INFORMATION, BEHAVIOR, AND BIOLOGY: USING RESPONSES TO SMOG ALERTS TO UNDERSTAND THE RELATIONSHIP BETWEEN OZONE AND HEALTH

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Abstract: This paper tests whether individuals engage in avoidance behavior in response to information about pollution, and whether this behavior explains the lack of epidemiological evidence of an association between ozone and health. Specifically, I examine the impact of "smog alerts" on attendance at outdoor activities and on hospital admissions in Southern California from 1983 through 1998. Since smog alerts are only issued when high ozone has been predicted at least a day in advance, I identify the effects of information by comparing outcomes on days when an alert was issued to days with comparable levels of observed ozone but when no alert was issued. This analysis provides robust evidence that attendance is lower on days when smog alerts are announced, suggesting that people increase avoidance behavior in response to this information. I also find there is a decrease in hospital admissions for various respiratory related illnesses when smog alerts are issued, indicating that ozone affects health. Lastly, the results indicate that estimates of the biological effect of ozone on health that do not account for individuals' responses to pollution are significantly biased.

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1. Introduction

Ozone regulation continues to be a hotly debated topic, with a large part of this controversy stemming from the discrepancy over the documented health benefits from ozone reductions. On one hand, controlled human-exposure and animal studies document a consistent effect of ozone on lung functioning and illnesses such as asthma. Outside of the laboratory setting, however, epidemiological-style regressions commonly find little evidence of an association between ozone air pollution concentrations and human health. This divergence has led to both questioning of the external validity of the experimental evidence and the reliability of the non-experimental evidence, and continues to fuel the controversy surrounding costly air quality regulations.

One possible explanation for this puzzle is that on high pollution days individuals alter their behavior to protect themselves, and not accounting for this behavior understates the biological effect of ozone on health. For example, figure 1 depicts a hypothetical scenario in which ozone has a causal effect on illnesses that result in hospitalizations. Once ozone crosses a particular threshold, an alert is issued to warn the public. People respond to this alert by decreasing their exposure to ozone (or increasing their avoidance behavior), and this leads to fewer hospitalizations than would have otherwise occurred. If we do not account for this response to the alert, we may therefore estimate no effect of ozone on hospitalizations and falsely conclude that ozone does not affect health. In general, it is difficult to test this explanation because it is based on individuals' unobserved compensatory decisions.

This paper exploits a rare opportunity to test whether individuals engage in avoidance behavior in response to information about pollution, and whether this behavior explains the lack of evidence of an association between ozone and health. Specifically, I look at the impact of air quality episodes, or “smog alerts”, on outdoor activities and health in Southern California. These alerts are issued when ambient ozone, a major component of urban smog, is forecasted to exceed a particular threshold. If people respond to these alerts by increasing avoidance behavior, we expect a decline in outdoor activities when alerts are issued. And if people decrease their exposure to ambient ozone by reducing outdoor activities, then we expect a decrease in illnesses related to ozone if it affects health.

The data gathered for this analysis are a unique combination from multiple sources, much of which has never been analyzed before. The data for outdoor activities comes from daily attendance at distinct major outdoor facilities in Southern California: the Los Angeles Zoo and Botanical Gardens, Griffith Park Observatory, and the Los Angeles County Arboretum and Botanical Gardens. This data consists of administrative records, which is less likely to be subject to the recall bias that may be present in survey data. For health outcomes, I use the California Hospital Discharge Data, which is rich dataset containing the exact date of admission and detailed geographic residence of the patient. These data are combined with pollution and meteorology data to produce an extensive database that span the years 1983 to 1998 at the daily level.

Since smog alerts are only issued when high ozone has been predicted at least a day in advance, I identify the effects of public information by comparing outcomes on days when an alert was issued to days with comparable levels of observed ozone but no alert was issued because there was no advance prediction. Given the difficulties inherent in forecasting ozone, these alerts are frequently forecasted with error, thereby providing a source of variation that is plausibly orthogonal to outdoor activity choices. I also generalize commonly used epidemiological dose-response functions to include smog alerts, thus enabling me to test if accounting for avoidance behavior impacts estimates of the biological effect of ozone on health.

This first finding from this analysis is that people increase avoidance behavior in response to information about pollution. Attendance is significantly lower on days when smog alerts are announced, with declines of between 4 and 9 percent at all three places considered. There are several empirical patterns that point towards the reliability of these findings. One, these findings are robust to various functional form considerations and the inclusion of numerous control variables. Two, I find that local residents, who are more likely to receive this information and have lower costs of substituting activities than tourists, have greater responses to the alerts than other groups. Three, I find no effect of smog alerts on automobile emissions (as proxied by carbon monoxide concentrations), suggesting that this effect is driven by health rather than altruistic concerns. Given these findings and the fact that these results come from three independently gathered data sources, it is difficult to dismiss the notion that people value the information provided by the smog alerts.

Given that people respond to alerts by limiting outdoor activities, I then examine whether this change in exposure to ozone (via smog alerts) affects health, holding fixed the level of ozone. I find that issuing smog alerts decreases hospital admissions for asthma and bronchitis, confirming that ozone does in fact affect health. An accurately forecasted alert reduces hospitalization costs by roughly $400,000, which is likely an understatement of the total savings from an alert. Interestingly, there is no effect of the alerts on working age adults, suggesting they are not displaying avoidance behavior, perhaps because the costs from changing activities are greatest for this group.

Perhaps the most important finding of this study is that accounting for behavioral responses to pollution can have a dramatic impact on our understanding of the biological relationship between ozone and health. Estimates that do not account for avoidance behavior imply little or no effect of ozone on hospitalizations, consistent with epidemiology evidence. Meanwhile, estimates that include smog alerts as a measure of avoidance behavior suggest significantly larger effects of ozone. These results support the idea that omitting behavioral responses to pollution may severely bias estimates of the biological effect of ozone on health, and can at least partially explain the discrepancy between experimental and non-experimental evidence. Given the prevalent role of information with respect to health risk, this finding readily extends beyond the pollution and health arena and suggests the importance of accounting for behavior in a wide range of statistical analyses that rely on observational data to understand biological relationships.

Background Information

Ozone and Health

Ground-level ozone, both its 1-hour and 8-hour concentration, is a criteria pollutant regulated under the clean air acts.[1] Ozone is not directly emitted into the atmosphere, but is formed from interactions of nitrogen oxides and volatile organic compounds, both of which are directly emitted, in the presence of heat and sunlight. Ozone formation also increases with solar radiation. Because of this process, ozone tends to peak in the summer and middle of the day when heat, sunlight, and solar radiation are at their maximum (U.S. EPA (2003)).

Research has demonstrated that ozone is believed to irritate lung airways and increase susceptibility to respiratory related health conditions as asthma and bronchitis. The purported

[1] Criteria pollutants are considered those most responsible for urban pollution. Ground level ozone is distinct from stratospheric ozone (the "ozone layer"), which protects people from UV radiation.

mechanism is that ozone impairs the barrier function of the lung, resulting in the entry of compounds that lead to inflammations in the lung (U.S. EPA (2003)). Symptoms can occur in as quickly as 1 hour, and normal lung functioning typically returns within 24 hours (U.S. EPA (2003)).[2] Much of this evidence comes from animal or controlled human exposure studies, and the external validity of these findings has been questioned on several grounds. For example, the controlled human exposure studies typically expose healthy, adult volunteers to ozone levels that may not reflect everyday conditions.

Using observational data, researchers have employed various methodologies to estimate the relationship between ozone and health. The most common type of analysis uses daily time-series data on doctor or ER visits matched with corresponding pollution measures. While such a strategy offers considerable benefits by enabling one to ignore factors that do not vary at a daily level, such as health care choices, one notable limitation is it may not capture illnesses that do not result in usage of medical care services. For example, there has been a tremendous growth in asthma management to empower individuals with a wide range of tools to control asthma symptoms before or as they develop, thereby decreasing the frequency of doctor visits. To overcome this concern, some studies follow individuals, commonly asthmatic children, over time and record daily lung functioning (U.S. EPA (2003), Kinney et al. (1996)) and other studies use asthma medication prescription refills as a indicator for asthma attacks (Dukic et al. (2004). Despite the offered improvements, these studies do not consider behavioral responses to ozone levels.[3] Perhaps in part due to these concerns, these estimates have produced a wide range of

[2] It is also believed that long term ozone exposure can affect health, such as lung tissue damage, but this relationship can not be tested with the given data.
[3] The studies that follow individuals over time also reintroduce concerns that the time-series studies avoid. For example, these studies frequently do not adjust for important confounding variables, such as weather and other pollutants, and only examine a susceptible part of the population, which limits the representativeness of the findings.

estimated correlations between the ozone and health outcomes (see, for e.g., U.S. EPA (2003), Neidell (2003), and Currie and Neidell (2003)).

