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Public Information and Avoidance Behavior: Do People Respond to Smog Alerts?

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Public Information and Avoidance Behavior: Do People Respond to Smog Alerts?

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Abstract: This paper examines whether individuals engage in avoidance behavior in response to information about air pollution. Specifically, I look at the impact of smog alerts on outdoor activities at three distinct outdoor facilities in Southern California. To identify the effect of smog alerts, I employ a regression discontinuity design that exploits the deterministic selection rule by which smog alerts are issued. Using this empirical strategy, I find considerable evidence that people increase avoidance behavior in response to information about pollution: attendance declines at all three places by 3 to 11 percent when alerts are issued. As smog alerts become increasingly frequent, however, people decrease their response to alerts, suggesting decreasing returns to substitute activities. I use this intertemporal impatience to estimate the costs of avoidance behavior, providing some of the first of its kind using data on revealed preferences. (*JEL* D80, I18, Q51, Q53)

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This paper examines whether individuals engage in avoidance behavior in response to information about air pollution. Avoidance behavior is a crucial distinction between willingness-to-pay (WTP) and cost-of-illness (COI) analyses. In the case of air 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. WTP, however, accounts for these behavioral adjustments in response to pollution.[1] 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. Despite the theoretical importance of avoidance behavior, there is limited empirical evidence to support its existence, especially with respect to air pollution. Furthermore, because this is a non-market activity that reflects the opportunity cost of time and value of leisure, even more elusive are estimates of the costs of avoidance behavior, especially from data on revealed preferences.

Understanding responses to information about health risk is also 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. Furthermore, 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. There is, however, limited evidence on observed responses to government provided information about risk and the speed with which people process such information.

[1] WTP also accounts for the direct utility effects of health. See Harrington and Portney (1987) for a full derivation.

To address these issues, this paper looks at the impact of air quality episodes, or "smog alerts", on outdoor activities in Southern California. If people respond to these alerts by increasing avoidance behavior, we expect a decline in outdoor activities. The data gathered for outdoor activities is unique, consisting of daily attendance at three 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. These data, available from 1989 to 1997 at the daily level, consist of administrative records, which is less likely to be subject to recall bias that may be present in survey data. Furthermore, because these data are gathered from three independent sources, it is less likely that any findings are due to features of the sample or errors from specification searches.

To identify the effect of smog alerts on outdoor activities, I employ a regression discontinuity design that exploits the deterministic selection rule by which smog alerts are issued. That is, smog alerts are only issued when ambient ozone is forecasted to exceed a particular threshold. If days just above or below this threshold do not vary systematically with outdoor activity decisions, this will enable me to obtain unbiased estimates of the causal effect of alerts on avoidance behavior. In support of this approach, the observable characteristics, such as weather and pollution, move smoothly around this threshold, suggesting that any change in attendance at this threshold can be directly attributed to smog alerts.

Using this empirical strategy, I find considerable evidence that people increase avoidance behavior in response to information about pollution. Attendance is significantly lower on days when smog alerts are announced, with declines between 3 and 11 percent across the three places considered. This response is considerably larger on the weekend, when people are more likely to have greater flexibility in the choice of leisure activities. I also find that local residents, who are more likely to receive this information and have lower costs of substituting activities than tourists, have a greater overall response to alerts. Furthermore, children and elderly, two susceptible groups specifically targeted by smog alerts, have a greater response than adults.

These results are robust to several specification checks. For example, people may not participate in these outdoor activities in order to limit their contribution to ozone levels, so any observed changes in behavior reflects altruism rather than avoidance behavior. I find that attendance for an indoor activity, the Museum of Natural History, increases when alerts are issued, suggesting that people are in fact substituting from outdoor to indoor activities. Furthermore, traffic fatalities, which is used as a proxy for traffic, is unaffected by the issuing of smog alerts. Given these findings, it is difficult to dismiss the notion that people value the information provided by the smog alerts.

To measure the costs of avoidance behavior, I exploit people's intertemporal impatience with regards to switching activities. That is, when smog alerts are issued on consecutive days, I find people decrease their response on the second day, presumably because of the increased costs from switching activities. Therefore, by accepting an increase in exposure to ozone and the corresponding health effects, the costs from switching activities are at least the expected increase in health costs. Preferred estimates indicate an increase in expected hospital costs for asthma, and therefore individual costs of avoidance behavior, of $40 to $250. While there are several limitations in interpreting these values, it is the first of its kind using revealed preferences, and is of considerable use for understanding individual's willingness to pay for improvements in environmental quality.

Lastly, this evidence suggests that the government appears to have provided a necessary public good, but there is room for improvement. This intertemporal impatience may extend more broadly to public provided information about risk. For example, although people may initially respond to terror alerts, they may no longer take actions to alerts that are constantly “code red”. Increased efforts to improve the accuracy of forecasts, which would lead to a decline in the number of alerts issued, could improve the effectiveness of this public good.

The rest of the paper proceeds as follows. The following section provides background information on air quality and reviews some relevant economics literature. Section 2 describes a simplified model of avoidance behavior that incorporates information about risk. Section 3 describes the data and section 4 presents the empirical strategy. Section 5 shows the main results and estimates of the cost of avoidance behavior, and section 6 concludes.

1. Background Information

Air Quality

Ground-level ozone, both its 1-hour and 8-hour concentration, is a criteria pollutant regulated under the clean air acts.[2] 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 levels vary considerably both across and within days, as it tends to peak in the summer and middle of the day when heat, sunlight, and/or solar radiation are at their maximum (U.S. EPA (2003)). Ozone is believed to irritate lung airways and increase susceptibility to respiratory related health conditions as asthma, with symptoms occurring in as quickly as 1 hour and normal lung functioning typically returning within 24 hours (U.S. EPA (2003)).

[2] 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.

Because of the perceived health threats regarding ozone[3], the U.S. Environmental Protection Agency developed the pollutant standards index (PSI) to inform the public of local air pollution levels. The PSI is indexed so that a value of 100 corresponds to the National Ambient Air Quality Standards as set forth in the Clean Air Acts. The PSI advises the public regarding associated health effects and precautionary steps to take when air pollution reaches unhealthful levels.[4] For example, a value in the range of 100-200 is considered unhealthful and is accompanied by a message stating that susceptible people should reduce outdoor activity, and others should reduce vigorous outdoor activity. 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)). Because the PSI is a nonlinear function of the parts per million (ppm) that observed ozone levels are recorded, I report the ozone forecast in ppm rather than PSI.

In addition to providing the ozone forecast, California state law requires the announcement of an air quality episode when the ozone forecast exceeds 0.20 ppm.[5] These episodes are more widely publicized than the ozone forecast, as they get announced on the television and radio. When an episode 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. Furthermore, schools are directly contacted and instructed to reschedule or cancel outdoor physical education classes, recess, and sports practices and competitions. The

[3] The health effects of ozone, however, are widely debated. See, for e.g., Neidell (2005).
[4] The PSI, which was replaced by the Air Quality Index in 1999, is also available for other criteria pollutants believed to affect health, such as particulate matter and carbon monoxide.

public is also encouraged to minimize their contribution to pollution by ride sharing, for example, although no financial incentives are offered to do so.

Although air quality episodes can be issued for any of the criteria pollutants, they have only been issued for ozone. Because ozone is a major component of urban smog, this has given 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. 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, but 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 of the SRAs within an AMA.

