larger estimated impact could be due to the instrument correcting for measurement error in park ozone monitor data (i.e., classical measurement error), additional unobserved confounders not controlled for in the fixed effects specifications, or because parks with strongly correlated upwind ozone are also the parks with the highest ozone levels (i.e., a stronger local average treatment effect). Kleibergen-Paap F statistics show that the instrument is strong, and the estimates are statistically significant at the 5% level.

#### **Ozone and Visitation at National Parks: Robustness**

Table S4 contains our robustness tests for the estimated impact of ozone on visitation (Table 1 results).

Panel A replaces monthly maximum daily 8-hour ozone readings with the monthly average of the daily average 1-hour ozone readings. We include both the fixed effects and IV specifications. We find larger and more precisely estimated negative effects in both specifications. A 1 ppb increase in average ozone concentrations is associated with a 1.9% and 4.9% decrease in visitation in the fixed effects and instrumental variables specifications, respectively.

Park clustered standard errors correct for autocorrelation but assumes independence across parks. Panel B presents the same estimates as in Table 1 but with two-way clustered standard errors at the park and year level. Clustering at the year allows for arbitrary correlation in the residuals across parks within a given year. Two-way clustering has no impact on our inference.

We use a log-level model as our main specification since the visitation data are highly right skewed. In Panel C, we re-estimate the fixed effects and IV specifications using a log-log model, replacing maximum ozone concentrations with the natural logarithm of the variable. We continue to find a negative relationship in both cases, though the fixed effects estimates are less precise. We estimate that a 1% increase in maximum ozone decreases visitation by 0.4% to 2.2% in the fixed effects and instrumental variables specifications, respectively.

Panel D explores the impacts of using alternative weather controls. We consider the following alterative weather controls: a three-knot linear spline, a global cubic polynomial, and a set of ten bins for all weather controls. Our results are stable across all specifications.

An identification concern motivated by the recreation demand literature is that pollution at nearby park sites may have correlated ozone concentration and play a role individuals' park visitation decisions. If this is true, ozone concentrations at alternative parks may create time-varying omitted variable bias and confound our results. Panel E explores this concern. We construct additional control variables for the average maximum ozone concentrations at all other national parks within a given radii of every park (50, 100, 250, and 500 km). Including these controls does not affect our results, suggesting that ozone concentrations at substitute park sites is not a major concern.

A related concern is the potential influence of ozone in nearby metropolitan areas on park visitation. For example, our results may be biased if poor air quality in nearby cities increases park visitation and increases ozone concentrations in parks. Panel F of Table S4 presents results from regressions that control for average maximum ozone concentrations at large, nearby metropolitan areas. We drop park observations that do not have a nearby large metropolitan area for each radii. For example, only thirteen parks in our sample have large metropolitan areas within 100 kilometers. Results are generally robust to these additional controls, though they are less precisely estimated due to the smaller sample sizes.

Panel G varies the number of upwind counties used to construct the instrumental variables. We use the top 5, 10, and 15 upwind counties as alternative controls. The point estimates are relatively insensitive to the choice of upwind counties. When we use only the top 5 upwind counties to construct the instrument, the estimated impact of ozone on visitation is smaller than in our main specification and statistically insignificant. Two potential reasons explain this result. First, limiting upwind counties decreases our sample size as some counties nearby parks do not have monitor readings. Second, using less upwind counties may reduce the instrument strength. Including more counties allows for fewer 'missing' upwind averages.

Panel H explores an additional concern – park congestion. Particularly popular parks at times experience high congestion rates, especially during summertime months. Our estimated relationship between ozone and visitation may be biased if, for example, congestion discourages trips to parks at the same time it increases ozone due to increased driving and idling on park roads. There is no established metric for congestion in national parks. We therefore ensure that our results are not impacted by excluding park-month observations in which congestion is likely highest. For this, we first construct a measure of impervious surface area within park boundaries using data from the 2011 National Land Cover Database. Impervious surfaces include roads, buildings,

concrete trails, and parking lots. For every park-month observation, we then calculate the number of visitors per acre of impervious surface. We say that a park is likely 'congested' in a given month if the number of visitors per acre of impervious surface is greater than the 75<sup>th</sup> or 90<sup>th</sup> percentile of all observations. Panel H presents results that exclude park-month observations flagged as 'congested.' Results are less precisely estimated than in Table 1 but are broadly similar to our main results.

#### **Impacts of Alternative Pollutants on Visitation at National Parks**

Here we explore whether visitation is associated with other pollutants. We run a similar set of regressions as in Table 1 but replace measures of ozone separately with other pollutants ( $NO<sub>2</sub>$ ,  $SO<sub>2</sub>$ ,  $PM<sub>2.5</sub>$ ). We report additional visitation results for the average daily 1-hour maximum readings of each pollutant (table S5). We do not find consistent significant relationships between visitation and any alternative pollutant.

