NATIONAL EVIDENCE ON AIR POLLUTION AVOIDANCE BEHAVIOR

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Do Americans adjust their outdoor leisure to mitigate the harmful effects of air pollution? We investigate this question by matching information on air pollution and public health warnings to daily time use diaries recorded by approximately 33,000 adults across the United States between 2003 and 2010. Surprisingly, people spend more time outdoors as pollution rises, partly due to correlation between pollution and weather. Conditional on weather, we find that children and older adults reduce outdoor leisure when pollution reaches very unhealthy levels. However, this avoidance behavior does not appear to be driven by the Environmental Protection Agency's health warnings.

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The U.S. Environmental Protection Agency (EPA 2011) estimates that the annual benefits of the Clean Air Act will be $2 trillion by 2020, outweighing costs by a factor of 31 to 1. Approximately 85% of these benefits stem from predicted reductions in mortality. The historical link between air pollution and mortality is well documented. Numerous studies have credibly identified concentration response functions of the effects of air pollutants on mortality and morbidity.[1] Yet, the mechanisms that underlie these reduced form models are not fully understood. Concentration response functions embed the collective decisions people have made in the past about their own exposure to air pollution, without revealing any direct evidence on those choices. Understanding this choice process is important for regulatory evaluations.

Consider a regulation targeting air pollution. The distribution of benefits will depend partly on how the improvements to air quality vary across space, partly on how people adjust their locations in space, and partly on how people adjust the duration of their exposure to pollution at each point in space. Several studies have investigated the first two mechanisms (e.g. Aufhammer, Bento, and Lowe 2009, Aufhammer and Kellogg 2011, Smith, Sieg, Banzhaf, and Walsh 2004, Banzhaf and Walsh 2008, Kuminoff, Smith, and Timmins 2013). In contrast, there is almost no direct evidence on the third. Neidell (2009) and Zivin and Neidell (2009) provided some of the first revealed preference evidence of air pollution avoidance behavior through an innovative study of the effects of smog alerts on attendance at a zoo and observatory in Los Angeles during the 1990s. We build on their work in this paper by using daily time use diaries to provide the first direct national evidence on how American adults adjusted the duration and intensity of their exposure to air pollution during the 2000's.

[1] EPA's pollution response functions are calibrated by scientific consensus. The effect of particulate matter on national mortality is set to lie roughly equidistant between the results of epidemiological cohort studies by Pope et al. (2002) and Landen et al. (2006). Economists have used novel instruments to improve the identification of other concentration response functions. Leading examples include Chay and Greenstone (2003), Neidell (2004, 2009), Currie and Neidell (2005), Currie et al. (2009), Currie and Walker (2011), Schlenker and Walker (2011), and Zivin and Neidell (2012).

In 1999, the EPA developed the Air Quality Index (AQI) to inform the general public about the health implications of exposure to outdoor air pollution. The AQI is scaled from 0 to 500 with larger numbers indicating greater risk of negative health outcomes. Index values are calculated on a daily basis for each of the five criteria pollutants regulated under the Clean Air Act.[2] The highest daily AQI value for any of the five pollutants in a given county defines that county's overall AQI rating for that day. To make the health implications of the AQI easily understood, EPA divides the index into six color-coded ranges: *good* (a score of 0-50) is represented by the green, *moderate* (51-100) is yellow, *unhealthy for sensitive groups* (101-150) is orange, *unhealthy* (151-200) is red, *very unhealthy* (201-300) is purple, and *hazardous* (301-500) is represented by the color maroon. Predicted and realized AQI values are printed in local newspapers, broadcast on televised weather reports, posted on websites such as weather.com, displayed on electronic billboards above freeways, and sent to people through smartphone apps. More than ever before, consumers have access to real time information about the health implications of their exposure to pollution.

The purpose of our research is to investigate the extent to which American adults adjust their outdoor leisure in response to air pollution. We focus on three questions. First, do people reduce the amount of time they spend outdoors on days with poor air quality? Second, do subpopulations who are particularly sensitive to pollution adjust more? Third, do people use the daily AQI as a basis for their decisions about outdoor leisure?

Our analysis draws on the most comprehensive and detailed data available on individual time allocation, air pollution, health warnings, and weather. We have assembled data from the American Time Use Survey describing the choices for outdoor leisure made by more than 33,000 individuals living in metropolitan counties across the United States between 2003 and 2010. We observe how and

[2] These include particulate matter, sulfur dioxide, carbon monoxide, nitrogen oxide, and ground level ozone.

where each individual spent their time over a 24-hour period and whom they spent it with. We observe the county-level AQI value on that day, as well as the temperature, precipitation, snowfall, and humidity. We also observe the individual's demographic and economic characteristics.

We find that, on average, Americans do not reduce their outdoor leisure as air pollution worsens. In fact, people spend more time outdoors! This perverse result appears to be driven by correlation between weather, geography, and pollution. Conditioning on weather, geography, and individual demographic characteristics, we do find evidence of avoidance behavior on the part of some sensitive groups. Adults appear to significantly reduce the amount of time they spend outdoors with sensitive family members—their children and parents (i.e. seniors)—when the AQI enters the *very unhealthy* range. In contrast, we find evidence of no adjustment for another sensitive group—people engaged in outdoor exercise.

In order to test the hypothesis that people use the AQI to inform their decisions for outdoor leisure we develop a regression discontinuity design similar to Neidell (2009) and Zivin and Neidell (2009). Looking at observations just above and just below the AQI color thresholds, we find no evidence to support this hypothesis. Finally, we document a special relationship between air pollution and outdoor leisure in Southern California. Relative to the rest of the country, people living in Southern California tend to spend more time outdoors on the summer and fall weekends, which is also when their air quality tends to be at its worst. This implies the marginal benefit per capita from improving air quality is likely to be larger in Southern California than in other areas with large urban populations and similar problems with air quality, such as Phoenix, AZ.

The rest of the paper proceeds as follows. Section I briefly reviews the relevant medical, epidemiological, and economic literature. Section II describes the data. Section III presents our evidence on the relationship between outdoor leisure and air pollution. Then section IV presents results from our econometric analysis of avoidance behavior. Finally, section V summarizes our findings and their policy relevance. A supplemental appendix provides additional details on the data and robustness checks on our main results.

I. Related Literature

There is strong evidence that air pollution increases mortality and morbidity. In one of the most influential studies of this causal relationship, Pope et al. (2002) use a prospective cohort sample of 1.2 million people to determine the consequences of long-term exposure to particulate matter (PM2.5).[3] They conclude that "each 10 microgram per cubic meter elevation in long-term average PM2.5 ambient concentrations was associated with approximately a 4%, 6%, and 8% increased risk of all-cause, cardiopulmonary, and lung cancer mortality, respectively." Similar conclusions can be found throughout the epidemiological literature (e.g. Bobak and Leon 1992, Dockery and Pope 1994, Pope et al. 1995, and Bell et al. 2004). Multiplying these response effects by the value of a statistical life generates the enormous benefit measures that underlie EPA's prospective analyses of the Clean Air Act.

Economists have added to this literature by using novel identification strategies to document negative effects of air pollution on worker productivity (e.g. Crocker and Horst Jr. 1981; Zivin and Neidell 2012), on the accumulation of human capital (e.g. Currie et al. 2007, Sanders 2012), and on health outcomes experienced by sensitive subpopulations, particularly infants and seniors (e.g. Chay and Greenstone 2003, Currie and Neidell 2005, Currie and Walker 2011, and Schlenker and Walker 2011). For example, in one of the most spatially comprehensive studies to date, Chay and Greenstone (2003) analyze 1970s data on air

[3] A prospective cohort study is one in which a healthy sample is selected at the onset; as time passes and illnesses arise, researchers look for evidence of common risk factors for a given illness. The sample used by Pope et al. initially consisted of healthy individuals aged 30 and over who agreed to participate in the American Cancer Society's Cancer Prevention Study II. Survey data on the individuals and their vital statistics were merged with air pollution data at the metropolitan level.

pollution and infant mortality in approximately 500 U.S. counties. They find that a 10% reduction in particulate matter caused a 4%-5% reduction in infant mortality. More recently, Schlenker and Walker (2011) demonstrate that carbon monoxide emitted by idling aircrafts at Los Angeles International Airport caused localized increases in asthma cases, acute respiratory problems, new heart conditions, strokes, and bone fractures among seniors.