Given the reporting process and the factors believed to affect ozone formation, the model used for issuing an alert can be summarized as:

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[5] 0.20 ppm corresponds with 200 PSI. Additionally, stage II air quality episode is issued when the ozone forecast exceeds 0.30 ppm or 250 PSI, but this only occurred once over the time period studied.

$$al_{at} = 1\{max_{at}(oz^{f}_{st} = f(w^{f}_{st}, oz_{st-1}, sr_{t}))\} \geq 0.20\} \quad (1)$$

where the subscripts *a, s* and *t* indicate AMA, SRA, and date, respectively, *al* is an alert, oz^f is the forecasted 1-hour level of ozone, w^f is the weather forecast, *oz* is observed 1-hour ozone, *sr* is solar radiation, and *1{•}* is an indicator function equal to 1 when the forecasted ozone exceeds 0.20 ppm and 0 otherwise. Alerts for ozone are only issued from March through October, compatible with the seasonal patterns of ozone.

Economics Literature

Despite the fact that these air quality forecasts and alerts have been around for quite some time, there is no published evidence to indicate whether people respond to them. More broadly, there is limited empirical evidence on the existence of avoidance behavior, especially with respect to air pollution. Breshnahan et al. (1997) find that people spend less time outdoors when air pollution levels rise. Their study relies on survey data, which is potentially subject to 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 (2004) 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.[6] 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.

There is also limited evidence on the costs of avoidance behavior, with all of it coming from stated preference surveys (see, for e.g., Chestnut et al. (1988), Rowe and Chestnut (1985), and Dickie and Gerking (1991) for studies in the U.S.). A limitation of these analyses is that people's stated behavior under hypothetical risk may differ from their actual behavior under real risks. For example, in Chestnut et al. (1988) several people responded they would be willing to pay "anything" to avoid an angina episode, which is an implausible response. This paper attempts to use revealed rather than stated actions to overcome such objections.

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 in the presence of a market failure, largely due to data limitations.[7] Furthermore, despite considerable evidence of responses to information about environmental risk, limited evidence shows observed responses to government provided information in the presence of an externality. For 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.

[6] This type of behavior is referred to as 'prevalence elastic behavior' in the economic epidemiology literature.

(1995)). This study provides direct evidence on the effect of actual public information about risk on observed changes in behavior on the same exact day the information is provided.

2. Theory

People may substitute between indoor and outdoor activities because they believe exposure to indoor and outdoor pollution affects health, and because of the direct utility they receive from engaging in these activities. If people divide their leisure time dichotomously between indoor and outdoor activities, we can explicitly define avoidance behavior as choosing the indoor activity in the presence of ambient pollution when the individual would have otherwise chosen the outdoor activity in the absence of pollution. Note that outdoor time by itself is an imperfect measure of avoidance behavior because it affects utility directly. 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 or actual) 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

[7] There is considerable evidence in financial markets on the speed by which information is incorporated, but such markets are widely considered to be efficient, so information takes on a different role .

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 ozone according to:

$$oz_k^e = \omega_{1k} \cdot al + \omega_{2k} \cdot oz^f \tag{3}$$

where oz^e is the expected amount of pollution, oz^f is the forecasted level of ozone (as a continuous measure), 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)[8]. This yields the following demand equation for outdoor activities:

$$o = o\,(q, n, l, w, al, oz^f, p, j, z) \qquad (4).$$

The main prediction from this model is that people increase avoidance behavior (spend less time outside and more time inside) 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

[8] Included in these expenditures are health care costs to remediate health effects from exposure to pollution.

ozone levels are typically uncorrelated with outdoor levels (see, e.g., Chang et al. (2000)).[9] Two, if ozone enters the utility function directly, outdoor time is less enjoyable as ozone 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.[10]

An important insight from this model is that if people are rational Bayesian updaters and know their susceptibility to ozone levels, then smog alerts may offer no additional information above and beyond what is provided by the ozone forecast. This occurs if 1) there are no costs to acquiring the ozone forecast and 2) the discrete nature with which a smog alert is issued is a simplification of a continuous relationship between ozone and health. Therefore, if susceptible people do not distinguish between the health effects from ozone levels of, say, 0.19 and 0.20, then the information provided in the smog alert is of no value if they know the ozone forecast. Note that this will not hold for individuals who do not know their susceptibility, such as young children or those with changing susceptibility. However, because there are likely costs associated with obtaining the forecast from the newspaper everyday, we would expect those more likely to benefit from the information – the susceptible population – to obtain it. This provides a slightly counterintuitive prediction: the more susceptible population is less likely to respond to an alert.

A limitation of this insight is if the provision of information and limitation of activities comes from a centralized source, then responses may occur similarly for all segments of the population. For example, as previously mentioned, schools are instructed to comply with alerts

[9] This low correlation is due to the fact that ozone forms in the presence of sunlight and heat, and therefore rapidly breaks down indoors because of the absence of either (or both) of these factors.
[10] 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.

by altering the scheduling of outdoor activities. Therefore, children, regardless of their susceptibility, may both be required to and only allowed to respond to alerts despite the availability of exact forecasts. Similar scenarios may arise for the elderly if their activities are planned by caretakers, such as a retirement community. This yields the more intuitive prediction that more susceptible people are more likely to respond to alerts, but which of the two explanations dominates is an empirical question.

3. Data

For measure of time spent outdoors, the dependent variable of interest, accurately recorded individual level time diaries would provide an ideal source of such data. Because such data are generally unavailable on a daily level over a sufficient period of time, 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 should provide a valid construct for testing whether people respond to the alerts.[11] 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.[12]

Total attendance data is available from 1989-1997 for the Zoo and Observatory and 1990-1997 for the Arboretum, with each place calculating attendance using different techniques. The Zoo, which is owned and operated by the City of Los Angeles and averages over 4700 people a day, charges an admission fee. The register is linked to an automated system that tracks attendance. The Observatory, also owned and operated by the City of Los Angeles and with

[11] 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.

[12] 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 admissions reflect advance ticket purchases

averages over 5600 people a day, does not charge an admission fee. Attendance is recorded from two turnstiles that people must pass through to enter the grounds, and these numbers are hand entered in daily log files. The Arboretum, jointly operated by the Los Angeles Arboretum Foundation and Los Angeles County, charges a nominal entrance fee for all customers, and averages nearly 450 people a day. Daily attendance is calculated by dividing the daily cash deposit by the admission price, and is hand-recorded in a log book.

In terms of the reliability of these data, the more sophisticated record keeping system used by the Zoo suggests attendance is more likely to be accurately measured. On the other hand, data from both the Observatory and Arboretum were hand-recorded, suggesting greater potential measurement error. Furthermore, because use of the Observatory is free of charge, people can leave and re-enter multiple times on the same trip.[13] Additionally, a turnstile at the Arboretum records attendance, but it is only noted at a monthly level in the log. This value is then compared to the sum of the daily measures, and this discrepancy is noted. If this measurement error is uncorrelated with smog alerts (using the regression discontinuity design), this will not induce bias in estimates, but will reduce its efficiency. Therefore, we expect more precise estimates of the effect of alerts for the Zoo, and less precise estimates for the Observatory and Arboretum.