Air Quality Forecasts and Smog Alerts

Because of the health concerns regarding ozone and other pollutants, the U.S. Environmental Protection Agency developed the pollutant standards index (PSI) to inform the public of local air pollution levels, and to advise the public regarding associated health effects and precautionary steps to take when air pollution reaches unhealthful levels.[4] For example, a value of 100 corresponds to the National Ambient Air Quality Standards as set forth in the Clean Air Acts, and a value in the range of 101-150 is considered "unhealthy for sensitive groups" and is accompanied by a message stating that "active children and adults, and people with respiratory disease, such as asthma, should limit heavy outdoor exertion" (U.S. EPA (1999)). In order to provide ample notification for the public to react, the PSI is typically forecast one day in advance, and major newspapers are required to report this information, usually in the weather section (U.S. EPA (1999)).

In addition to providing the PSI, California state law requires the announcement of an air quality episode when the PSI exceeds 200 units.[5] When this occurs, susceptible members of the population – those with a history of respiratory illness or part of a more vulnerable segment of the population, such as children or elderly – are encouraged to remain indoors and shift outdoor activities to the night, while all other members of the population are encouraged to avoid rigorous outdoor activity during the day. The public is also encouraged to minimize their contribution to pollution by ride sharing, for example, although there are no financial incentives offered to do so. Although air quality episodes can be issued for any of the criteria pollutants,

[4] The PSI was replaced by the Air Quality Index in 1999.

they have only been issued for ozone, giving rise to the name "smog alerts." While these alerts are determined on a statewide basis, Southern California has received much attention for its exceptionally high levels of ozone and history of smog alerts, which is in part due to its unique geography.

The agency responsible for providing air quality forecasts and issuing smog alerts for Southern California is the South Coast Air Quality Management District (SCAQMD), one of 17 air quality management districts in California. An air quality forecast is produced by noon the day before in order to give enough time to disseminate the information. Because SCAQMD covers all of Orange county and the most populated parts of Los Angeles, Riverside, and San Bernardino counties (an area with considerable spatial variation in ozone), this forecast is provided for each of the 38 source receptor areas (SRAs) within SCAQMD. The media, however, greatly condense this information. For example, the Los Angeles Times provides air quality forecasts, and therefore alert status, for only 10 air monitoring areas (AMAs)) in SCAQMD by taking the maximum forecasted value within an AMA. The model used for issuing an alert can be summarized as:

$$al_{at} = 1\{max_{at}\{\widehat{oz_{st}} = f(\widehat{w_{st}}, oz_{st-1}, sr_t)\} \geq 200\} \quad (1)$$

where the subscripts a, s and t indicate AMA, SRA, and time, respectively, al_{at} is an alert, $\widehat{oz}$ is the forecasted 1-hour level of ozone, $\hat{w}$ is the weather forecast, oz is observed 1-hour ozone, sr_t is solar radiation, and $1\{\bullet\}$ is an indicator function equal to 1 when the forecasted ozone exceeds 200 PSI and 0 otherwise. Alerts for ozone are only issued from March through October, compatible with the seasonal patterns of ozone.

[5] For ozone, this corresponds to a one-hour average of 0.20 ppm. Additionally, stage II alert is issued when the PSI exceeds 250, but this seldom occurred over the time period studied.

Since this agency is required to provide the forecast to the newspaper regardless of alert status, the costs of the smog alert program are only the additional efforts involved in disseminating the alert to the public. When an alert is issued, the staff at SCAQMD directly contacts a set list of recipients, including local schools and newspapers, which is currently done via an automated process. The media then further circulate the information to the public, so its efforts are largely private costs likely to be internalized by the specific media firm. Therefore, the costs to the public for administering the smog alert program are minimal.

B. Relevant Economics Literature

The consideration of avoidance behavior is a crucial distinction between willingness-to-pay (WTP) and cost-of-illness (COI) analyses. In the case of pollution, COI measures the loss in income and medical expenditures that results from a change in health, but does not include actions taken to reduce the impact of pollution. A major difference between WTP and COI is that WTP accounts for these behavioral adjustments in response to pollution.[6] For example, if people respond to pollution by staying indoors instead of outdoors, then this action has direct costs on well-being that are included in WTP but not in COI. In general, COI is viewed as a lower bound to WTP.

There is a limited amount of empirical evidence of avoidance behavior resulting from air pollution. Breshnahan et al. (1997) find that people spend less time outdoors when pollution levels rise. Their study relies on survey data, which is potentially subject to a recall bias, and looks at responses to actual pollution levels rather than information about pollution. Therefore, it is unclear whether people reducing their time outside is evidence of avoidance behavior or because they are experiencing health symptoms from exposure to the elevated pollution levels. Neidell (2003) finds that smog alerts lower hospital admissions for asthma. His study uses a monthly measure of smog alerts, which is potentially correlated with other factors related to ozone and health, and does not provide direct evidence that people are responding to the alerts. To overcome these concerns, this paper uses daily administrative data on attendance at various localities to directly test if people respond to information about pollution.

Another strand of evidence on avoidance behavior comes from economic studies of disease epidemics.[7] All studies find an increase in avoidance behavior from increases in diseases: the demand for contraceptive devices in response to local AIDS prevalence (Ahituv et al. (1996)); the differential use of influenza vaccinations by age during influenza season (Mullahy (1999)); and vaccinations for measles, mumps, and rubella in response to regional case loads (Philipson (1996)). As noted in Philipson (2000), however, these studies are unable to distinguish how information is transmitted as a disease spreads, whether by private or public information. This paper attempts to explicitly identify the effect of public information on individual's responses.

Although the evidence on responses to disease provides potential insights for environmental quality, evidence of responses to pollution is of particular interest because the provision of information has become an increasingly important part of governmental policy with respect to the environment and health risk. For example, the Emergency Planning and Community Right-to-Know Act (that lead to the development of the toxic release inventory) and Safe Drinking Water Act Amendments approved in the past 20 years are major steps taken to increase the public's knowledge of environmental risk. Researchers have provided considerable evidence examining responses to information about environmental risk, but little on observed responses to government provided information in the presence of a negative externality. For

[6] WTP also accounts for the direct utility effects of health. See Harrington and Portney (1987) for a full derivation.
[7] This type of behavior is referred to as 'prevalence elastic behavior' in the economic epidemiology literature.

example, people state they intend to adjust their behavior in response to information on exposure to chemical hazards (Viscusi et al. (1986)), people update their risk perceptions in response to information on radon (Smith and Johnson (1988)), and people engage in actions to minimize exposure in response to private information on radon (Smith et al. (1995)). This study provides direct evidence on the effect of actual public information about risk exposure resulting from an externality on observed changes in behavior.

Furthermore, economists have extensively studied how information affects individual decision making in a wide range of scenarios, but have not investigated the speed at which consumers respond to information, largely due to data limitations. For example, Ippolito and Mathios (1990) find that consumers alter their cereal consumption in response to advertised health benefits within a year, and Duflo and Saez (2003) find that individuals who receive information on retirement plans increase enrollment within 5 months. This study provides evidence on responses the same exact day the information is provided. Knowledge of how quickly people learn about information can be useful for understanding the potential effectiveness from information about urgent dangers from such events as disease outbreaks and terrorism.

2. Conceptual Framework

People may substitute between indoor and outdoor activities because they believe exposure to indoor and outdoor pollution affects health. If people divide their leisure time in discrete units between indoor and outdoor activities, we can explicitly define avoidance behavior as choosing the indoor activity in the presence of ambient pollution (a negative externality) when the individual would have chosen the outdoor activity in the absence of pollution. Therefore, the total cost of avoidance behavior to an individual is the utility from choice in the absence of pollution minus the utility from choice in presence of pollution.

To derive a demand for outdoor activities, I begin with a simplified version of the model developed by Breshnahan et al. (1997) and extend it to include information about pollution. Assume individuals maximize a utility function defined over consumption (c), health (*h*), outdoor activities (*o*), and the (expected) quality of the outdoor environment, such as (forecasted) weather (*w*), ozone (*oz*), and other ambient pollutants (*p*). Short-term health is produced according to the following production function:

$$h = h\,(o, oz, p, i, j, m, z) \qquad (2)$$

where *i* is indoor activities, *j* is indoor pollution levels, *m* is a vector of other inputs that affect health, such as medical services and exercise, and *z* is existing health capital. Consistent with the biological plausibility by which ozone is believed to affect health, equation (2) includes lags of ozone. Leisure time (*l*) is exogenously determined and gets divided between indoor and outdoor activities ($l=o+i$).