Can these negative health outcomes be mitigated inexpensively through an information campaign? Or are consumers already making fully informed decisions about their own exposure to pollution? While EPA has ensured that most Americans can easily find information about local air quality, it is not clear whether the average American goes to the trouble of obtaining this information.

There is mixed evidence on the extent to which consumers are swayed by information campaigns. On the one hand, aggregate consumption has been shown to adjust to new information about health risks posed by poor restaurant hygiene (Jin and Leslie 2003), mercury contamination of seafood (Shimshack, Ward, and Beatty 2007), and physical proximity to hazardous waste sites (Gayer, Hamilton, and Viscusi 2000). On the other hand, a change in aggregate consumption does not prove that most consumers adjusted their behavior. Indeed, there is evidence that many people ignore information about environmental risks and nuisances, unless they are legally compelled to pay attention. For example, Pope (2008a,b) finds that homebuyers in North Carolina routinely ignored information about flood risk and airport noise in the vicinity of houses they were buying, until laws were passed requiring them to sign disclosure statements certifying that they were aware of the (dis)amenities. Similarly, Sloan, Smith, and Taylor (2002) argue that anti-smoking campaigns have not been the main determinant of the long-term decline in smoking. These findings raise doubts about whether the average consumer would use EPA's air quality index to inform their allocation of leisure time.

The most direct revealed preference evidence on air pollution avoidance behavior comes from a pair of innovative studies by Neidell (2009) and Zivin and Neidell (2009).[4] Both analyze the effect of smog alerts on attendance at the Los Angeles Observatory, Zoo, and Botanical Gardens during the 1990s.[5] Neidell (2009) uses discontinuities in the provision of information to distinguish the responsiveness to *information* about air quality from the responsiveness to air quality itself. He finds that attendance dropped by 13% at the zoo and by 6% at the observatory on days when a smog alert was issued relative to days with similar levels of air pollution, but no smog alert. On the second consecutive day of an alert, however, there is less evidence of adjustment, suggesting that the costs of substituting activities may be increasing over time (Zivin and Neidell 2009).

The reductions in zoo and observatory attendance documented by Neidell and Zivin and Neidell (2009) raise several important questions about behavioral adjustments. First, what did people do with the time that they would have spent at the zoo / observatory? Did they stay indoors the entire time? Or did they spend some of that time at a different outdoor location exposed to air pollution? Second, what happened to attendance at outdoor venues offering cooler or less expensive opportunities for recreation, such as waterslides and public parks? Third, do avoidance behaviors differ for subpopulations that are more susceptible to the health effects of air pollution such as people engaged in vigorous physical activity? Finally, can results for Los Angeles be generalized to the rest of the country?[6] We have developed a unique database that allows us to investigate these and other important questions about avoidance behavior.

[4] There is some stated preference evidence from small scale surveys suggesting that households containing people with respiratory conditions are more likely to engage in avoidance behavior (Bresnahan, Dickie, and Gerking 1997, Mansfield, Johnson, and Van Houtven 2006).

[5] The Observatory and Zoo / Botanical Gardens are located next to each other in Griffith Park, Los Angeles.

[6] Sorting models of household location choice hypothesize that people choose to live in highly polluted areas, in part, because they are relatively tolerant to air pollution (Kuminoff, Smith, and Timmins 2013). Such tolerance could reflect a lower individual cost of avoidance behavior, or it could reflect a general lack of concern about the health effects of pollution exposure.

II. Data

We assembled the data for this analysis by linking information from three publicly available sources: (i) county level air quality index values extracted from EPA's Air Quality System; (ii) weather conditions recorded at individual monitoring stations by the National Climatic Data Center; and (iii) time use diaries, demographic characteristics, and residential locations of individuals participating in the American Time Use Survey. We obtained daily data from each source from January 1, 2003 to December 31 2010 and then merged them at the highest possible level of spatial resolution—a county. This allows us to provide the first national database to link individual decisions about outdoor leisure time to public information about the health implications of exposure to outdoor air pollution.

A. The Air Quality Index (AQI)

In July 1999, the EPA created the Air Quality Index (AQI).[7] The AQI is scaled from 0 to 500 with larger numbers indicating greater health risks of exposure to outdoor air pollution. Index values are a function of observed levels of the five criteria pollutants regulated under the Clean Air Act: ground-level ozone, particulate matter, carbon monoxide, sulfur dioxide, and nitrogen dioxide. Ambient concentrations of each pollutant are translated into an AQI value that represents the associated health risk. A county's overall AQI score on any given day is then determined by the highest AQI value observed for any of the five pollutants at any monitoring station in the county.

To convey information about health risk to the public, EPA partitions the AQI into six color-coded ranges shown in table 1. The EPA defines "sensitive groups" as children, seniors, anyone who is active outdoors, and anyone with heart disease

[7] Air quality reporting began with the Pollutant Standards Index (PSI), developed in 1976 for states and local governments to use on a voluntary basis. The PSI aggregated the five criteria pollutants regulated under the Clean Air Act into an overall index. In 1979, the EPA first required mandatory reporting of PSI values in Metropolitan Statistical Areas (MSAs) containing more than 250,000 persons. In July 1999, the EPA replaced the PSI with the AQI in order to reflect newer standards on particulate matter 2.5 and ozone.

or a respiratory condition.[8] As the AQI increases, people are advised to reduce their outdoor exertion and to spend less time outdoors. The last column of table 1 illustrates EPA's specific recommendations in the case of ozone. Similar recommendations are made for the other four criteria pollutants (EPA 2009).

Table 1: Air Quality Index, Health Concerns, and Recommended Actions

Air Quality Index (AQI) Values	Levels of Health Concern	Colors	Actions to Protect Your Health From Ozone
When the AQI is in this range:	*..air quality conditions are:*	*...as symbolized by this color:*	
0-50	Good	Green	None
51-100	Moderate	Yellow	Unusually sensitive people should consider reducing prolonged or heavy outdoor exertion
101-150	Unhealthy for Sensitive Groups	Orange	The following groups should reduce prolonged or heavy outdoor exertion: • People with lung disease, asthma • Children and older adults • People who are active outdoors
151 to 200	Unhealthy	Red	The following groups should avoid prolonged or heavy outdoor exertion: • People with lung disease, asthma • Children and older adults • People who are active outdoors Everyone else should limit prolonged or heavy exertion
201 to 300	Very Unhealthy	Purple	The following groups should avoid all outdoor exertion: • People with lung disease, asthma • Children and older adults • People who are active outdoors Everyone else should limit outdoor exertion.
301 to 500	Hazardous	Maroon	

Note: This table was compiled from information provided on EPA's AIRnow website and publication #EPA-456/F-09-002 available here: http://www.epa.gov/airnow/aqi_brochure_08-09.pdf.