The Zoo, because it charges varying admission fees, also offers a breakdown of attendance for adults, children under 4, juniors, seniors, and GLAZA (Greater Los Angeles Zoo Association) members for all years[14]. While the Zoo is both a tourist and local attraction,

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and involve sedentary activities. In accord with this, I found no statistically significant effect of the alerts on attendance, though sample sizes were quite small.

[13] An employee of the Observatory noted this occurs because of the interest in immediately adjacent areas that requires leaving the official grounds by passing through one set of turnstiles. If customers had originally entered through a different set of turnstiles and seek to exit through the original set, they must re-enter the Observatory and hence will be double counted in the attendance figures.

[14] GLAZA members do not pay an admission fee.

GLAZA members are typically only local residents, and it is possible that local residents have different responses to the alerts than tourists. They may be more likely to be aware of alerts or may find it easier to switch activities. The demographic breakdown by age permits testing responses to alerts by susceptibility. As previously mentioned, it is unclear whether more susceptible groups – children and the elderly – are more or less likely to respond to alerts. Parents of children under age 4, however, may not know their susceptibility because it is difficult to detect respiratory illnesses at such a young age. Because this group is considered particularly vulnerable to ozone, we would expect a larger response to alerts for this group.

In terms of hours of operation, the Zoo and Arboretum are only day time activities, while the Observatory is both a day and night activity. The Zoo 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, and the Arboretum is open from 9 a.m. to 5 p.m. everyday.[15] The Observatory 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. Many people frequent the Observatory for stargazing, which is clearly a nighttime activity that may not be affected by smog alerts. 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.

In terms of ozone levels, the Arboretum, which is located in Arcadia about 15 miles northeast of downtown LA, experiences the highest levels 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. The Zoo and Observatory, both located in Griffith Park in the Hollywood Hills (a short distance from downtown Los Angeles), experience comparable levels

[15] The Arboretum offers a “Free Tuesday” once a month in which attendance is not recorded.

of ozone. In accordance with this, there are more alerts issued in the AMA in which the Arboretum resides.

Because of the constraint imposed that leisure time is divided between outdoor and indoor activities, it is also possible to test if attendance at indoor places increase when alerts are issued. That is, if people decrease their time outdoors, in order to avoid exposure to ozone they may increase their time indoors. To test this, I collected data from the Natural History Museum of Los Angeles from 1991 to 1997. It is located in central Los Angeles and open during daylight hours only everyday except Monday, with an average of just over 900 people per day. Attendance is also recorded automatically in a fashion similar to the Zoo, except the first Tuesday of each month when admission is free.

To assign smog alert status and forecasted ozone to each of the places, I obtained the forecasted ozone directly from the Los Angeles Times, thus making the AMA the finest geographic resolution the smog alert data is available. The resulting measurement error in alert status, if random, will attenuate the estimated coefficients. Although smog alerts have been issued since 1978, the reporting format for the forecasted ozone changed considerably midway through 1988, so I limit the analysis to the years 1989-1997. Although I do not have information on the AMA in which an alert is issued, I use the selection rule in equation (1) to assign alert status. To verify the appropriateness of this approach, I use an administrative file from SCAQMD that contains dates when alerts where issued anywhere in the district and compute the maximum ozone forecast within the district. Figure 1 shows that the selection rule is strictly followed: there are only 7 inconsistencies of the 2138 data points available over the period studied.

To assess the accuracy of these alerts, I compare predicted alert status to realized alert status using the maximum 1-hour ozone level in each AMA. Also shown in table 1, accuracy is quite low. Of the 104 alerts issued in the AMA for the Zoo, less than 20% were correctly issued, and there were 35 days where ozone surpassed 0.20 ppm but no alert was issued. Accuracy improves for the AMA for the Arboretum, with 25% correctly issued and only 17 days missed. Furthermore, the R-squared from a regression of observed ozone on forecast ozone is roughly 0.5 for each place, suggesting much of ozone formation is explained by factors not considered in the ozone prediction model. Also shown in table 1, the number of alerts issued has dropped considerably over this period, in accordance with decreases in ozone levels. While the inaccuracy of alerts may be problematic for encouraging people to respond to alerts, it is useful for the research design employed in this study. If scientists and meteorologists can not distinguish between days above and below the threshold, it is likely that individuals can not as well.

Other factors affecting the outdoor decision in equation (4) are obtained from the following sources. Using the date, I assign year-month dummies, day of week dummies, a holiday indicator, and summer schedule indicator to account for changes in leisure time.[16] Daily 1-hour ozone, 8-hour carbon monoxide (CO) and 1-hour nitrogen dioxide (NO_2) are readily available from the California Air Resources Board air pollution monitoring network. Data on weather (maximum temperature, precipitation, and maximum relative humidity) were obtained from the National Climatic Data Center. Each outdoor place is assigned to the closest pollution and weather station, and all data are linked at the daily level.

I also collect data on traffic fatalities in order to test whether people are reducing their driving in response to the alerts. That is, if people are driving less, we should see less traffic fatalities. These data come from Fatality Analysis Reporting System (FARS), a web-base encyclopedia maintained by National Center for Statistics and Analysis of the National Highway Traffic Safety Administration, a division of U.S. Department of Transportation (http://www-fars.nhtsa.dot.gov/main.cfm). Local police departments are required by federal law to collect information on vehicle accidents that involve a fatality, including the time, date, and location of the accident. Because the primary interest is on driving during they day when alerts are in effect, I limit the sample to daylight hours (6 a.m. - 8 p.m.). I merge this information with the other data using the location and date of the accident, with summary statistics also shown in table 1.

4. Empirical Strategy

The main objective is to estimate the demand equation given in (4) separately for each place, thereby allowing 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:

$$y_t = \beta_0 + \beta_1 \cdot al_t + \beta_2 \cdot oz^f_t + \beta_3 \cdot x_t + \beta_4 \cdot u_t + \varepsilon_t \qquad (5)$$

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. 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.

The main limitation in estimating (5) is the unobserved variables may be correlated with both the decision to issue an alert and engage in outdoor activities, such as forecasted weather. Since alerts are a deterministic function of the forecasted ozone as indicated in equation (1),

[16] The monthly dummies also account for solar radiation.

forecasted ozone fully governs the alert selection rule and makes it possible to leverage a regression discontinuity design. To do this, specify (5) as:

$$y_t = \beta_0 + \beta_1 \cdot al_t + f(\beta_2, oz^f_t) + \beta_3 \cdot x_t + v_t \qquad (6)$$

where f is a function that relates the ozone forecast to attendance and v_t is the composite error term ($v_t = \beta_3 \cdot u_t + \varepsilon_t$). If days just below forecast ozone levels of 0.20 ppm are identical to days just above 0.20, then the discontinuity in attendance that occurs at 0.20 ppm represents the causal effect of alerts.

While it is impossible to know if the unobservables are identical across such days, we can look at how well the observable covariates balance across alert status for days with ozone forecasts near 0.20 ppm. If the observed factors balance, then it may be reasonable to believe that the unobserved factors do as well. Figure 2 shows a plot of three likely influential covariates (temperature, humidity, and carbon monoxide (CO)) and attendance averaged by ozone forecast levels. All three covariates evolve smoothly throughout this plot, suggesting they are unaffected by smog alerts. Attendance, however, is slowly increasing up until 0.20, the point at which an alert is issued, and then shows a sharp drop in attendance. After that, attendance continues to increase in forecasted ozone. This figure provides the first piece of evidence that smog alerts cause a decrease in attendance.