To understand how smog alerts (*al*) enter this process, assume that people process information about pollution according to:

$$oz_k^e = \omega_{1k} \cdot al + \omega_{2k} \cdot \widehat{oz} \qquad (3)$$

where oz^e is the expected amount of pollution, the ω's are the weights people place on alerts and the forecasted ozone reported in the newspaper ($\omega_{1k}, \omega_{2k} \geq 0,\ \omega_{1k}+\omega_{2k}=1$), and subscript *k* indicates heterogeneity in individual's knowledge of pollution levels. To remain consistent with the EPA's targeting of two distinct groups with the forecasted information, I assume two types of people: susceptible and unsusceptible. Accordingly, susceptible people benefit more from knowledge of pollution levels than unsusceptible people.

To obtain a demand equation for outdoor time, assume the only uncertain factor in this model is outdoor pollution and replace *oz* with oz^e as specified in equation (3). Utility is maximized by choosing *c*, *o*, and *m*, subject to the health production function and a budget constraint that limits expenditures on all choices with price vector *q* to be less than or equal to total income (*n*). This yields the following demand equation for outdoor activities:

$$o = o\,(q, n, l, w, al, \widehat{oz}, p, j, z) \qquad (4).$$

The main prediction from this model is that people increase avoidance behavior (spend less time outside) when expected ozone increases if two conditions hold. One, more time outside is expected to worsen health as ozone increases. This condition seems likely to hold because this is precisely what smog alerts attempt to convey and because indoor ozone levels are typically uncorrelated with outdoor levels (see, e.g., Chang et al. (2000)).[8] Two, if ozone enters the utility function directly, outdoor time is less enjoyable as pollution increases. Of the outdoor places considered, pollution is likely to only affect the Observatory decision because it diminishes visibility and thus the quality of the view, so this condition is likely to hold as well.[9]

A second prediction from this model, under certain assumptions, is that susceptible people are less likely to respond to an alert than unsusceptible people. Sufficient assumptions for obtaining this prediction are 1) people are rational bayesian updaters who know their own susceptibility; and 2) susceptible (unsusceptible) people believe they are affected by ozone levels less than (greater than) 200 PSI. Under this scenario, susceptible people obtain the ozone forecast from the newspaper because it is less expensive than the expected health costs from not avoiding ozone, so a smog alert offers no additional information because is a deterministic

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[8] This low correlation is due to the fact that ozone forms in the presence of sunlight and heat, and it therefore rapidly breaks down indoors because of the absence of either (or both) of these factors.

[9] Although ozone does not directly affect visibility, it is highly correlated with other pollutants that do, such as particulate matter. See Breshnahan et al. (1997) for a detailed derivation of this prediction.

function of the forecasted ozone. On the other hand, unsusceptible people do not obtain the ozone forecast from the newspaper because they don't expect ozone to affect their health when it is less than 200, so an alert is the sole piece of information they use to form their beliefs about pollution levels and are therefore more likely to respond to it.

Although I do not test this prediction empirically and there are plausible alternatives to this stylized case, it is potentially important for interpreting the estimated parameters. If pollution affects those generally considered unsusceptible to ozone in addition to susceptible ones, then we expect to see an (indirect) effect on health from issuing an alert. On the other hand, if susceptible types are the only ones affected by ozone but they do not respond to alerts, then it is possible to see no change in health outcomes when alerts are issued.[10]

3. Data

Information on smog alerts comes from both SCAQMD and the Los Angeles Times (LAT). SCAQMD provided information on the specific day an alert was issued, but not the SRA it was issued. Given that the PSI is reported in the LAT but only at the AMA level, I gathered information on the AMA it was issued, making it the finest geographic resolution the smog alert data is available. Although it would be ideal to obtain data for each SRA, it is not clear whether individuals respond to an alert only in their SRA or to an alert in neighboring SRAs. Therefore, although this may induce measurement error in the smog alert variable, the bias it introduces is hopefully minimal. Although smog alerts have been issued since 1978, SCAQMD data are only available from 1983 to 2000. Over this period, shown in table 1, there were 824 days where at least one smog alert was issued. The AMAs of San Bernardino/Riverside and San Gabriel/Pomona were most likely to experience an alert, with 690 and 742 issued there,

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[10] The alerts still contain a signal for some people because it is not possible to distinguish between the alerts and forecasted ozone for people with a tolerance threshold near 200 PSI.

respectively, while the Coastal Areas AMA experienced only 17 alerts during this time. Alert accuracy is roughly 43% over all AMAs, with accuracy by AMA positively correlated with the number of alerts issued. The number of alerts issued has dropped considerably over this period, in accordance with decreases in ozone levels, with over 70 per year in the earlier years and around 10 in the later years.

For measure of time spent outdoors, accurately recorded individual level time diaries would provide an ideal source of such data. Because this data is generally unavailable on a daily level over a broad period of time compatible with the smog alert data, I use daily aggregate measures of attendance at various outdoor facilities within the boundaries of the SCAQMD as a substitute. If outdoor time and attendance at these places are positively correlated, this still enables a test of whether people respond to the alerts. Two notable limitations of these data are that it does not cover responses throughout all of SCAQMD and provides limited demographic information about who attends.

The three distinct outdoor attractions from which data were collected are the Los Angeles Zoo and Botanical Gardens, Griffith Park Observatory, and the Los Angeles County Arboretum and Botanical Gardens, with descriptive statistics for each shown in table 1.[11] The Zoo, which is located in Griffith Park in the Hollywood Hills, offers both total daily attendance and a breakdown of attendance for adults, children under 4, juniors, seniors, and 'glaza' members from 1983 to 1998. While the Zoo is both a tourist and local attraction, the glaza members are typically only local residents, and it is possible that local residents have different responses to the alerts than tourists. The Zoo is only a day time activity: it is open everyday from 10 a.m. to 5 p.m., with the closing time extended to 6 p.m. from July 1 to Labor Day. It attracts nearly 5000 people each day, and experiences ozone levels of roughly 100 PSI prior to 1991 and 81 PSI after 1991 during the ozone season of march through October.

The Observatory, also located in Griffith Park, has total attendance data only, available from 1986 to 1997 with an average of nearly 5700 people per day. The Observatory is not just a daytime activity, as it is open from 2 p.m. to 10 p.m. Tuesday through Friday and 12:30 p.m. to 10 p.m. on Saturday and Sunday. When school lets out, it is open from 12:30 p.m. to 10 p.m. everyday. The Observatory is a popular tourist destination because of its proximity to Hollywood and the panoramic views of the city and ocean. Many people also frequent the Observatory for stargazing, which is clearly a nighttime activity that may not be affected by ozone levels. Therefore, because it is possible that people shift their outdoor activities to the night when alerts are announced, there may be less of a response for the Observatory. Given its proximity to the Zoo, ozone levels are comparable to those at the Zoo.

The Arboretum is located in Arcadia, about 15 miles northeast of downtown LA, with data available from 1991 to 1997. It is open from 9 a.m. to 5 p.m. everyday, with an average attendance of 465 people. The Arboretum experiences the highest levels of ozone of the places considered because it is located on the north side of the Hollywood hills, where ozone is trapped in the valley by the surrounding mountains, with ozone levels averaging 112 PSI during the ozone season.

For health data, an ideal measure would be indicator of health status or detailed descriptions of health conditions. Because such data are also difficult to find on a daily level that spans a comparable time period as the smog alert data, I instead use various respiratory related hospitalizations from the California Hospital Discharge Data (CHDD). There are several factors

[11] I also obtained attendance for the Los Angeles Dodgers and California (Anaheim) Angels, both major league baseball teams, but chose not to include them in the analysis because most admissions involve advance ticket

that make these data an attractive option. First, it includes the exact date of admission to the hospital, enabling me to merge it to the smog alert, weather, and pollution data at a daily level. Second, it contains the entire universe of discharges from 1983 to 1998 and the primary diagnosis of the patient, providing a large enough population necessary to detect specific illnesses believed to be related to ozone at such a high frequency. Third, it provides the zip code of residence, enabling me to assign each individual to an AMA. Because non-emergency hospitalizations can be pre-arranged and therefore have day of week patterns, I limit the sample to only emergency room (ER) admissions in order to use unplanned illnesses that are more likely to be an immediate reaction to ozone. Table 1 also shows the daily number of ER admissions for all of the residents of SCAQMD for asthma and bronchitis by commonly defined age groups used when studying the health effects of ozone.