Under the Protection of the Environment Law, each state is required to use major media outlets to report daily AQI values to residents of all metropolitan sta-

[8] Ozone may affect the lungs by irritating the respiratory system reducing lung function, inflaming the cells that line the lungs, making the lungs more susceptible to infection, aggravating asthma (or other chronic lung disease), and causing permanent damage. Particulate matter can also aggravate lung or heart disease, increase emergency room visits and mortality rates for older adults, create chest pain, shortness of breath, or fatigue, or increase susceptibility to respiratory infections. Physical activity may exacerbate these effects as individuals absorb more of the pollutants.

tistical areas containing over 350,000 residents.[9] As of 2010, this requirement covered 65% of the U.S. population. To satisfy EPA guidelines, a report must include the AQI level, the critical pollutant, the categorical label and color, and special warning statements for sensitive groups if the AQI exceeds 100.[10]

Current AQI levels (usually reported at the county level) and next day forecasts (in some areas) are included as a regular feature of televised weather reports on local news stations and in the weather sections of local and national newspapers such as USA Today and LA Times. AQI values are also reported on popular websites for local weather information, such as *weather.com*. Anyone searching the internet for their local air quality is likely to be directed to *airnow.gov*, EPA's official website for current air quality information. People can also arrange to have their local AQI automatically downloaded to their computers, tablets, and smartphones using apps such as *myAirQuality* and *AIRNow*. In addition, the EPA has developed tools for parents and educators to teach children about the AQI. For example, *Why is Coco Orange?* is a children's story in which Coco the chameleon changes his skin color to match the AQI, while learning how to adjust the intensity of his play to protect himself from the harmful effects of air pollution.[11] The EPA also sponsors a school flag program that raises colored flags matching the current AQI to notify teachers, coaches, and students about the implications of exercise. Older children and science teachers are encouraged to experiment with "Smog City 2" a computer simulation that allows students to explore the mechanisms generating pollution. Thus, there is an abundance of air quality information for those who care to obtain it.

With help from the EPA, we obtained the county-level AQI values that were

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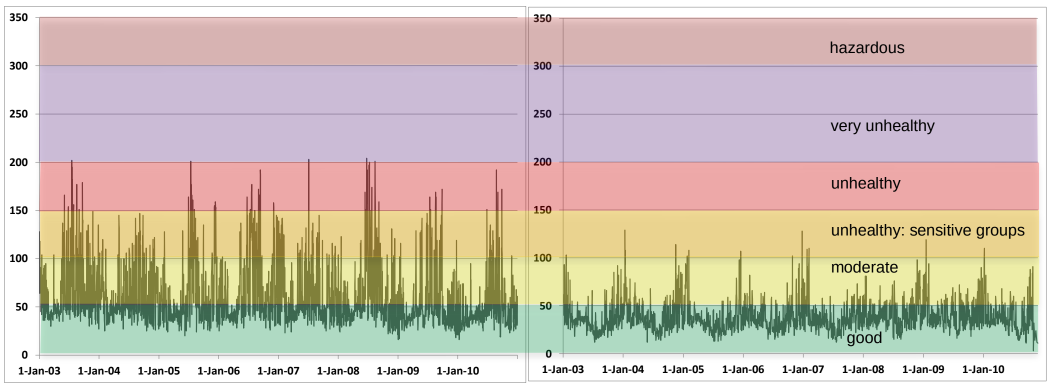
[9] Daily reporting of the AQI means at least five days per week. In the EPA's Guidelines for the Reporting of Daily Air Quality, the agency notes that states must "distribute to the local media, provide via a recorded telephone message, or publish on a publicly accessible Internet site"

[10] The EPA *Guidelines for the Reporting of Daily Air Quality* state that "whenever the AQI exceeds 100, reporting agencies should expand reporting to all major news media, and at a minimum, should include notification to the media with the largest market coverage for the area in question."

[11] Copies can be ordered or downloaded from www.airnowlgov/picturebook.

reported to the general public every day from 2003 through 2010. There is considerable variation in the AQI across space and time. Figure 1 provides an illustration by comparing daily AQI values for two California counties located about 80 miles apart: Sacramento (on the left) and San Francisco (on the right).

Figure 1: Air Quality Indices for Sacramento and San Francisco, California



Note: The figure illustrates daily air quality index values for Sacramento County (left) and San Francisco County (right) from January 1, 2003 through December 31, 2010, with an overlay of the corresponding AQI color. These data were extracted from EPA's Air Quality System.

The average daily AQI score for San Francisco was 38.5. This is very close to the national median (37.9). In contrast, Sacramento has some of the worst air pollution in the country. It is a federal nonattainment area for both ozone and particulate matter and its average AQI of 60.9 puts it in the 98th percentile.

Together, San Francisco and Sacramento illustrate three key sources of variation in air pollution that underlie our econometric tests of avoidance behavior. First, the AQI can vary greatly over a small geographic area at a point in time, reflecting spatial heterogeneity in the concentration of pollution sources relative to wind patterns and landscape features. Second, air pollution varies seasonally at a point in space, often producing a cyclical pattern of AQI values. The AQI generally peaks in mid to late summer (when more sunlight and drier air increase ambient ozone) and/or in the winter (when furnaces, woodstoves, and idling cars increase particulate matter). Third, there are many days when the AQI is just above or just below one of the color coded information thresholds.[12] This is important. While a small change in the AQI itself is difficult to perceive, crossing a color threshold produces a discontinuous change in the level of health concern reported to the public. Observing AQI values that lie just above and just below an information threshold in similar geographic areas and time periods can, in principle, allow us to disentangle avoidance behavior in response to AQI health warnings from avoidance behavior in response to visual pollution cues, such as smog. This feature of our identification strategy is very similar to 1990s smog alert studies of Los Angeles by Neidell (2009) and Zivin and Neidell (2009).

B. Weather

Weather conditions are likely to affect both air quality and the amount of time people spend outdoors. We control for local weather using the National Climate Data Center's daily summaries of the weather recorded at individual monitoring stations. The variables we collected include the minimum temperature observed over the course of a day, the maximum temperature, precipitation, snowfall, maximum relative humidity, and minimum relative humidity. Most counties have several weather stations. We constructed county-level measures of weather by taking the median of each variable over the weather stations in that county. [13]

Unfortunately, data on humidity were only available for 58% of all county-days.[14] We attempted to fill in these gaps in our data with information from nearby counties. Specifically, we used GIS software to calculate the distance between county centroids and then we matched each county to all other counties within 30

[12] A fourth distinct pattern in the AQI data is a slight but steady improvement over the 2000's. For example, the national percentages of all daily AQI observations that were good and unhealthy changed from 77% and 0.39% in 2003 to 83% and 0.14% in 2010. See the supplemental appendix for additional details.

[13] A few counties contain weather stations with extreme observations relative to other stations in the county. Using the median limits the influence of these data points. For example, Pierce County WA contains Mount Rainer (elevation 14,000 feet), but its largest city is Tacoma (elevation 400 feet). On January 2, 2003, the weather station on Mount Rainer recorded a daily maximum temperature of 36 and 13 inches of snowfall, while the three weather stations located near the county's population centers recorded maximum temperatures of 56, 57, and 59 and no snowfall. Using the median temperature (57) thus ensures that our measure reflects the weather conditions experienced by the local population.

[14] Other variables such as wind speed and cloud cover were reported too infrequently to use.

miles. The humidity reading at the nearest reporting county within that 30-mile radius was then used as a proxy for the missing humidity variable. We use these proxy data as control variables in some, but not all specifications of our models.

Weather affects air quality in predictable ways. More than 75% of counties have a positive correlation between daily AQI and daily maximum temperature (reflecting the role of light and heat in the formation of ozone). Likewise, more than 95% of counties have a negative correlation between AQI and precipitation (since precipitation removes particles from the air). However the magnitudes of these correlations vary greatly due to climate and geography. For example, the interquartile range of county-specific correlation coefficients between AQI and daily maximum temperature is $[0.14, 0.42]$.[15] Thus our data include considerable variation in air quality, both within and across counties, conditional on weather.