Specification of f is crucial to the RDD – it enables one to use points far from the alert threshold to improve efficiency and generalizability, but misspecification can render biased estimates of β_1 (Dinardo and Lee (2004)). Figure 2 suggests that attendance at the Zoo is roughly linear in forecasted ozone, so I estimate that specification as well as one with a fifth order polynomial in forecasted ozone to allow forecasted ozone to enter more flexibly. As an additional specification, I estimate (6) using only observations centered near the threshold and omit forecasted ozone from the equation. While this approach is more likely to yield unbiased estimates, a shortcoming is that it limits the generalizability of these results to alerts that may occur at other levels. I display results from all specifications to assess the sensitivity of estimates of β_1 to the functional form of f.[17]

There are two additional assumptions necessary to obtain unbiased estimates of β_1. The first is there is no supply-side response, i.e., alerts are conditionally uncorrelated with ε_t. For example, facilities can't lower their price to entice customers or keep animals inside to protect their health on alert days, or they don't reach maximum capacity on non-alert days such that they turn customers away. 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, there is less crowding, which may induce other people to go to these outdoor places. Therefore, this offsetting behavior will understate the amount of avoidance behavior.

The second assumption is alert status is not "corrected" once actual levels of ozone are realized, i.e. alert status is correctly dictated by equation (1). Officials at SCAQMD indicated this rule was strictly followed 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 would be received by

[17] In this application, the covariate (ozone forecast) that determines the treatment (smog alert) is discrete. If the deviations from the continuous measure are random, this can be modeled econometrically by accounting for the group structure of the ozone forecast (Card and Lee (2004)). This involves computing standard errors clustered on each value of forecasted ozone.

the public, sunlight has decreased and ozone levels have typically fallen to safer levels, so this assumption is likely to be satisfied.

5. Results

Main Results

The main set of regression results, shown in table 3, provides further evidence that people respond to smog alerts by decreasing outdoor activities. For the Zoo, in columns (1)-(4), attendance shows a statistically significant drop of 15% and 10% in the linear and fifth order polynomial specifications, respectively, and a drop of 11% and 9% when limiting the sample to forecasted ozone values between 0.15 and 0.24 and 0.17 and 0.22, respectively. The coefficient on forecasted ozone is surprisingly positive in columns (1) and (2). The focus, however, was not on identifying this parameter but to include it to identify the smog alert parameter. Therefore, forecasted ozone could be proxying for other factors that affect outdoor decisions, such as the weather forecast, which may lead to an estimated positive effect. The other control variables have the expected sign, although they typically become smaller and less precisely estimated in the restricted sample. For example, precipitation is statistically significant and negative in columns (1) and (2), but much smaller and statistically insignificant in columns (3) and (4).

Results for the observatory, shown in columns (5)-(8), also vary somewhat by functional form: in all but the most restricted sample, attendance declines by roughly 3%, but in the most restricted sample attendance declines by nearly 5%. The results are generally statistically insignificant, though the point estimates for the most restricted sample is significant at 10%. The effect of alerts is smaller in magnitude than the Zoo, which is as expected given that the Observatory includes nighttime hours. Attendance at the Arboretum, shown in columns (9)-(12), also suggests a decline in attendance when alerts are issued, though it is generally not statistically significantly different from zero and is more sensitive to functional form. As discussed above, estimates for the Observatory and Arboretum are less precise as expected because of the greater potential measurement error in attendance as compared with the Zoo.

The discrepancy in estimates of the effect of smog alerts by functional form of forecasted ozone suggests that using points far from the alert threshold may be inducing a bias, making the preferred specification the restricted samples. These findings, therefore, may not be easily extrapolated to warnings issued at other levels. The remaining models will only show results from these restricted samples.

These results suggest a drop in attendance of 3 to 11 percent from an alert at all three places. This is of the same order of magnitude despite coming from three distinct sources, making it unlikely these results are due to sampling variability or general misspecification. Given that some people are unlikely to be aware of alerts and some may respond directly to the ozone forecast, this implies for at least 3 to 11 percent of the population, the costs of avoidance behavior for a single day are smaller than the costs of the outdoor activity. Overall, the results suggest smog alerts are causing a considerable reduction in attendance.

Response to alert may vary by the amount of leisure time available. For example, people have greater discretion over their time on weekends and may find it easier to switch activities, suggesting a potentially larger effect of an alert on the weekend. Table 4, which shows results including an interaction between alerts and an indicator for weekend, shows that responses are larger on the weekend for all three places in all specifications. While the weekend effect is not statistically significantly different from the main effect in most specifications, the overall weekend effect (a joint test of alerts and alerts interacted with a weekend indicator) is statistically significant in nearly every specification. These results suggest a larger response to alerts issued on the weekend than during the week, and, combined with the results from table 3, suggest any declines in attendance at the Observatory and Arboretum from an alert are largely due to weekend responses.

Using the demographic breakdown of attendance for the Zoo, I also explore how different segments of the population respond to alerts. If the costs of avoiding these activities are lower for local residents, either because they are more informed or have lower costs of substitution, then we expect to see larger responses for locals. Shown in the first two columns of table 5, GLAZA members, who are likely to be local residents, reduce attendance by 17%. This is considerably larger than the overall response of around 10%.

In examining the effects by age, as previously mentioned it is unclear whether the effect should be larger or smaller for children and the elderly as compared to the rest of the population. If the most susceptible people are obtaining ozone forecasts, then alerts should have less of an effect for children and elderly. But if information and activity planning is centralized, then alerts should have a larger effect for children and elderly because the benefits of avoiding are larger for these more susceptible segments of the population. The patterns in table 5 are consistent with the centralized information argument: the responses for children and seniors range from 13 to 20% as compared to an overall response of around 10%. The largest response is for children under age 4, who decrease attendance by 20% when an alert is issued. This is consistent with parents being most protective of their youngest children because they are unlikely to know their child's susceptibility to pollution. In general, these results further strengthen the main finding that people are responding to these alerts.

Since alerts are widely publicized, people may respond to alerts in neighboring AMAs. People may recognize the inaccuracy involved in forecasting ozone levels and use alerts in neighboring areas as a potential signal of information, suggesting neighboring alerts would have a negative effect on attendance. Alternatively, if people are aware of an alert in a particular area, they may choose to go to a neighboring AMA without an alert because there are lower expected levels of ozone, indicating a positive effect on neighboring alerts. To test spatial responses to alerts, I include alerts from neighboring AMAs in equation (6). The results, shown in panel A of table 6, though statistically insignificant, indicate different responses to neighboring alerts at each place. For the Zoo, there is no detectable effect from neighboring alerts, and the coefficient on own alerts is unchanged by including neighboring alerts. For the Observatory, the effect from a neighboring alert is positive and comparable in magnitude to the effect from an alert in its own AMA, suggesting people substitute to the Observatory when there is an alert in a neighboring AMA. For the Arboretum, the effect of an alert in a neighboring AMA is negative and larger than the effect from an alert in its own AMA. This suggests people are more likely to use information from surrounding areas when attending the Arboretum. One potential explanation for the difference by outdoor place is people who attend the Arboretum are more cautious because of the higher levels of ozone experienced there on average. These estimates are imprecise, though, and are merely suggestive of such patterns. Importantly, the main effects of alerts are unaffected by including neighboring alerts, which supports the main empirical strategy.