For computing pollution and meteorology at the AMA level, I assign each pollution monitor or weather station to the AMA in which it resides, and take the mean when there are multiple units within an AMA. Daily pollution data was obtained from the California Air Resources Board. In SCAQMD, there are roughly 30 pollution monitors that contain data on 1-hour ozone, and roughly 20 that contain data on 8-hour carbon monoxide (CO) and 1-hour nitrogen dioxide (NO_2), two other pollutants that are necessary to consider because of their correlation with ozone and potential health effects. Although there are considerable disagreements over how to assign pollution from monitors to individuals, this approach is justified on the grounds that an AMA represents an area with common pollution concerns by accounting for geographic and population differences within SCAQMD, so there is less spatial variation in ozone within an AMA. Weather data was obtained from the National Climactic Data Center. There are 30 weather stations in SCAQMD that contain data on maximum

purchases and involve sedentary activities. In accord with this, I found no effect of the alerts on attendance.

temperature and precipitation, but only one (Los Angeles International Airport) with a complete history of maximum relative humidity and cloud cover, so its values are assigned to all of SCAQMD. These data are then merged with the data on attendance and hospitalizations by AMA and date.

4. Estimation Strategy

Outdoor Activities

The first objective is to estimate the demand equation given in (4) separately for each place to allow differential responses to alerts. For example, as noted above, the Observatory is open during the evening and thus experiences night time customers. Assuming a linear form gives:

$$y_t = \beta_0 + \beta_1 \cdot al_t + \beta_2 \cdot x_t + \beta_3 \cdot u_t + \varepsilon_t \qquad (5)$$

where y_t is the log of aggregate attendance at day t (as a measure of outdoor time), al_t is dummy variable indicating if there was a smog alert issued in the AMA in which the outdoor place resides, x_t are observed covariates from equation (4), u_t are unobserved covariates from equation (4), and ε_t is an i.i.d. error term.[12] The observed covariates in x include: monthly dummy variables to account for solar radiation or leisure; weather variables to account for ozone formation and outdoor quality; annual dummy variables for price or structural changes in the facilities; day of week, summer, and holiday dummy variables for leisure; and carbon monoxide and nitrogen dioxide to account for other outdoor pollutants. The unobserved covariates include such factors as forecasted ozone, indoor air quality, unobserved air quality, and forecasted weather. Based on the prediction from the avoidance behavior model, we expect $\beta_1 < 0$: outdoor attendance at the specific place decreases when alerts are announced.

[12] As equation (1) indicates, there is temporal dependence in ozone levels. Therefore, the standard errors in these regressions account for serial correlation up to a 7-day lag.

The main limitation in estimating (5) is the unobserved variables (u_t) may be correlated with both the decision to issue an alert and engage in outdoor activities, most notably forecasted ozone. To address this, I exploit the fact that smog alerts are issued a day in advance and, given the stochastic process of ozone formation, are frequently issued with error. Since alerts are a deterministic function of the forecasted ozone as indicated in equation (1), forecasted ozone fully governs the selection rule and including it would make estimation straightforward. If ozone levels are forecasted with some degree of accuracy, however, then the observed ozone concentration can proxy for forecasted ozone and function as a single index for all unobservables that vary with alert status. Therefore, I include the maximum observed ozone concentration in the AMA as a covariate, and allow for a flexible functional form by creating ozone "fixed effects". For example, I include separate constants for ozone levels of 80-90, 90-100, 100-110, etc. in order to compare differences in attendance by alert status within the same ozone cell. Equation (5) can be restated as:

$$y_t = \beta_0 + \beta_1 \cdot al_t + \beta_2 \cdot x_t + f_y\,(maxoz_t, \varphi) + v_t \tag{6}$$

where f_y is a function that relates ozone to attendance, $maxoz_t$ is the maximum observed AMA ozone concentration and v_t is the composite error term ($v_t = \beta_3 \cdot u_t + \varepsilon_t$).

Figure 2 develops the intuition behind this estimation strategy. It shows a non-parametric plot[13] of Zoo attendance, adjusted by all included covariates except smog alerts and observed AMA maximum ozone, against the AMA maximum ozone separately for days with no alerts (solid line) and with alerts (dashed line). By controlling for observed ozone, I compare attendance on days when smog alerts were issued to attendance on days with the same level of ozone but when smog alerts were not issued. I assume unobserved factors that might affect the

[13] The non-parametric plot is a local polynomial regression with uniform weighting and bandwidth 0.8. The plot is insensitive to the weighting and bandwidth choice.

decision to spend time outside, such as visibility, indoor air quality, or allergens, are unlikely to differ across days with the same level of ozone regardless of alert status. Therefore, the difference in attendance by alert status, reflected by the distance between the solid and dashed lines, represents the effect of alerts on attendance. As seen in this figure, outdoor attendance is almost always lower for every value of ozone on alert days, suggesting that people reduce their outdoor exposure in response to the alerts.

There are three assumptions necessary to obtain unbiased estimates of β_1. The first assumption is that alerts are conditionally uncorrelated with ε_t, meaning there is no supply-side response. For example, facilities can't change their price or keep animals inside on alert days, or they don't reach maximum capacity on non-alert days. Of the places considered, none violate this concern. It is possible, however, that a more crowded atmosphere, although under capacity, provides less enjoyment because of longer waiting times, for example. In this case, if attendance drops in response to an alert being issued, capacity constraints are less likely to be a concern as compared to no alert being issued. Therefore, y_t decreases when $al_t = 0$, and this will understate the amount of avoidance behavior.

The second assumption is alerts are conditionally uncorrelated with the ozone forecast error. This means that errors in issuing alerts are not "corrected" once they are realized, e.g. non-alert days where ozone exceeds 200 PSI are not announced once detected. This assumption is unlikely to be violated because of the flaws inherent in detecting and disseminating an alert the day it occurs. For example, ozone typically peaks in the late afternoon, around 3:00. This data is not received until an hour later, and once a violation is detected, it must be double-checked to ensure its accuracy. At this point, the media is first made aware, which can be up to 2 hours from when the violation was detected. By the time this information is received by the public, sunlight has decreased and ozone levels have typically fallen to safer levels, so this assumption is likely to be satisfied.

The final assumption is that alerts are conditionally uncorrelated with the unobservable covariates. While many of these variables seem unlikely to differ by alert status conditional on observed ozone levels, the biggest concern relates to weather forecasts because it can affect outdoor activities and enters directly into the ozone forecast and smog alert equation. If this forecast only slightly differ from observed weather, it is unlikely to introduce a bias because the difference between observed and forecasted ozone is minimal. If, however, this forecast is considerably different from observed weather, then observed ozone may not sufficiently proxy for forecasted ozone, thus violating this assumption. Since lagged weather is a crucial element used in forecasting weather, I add lagged weather to (6) to attend to this concern.

To assess how randomly treatment (alert days) and controls (non-alerts days) are assigned using this empirical strategy, table 2 shows the number of alerts and the difference between the observed variables for the Zoo within each ozone cell after adjusting for month. Although I directly control for these variables in the regression, the empirical strategy relies on the unobserved factors (u_{it}) to be uncorrelated with the smog alerts. If the observed factors balance across the treatment and control group, then it may be reasonable to believe that the unobserved factors balance as well. Furthermore, if the observables are mean independent across treatment status, this accounts for any functional form concerns of the observable variables. For the most part, there are no considerable differences for any of the variables considered in table 2 except for maximum temperature, which is almost always higher on alert days. Because of this concern, I also perform analyses where I create fixed effects based on the interaction between AMA maximum ozone cells and temperature cells.

Hospital Admissions

After estimating if people respond to the alerts, the next step is to examine how this response affects health. I do this by estimating the health production function given in (2) separately for each age group specified as:

$$h_{at} = \gamma_0 + \gamma_1 \cdot y_{at} + \gamma_2 \cdot y_{at} \cdot oz_{at} + \gamma_3 \cdot oz_{at} + \gamma_4 \cdot x_{at} + \alpha_a + u_{at} \qquad (7)$$

where the subscript a indicates AMA, x_{at} are as defined above, α_a is an AMA fixed effect, and u_{at} is an i.i.d. error term.[14] I include outdoor time and its interaction with ozone to allow the effect of being exposed to ozone to vary with the level of ozone. For example, if people respond to an alert but ozone ends up being only 50 PSI, we might expect less of an effect on health outcomes than if ozone ends up being 200 PSI. A considerable advantage of using a daily time series is that we do not need to explicitly control for m_t and z_t because they do not vary at a daily level and are absorbed into the constant.

An important aspect of this equation is that it nests the commonly used epidemiology dose-response equation – if we remove outdoor time and its interaction with ozone from this equation, it reduces to a standard epidemiological equation (Katsouyanni et al. (1996)) – and therefore allows a unique interpretation of the ozone-related parameters. The parameter γ_3 is the biological effect of ozone on health and $\gamma_2 \cdot y_{at} + \gamma_3$ is the "behavioral" effect of ozone on health.[15] The two can differ significantly from each other. For example, if there is a biological effect of ozone but people are able to perfectly compensate for changes in ozone so that they offset any health effects ($-\gamma_2 \cdot y_{at} = \gamma_3$), then there is no behavioral effect of ozone on health.[16] If

[14] I omit all lagged variables from this equation for ease of exposition, but consider them in the empirical section.