C. Time Spent Outdoors

Our data on time use are drawn from public use micro data samples of the American Time Use Survey (ATUS).[16] The ATUS data are generated by asking a subset of adults from the outgoing rotation of the Current Population Survey (CPS) to keep a diary of their activities for one day. The diary format is quite detailed. People track what they are doing (e.g. sleeping, watching television, shopping, playing basketball), where they are doing it (e.g. home, a friend's house, a shopping mall, a park), how much time they spend doing it, and who else joined them in the activity (e.g. children, parents, spouses, friends, relatives). These data have previously been used to document trends in leisure time (Aguiar and Hurst 2007) and to investigate the relationships between leisure time and food consumption (Bertrand and Schanzenbach 2009) and unemployment (Kreuger and Mueller

[15] The distribution of correlation coefficients is summarized in the supplemental appendix.
[16] ATUS is conducted by the Bureau of Labor Statistics in conjunction with the U.S. Census Bureau. It is the first federal survey designed to measure how individuals divide their day between activities. ATUS was developed in the 1990s, a full pilot test was conducted in 2001, and it was implemented fully beginning in January 2003.

2012; Aguiar, Hurst, and Karababbounis 2012).[17] Our study is the first to use ATUS to examine the relationship between leisure time and air quality.[18]

We use self-reported information on individuals' locations and activities throughout the day to develop measures of their "daily minutes outdoors" and "daily minutes engaged in physical outdoor activity". Our interest in the latter measure stems from the fact that EPA defines anyone engaged in physical activity as a sensitive group. The coding process was generally straightforward. Most leisure activities are clearly designated as occurring in either indoor or outdoor locations. However, the flexibility in ATUS's coding lexicon does occasionally create ambiguity, in which case we used our best judgment. For example, the individuals who report playing basketball variously list their locations as being a gym, their own house, a friend's house, a park, and so on. While a basketball hoop can technically be placed inside a house with a tall ceiling, we feel comfortable assuming that all basketball games not played at a gym are played outdoors. Similarly, we assume that individuals who report "own home" as the location for a run are actually running on indoor treadmills.

Running, biking, and baseball are representative examples of the activities we define to be physical outdoor activity. Fishing, boating, and yoga are examples of the activities that are included in our measures of time spent outdoors but excluded from our measure of physical activity. We do not count them as "physical activity" because they are less likely to involve aerobic exercise that would accelerate the rate of pollutant intake relative to ordinary breathing. Finally, if someone drives to an indoor location, such as a grocery store or theatre, we do not count

[17] The ATUS webpage provides a more comprehensive list of publications and working papers using their data on leisure time: http://www.bls.gov/tus/research.htm.

[18] In research conducted simultaneously with ours, Sexton and Beatty (2013) examine the impact of air quality *alerts* on time use in Core Business Statistical Areas. Unlike our AQI measure of actual air quality conditions, the alerts are issued in a preventative fashion based on forecasts in a given locality and surrounding locations. Interestingly, the correspondence between advance alerts and actual air pollution is weak. Nearly half the time an alert is issued, air pollution ends up being in the healthy or moderate range. Sexton and Beatty find evidence that sensitive groups respond to alerts by substituting away from outdoor leisure altogether instead of adjusting their outdoor leisure over the course of a day to spend more time outdoors when the air quality is relatively better.

the time they spend walking to and from their car as time spent outdoors. We consider that time to be incidental to their chosen leisure activity. As a result, we find that a slight majority of respondents spend no leisure time outdoors on the date we observe them.[19] The ATUS activity codes and location codes that underlie our measures of outdoor leisure time are summarized in appendix table 1.

By matching our ATUS sample to the general monthly CPS files, we are able to obtain detailed information on the demographic characteristics of ATUS participants. We use variables such as education, age, gender, race, wage, and occupation as proxy measures for physical, cultural, and economic factors that may help to explain heterogeneity in individual leisure time. Finally, we use the diary date and home county of each ATUS participant to match their outdoor leisure to local air quality and weather.

D. Summary Statistics and Data Caveats

Table 2 reports summary statistics for the explanatory variables in our analysis. It is readily apparent that ATUS is a stratified sample. Each weekday comprises 10% of the observations whereas Saturdays and Sundays are oversampled such that half of all observations occur on weekends.[20] Figure 2 illustrates our geographic coverage. Because so many counties are missing data on humidity, we distinguish between counties with complete data, counties with complete data except humidity, and counties where we have no data. Counties are excluded from our analysis for one of four reasons: (i) the county has fewer than 100,000 residents, the minimum size at which a respondent's home county is identified in public use samples of ATUS and CPS data; (ii) core weather variables are never reported for the county, (iii) the county is too small to be represented in the ATUS

[19] On average, people who spend no time in outdoor leisure spend 11 additional minutes sleeping, 21 additional minutes watching television, and 59 additional minutes working. The supplemental appendix provides a more detailed comparison of average time allocation patterns between people do and do not spend any time outdoors.

[20] The hourly wage variable contained in the ATUS is top-coded such that the weekly wage can be no more than $9.999.99. However, this is not likely to affect our results because only 0.12% of our observations are top-coded.

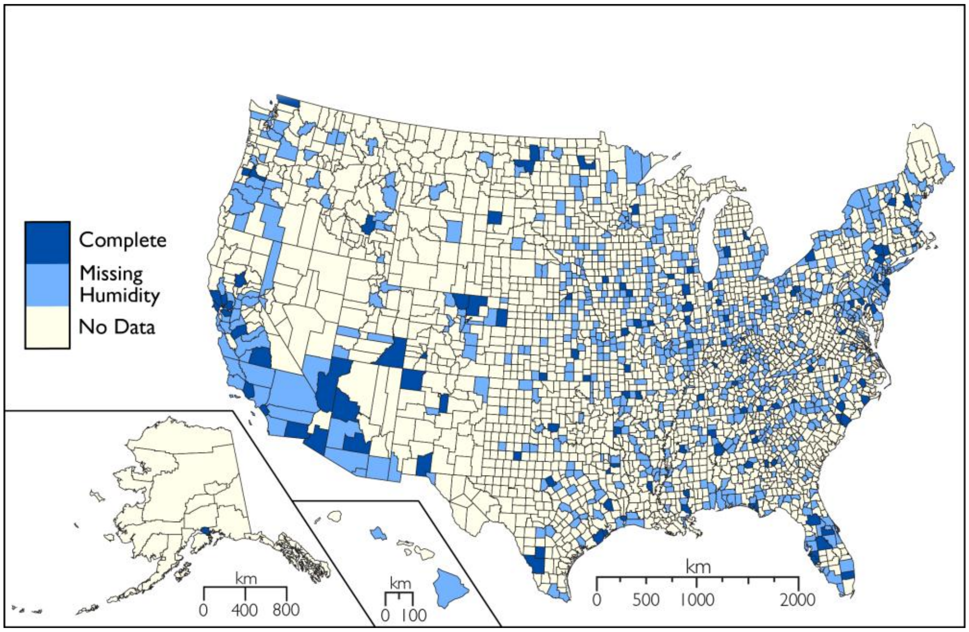
survey, or (iv) we cannot link CPS and ATUS records because town is the legal entity of residence (this occurs in a few New England states). The 495 counties in our final sample account for 49.2% of the U.S. population.