I provide one general specification test for this model by including future alerts in equation (6). People can not respond to a forecasted alert before it occurs, so a significant effect would suggest misspecification. If people use a naïve version of equation (1) to forecast ozone on their own, however, then they may anticipate future smog alerts by increasing current outdoor activities, suggesting a positive coefficient on future alerts. Therefore, only a negative coefficient on future alerts would suggest misspecification. The results, shown in panel B of table 6, show effects from contemporaneous alerts are unaffected by the inclusion of future alerts. Furthermore, the table shows a positive effect from future alerts for all three places, though they are imprecisely estimated. This suggests people may be anticipating future smog alerts by increasing attendance today, but mainly this table validates the main regression specification.

One concern with the evidence presented thus far is people may respond to alerts out of altruistic rather than health concerns.[18] When an alert is issued people may not go to certain outdoor activities 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 display no avoidance behavior. To address this issue, I estimate two models. First, I use attendance at the Museum of Natural History as the dependent variable in (6) to test if people substitute from outdoor to indoor activities. The results, shown in the first two columns of panel C in table 6, indicate people increase their attendance at the Museum when alerts are issued, though this is imprecisely estimated. Attendance increases by over 20% in the restricted samples, which is considerably larger in magnitude than for any of the outdoor places, but this is perhaps less surprising because children are a high fraction of attendees at the Museum.

As a second test of altruism, I use traffic fatalities as the dependent variable in (6). If people drive less in response to an alert, there should be an accompanying decrease in traffic fatalities, all else equal. This specification is slightly different than previous specifications because I observe fatalities for all areas of SCAQMD. Therefore, I specify the dependent variable as traffic fatalities per AMA and include a separate constant for each AMA. The results

[18] The theoretical model could be accommodated to include altruism by entering ozone directly in the utility function.

from this specification, shown in the last two columns of panel C in table 6, indicate there is no effect of alerts on fatalities. Furthermore, given the automobiles are the primary source of CO and CO evolves smoothly through the alert threshold, as indicated in figure 2, this is also suggestive evidence that people do not respond to alerts by driving less. This effect helps to substantiate the overall evidence that people are displaying avoidance behavior in response to information about pollution.

<u>Costs of Avoidance Behavior</u>

As alerts become increasingly common it may become more costly to switch activities; it may be easy to switch activities upon hearing one alert or people may simply tire of responding. To assess this, I create an indicator variable if there was a smog alert issued on two consecutive days ($al_t{*}al_{t-1}$) and include this in equation (6). If this coefficient has a positive effect, it indicates that the cost of switching activities is increasing over time.[19] Given that alerts issued two days in a row is relatively uncommon, these estimates are likely to be imprecise. Panel A of table 7 shows that when an alert gets issued one day only, responses are slightly higher for the Zoo and considerably higher for the Observatory than reported in table 3. When alerts are issued two days in a row, however, the response to alerts decreases, and this decrease is statistically significant for the Zoo and Observatory. In fact, these estimates suggest that avoidance behavior completely disappears on the second day. The same pattern does not occur for the Arboretum, with responses on the second day being slightly larger than the first. This is consistent with the results from table 6 that suggests attendees of the Arboretum may be more cautious than those at the Zoo and Observatory. Responses on the second day may vary depending on the accuracy of the first day. Panel B of table 7 produces results for days when an alert was correctly forecasted

[19] An alternative explanation is that the media may not report an alert as vigorously on the second day. It is unfortunately not possible to distinguish this explanation from the above explanation.

the previous day. This yields a similar pattern to panel A, though the decrease in avoidance behavior from the second day is smaller when followed by a correctly issued alert.

Consecutive alerts are more likely during the peak times of the smog season, and responses to alerts may vary throughout the season. Therefore, I limit the analysis by running separate regressions for the first day response (given that one is issued on the second day) and for the second day response (given that one is issued on the first day). The results from this specification for the Zoo and Arboretum, shown in panel C of table 7, are quite comparable to those from panel B: an alert on the first day reduces attendance by 6 to 11%, but an alert on the second day reduces attendance by only 3 to 7%. In this specification, the results for the Arboretum are now considerably larger on the first day than both the second day effect and the baseline effect in table 3. Despite both exercises being increasingly taxing on the data, they support decreasing returns to substitute activities.

Without knowing the value people receive from the activity they switch to, it does not seem possible to measure the costs of avoidance behavior. This intertemporal impatience, however, can be used to estimate the cost of avoidance behavior. If people choose not to respond to an alert the second day in a row, then the cost of avoidance behavior is at least as much as the increased cost in expected illness they face from increasing their exposure to ozone. This can be summarized by the following equation:

$$p_o|_{oz=oz*} \geq p_h * [\delta h/\delta o|_{oz=oz*}] * [\delta o/\delta al_t \cdot al_{t-1}] \qquad (7)$$

where $p_o|_{oz=oz*}$ represents both the monetary and opportunity costs associated with avoidance behavior for a given level of ozone oz*, p_h is the costs associated with the change in health, $\delta h/\delta o|_{oz=oz*}$ is the effect of spending time outside on health at a given level of ozone $oz*$, and $\delta o/\delta al_t \cdot al_{t-1}$ is the impatience associated with alerts being issued two days in a row. For estimates of $\delta h/\delta o|_{oz=oz*}$, I use estimates of the effect of exposure to ozone via smog alerts on asthma hospitalizations for the age groups defined in Neidell (2005), and assume avoidance behavior is the same for these groups. For estimates of p_h, one option is to use the average cost of hospitalization for asthma. If people have insurance, however, the hospital bill does not reflect individual private costs, but instead represents social costs of hospitalizations that may not be internalized by the individual. Therefore, I use \$50 for p_h, a common insurance co-payment for hospitalizations. Estimates of $\delta o/\delta al_t \cdot al_{t-1}$ are from the three panels of results in table 7, but only for the Zoo.

It is important to note at least two caveats regarding these estimates, one of which I offer a potential solution. One, there could be other illnesses associated with exposure to ozone that either do not result in hospitalizations or results in other illnesses. Using numbers from the CDC that there are roughly 10 and 27 non-hospital visits for each hospital visit for the two age groups, respectively (Mannino (2002)), I scale these numbers accordingly.[20] There are no readily available numbers for illnesses other than asthma, so I can not include them. Two, the insurance co-payment does not necessarily reflect the full costs of illness for the individual, as it ignores any lost time or discomfort associated with asthma. Therefore, these numbers likely represents a lower bound of the costs of avoidance behavior.