[15] While both effects are of interest for various reasons, it is important to note that knowledge of the biological effect is useful for prescribing avoidance behavior given that the biological effect is debated, for understanding the discrepancy between experimental and non-experimental studies, and because current EPA policy is based on the biological effect.

[16] This would not imply regulation of ozone is unnecessary because avoidance behavior may be costly to individuals.

avoidance behavior occurs only in response to ozone and is not included in equation (7), then the coefficient on ozone will represent the behavioral effect of ozone – which can precisely explain why many studies find no effect of ozone even if one exists.

The main limitation in estimating this equation is that we do not observe outdoor time everywhere. Because we observe alerts everywhere, however, I use this in place of outdoor time and include the maximum AMA observed ozone to account for the selection rule:

$$h_{at} = \gamma_0 + \pi_1 \cdot al_{at} + \pi_2 \cdot al_{at} \cdot oz_{at} + \gamma_3 \cdot oz_{at} + \gamma_4 \cdot x_{at} + f_h\,(maxoz_{at}, \zeta) + \alpha_a + u_{at} \qquad (8)$$

where f_h is a function that relates AMA maximum ozone to attendance. Using this equation, the first main test of interest is the reduced form parameter π_2 (= $\gamma_2 \cdot \beta_1$). This parameter, the indirect effect of smog alerts on health, represents whether a change in exposure to ozone via smog alerts affects health, conditional on the level of ozone. If $\pi_2 < 0$, this implies that both this age group is responding to alerts ($\beta_1 < 0$) and exposure to ozone affects their health ($\gamma_2 > 0$). Therefore, if I find evidence that people are responding to alert and $\pi_2 < 0$, I can deduce that ozone affects health

By controlling for observed maximum ozone concentrations, the intuition for how this parameter is identified is similar to that for outdoor activities. I compare health outcomes on days when smog alerts were issued to outcomes on days with the same maximum AMA ozone level but when smog alerts were not issued. Therefore, estimates of π_2 are unbiased under the same assumptions given for the outdoor demand equation.

In terms of testing whether $\gamma_3 > 0$, at least two additional difficulties arise.[17] One, there may be additional types of avoidance behavior occurring through mechanisms other than alerts, such as the use of peak-expiratory flow meters, that are not accounted for. If these other avoidance opportunities alter behavior in the same fashion as alerts do, then the bias from omitting them should be in the same direction as that from omitting the alerts. Two, given that the sources of pollution do not vary at a daily level that is adequate for explaining the variation in pollution, there are concerns over what drives the day to day variation in pollution. If it affects health and is unobserved, then estimates of the effect of ozone on health may be due to spurious correlation. Because the main focus of this study is not in obtaining unbiased estimates of this parameter, I do not attempt to overcome these concerns. Instead, I attempt to show how including responses to ozone affects the point estimates of ozone to see if it can partially explain the lack of evidence of an association between ozone and hospital admissions. Therefore, the second main test of interest is to assess if adding smog alerts to equation (8) affects estimates of γ_3, which is done via a Hausman test.

The main finding of this analysis is depicted in figure 3, a non-parametrically smoothed scatter plot of adjusted hospitalizations for asthma and bronchitis against contemporaneous ozone levels by smog alert status.[18] When not accounting for smog alerts, there appears to be no relationship between ozone and hospitalizations, supporting the lack of an effect commonly found in epidemiology studies. Looking at days when no smog alert was announced, however, paints an entirely different story. It shows a positive and linear relationship between ozone and health, and the gap between the two lines increases with the level of ozone, supporting the appropriateness of interacting ozone with smog alerts. This suggests that ozone does in fact affect health and not accounting for avoidance behavior can completely alter our conclusion about the relationship between ozone and health.

5. Results

Outdoor Activities

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[17] Note that these concerns are not unique to this analysis, and apply to other analyses using daily time series.

The first set of regression results, shown in table 3, provides the first set of evidence that people respond to smog alerts by decreasing outdoor activities. For each outdoor place, I estimate models with a linear control for the AMA maximum ozone, with ozone cells of size 10 PSI, and with ozone cells of 10 interacted with temperature cells of 5 degrees. Shown in columns (1) through (3), both the Zoo and Arboretum experience an 8% drop in attendance from smog alerts, while the Observatory has a more modest decrease in attendance of 5% drop from the announcement of an alert. The other control variables have the expected sign for each place. For example, attendance increases when school is out of session and as temperature increase until a certain point. The control variables explain a considerable amount of variation in attendance, with R-squares of 0.75, 0.66, and 0.84 for the Zoo, Observatory, and Arboretum, respectively.

Several factors point to the reliability of these results. First, the results are of the same order of magnitude despite coming from three distinct sources. Second, the activities with the greatest amount of daytime hours have higher responses. The Zoo and Arboretum, which are limited to daylight hours, both have a larger response than the Observatory, which includes nighttime hours. Third, the estimates for all three places are generally insensitive to the functional form of maximum ozone, shown in columns (4) through (9). Fourth, although estimates for the Zoo and Arboretum show a small drop from including weather variables of one lag (shown in table 4), they are unaffected by the inclusion of additional lags, suggesting the omission of weather forecasts does not appear to be a major concern.

Using the demographic breakdown of attendance for the Zoo, I also explore how different groups respond to the alerts. If the costs of avoiding these activities are lower for local residents,

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[18] Figure 1 is different from this figure because, in addition to being hypothetical, figure 1 assumed ozone was forecasted perfectly, which was done for ease of exposition.

either because they are more informed or have lower costs of substitution, then we expect to see larger responses for locals. Table 5 shows estimates for the separately categorized groups for the Zoo, and suggests that glaza members are more likely to respond than the other groups (which may consist of both tourists and locals), reducing their attendance by 13% when alerts are announced. Because the benefits from avoiding pollution are likely to be greatest for the most vulnerable segments of the population, it may at first seem surprising that there is not a greater response for seniors and children under age 4, also shown in table 5. Two potential explanations are because children go to the zoo with their parents they both have identical responses to alerts and, as offered in the theory section, the most vulnerable segments of the population may be less likely to respond specifically to an alert.

I also examine whether people are responding to these alerts out of altruistic rather than health concerns. For example, when an alert is issued people may not go to the Zoo because this involves driving, and they do not want to contribute to pollution on a day already considered highly polluted. If this is so, people may not limit their overall outdoor time and therefore experience no change in ozone exposure. To test if people drive less in response to an alert, I use carbon monoxide (CO) as the dependent variable in equation (8) as a proxy for automobile exhaust[19] and estimate if alerts affect both aggregate levels of CO for all of SCAQMD and CO levels at the AMA level. These results, shown in table 6, support an opposite effect, if anything: alerts have a positive effect on CO, although insignificant, indicating that people may actually drive more when an alert is issued. Therefore, these results suggest that people respond to these alerts primarily to protect their health rather than to minimize contribution to pollution.

Using the estimates from table 3, I can unfortunately only provide wide bounds on the cost of avoidance behavior because these costs are greatly affected by the degree of intertemporal and contemporaneous substitution. At one extreme, the costs of substitution are zero if people only go to the Zoo, say, once a year, and therefore choose to go on a day when there are no smog alerts. If this is the case, the costs of avoidance behavior are zero. At the other extreme where substitution costs are infinite, the costs of avoidance behavior are the lost utility from participating in the outdoor activity. Without knowing the utility people derive from this activity, the costs are at least the price of the activity. For example, when an alert is issued there is a drop in attendance at the Zoo of nearly 450 customers on average. Given the current admission price of $9, this results in costs to consumers of roughly $4000 per alert. Note that this only represents the possible costs associated with the specific activity mentioned, and does not include other actions people may take in response to the smog alerts.

For this part of the analysis, however, the main focus was not about calculating the costs of avoidance behavior, but about determining *if* people respond to the alerts. Given that people respond to these alerts and it appears to be driven out of health concerns, then they are decreasing their exposure to ozone. Therefore, if ozone affects health, we expect to see a decrease in illnesses related to ozone, which leads to the second part of the empirical analysis.

<u>Hospital Admissions</u>

Table 7 presents estimates of equation (8) with asthma and bronchitis ER admissions as the dependent variable, separately for each age group. Within each age group, I present results from four specifications. The first column contains results without controls for smog alerts, and the second column adds smog alerts along with its interaction with ozone levels. The third and fourth columns are analogous to the first two, but also include three lags of pollution, alerts, and

[19] As much as 95% of CO in cities is generated by automobile exhaust.

weather.[20] The main objective is to test if the alerts have a significant effect on hospitalizations and if including them affects the coefficient on ozone.