Table 2. Summary Statistics

	# Observations	Mean	St. Dev	Median	Min	Max
Air Quality Index						
good	33,328	0.63	0.48	0	0	1
moderate	33,328	0.29	0.45	0	0	1
unhealthy for sensitive groups	33,328	0.06	0.25	0	0	1
unhealthy	33,328	0.01	0.11	0	0	1
very unhealthy	33,328	0.00	0.05	0	0	1
Daily Weather						
minimum temperature	33,328	52.12	15.68	54	-25	91
maximum temperature	33,328	73.18	17.31	76	-2.5	117
precipitation	33,328	0.09	0.30	0	0	8
minimum humidity	28,034	44.16	18.83	44	1	100
maximum humidity	28,034	82.44	17.27	87	10	100
Day						
Tuesday	33,328	0.10	0.30	0	0	1
Wednesday	33,328	0.10	0.30	0	0	1
Thursday	33,328	0.10	0.30	0	0	1
Friday	33,328	0.10	0.30	0	0	1
Saturday	33,328	0.25	0.43	0	0	1
Sunday	33,328	0.26	0.44	0	0	1
Holiday	33,328	0.02	0.13	0	0	1
Individual Characteristics						
college	33,328	0.47	0.50	0	0	1
advanced degree	33,328	0.12	0.33	0	0	1
hispanic	33,328	0.18	0.39	0	0	1
white	33,328	0.80	0.40	1	0	1
black	33,328	0.13	0.34	0	0	1
ill or disabled	33,328	0.00	0.06	0	0	1
age	33,328	46.01	17.48	44	15	85
male	33,328	0.43	0.50	0	0	1
hourly wage	33,328	4.64	8.89	0	0	100
manual labor	33,328	0.08	0.27	0	0	1
student	33,328	0.08	0.27	0	0	1
has partner	33,328	0.53	0.50	1	0	1

Note: This table summarizes the explanatory variables used in our econometric models. AQI data are from the EPA, weather data are from the National Climatic Data Center, and all other demographic data come from the American Time Use Survey and the Current Population Survey.

Figure 2. Geographic Coverage



While our database is the first to link micro data on outdoor time use to local air quality, there are two notable limitations. First, ATUS is not a panel. We only observe each individual over a single 24-hour period, precluding the use of individual fixed effects during the estimation. Instead, we use a difference in differences strategy that relies on the random sampling within ATUS's stratified research design to compare time use by the average individual (conditional on covariates) under different air quality conditions. This limitation is shared by all studies using ATUS data as well as the studies of air pollution avoidance behavior in Los Angeles (Aguiar and Hurst 2007, Neidell 2009, Zivin and Neidell 2009, Aguiar, Hurst, and Karababbounis 2012, Kreuger and Mueller 2012).

Another limitation is that the data do not allow us to investigate spatial substitution. We observe each individual's home county and time allocation conditional on their county's AQI, but we cannot observe whether they adjusted the physical location of their outdoor leisure to avoid air pollution. For example, if the local air quality is bad a prospective hiker could drive up to the mountains to go hiking, either in their home county or in a nearby county. In our opinion, such adjustments are likely to be rare. Travel costs are likely to make intertemporal substitutions cheaper. Furthermore, while studies such as Aufhammer and Kellog (2011) and Auffhammer, Bento, and Lowe (2009) clearly demonstrate that air pollution varies within counties, the public information about air quality does not.[21]

III. The Relationship between Outdoor Leisure and Air Quality

Table 3 documents the statistical relationship between outdoor leisure and local air quality. Panel A summarizes our sample size by AQI category. The data consist of 33,328 ATUS diary days and approximately one third of these observations occur on days where the AQI is within 10 points of an information threshold. For example, we observe 1,582 diary days on which the AQI is close to the threshold between *moderate* and *unhealthy for sensitive* groups; 789 days just below the threshold and 793 days just above.

Panel B reports the shares of ATUS respondents who spent time outdoors, spent time in physical outdoor activity, and spent time outdoors with their own parents and/or children. Panel C reports the average number of minutes these individuals spent outdoors. It is striking that as pollution increases the general population is both *more likely* to go outdoors and likely to *increase* the duration of their exposure. Moreover, these effects increase for sensitive groups! People engaged in physical activity are 18% more likely to spend time outdoors on an *unhealthy* day compared to a *good* day, and the number of minutes they spend increases by 15%. Likewise, ATUS respondents are 17% more likely to spend time outdoors with their parents or children on an *unhealthy* day compared to a good

[21] In the popular media, the AQI is almost always reported at the level of a county. In principle, the general public could go to the same trouble of collecting and processing raw monitor data as studies such as Auffhammer and Kellog (2011) and Auffhammer et al. (2009). But we believe this is unlikely.

day. The only potential evidence of avoidance behavior is a sharp drop in time spent with parents/children when the AQI moves from *unhealthy* to *very unhealthy*.

Table 3: Air Quality, Time Use, and Weather: 2003-2010

	Air Quality Index Category				
	good	moderate	unhealthy sensitive	unhealthy	very unhealthy
	A. Number of observations (ATUS diary days)				
total	21,087	9,617	2,142	390	92
within 10 AQI points of upper bound	6,761	789	213	30	--
within 10 AQI points of lower bound	--	3,526	793	139	78
	B. Percent of ATUS respondents spending any time:				
outdoors	39	42	45	46	45
physical outdoor activity	30	32	34	36	37
outdoors with their parents / children	12	13	14	14	13
	C. Mean minutes for ATUS respondents spending any time:				
outdoors	105	106	108	113	113
strenuous outdoor activity	84	83	91	97	104
outdoors with their parents / children	79	76	87	92	34
	D. Mean daily conditions				
minimum temperature (F)	50	54	60	63	65
maximum temperature (F)	70	77	86	91	92
precipitation (in)	0.12	0.04	0.02	0.01	0.004
probability of occurring on weekend	29	28	28	33	45

Note: An ATUS diary day refers to our ability to observe all of the activities performed by one individual during a single 24-hour period. The AQI data are from the EPA, the weather data are from the National Climatic Data Center, and the time spent outdoors data are from the American Time Use Survey.

The seemingly perverse behavior in panels B and C is likely driven by weather. Panel D illustrates that, on average, as air pollution worsens, temperature rises and precipitation falls. People are likely going outdoors when the weather is nicer in spite of the air pollution, not because of it. The last row of the table also illustrates that *unhealthy* and *very unhealthy* days disproportionately occur on weekends. If an *unhealthy* day were equally likely to occur any day of the week, then the probability of occurring on a weekend would be 2/7=.285. In contrast, after we adjust for ATUS's oversampling of weekends, we find that the probabilities of *unhealthy* and *very unhealthy* days on weekends are 0.33 and 0.45 respectively. This pattern appears to be caused by California's "weekend ozone effect".

Emissions of ozone precursors are generally expected to be lower on weekends than on weekdays. Nonetheless, ozone readings around the San Francisco and Los Angeles metro areas tend to be systematically higher on weekends compared to weekdays between March and October, the time of the year when ozone is the predominant trigger for air quality warnings. This counterintuitive phenomenon is well known to atmospheric scientists, if not entirely understood (California Air Resources Board 2003).[22]

Table 4: Weekday and Weekend Exposure to Air Pollution

	Average minutes spent outdoors				
	good	moderate	unhealthy sensitive	unhealthy	very unhealthy
Weekdays	32	36	42	35	38
Weekends	51	54	55	64	54

Note: Average minutes are calculated over all diary days in the ATUS sample, regardless of whether an individual spent any time outdoors.

The weekend ozone effect is especially important for people living in Los Angeles, San Bernardino, Riverside, Fresno, and Kern counties (5% of the U.S. population). Between 2003 and 2010, these five southern California counties accounted for more unhealthy air days (i.e. AQI > 150) than all other counties with populations exceeding 500,000 combined (1,258 compared to 1,057). Moreover,

[22] For more information on the weekend ozone effect and its possible causes, see the July 2003 special issue of the Journal of Air and Waste Management.

unhealthy air days were twice as likely to occur on weekends in the 5-county area relative to the rest of the country (36% versus 18%). Thus, the air quality in these five highly populated counties is often at its worst when both the weather is nicest and when people tend to have the most leisure time (weekends from March through October). Table 4 summarizes the consequences—the average person spends 83% more time outdoors on *unhealthy* weekends than on *unhealthy* weekdays and 25% more time outdoors on *unhealthy* weekends than on *good* weekends. Thus avoidance behavior is obviously not the main force behind the average person's allocation of leisure time. Nevertheless, a positive relationship between pollution and outdoor leisure does not preclude the presence of some avoidance behavior.