Results for this exercise are shown in table 8. For explaining the values in each cell, focus on column (1) for children ages 0-5. The first row indicates there are roughly 1.5 more hospital admits for asthma from the change in time spent outside as a result of an alert being correctly issued (ozone reaches a level of 0.20 ppm). If there are 10 times more non-hospital

[20] To arrive at this number, in 1999 there were 1.15 million physician visits and hospital outpatient department visits, 269,000 emergency department (ED) visits, and 105,000 hospital visits for asthma for children under age 4. I assume all hospital and ED visits are also recorded in this first number. Therefore, the ratio of non-hospital to

admits for every hospital admit, this results in 14.5 total formal visits for care. Valuing these visits at $50 and assuming a 10% increase in exposure leads to costs of avoidance behavior of $72.91 per person. For the youngest age group, a correctly issued alert results in costs of between $25 and $93 depending on the specification from table 7. For children ages 5-19, the corresponding estimates are considerably larger at $130 and $489. The results are considerably smaller for adults, but this is largely due to the fact that responding to smog alerts has less of a health impact for these age groups.[21] Other than the upper ranges of estimates for the older children, the estimate for children appear somewhat reasonable depending on the amount of time people spend at these activities and given the monetary costs of these activities. Although this exercise is considerably demanding on the data and the results are relatively imprecise as a result, it is suggestive that costs of avoidance behavior are important to consider in environmental policy.

7. Conclusion

Using a regression discontinuity design to estimate whether people display avoidance behavior in response to information about pollution, I find a significant decrease in time spent outdoors when smog alerts are issued. The costs to responding, which should be interpreted with caution, appear non-negligible, suggesting that people's actions to reduce the impact of an externality should be considered when computing welfare costs, such as that offered in the willingness to pay approach. These results also suggest that people respond quickly to publicly provided information about risk. However, people's patience for responding wanes as more warnings are supplied, suggesting that policy makers should account for this when deciding how often to provide information. If people respond to information about pollution, this can also

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hospital visits is ((1.15 - .269 - .105) + .269) / .105. Similar number for children ages 5-14 are 2.387 physician visits, .389 ED visits, and .85 hospital visits.

affect our understanding of the biological effect of ozone on health, which is explored in more detail in Neidell (2005). That is, estimates of the biological effect of ozone on health that do not account for individuals' responses to pollution may be biased.

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[21] The estimates for $\delta h/\delta o$ are statistically insignificant for these two age groups (Neidell (2005)).

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Figure 1. Adherence to Smog Alert Selection Rule

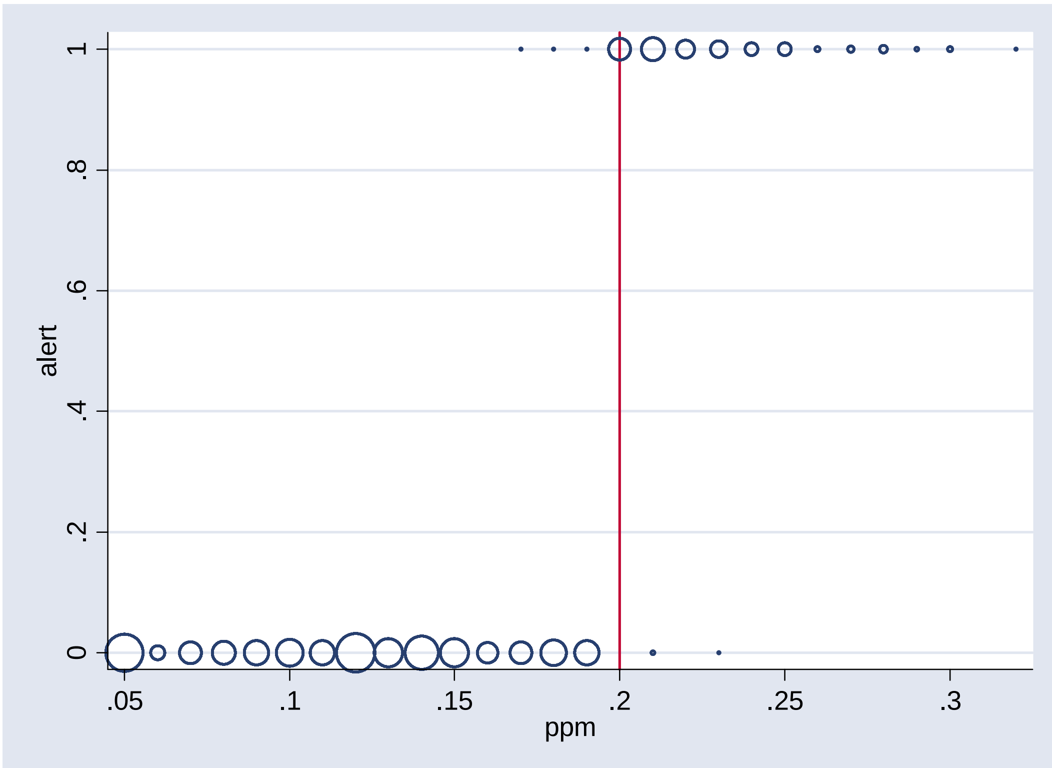

Figure 2. Zoo Attendance and Covariates by Ozone Forecast

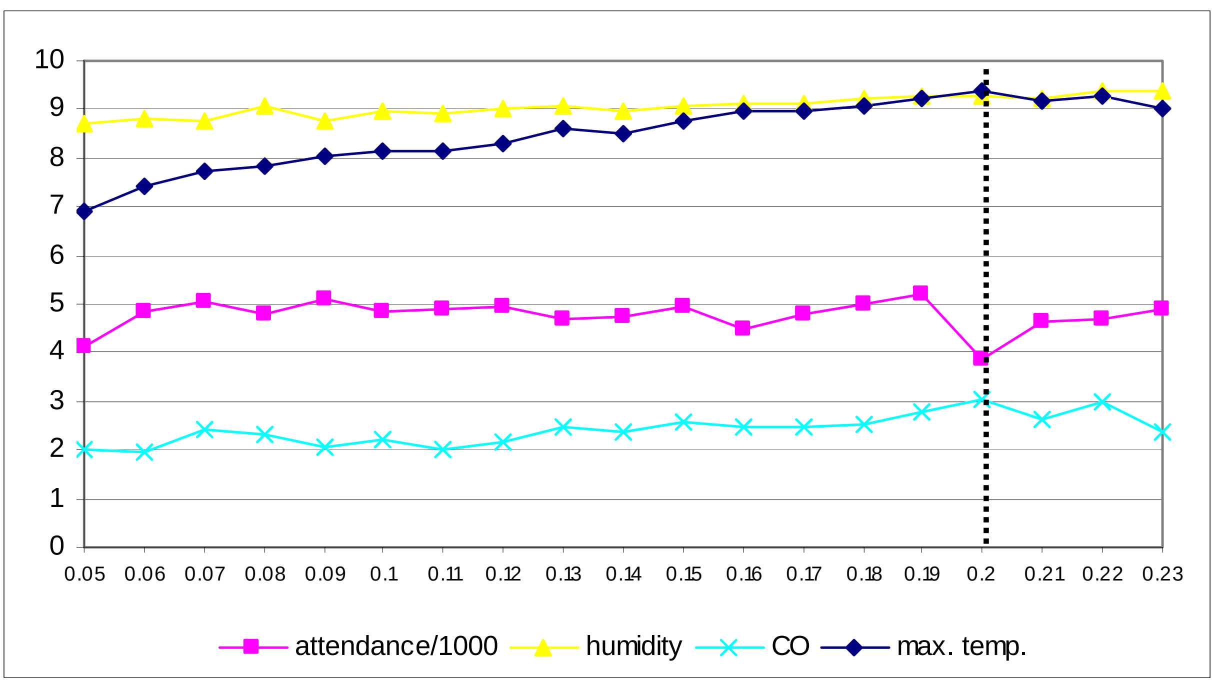

Table 1. Summary Statistics for Outdoor Places and Smog Alerts

Zoo (n=1919)	mean	std. dev.
attendance	4757	3169
alert	0.05	0.23
ozone forecast (ppm)	0.12	0.05
ozone (ppm)	0.08	0.04
max.temp./10	8.22	0.97
precip. (in.)	0.22	1.63
relative humidity/10	8.98	0.72
carob monoxide (ppm)	2.31	1.24
nitrogen dioxide (ppm)	0.07	0.03
juniors	766	776
seniors	81	51
adult	1532	1661
glaza members	713	532
under 4	301	364