In general, I find considerable evidence supporting the importance of avoidance behavior. For asthma and bronchitis admissions, the results in column (1) for children under age 5 indicate no effect of ozone on asthma and bronchitis, consistent with much of the epidemiology evidence. In moving to column (2), however, the smog alert interaction term has a statistically significant negative effect on admissions, suggesting that a decrease in exposure to ozone reduces hospital admissions. Furthermore, the coefficient on ozone becomes significant and positive, and is significantly larger than the coefficient without controlling for alerts. This same pattern emerges when including lagged variables: column (3) shows no effect of ozone on hospitalizations when not controlling for alerts, while column (4) shows the lagged alerts are jointly significant and including them induces a significant and positive effect of ozone. For children ages 5-19, a similar pattern emerges, with one difference being that the ozone coefficient is significant when not including alerts. For people ages 20-64, ozone is positive and significant without smog alerts, and including alerts does not cause a significant change in the ozone coefficients. For people over age 64, I also find that estimates of ozone are significantly increased from including alerts, although the alerts themselves are not jointly significant at conventional levels. These results support the argument that ozone affects health but people respond to it, and not including this response affects estimates of the relationship between ozone and health.

The disparity in estimates across age groups also provides useful insights about heterogeneity in avoidance behavior. Differences by age can arise if either the biological effect of ozone or avoidance behavior varies by age. I find evidence of a biological effect for nearly all

[20] To reduce clutter in the tables, I do not include regressions that address the functional form of maximum AMA ozone. Consistent with the results for outdoor activities, the results for hospitalizations were robust to this concern.

age groups, but no evidence of an effect of the alerts or changes in estimates of the effect of ozone from including alerts for adults age 20-64. This suggests they are the least likely group to engage in avoidance behavior, which seems plausible because they are the group that is most likely to be employed and therefore face the greatest costs to changing activities.

Using these results, table 8 provides estimates of the benefits from reduced hospitalizations from the announcement of an alert. Because the effect of an alert varies with the amount of pollution, I provide estimated benefits from ozone levels of 200 PSI, the level at which an alert is issued.[21] I determine the change in hospitalizations by adding the individual effects from coefficients in the specification with three lags, and multiple this by the average cost of hospitalization. These results indicate a savings of roughly $400,000 per alert in asthma and bronchitis admissions when ozone is 200 PSI. An alert announced at 100 PSI, the level that corresponds with air quality standards, would provide half the benefits. Without more detailed knowledge on the costs of avoidance behavior, it is difficult to asses the cost effectiveness of this public health information program. Furthermore, this is likely to represent an understatement of the total health savings for at least two reasons: 1) although hospital admissions are likely to be the costliest type of health care, there are additional health affects that may not result in hospitalizations that may far exceed the number of hospitalizations; and 2) these costs only include the hospital bill, and do not include other costs associated with the illness, such as any direct utility effects from illness.

There are also potential health costs from responding to the alerts that cannot be detected in this analysis. If people spend more time inside as a result of the alerts, this can influence people to adopt a more sedentary lifestyle. Although one day alone may not induce any changes in behavior, a longer string of alerts might. For example, an alert was issued every single day in

August of 1986 in the San Bernardino and Riverside areas. A sedentary lifestyle is unlikely to effect short-term health, but may affect longer-term health outcomes, such as obesity. Therefore, although policies with announcements at lower pollution levels, which are becoming increasingly popular, may improve short-term health outcomes, they may also induce longer-term negative effects on health as well.

6. Conclusion

This paper provides empirical support for one explanation why many studies are unable to find an association between ozone and health: as pollution increases, information about pollution increases. People respond to this information by spending less time outside and reducing their exposure to ozone. By not accounting for this response, there is no observed effect of ozone on their health. This evidence is uncovered by looking at the effect of smog alerts on various outdoor activities and hospital admissions in California. By exploiting the fact that alerts are issued a day in advance and often with error, I compare outdoor activities and hospital admissions on days with the same observed levels of ozone but different alert status. When smog alerts are issued, attendance falls between 4 and 9% at three outdoor facilities considered in Southern California. By responding to these alerts and lowering their exposure to ozone, this results in fewer hospital admissions for asthma and bronchitis.

Most importantly, I find that including avoidance behavior significantly impacts estimates of the biological effect of ozone. Although epidemiological investigations of the relationship between ozone and health pay considerable attention to exploring environmental confounding factors, such as weather, they frequently pay little attention to behavioral confounding factors. This analysis not only suggests that people directly respond to ozone levels, but not accounting for this response alters conclusions about the effect of ozone on health

[21] Using equation (8), the marginal effect of an alert on hospitalizations is $\pi_1 + \pi_2 \cdot oz_{at}$.

and helps to explain part of the discrepancy between experimental and non-experimental evidence.

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Figure 1. Hypothetical Relationship between Ozone, Health, and Avoidance Behavior