We may also be concerned that visibility estimates in Table 2 are confounded by particulate matter (PM2.5) concentrations in parks. In Panel B of table S5 we report visibility estimates with and without controlling for PM2.5 concentrations. We find that controlling for PM2.5 significantly affects our estimates of visibility such that there is now a statistically significant positive association. However, only 8 parks have consistent monitoring of both PM2.5 and visibility so we interpret this finding with caution.



**Fig. S1. Unconditional trends in maximum daily 8-hour pollution and days with maximum daily 8-hour pollution exceeding 70 ppb in large metro areas and national parks. (A)** Average annual maximum 8-hour pollution trends. **(B)** Average summer maximum 8-hour pollution trends. **(C)** Average days per year with maximum 8-hour ozone concentrations exceeding 70 ppb. Shaded areas are 95% confidence intervals.



**Fig. S2. Nonlinear impacts of ozone and weather on visitation.** The figures graph conditional, non-parametric estimates of each variable on visitation. Estimates are computed by regressing log visitation on ventile indicators for every variable. **(A)** Max ozone**. (B)** Temperature. **(C)** Precipitation. **(D)** Humidity. **(E)** Wind speed. Standard errors are clustered at the park using a bootstrap procedure with 500 replications.



**Fig. S3. Seasonal trends in control and outcome variables.** Each figure graphs seasonal patterns for each variable. Estimates are computed by regressing every variable on month-of-year indicators, conditional on park and year fixed effects. **(A)** Max ozone. **(B)** Exceedance fraction. **(C)** Log visitation, **(D)** Mean visibility. **(E)** Temperature. **(F)** Humidity. **(G)** Wind speed. **(H)** Precipitation. Standard errors are clustered at the park using a bootstrap procedure with 500 replications.



Fig. S4: Estimates impact of exceedance days by AQI category on log visitation from 1990 to 2014. The figure presents estimates of an additional day in a month with ozone levels the given AQI category relative to a 'Good' AQI day. Dots represent point estimates, and vertical lines represent standard errors. Standard errors are clustered at the park using a bootstrap procedure with 500 replications.



**Table S1. Pollution monitors, visitation, upwind ozone, and weather data by national park and year.** Parks included in analysis are *bolded and italicized.*







**Table S2. Top 20 U.S. cities:** The table presents the rank, estimated 2015 population, and counties from which pollution monitor readings were drawn**.** The table also presents years for which we observe ozone pollution readings and the average number of monitors per location per year. (Sources: U.S. Census Bureau; Environmental Protection Agency)





**Table S3. Estimated impact of monthly average maximum ozone concentrations (ppb) in national parks on log visitation from 1990 to 2014 (additional**  specifications). Some specifications include weather controls, park-by-year fixed effects, and month-of-year fixed effects. Column 4 instruments in-park monthly average maximum ozone using ozone concentrations from upwind counties. Columns five to seven examine effects of ozone by season. Values in parentheses are robust standard errors clustered at the park using a bootstrap procedure with 500 replications. \*\*\*P<0.01, \*\*P<0.05, \*P<0.1. The Stock-Yogo weak identification critical value for the Kleibergen-Paap F-Test is 16.38 for a 10% maximal instrumental variable bias relative to OLS.



**Table S4. Estimated impact of monthly average maximum ozone concentrations (ppb) in national parks on log visitation from 1990 to 2014 (robustness checks).** Some specifications include weather controls, park-by-year fixed effects, and month-of-year fixed effects. Instrumental variable specifications instrument for in-park ozone using ozone concentrations from upwind counties. Values in parentheses are robust standard errors clustered at the park using a bootstrap procedure with 500 replications. \*\*\*P<0.01, \*\*P<0.05, \*P<0.1. The Stock-Yogo weak identification critical value for the Kleibergen-Paap F-Test is 16.38 for a 10% maximal instrumental variable bias relative to OLS.







**Table S5. Estimated impact of alternative monthly average pollution levels in national parks on log visitation from 1990 to 2014.** Max 'Pollutant' is the average 1-hour maximum daily average monitor reading for each pollutant. Monitor data report these pollutants as 1-hour measures instead of 8-hour like ozone. Specifications include weather controls, park-by-year fixed effects, and month-of-year fixed effects. Instrumental variable specifications instrument for in-park ozone using ozone concentrations from upwind counties. Values in parentheses are robust standard errors clustered at the park using a bootstrap procedure with 500 replications. \*\*\*P<0.01, \*\*P<0.05, \*P<0.1. The Stock-Yogo weak identification critical value for the Kleibergen-Paap F-Test is 16.38 for a 10% maximal instrumental variable bias relative to OLS.



**Table S5 (cont.). Estimated impact visibility on log visitation controlling for PM2.5 concentrations from 1990 to 2014.** Specifications include weather controls, park-by-year fixed effects, and month-of-year fixed effects. Values in parentheses are robust standard errors clustered at the park using a bootstrap procedure with 500 replications. \*\*\*P<0.01, \*\*P<0.05, \*P<0.1.

#### **Panel B: Effect of Visibility While Controlling for PM**