IV. Econometric Tests of Avoidance Behavior

This section summarizes the results from simple tests of whether people choose to reduce their exposure to air pollution, conditional on weather, day of the week, and individual demographic characteristics. We consider the extensive margin decision of whether to spend any time outdoors separately from the intensive margin decision of how much time to spend outdoors, conditional on going outdoors.

A. Models

Equation (1) summarizes our basic econometric model.

$$Time_{imc} = \beta A_{mc} + \gamma C_{mc} + \delta D_{imc} + a_{mc} + \varepsilon_{imc} \tag{1}$$

The dependent variable measures the number of minutes spent outdoors by person i observed during month m in county c. The treatment effect, A, is a vector of indicators for the five AQI categories. C is a vector including controls for weather along with indicators for day of the week and for whether the diary day was a holiday. D is a vector describing the individual's demographic characteristics, specifically whether they have a 2 or 4 year college degree, whether they have a graduate degree, their race, gender, and student status, whether they live with a partner, a quadratic function of age, their hourly wage, whether they are a manual laborer, and whether they missed work that day due to a serious illness or disability. Finally, a_{mc} is a county-month fixed effect.

The fixed effects are intended to capture variation in spatial and temporal factors affecting the opportunity cost of spending time outdoors. Examples include seasonal variation in television programming, variation in the amount of daylight (due to latitude, time of the year, and time zone), and variation in the mapping between weather and comfort. That is, many people would prefer to be outside on a 100-degree day in Phoenix, Arizona (with near zero humidity) than on a 100-degree day in Washington, DC (with high humidity). Furthermore, residents of Phoenix may be better adapted to 100+ degree days than residents of San Diego. While we can attempt to model the complex relationship between temperature, humidity, and comfort using flexible polynomial functions of the weather variables, we believe that the fixed effects will be more effective in capturing spatio-temporal variation in weather and heterogeneity in local adaptations to it.

We estimate several additional models that are variations on (1). These include probit models of the extensive margin decision for whether to spend time outdoors, and a regression discontinuity design that focuses on observations just on either side of an AQI information threshold. The later research design allows us to test for avoidance behavior in response to AQI information separately from avoidance behavior to air pollution itself. We also consider several alternative specifications of the treatment and control variables as robustness checks. All specifications use robust standard errors, generally clustered at the county level.

B. Extensive Margin

Table 5 reports our main results for the extensive margin decision of whether or not to spend any leisure time outdoors. The top of the table describes the control variables used in each of 6 models and panels A through C summarize our estimated impact of avoidance behavior on three outcomes: (A) outdoor leisure in general, (B) physical activity in particular, and (C) outdoor leisure with the respondent's parents and/or children. The coefficients on the four AQI categories are measured relative to the excluded category, *good*.

Column 1 just reiterates the positive association between air pollution and the probability of going outdoors from tables 3 and 4. This relationship disappears when we add controls for weather, day of the week, and individual demographics in column 2. Most of the control variables are statistically significant at the 1% level with intuitive signs. As we would expect, people are more likely to spend their leisure time outdoors on weekends, holidays, and when temperatures are warmer and drier. Likewise the probability of going outdoors is decreasing in the hourly wage. It is also lower for males and people with college education, likely reflecting a higher probability of working full time. Coefficients for the control variables are suppressed for brevity here, but available upon request.

Columns 3-5 add increasingly refined sets of fixed effects. In column 3 we add indicators for month and county. Column 4 replaces these with state-by-month indicators, which are in turn replaced by county-by-month indicators in column 5. There is a tradeoff here. The county-by-month indicators provide the most flexibility in controlling for unobservables, but they also add nearly 6000 explanatory variables to the regression.

Table 5: Testing for Avoidance Behavior at the Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)
controls for weather, day, demographics		x	x	x	x	x
county fixed effects			x			
month fixed effects			x			
state-by-month fixed effects				x		
county-by-month fixed effects					x	x
probit model	x	x	x	x	x	
linear probability model						x
			A. Time outdoors			
Moderate	0.07***	0.02	0.03	0.04**	0.04**	0.02**
Unhealthy sensitive	0.15***	0.03	-0.01	-0.02	0.01	0.00
Unhealthy	0.17***	0.04	-0.07	-0.09	-0.04	-0.01
Very unhealthy	0.13	-0.03	-0.17	-0.16	-0.15	-0.06
Pseudo R^2 (or R^2)	0.001	0.018	0.048	0.042	0.084	0.14
observations	33,328	33,328	33,313	33,195	31,853	33,328
			B. Physical activity			
Moderate	0.05***	0.02	0.01	0.04**	0.02	0.01
Unhealthy sensitive	0.11***	0.05	0.00	0.01	0.01	0.00
Unhealthy	0.15**	0.07	-0.04	-0.04	0.00	0.00
Very unhealthy	0.18	0.12	-0.06	0.01	-0.04	-0.01
Pseudo R^2 (or R^2)	0.001	0.019	0.055	0.044	0.087	0.14
observations	33,328	33,328	33,298	33,137	31,037	33,328
			C. Time outdoors with parents and/or children			
Moderate	0.05***	0.01	0.03	0.02	0.05*	0.01*
Unhealthy sensitive	0.08**	-0.03	-0.07	-0.07*	-0.05	-0.01
Unhealthy	0.18***	0.03	-0.07	-0.07	-0.05	-0.01
Very unhealthy	-0.02	-0.27	-0.39**	-0.38**	-0.41**	-0.07*
Pseudo R^2 (or R^2)	0.001	0.074	0.096	0.095	0.135	0.13
observations	33,328	33,328	33,163	32,371	26,462	33,328

Note: The first five columns reports results from probit models of the decision for whether or not to spend any leisure time outdoors. The sixth column reports results from a linear probability model. The control variables for weather, day, and demographics include minimum and maximum temperature, precipitation, snowfall, age, age^2, wage, and indicators for day of the week, holiday, college degree, advanced degree, race, occupation, student, lives with a partner, and ill or disabled. *p<.1, **p<.05, ***p<.01.

In panel A, adding spatiotemporal fixed effects to the model suggests the probability of going outdoors decreases systematically as the air pollution increases. However, the coefficients are not precisely estimated. P-values for the coefficients on *unhealthy* and *very unhealthy* lie between 0.1 and 0.3. The results in panels B and C provide some evidence that the results for the general population are driven largely by people spending time with their parents or children. Interestingly, there appears to be virtually no response for people engaged in physical activity.[23]

The statistically significant coefficients on *very unhealthy* in columns 4-5 of panel C suggest an 8% to 10% reduction in the probability that the average respondent chose to spend leisure time outdoors with his or her parents or children on a day when the AQI exceeded 200 between 2003 and 2010. In comparison, the linear probability model in column 6 suggests a 7% reduction. These findings are consistent with those of Neidell (2009). His table 3 reports a 19% to 24% reduction in attendance by children and seniors at the Los Angeles zoo on smog alert days between 1989 and 1997. The threshold for a smog alert is nearly the same as for a *very unhealthy* day.[24] Moreover, while our study period begins six years after his ends, the geography of the treatment counties is similar because the majority of *very unhealthy* days in our sample occurred in Los Angeles.[25] Given the similarity in treatment and geography, the fact that our estimated response effects are smaller than Neidell's is consistent with the idea that not everyone who chose to avoid the zoo and observatory would have necessarily chosen to forego all forms of outdoor leisure.

[23] The general pattern of results is also robust to a variety of alternative specifications summarized in the supplemental appendix. These include data cuts that allow us to add controls for humidity and to separately estimate the effects for subpopulations such as people spending time with parents only, people spending time with children only, and respondents who are over the age of 65.

[24] According to Neidell, smog alerts were issued when the PSI exceeded 200. The PSI is the precursor to the AQI.

[25] Los Angeles accounts for 78% of all the very unhealthy days in our ATUS sample. This occurs partly because Los Angeles accounts for a large proportion of all the very unhealthy AQI days in the U.S. and partly because Los Angeles is one of the most populous counties in the nation and has a correspondingly large ATUS sample. Los Angeles does not account for the majority of days that are deemed unhealthy for anyone.