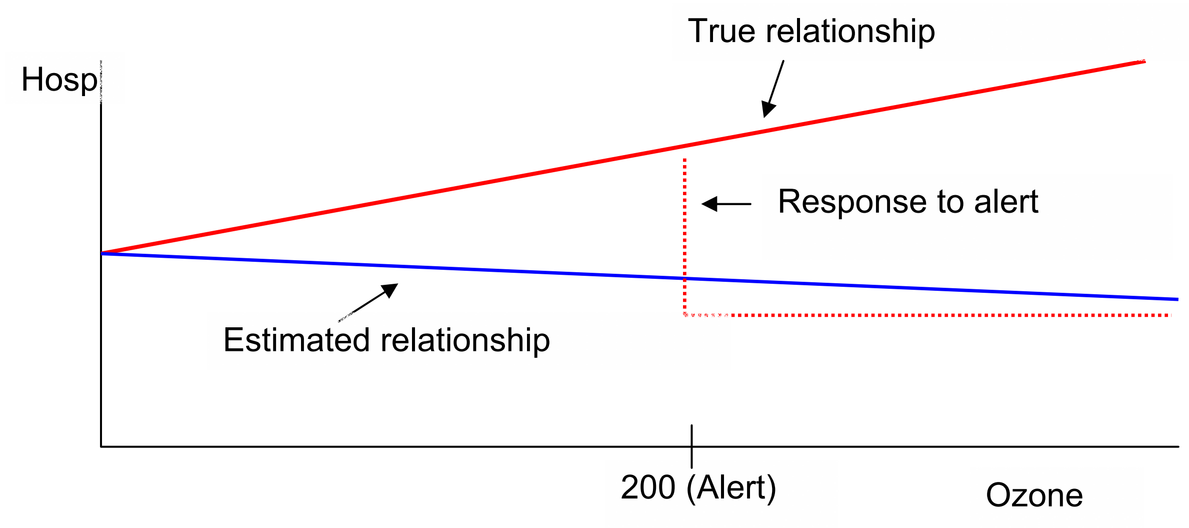

Figure 2. Plot of Attendance at LA Zoo on Ozone by Alert Status

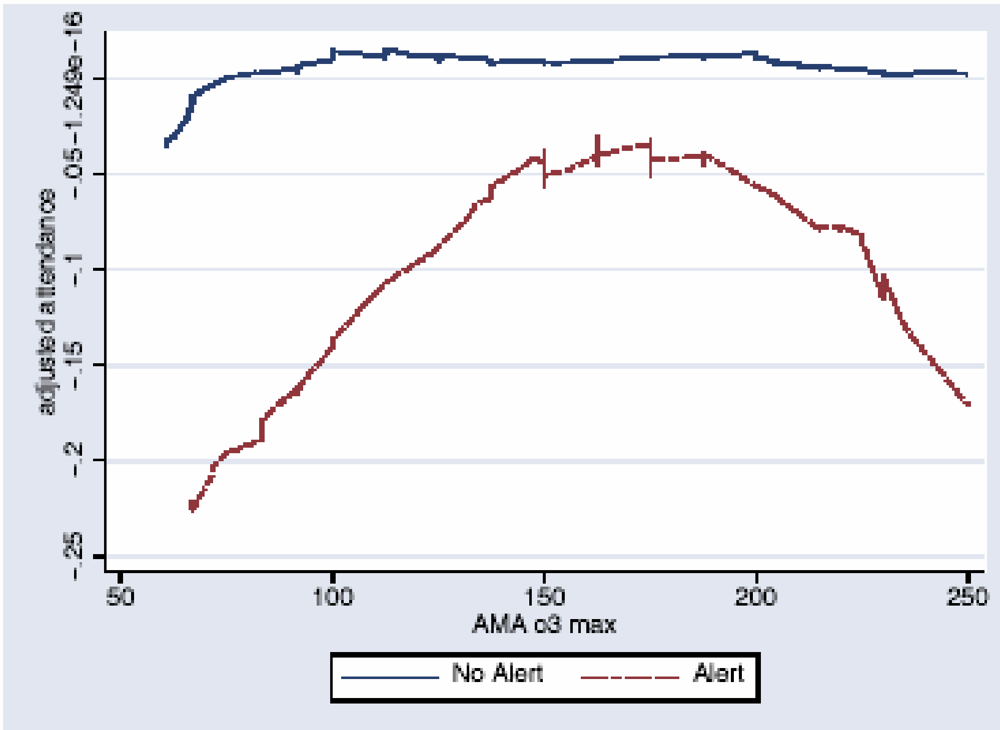

Figure 3. Plot of Asthma/Bronchitis Admissions on Ozone by Alert Status

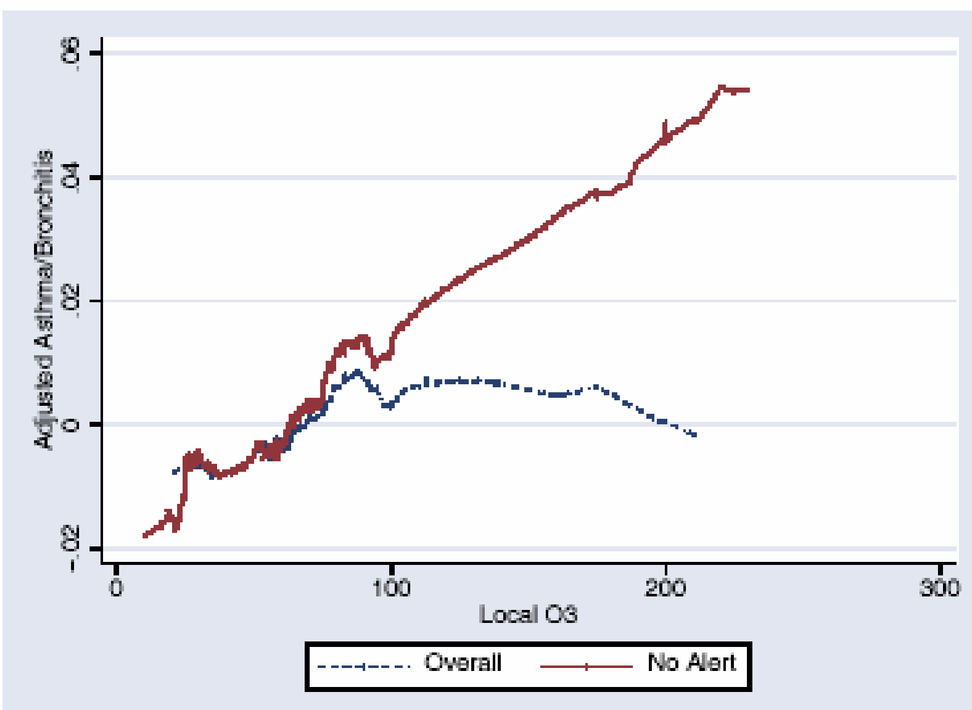

Table 1. Basic Summary Statistics

Smog Alerts

Air Monitoring Area	**AMA**	**# of alerts**	**% correct**
Metropolitan Los Angeles	1	93	27%
Coastal areas	2	17	6%
San Fernando, Santa Clarita	3	257	33%
San Gabriel, Pomona	4	742	52%
San Bernardino, Riverside	5	690	45%
Hemet-Elsinore area	6	61	8%
Inland Orange County	7	19	26%
High deserts	10	38	47%
Low deserts	11	7	0%
Big Bear Lake	12	2	n/a
Banning area	13	18	22%
Total		1,944	43%

Year	**1983**	**1990**	**1998**
# of alerts	70	51	10

All	**N**	**Mean**	**Std. Dev**
Alert	2092	0.33	0.47
Max. Rel. Humidity/10	2092	8.98	0.67
% Cloud Cover	2092	0.43	0.31
Los Angeles Zoo			
Local O3 < 91 (PSI/100)	1269	1.00	0.42
Local O3 >= 91 (PSI/100)	823	0.81	0.33
Max. Temp./10	2092	8.52	0.81
Precip/10 (in.)	2092	0.01	0.13
Total Attendance	2092	5090.12	3232.29
Junior	1640	894.85	771.50
Senior	1640	92.14	52.55
Adult	2090	1854.47	1832.52
Glaza	2092	582.36	484.65
Under 4	2092	486.56	519.99
Griffith Park Observatory			
Local O3 < 91 (PSI/100)	654	0.88	0.34
Local O3 >= 91 (PSI/100)	557	0.79	0.25
Max. Temp./10	1211	8.36	0.67
Precip/10 (in.)	1211	0.00	0.05
Total Attendance	1211	5705.33	2336.18
Los Angeles County Arboretum			
Local O3 >= 91 (PSI/100)	1059	1.12	0.45
Max. Temp./10	1059	8.64	0.69
Precip/10 (in.)	1059	0.01	0.21
Total Attendance	1059	487.63	494.02
Health Outcomes			
Asthma/Bronchitis <5	30855	7.74	4.32
Asthma/Bronchitis 5-19	30855	5.30	3.40
Asthma/Bronchitis 20-64	30855	19.31	5.58
Asthma/Bronchitis >64	30855	14.90	5.66

Table 2. Number of Alerts and Difference between Covariates at Los Angeles Zoo within Ozone Cell

Ozone	Number of Observ.	Number of Alerts	AMA O3 Max	Summer Schedule	Holiday	Weekend
75-100	630	77	31.441	-0.079	0.015	-0.041
			[0.000]	[0.179]	[0.697]	[0.701]
100-125	380	105	-0.763	-0.023	0.009	0.038
			[0.919]	[0.665]	[0.804]	[0.696]
125-150	263	118	9.630	0.055	-0.013	0.096
			[0.055]	[0.199]	[0.554]	[0.199]
150-175	236	138	-0.640	0.127	0.034	-0.008
			[0.874]	[0.015]	[0.340]	[0.936]
175-200	149	106	5.072	0.115	0.042	0.033
			[0.147]	[0.013]	[0.124]	[0.675]
200-225	143	116	6.538	0.096	0.000	0.442
			[0.543]	[0.581]	[.]	[0.071]

Ozone	Year	Relative Humidity/10	% Cloud Cover	Max. Temp./10	Local O3	Local CO
75-100	-0.970	0.166	0.049	0.493	0.117	10.219
	[0.190]	[0.236]	[0.468]	[0.002]	[0.002]	[0.000]
100-125	1.177	0.129	0.127	0.450	0.015	3.541
	[0.115]	[0.364]	[0.038]	[0.001]	[0.780]	[0.162]
125-150	0.283	0.198	0.059	0.315	0.051	1.322
	[0.591]	[0.070]	[0.259]	[0.003]	[0.313]	[0.497]
150-175	0.686	0.015	-0.012	0.221	-0.024	-1.529
	[0.222]	[0.899]	[0.826]	[0.052]	[0.722]	[0.546]
175-200	0.031	0.250	0.132	-0.149	0.033	0.295
	[0.952]	[0.023]	[0.016]	[0.166]	[0.652]	[0.866]
200-225	-2.327	-0.402	-0.137	0.706	0.213	2.937
	[0.027]	[0.196]	[0.375]	[0.022]	[0.445]	[0.587]

Notes: P-values in brackets. All variables are adjusted by monthly dummy variables.