Observatory (n=1745)		
attendance	5614	2363
alert	0.06	0.23
ozone forecast (ppm)	0.12	0.05
ozone (ppm)	0.08	0.04
max.temp./10	8.25	0.97
precip. (in.)	0.19	1.37
relative humidity/10	8.98	0.71
carob monoxide (ppm)	2.30	1.24
nitrogen dioxide (ppm)	0.07	0.03

Arboretum (n=1653)		
attendance	449	477
alert	0.15	0.36
ozone forecast (ppm)	0.13	0.05
ozone (ppm)	0.10	0.05
max.temp./10	8.35	0.87
precip. (in.)	0.21	1.50
relative humidity/10	9.00	0.70
carob monoxide (ppm)	1.57	0.76
nitrogen dioxide (ppm)	0.06	0.03

Museum (n=1111)	mean	std. dev.
attendance	910	589
alert	0.01	0.10
ozone forecast (ppm)	0.09	0.03
ozone (ppm)	0.07	0.03
max.temp./10	8.05	0.81
precip. (in.)	0.19	1.39
relative humidity/10	9.01	0.71
carob monoxide (ppm)	2.31	1.25
nitrogen dioxide (ppm)	0.07	0.04

Traffic Fatalities (n=18,895)		
daytime fatalities (6 am - 8 pm)	0.20	0.50
alert	0.05	0.21
ozone forecast (ppm)	0.10	0.05
ozone (ppm)	0.08	0.04
max.temp./10	8.20	1.18
precip. (in.)	0.22	1.62
relative humidity/10	9.00	0.73
carob monoxide (ppm)	1.70	0.90
nitrogen dioxide (ppm)	0.06	0.02

Accuracy of alerts

	Zoo	**Observ.**	**Arboretum**
issued	104	99	254
correct	19	19	65
missed	35	34	17

Number of alerts over time

year	**Zoo**	**Observ.**	**Arboretum**
1989	16	16	-
1990	12	10	54
1991	20	19	37
1992	24	22	48
1993	10	10	36
1994	15	15	37
1995	7	7	27
1996	0	0	14
1997	0	0	1

Table 3. Effect of Smog Alerts on Outdoor Attendance

	Zoo				Observatory				Arboretum			
	1	2	3	4	5	6	7	8	9	10	11	12
	linear	polynomial	.15-.24	.17-.22	linear	polynomial	.15-.24	.17-.22	linear	polynomial	.15-.24	.17-.22
alert	-0.149**	-0.101*	-0.105**	-0.087*	-0.028	-0.032	-0.027	-0.051	-0.089	-0.007	-0.062*	-0.030
	[0.035]	[0.045]	[0.026]	[0.028]	[0.022]	[0.036]	[0.019]	[0.027]	[0.048]	[0.049]	[0.030]	[0.026]
ozone forecast	1.188**	35.324			0.245	-15.143			0.129	7.372		
	[0.401]	[19.345]			[0.262]	[14.428]			[0.589]	[18.033]		
max. temp.	1.736**	1.519**	0.642	1.652	0.337**	0.281**	-0.122	1.022	2.709**	2.447**	1.759	2.405*
	[0.263]	[0.265]	[0.553]	[1.062]	[0.074]	[0.082]	[0.428]	[0.853]	[0.209]	[0.232]	[0.905]	[0.998]
max. temp. sq.	-0.110**	-0.097**	-0.049	-0.104	-0.020**	-0.017**	0.004	-0.057	-0.164**	-0.149**	-0.111*	-0.146*
	[0.016]	[0.016]	[0.031]	[0.060]	[0.004]	[0.005]	[0.023]	[0.046]	[0.013]	[0.014]	[0.051]	[0.056]
precip.	-0.068**	-0.066**	-0.02	-0.002	-0.004	-0.003	0.060**	0.065**	-0.079**	-0.076**	-0.483	-1.495*
	[0.010]	[0.008]	[0.013]	[0.018]	[0.002]	[0.002]	[0.010]	[0.015]	[0.013]	[0.011]	[0.354]	[0.413]
humidity.	-0.048	-0.05	0.107	0.091	-0.01	-0.011	0.026	0.043	-0.053	-0.054	-0.009	-0.003
	[0.040]	[0.040]	[0.063]	[0.069]	[0.009]	[0.009]	[0.046]	[0.064]	[0.028]	[0.028]	[0.022]	[0.034]
summer sch.	0.256**	0.269**	0.293**	0.158	0.133**	0.136**	0.182**	0.239**	0.327**	0.344**	0.354**	0.404**
	[0.061]	[0.061]	[0.087]	[0.076]	[0.024]	[0.024]	[0.038]	[0.021]	[0.036]	[0.037]	[0.053]	[0.056]
holiday	1.227**	1.215**	1.160**	1.280**	0.705**	0.705**	0.589**	0.514*	1.010**	0.994**	0.850**	0.694**
	[0.069]	[0.068]	[0.168]	[0.284]	[0.069]	[0.068]	[0.126]	[0.154]	[0.078]	[0.079]	[0.092]	[0.078]
sunday holiday	-0.543**	-0.542**	-0.541**	-0.437*	0.024	0.024	-0.141	-0.154*	0.084	0.065	0.16	-0.259
	[0.107]	[0.102]	[0.082]	[0.114]	[0.043]	[0.043]	[0.074]	[0.046]	[0.078]	[0.079]	[0.259]	[0.141]
carbon monox.	0.031	0.031	0.022	0.027	-0.018	-0.018	-0.026*	-0.023	-0.004	-0.012	-0.048	-0.024
	[0.020]	[0.020]	[0.023]	[0.031]	[0.012]	[0.012]	[0.009]	[0.020]	[0.016]	[0.015]	[0.030]	[0.032]
nitrogen diox.	-0.591	-0.689	-1.562	-1.992	0.439	0.425	0.819	0.493	1.122	1.203	0.393	-1.23
	[0.523]	[0.504]	[0.903]	[0.958]	[0.340]	[0.342]	[0.439]	[0.576]	[1.128]	[1.141]	[1.247]	[1.871]
Observations	1919	1919	520	300	1745	1745	497	292	1653	1653	579	371
R-squared	0.75	0.76	0.82	0.85	0.68	0.68	0.72	0.8	0.82	0.82	0.83	0.85

* significant at 5%; ** significant at 1%. Standard errors clustered on ozone forecast that account for heteroskedasticity in brackets. Column (1) includes a linear term for ozone forecast, (2) includes a fifth order polynomial in ozone forecast, and (3) and (4) are limited to ozone forecasts values in the range specified in the header. All regressions include day of week dummies and year-month dummies. The regressions for the Arboretum also include an indicator if the day was an insect or environmental fair.