C. Intensive Margin

Table 6 reports our main results for the intensive margin decision of how much time to spend outdoors. These models are estimated for the subset of individuals who report spending at least some time outdoors. The format for the table is the same as table 5 and scaling the dependent variable in terms of minutes allows a direct interpretation of the coefficients.

The overall pattern of results is similar as the extensive margin. We see suggestive evidence of avoidance behavior in the general population in panel A, but most of the coefficients are imprecisely estimated and small in magnitude. In comparison, there is no evidence of adjustment on the part of physically active individuals. The coefficients in panel B models with fixed effects are close to zero even when the air pollution is very unhealthy.

Once again, panel C strongly suggests the presence of avoidance behavior on the part of adults spending time with their own parents and/or children. Our preferred specifications in columns 3-5 suggest that moving from a *good* AQI day to a *very unhealthy* AQI day causes people to reduce the amount of time they spend outdoors by an economically significant amount of approximately 40 minutes (from a baseline of about 80 minutes). However, it is also notable that we do not see evidence of any reduction in outdoor activity on days when the AQI is *unhealthy* or *unhealthy for sensitive groups*.[26] Since the majority of *very unhealthy* days occurred in Los Angeles, one possible explanation for the apparent non-response to weaker information treatments is that people have become conditioned to pay attention to the Los Angeles smog alerts, but not to the AQI.

[26] These results are robust to a wide variety of alternative specifications summarized in the supplemental appendix. These include data cuts that allow us to add controls for humidity and to separately estimate the effects for subpopulations such as people spending time with parents only, people spending time with children only, and respondents who are over the age of 65.

Table 6: Testing for Avoidance Behavior at the Intensive Margin

	(1)	(2)	(3)	(4)	(5)
controls for weather, day, demographics		x	x	x	x
county fixed effects			x		
month fixed effects			x		
state-by-month fixed effects				x	
county-by-month fixed effects					x
			A. Time outdoors		
Moderate	0.50	-3.56	1.09	-1.74	2.06
Unhealthy sensitive	2.22	-7.15	-4.93	-3.83	1.76
Unhealthy	7.67	-3.14	-1.03	2.45	12.40
Very unhealthy	8.08	-16.92***	-7.59	-13.55	-2.35
R^2	0.00	0.08	0.12	0.12	0.28
observations	13,544	13,544	13,544	13,544	13,544
			B. Physical activity		
Moderate	-1.48	-6.00**	-4.07	-4.58*	-1.06
Unhealthy sensitive	6.78	-3.48	-3.81	-2.95	2.22
Unhealthy	12.87	-1.63	-2.99	1.49	8.10
Very unhealthy	19.90**	-2.85	0.33	-2.19	6.71
R^2	0.00	0.07	0.11	0.12	0.30
observations	10,394	10,394	10,394	10,394	10,394
			C. Time outdoors with parents and/or children		
Moderate	2.56	-1.38	-1.28	-1.42	-1.94
Unhealthy sensitive	8.93*	2.47	1.79	4.39	0.11
Unhealthy	4.12	-3.46	-4.05	-1.28	3.91
Very unhealthy	-27.18***	-41.67***	-41.22***	-42.30***	-39.98***
R^2	0.00	0.10	0.18	0.19	0.47
observations	3,928	3,928	3,928	3,928	3,928

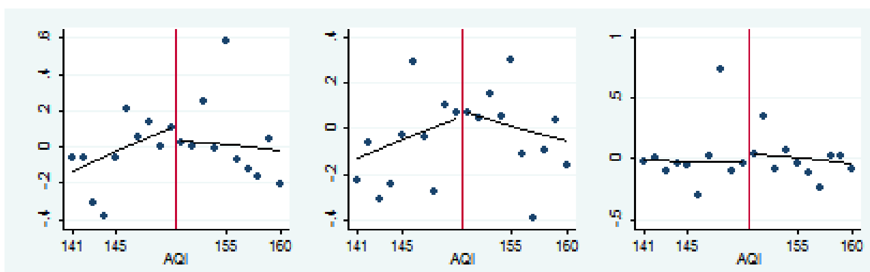
Note: The table reports results from models of the decision for how much leisure time to spend outdoors. The control variables for weather, day, and demographics include minimum and maximum temperature, precipitation, snowfall, age, age^2, wage, and indicators for day of the week, holiday, college degree, advanced degree, race, occupation, student, lives with a partner, and ill or disabled. Measures of statistical significance are based on robust standard errors clustered at the county level: *p<.1, **p<.05, ***p<.01.

D. Has the Air Quality Index Changed Behavior?

Our regression discontinuity design exploits the idea that people are unlikely to visually perceive small changes in air pollution near an AQI threshold. As we cross each threshold, air pollution changes continuously whereas public information about the health risks of exposure to air pollution changes discontinuously. Therefore if people were to adjust their behavior based on AQI health warnings, then we would expect to see discrete drops in the average person's outdoor leisure as we move from just below an AQI threshold to just above it, conditional on weather, day of the week, and other covariates.

Figure 3: Extensive Margin Residuals around Information Thresholds

A. Time Outdoors *B. Physical Activity* *C. Parents / Children*



Note: This figure illustrates the mean residual at each AQI level around the thresholds from *unhealthy for sensitive groups* to *unhealthy* (150). Residuals are based on the probit models in column 5 of table 5, omitting the indicators for AQI categories. Panel A corresponds to the dependent variable time outdoors, panel B corresponds to time spent in physical outdoor activity, and panel C corresponds to time spent outdoors with parents and/or children. Each figure shows linear trends fitted separately on each side of the threshold.

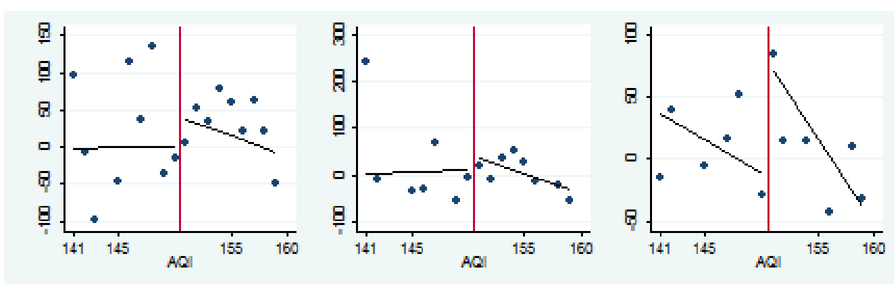
Figures 3 and 4 provide some initial evidence against the hypothesis that the AQI changed behavior. Figure 3 plots residuals from probit models equivalent to the ones in column 5 of table 5, except that we exclude the AQI categorical indicators. Thus, the residuals will reflect any adjustment to the AQI after we control for weather, day of the week, and the other covariates. Each panel focuses on the threshold between *unhealthy for sensitive groups* and *unhealthy*. We focus on this threshold for two reasons. First, EPA's *unhealthy* designation is the first to convey a health warning to the general population (table 1). It also conveys a strengthened warning for sensitive groups. Second, we are able to exploit a relatively large number of observations (352) within 10 AQI points of the threshold.

Each data point represents an average over all of the residuals we observe for that AQI level. Linear trends are then fitted to the average residuals on each side of a threshold. Similarly, figure 4 summarizes residuals for the linear fixed effects model of behavior at the intensive margin from column 5 of table 6.

Consistent with our earlier results, the *unhealthy* segments of each panel in figures 3 and 4 have downward sloping trend lines, suggesting that people tend to spend less time outdoors as air pollution worsens, conditional on all other covariates. However, visual inspection of the residuals at each of the 6 thresholds suggests that people did not adjust their behavior in response to discrete changes in AQI health warnings. That is, we never observe a discrete drop in the residuals as we cross the information threshold.