Table 3. Main Regression Results for Outdoor Attendance

	1	2	3	4	5	6	7	8	9
	Linear Ozone			Ozone Fixed Effect			Ozone-Temperature Fixed Effect		
	Zoo	**GPO**	**Arbrtm.**	**Zoo**	**GPO**	**Arbrtm.**	**Zoo**	**GPO**	**Arbrtm.**
Alert	-0.083**	-0.050	-0.083*	-0.079**	-0.043	-0.088*	-0.088**	-0.036	-0.088*
	[0.027]	[0.037]	[0.035]	[0.026]	[0.037]	[0.036]	[0.026]	[0.038]	[0.042]
Summer Schedule	0.239**	0.165**	0.335**	0.240**	0.171**	0.329**	0.240**	0.166**	0.312**
	[0.059]	[0.027]	[0.059]	[0.059]	[0.026]	[0.060]	[0.058]	[0.028]	[0.060]
Max. Temperature/10	1.161**	0.255	2.234**	1.167**	0.276	2.214**	0.782	0.385	3.213**
	[0.291]	[0.203]	[0.365]	[0.302]	[0.215]	[0.377]	[0.675]	[0.461]	[0.786]
Max. Temperature/10 squared	-0.072**	-0.016	-0.137**	-0.072**	-0.017	-0.136**	-0.053	-0.023	-0.183**
	[0.017]	[0.012]	[0.021]	[0.018]	[0.013]	[0.022]	[0.039]	[0.026]	[0.044]
Precipitation/10	-0.019	-0.066	0.018	-0.027	-0.058	0.014	-0.040	-0.067	0.027
	[0.053]	[0.165]	[0.021]	[0.049]	[0.175]	[0.022]	[0.046]	[0.177]	[0.027]
Max. Relative Humidity/10	-0.001	0.007	0.009	-0.001	0.008	0.008	-0.006	0.011	0.007
	[0.017]	[0.015]	[0.021]	[0.017]	[0.015]	[0.022]	[0.019]	[0.015]	[0.023]
Cloud Cover	0.021	-0.041	-0.065	0.025	-0.038	-0.06	0.029	-0.036	-0.05
	[0.031]	[0.027]	[0.039]	[0.031]	[0.026]	[0.040]	[0.033]	[0.027]	[0.040]
Observations	2092	1211	1059	2092	1211	1059	2092	1211	1059
R-squared	0.75	0.66	0.84	0.75	0.66	0.84	0.76	0.68	0.86

Notes: * significant at 5%, ** significant at 1%. Newey-West standards errors that correct for heteroskedasticity and serial correlation in brackets. All regressions include annual, monthly, holiday and day of week dummy variables and controls for carbon monoxide and nitrogen dioxide. 'Linear Ozone' includes the AMA maximum ozone concentration as a control variable. 'Ozone Fixed Effect' includes separate constants for AMA maximum ozone concentration for each interval of 10 PSI. 'Ozone-Temperature Fixed Effect' includes separate constants for AMA maximum ozone concentration for each interval of 10 PSI interacted with maximum temperature for each interval of 5 degress.

Table 4. Regression Results for Outdoor Attendance Including Lagged Weather

	1 0 lag	2 1 lag	3 2 lag	4 3 lag
Zoo				
Alert	-0.083**	-0.073**	-0.077**	-0.073**
	[0.027]	[0.025]	[0.025]	[0.025]
Observations	2092	2050	2010	1971
R-squared	0.75	0.75	0.75	0.75
GPO				
Alert	-0.050	-0.056	-0.085	-0.066
	[0.037]	[0.043]	[0.045]	[0.039]
Observations	1211	1122	1034	940
R-squared	0.66	0.7	0.68	0.66
Arboretum				
Alert	-0.083*	-0.057	-0.055	-0.060
	[0.035]	[0.033]	[0.034]	[0.036]
Observations	1059	1005	954	904
R-squared	0.84	0.85	0.85	0.85

Notes: * significant at 5%; ** significant at 1%. All regressions include the same controls as the 'Linear Ozone' specification in table 3. Each column also contains the specified number of lags of weather variables.

Table 5. Estimates of the Impact of Smog Alerts on Attendance at Los Angeles Zoo by Demographic

	1 Adults	2 Glaza Members	3 Juniors	4 Seniors	5 Under 4
Alert	-0.076**	-0.131**	-0.057	-0.062*	-0.088*
	[0.024]	[0.033]	[0.038]	[0.029]	[0.044]
Observations	2090	2090	1640	1640	2092
R-squared	0.86	0.67	0.78	0.7	0.64

Notes: * significant at 5%; ** significant at 1%. All regressions include the same controls as the 'Linear Ozone' specification in table 3.

Table 6. Effect of Smog Alerts on Automobile Emissions Using Carbon Monoxide as a Proxy

	1 Aggre-gate CO	2 AMA CO
Alert	0.159	0.077
	[0.359]	[0.211]
Observations	2577	13124
R-squared	0.62	0.67

Notes: * significant at 5%; ** significant at 1%. All regressions include the same controls as the 'Linear Ozone' specification in table 3 except for carbon monoxide and nitrogen dioxide.

Table 7. Results for Asthma/Bronchitis by Age

	Age < 5				Age 5-19			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
	0 lag	**0 lag**	**3 lag**	**3 lag**	**0 lag**	**0 lag**	**3 lag**	**3 lag**
Alert*o3		-0.118*		-0.066		-0.041		0.003
		[0.055]		[0.061]		[0.041]		[0.045]
Alert*o3 (lag 1)				-0.006				-0.036
				[0.057]				[0.047]
Alert*o3 (lag 2)				-0.023				-0.015
				[0.059]				[0.051]
Alert*o3 (lag 3)				-0.193**				-0.073
				[0.058]				[0.047]
Alert		0.078		0.087		-0.022		-0.075
		[0.085]		[0.092]		[0.064]		[0.068]
Alert lag 1				-0.047				0.037
				[0.080]				[0.069]
Alert lag 2				0.016				-0.017
				[0.086]				[0.073]
Alert lag 3				0.144				0.050
				[0.085]				[0.068]
F-stat		8.390		7.650		7.350		4.600
Prob > F		0.000		0.000		0.001		0.000
o3 PSI	0.013	0.327**	0.042	0.133	0.032*	0.359**	0.026	0.184**
	[0.019]	[0.067]	[0.022]	[0.078]	[0.015]	[0.053]	[0.018]	[0.062]
o3 PSI lag 1			-0.001	0.164*			0.026	0.159*
			[0.024]	[0.082]			[0.020]	[0.066]
o3 PSI lag 2			0.000	0.077			0.020	0.178**
			[0.025]	[0.086]			[0.021]	[0.065]
o3 PSI lag 3			-0.066**	0.293**			0.010	0.181**
			[0.023]	[0.077]			[0.019]	[0.067]
χ^2		6.285		11.418		3.646		9.511
Pr > χ^2		0.012		0.022		0.056		0.050
Observations	30885	30885	29047	28417	30885	30885	29047	28417
R-squared	0.38	0.39	0.39	0.39	0.32	0.32	0.32	0.32

Table 7. Results for Asthma/Bronchitis by Age (continued)

	Age 20-64				Age >64			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
	0 lag	**0 lag**	**3 lag**	**3 lag**	**0 lag**	**0 lag**	**3 lag**	**3 lag**
Alert*o3		0.109		0.087		-0.135		-0.151
		[0.085]		[0.090]		[0.077]		[0.083]
Alert*o3 (lag 1)				0.158				-0.051
				[0.098]				[0.087]
Alert*o3 (lag 2)				0.057				0.012
				[0.098]				[0.083]
Alert*o3 (lag 3)				-0.038				-0.010
				[0.093]				[0.080]
Alert		-0.182		-0.223		0.186		0.167
		[0.123]		[0.132]		[0.118]		[0.125]
Alert lag 1				-0.177				0.121
				[0.142]				[0.126]
Alert lag 2				-0.206				-0.012
				[0.137]				[0.122]
Alert lag 3				-0.011				0.021
				[0.134]				[0.116]
F-stat		1.130		2.720		1.550		0.790
Prob > F		0.325		0.005		0.212		0.613
o3 PSI	0.193**	0.278*	0.126**	0.123	0.105**	0.408**	0.062*	0.273**
	[0.029]	[0.108]	[0.034]	[0.124]	[0.025]	[0.091]	[0.030]	[0.104]
o3 PSI lag 1			0.141**	0.333**			0.124**	0.156
			[0.039]	[0.124]			[0.033]	[0.106]
o3 PSI lag 2			0.060	0.035			0.015	0.205
			[0.039]	[0.130]			[0.033]	[0.105]
o3 PSI lag 3			0.048	0.260*			0.031	0.005
			[0.035]	[0.122]			[0.030]	[0.101]
χ^2		1.111		1.380		10.768		16.005
Pr > χ^2		0.292		0.848		0.001		0.003
Observations	30885	30885	29047	28417	30885	30885	29047	28417
R-squared	0.57	0.57	0.57	0.57	0.47	0.47	0.47	0.47

* significant at 5%; ** significant at 1%

Notes: Newey-West standards errors that correct for heteroskedasticity and serial correlation in brackets.

All regressions include the same controls as 'Linear Ozone' in table 3, and a separate constant for each AMA.

The coefficients on alert*o3 and o3 are multiplied by 100.

Table 8. Savings in Hospital Costs from Smog Alerts

	Age < 5	Age 5-19	Age 20-64	Age > 64	Total
Asthma/Bronchitis					
Average cost of hosp.	$5,209	$4,930	$6,156	$7,931	
Change in hosp., ozone = 200 PSI	57.4	24.205	-52.183	39.703	69.125
Savings	$299,007	$119,335	-$321,257	$314,873	$411,957
Change in hosp., ozone = 100 PSI	28.6	12.105	-25.783	19.703	34.625
Savings	$148,982	$59,680	-$158,729	$156,259	$206,192