Table 3. Effect of Alerts on Outdoor Attendance by Day of Week

	Zoo		Observatory		Arboretum	
	1	2	3	4	5	6
	.15-.24	.17-.22	.15-.24	.17-.22	.15-.24	.17-.22
alert	-0.054	-0.066	0.009	-0.028	-0.046	-0.023
	[0.047]	[0.062]	[0.034]	[0.043]	[0.036]	[0.024]
alert*weekend	-0.182	-0.077	-0.123*	-0.077	-0.049	-0.021
	[0.106]	[0.139]	[0.053]	[0.061]	[0.039]	[0.052]
F-statistic	10.92	3.04	18.5	13.93	8.21	0.75
Prob > F	0.009	0.142	0.002	0.014	0.019	0.427
Observations	520	300	497	292	579	371
R-squared	0.82	0.85	0.72	0.8	0.83	0.85

See notes to table 3. The F-statistic is a joint test of alert and alert*weekend.

Table 4. Effect of Alerts on Zoo Attendance by Demographic

	GLAZA members		Juniors		Seniors		Under 4	
	1	2	3	4	5	6	7	8
	.15-.24	.17-.22	.15-.24	.17-.22	.15-.24	.17-.22	.15-.24	.17-.22
alert	-0.171**	-0.166**	-0.178**	-0.137*	-0.173**	-0.143**	-0.200**	-0.203*
	[0.030]	[0.026]	[0.050]	[0.052]	[0.029]	[0.027]	[0.061]	[0.068]
Observations	520	300	520	300	520	300	520	300
R-squared	0.63	0.62	0.85	0.88	0.77	0.80	0.71	0.76

See notes to table 3.

Table 5. Specification Checks

	1	2	3	4	5	6
	0.15-0.24	0.17-0.22	0.15-0.24	0.17-0.22	0.15-0.24	0.17-0.22
A. Include Neighboring AMA Alerts						
	Zoo		Observatory		Arboretum	
alert	-0.128**	-0.081	-0.014	-0.033	-0.065*	-0.034
	[0.033]	[0.032]	[0.024]	[0.037]	[0.032]	[0.029]
neighbor alert	-0.043	0.011	0.024	0.029	-0.107	-0.106
	[0.035]	[0.044]	[0.027]	[0.026]	[0.108]	[0.127]
Observations	520	300	497	292	579	371
R-squared	0.82	0.85	0.72	0.80	0.83	0.85
B. Include Future Alerts						
	Zoo		Observatory		Arboretum	
alert	-0.103**	-0.087*	-0.026	-0.049	-0.073*	-0.035
	[0.024]	[0.029]	[0.019]	[0.027]	[0.034]	[0.027]
alert t+1	0.081	0.053	0.028	0.010	0.055	0.029
	[0.057]	[0.082]	[0.031]	[0.024]	[0.041]	[0.036]
Observations	506	293	485	285	560	357
R-squared	0.81	0.85	0.71	0.80	0.83	0.85
C. Indoor Time and Traffic Fatalities						
	Museum		Daytime Fatalities			
alert	0.201	0.363	-0.011	-0.003		
	[0.200]	[0.305]	[0.016]	[0.022]		
Observations	70	30	3157	1852		
R-squared	0.86	0.91	0.16	0.14		

See notes to table 3.

Table 6. Effect of Consecutive Alerts on Outdoor Attendance

	Zoo		Observatory		Arboretum	
	1	2	3	4	5	6
	.15-.24	.17-.22	.15-.24	.17-.22	.15-.24	.17-.22
A. Two in a row						
$alert_t$	-0.117**	-0.119**	-0.071*	-0.094**	-0.015	0.015
	[0.019]	[0.024]	[0.022]	[0.018]	[0.044]	[0.045]
$alert_t$*$alert_{t-1}$	0.100	0.130*	0.093	0.113*	-0.032	-0.064
	[0.058]	[0.064]	[0.050]	[0.044]	[0.071]	[0.091]
Observations	503	295	467	280	545	359
R-squared	0.82	0.86	0.71	0.81	0.84	0.86
B. Two in a row, first day correct						
$alert_t$	-0.094**	-0.086*	-0.040*	-0.059*	-0.039	-0.005
	[0.022]	[0.029]	[0.019]	[0.020]	[0.031]	[0.024]
$alert_t$*$alert_{t-1}$	0.067	0.025	0.027	0.034	-0.049	-0.217*
	[0.077]	[0.079]	[0.048]	[0.042]	[0.127]	[0.106]
Observations	503	295	467	280	545	359
R-squared	0.82	0.86	0.71	0.81	0.84	0.86
B. Separate effect for 1st day and 2nd day						
alert 1st day	-0.105*	-0.089	-0.071*	-0.059*	-0.160*	-0.117**
	[0.055]	[0.055]	[0.037]	[0.029]	[0.054]	[0.019]
alert 2nd day	-0.045	-0.048	-0.028	-0.070	-0.068	-0.089
	[0.049]	[0.075]	[0.041]	[0.067]	[0.054]	[0.072]
Observations	93	74	90	72	179	140
R-squared	0.92	0.92	0.82	0.9	0.86	0.87

See notes to table 3.

Table 7. Estimate of the Cost of Avoidance Behavior by Age

Age 0-5

	1	2	3	4	5	6
	.15-.24	.15-.24	.15-.24	.17-.22	.17-.22	.17-.22
$\partial h/\partial o\|_{oz=0.20}$	1.465	1.824	1.633	1.441	1.993	1.926
$\delta o/\delta al_t \cdot al_{t-1}$	0.100	0.067	0.060	0.130	0.025	0.041
$p_o\|_{oz=0.20}$	$72.91	$60.80	$48.75	$93.19	$24.80	$39.30

Age 5-19

	1	2	3	4	5	6
	.15-.24	.15-.24	.15-.24	.17-.22	.17-.22	.17-.22
$\partial h/\partial o\|_{oz=0.20}$	2.823	3.514	3.146	2.776	3.841	3.712
$\delta o/\delta al_t \cdot al_{t-1}$	0.100	0.067	0.060	0.130	0.025	0.041
$p_o\|_{oz=0.20}$	$382.31	$318.82	$255.60	$488.65	$130.03	$206.06

Age 20-64

	1	2	3	4	5	6
	.15-.24	.15-.24	.15-.24	.17-.22	.17-.22	.17-.22
$\partial h/\partial o\|_{oz=0.20}$	0.051	0.064	0.057	0.050	0.070	0.067
$\delta o/\delta al_t \cdot al_{t-1}$	0.100	0.067	0.060	0.130	0.025	0.041
$p_o\|_{oz=0.20}$	$6.94	$5.79	$4.64	$8.88	$2.36	$3.74

Age 65+

	1	2	3	4	5	6
	.15-.24	.15-.24	.15-.24	.17-.22	.17-.22	.17-.22
$\partial h/\partial o\|_{oz=0.20}$	0.087	0.109	0.097	0.086	0.119	0.115
$\delta o/\delta al_t \cdot al_{t-1}$	0.100	0.067	0.060	0.130	0.025	0.041
$p_o\|_{oz=0.20}$	$11.81	$9.84	$7.89	$15.09	$4.02	$6.36

Columns (1) and (4) use estimates from the corresponding columns in Panel A of table 7, columns (2) and (5) use Panel B, and columns (3) and (6) use the difference between the coefficient on the first and second day from Panel C.