Figure 4: Intensive Margin Residuals around Information Thresholds

A.Time Outdoors *B. Physical Activity* *C. Parents / Children*



Note: This figure illustrates the mean residual at each AQI level around the thresholds from *unhealthy for sensitive groups* to *unhealthy* (150). Residuals are based on the models in column 5 of table 6, omitting the indicators for AQI categories. Panel A corresponds to the dependent variable time outdoors, panel B corresponds to time spent in physical outdoor activity, and panel C corresponds to time spent outdoors with parents and/or children. Each figure shows linear trends fitted separately on each side of the threshold.

Table 7 reports results from a more formal test of the responsiveness to information. We estimate models for the *moderate* to *unhealthy for sensitive groups* threshold and for the *unhealthy for sensitive groups* to *unhealthy* threshold. In each of the 12 models summarized in the table, we limit our analysis to diary days that fall within 5 AQI points of a threshold. The treatment effect is simply an indicator for the threshold itself. Limiting the analysis to a small neighborhood around the information thresholds means that our sample sizes are relatively small. This precludes the use of county-by-month fixed effects. We instead estimate more parsimonious models with fixed effects for months and states.

If people respond to the AQI information by reducing time outdoors, then we would expect to see large negative coefficients. In contrast, most of the estimated effects are small, positive, and insignificant. These point estimates reinforce the residual analysis in figures 3-4, suggesting that changes in AQI categories did not cause people to spend less time outdoors.

Table 7: Regression Discontinuity Results

	Change in Minutes of:			Change in Probability of:		
	time outdoors	physical activity	parents / children	time outdoors	physical activity	parents / children
	A. Within 5 points of threshold: *moderate* to *unhealthy sensitive*					
Estimates	10.0	3.9	6.6	-0.5	0.1	1.8
	(11.5)	(13.5)	(10.9)	(2.8)	(3.8)	(1.6)
95% CI lower bound	-13.5	-23.7	-15.7	-5.9	-7.3	-1.4
# observations	378	378	378	898	886	818
	B. Within 5 points of threshold: *unhealthy sensitive* to *unhealthy*					
Estimates	21.0	28.7	4.9	-3.1	7.6	2.6
	(14.5)	(9.0)	(5.0)	(3.1)	(3.8)	(3.5)
95% CI lower bound	-10.9	8.9	-6.2	-9.1	0.2	-4.2
# observations	95	95	95	154	156	137

Note: This table reports results from regression discontinuity models. The last three columns are based on marginal effects from probit models. All specifications include controls for weather, weekends, and fixed effects for months and states. Robust standard errors are clustered by county in panel A and by state in panel B.

In summary, our regression discontinuity analysis provides no statistically significant evidence to suggest that AQI health warnings have caused people to adjust their behavior. At the same time, we cannot conclude the AQI had no effect. We have too few data points near the *unhealthy* to *very unhealthy* threshold to support a regression discontinuity design with any degree of statistical precision (only 53 diary days where people go outside). To consider an extreme scenario for the lower two thresholds, we report lower bounds on 95% confidence intervals around our point estimates in table 7. For example, the lower bounds in panel A would suggest that the average adult who is spending time outdoors with his parents or children reacts to an AQI warning of *unhealthy for sensitive groups* by spending 16 fewer minutes outdoors (down from a baseline of 84 minutes). Likewise, the probability of this group participating in any outdoor leisure declines by 1.4% at the 95% confidence bound (down from a baseline of 13.5%). Even in this extreme scenario, the reductions seem modest.

Thus, people do not appear to be paying much attention to EPA's health warnings about current air pollution, despite the serious health risks involved. While we do find that adults spending time with their parents and children decrease their outdoor leisure when pollution reaches very unhealthy levels (table 5-6), our regression discontinuity analysis suggests that the adjustments we observe may reflect responses to visual stimuli that coincide with very high levels of air pollution such as dust storms, smoke from forest fires, and smog. At the same time, there is growing evidence that people respond to advance information about future air pollution such as smog alerts issued by local authorities (Neidell 2009; Zivin and Neidell 2009; Sexton and Beatty 2013). This is not inconsistent with our findings. Sexton and Beatty observe that nearly half of all alerts are issued unnecessarily in the sense that air quality actually ends up being in the *healthy* to *moderate* range. If people respond to these false alarms by reducing their outdoor leisure, then the high frequency of false alarms will significantly weaken the relationship between leisure time and actual air pollution. This suggests there may be large welfare gains from developing more accurate forecasting tools and/or encouraging sensitive groups to pay attention to actual pollution levels rather than forecasts that often end up being wrong.

V. Summary and Policy Relevance

We have assembled the first nationally representative micro data on outdoor leisure time, air pollution, and EPA's health warnings about current air pollution. Our analysis yielded several novel findings that are relevant for regulatory policy. First, as air pollution worsens people generally spend more time outdoors. This association appears to be due to a combination of geographic and climatic factors that cause air pollution to be higher on days when the weather is warmer and higher on weekends in the summer and fall seasons in southern California.

Second, we use time use diaries to document direct evidence of avoidance behavior. The behavior we observe in the general population appears to be driven by older adults and children, who are known to be particularly sensitive to the health effects of air pollution. We find that, all else constant, moving from a *good* air quality day to one which the EPA deems *very unhealthy* decreases the probability that adults spend time outdoors with their own parents or children by 8% to 10%. This result reinforces indirect evidence of avoidance behavior documented by Neidell (2009) and Zivin and Neidell (2009). Furthermore, we find that the people who do choose to go outside on very unhealthy days also demonstrate avoidance behavior along the intensive margin, reducing the amount of time they spend outdoors by about 40 minutes (50%).

Third, not all sensitive groups adjust. Anyone participating in physical outdoor activity such as jogging or basketball is more susceptible to the health effects of air pollution due to an accelerated intake of pollutants during aerobic and anaerobic exercise. Yet, as air pollution worsens these individuals *do not* reduce their outdoor leisure at either the intensive or extensive margins. Perhaps they do not consider themselves to be a sensitive group.

Fourth, we used a regression discontinuity design to attempt to disentangle the extent to which avoidance behavior is driven by EPA's health warnings issued through the AQI relative to other stimuli. While our sample sizes are too small to provide a definitive answer, it does seem clear that EPA's health warnings about current air pollution are not the primary factor driving the avoidance behaviors we observe. This is consistent with prior evidence on inattention to public information about health risks and environmental nuisances (Pope 2008a,b; Sloan, Smith and Taylor 2002).

The apparent lack of attention to health warnings about current air pollution is particularly interesting in light of evidence that people reduce outdoor leisure in response to smog alerts issued by local authorities. While the alerts are more highly publicized than the AQI, nearly half of all alerts end up being false alarms (Sexton and Beatty 2013). As a result, there may be large welfare gains from developing better forecasting tools or information campaigns that encourage sensitive groups to pay attention to actual pollution levels rather than highly uncertain forecasts.

Our findings have several additional policy implications. For example, they suggest there is scope for improving benefit-cost analyses of federal regulations by recognizing that human exposure to pollutants tends to be higher on the weekends in Southern California and higher during the warmer months of the year in most major metropolitan areas. Thus, the benefit of a marginal improvement in air quality on a summer or fall weekend in Sothern California is likely greater than the benefit of that same reduction on a winter weekday. Furthermore, analyses that focus solely on health effects and ignore preexisting avoidance behaviors may tend to systematically understate the welfare gains to consumers. In addition to the direct health effects, a reduction in pollution may increase consumer welfare by mitigating the costs associated with adjusting one's preferred allocation of time.

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Appendix

Table A1: Activities and ATUS Codes Used to Define Time Spent Outdoors and Time in Physical Activity

Activity Code	Activity	Location	Classification	Additional Restrictions (if any)
Any	Any Besides Working	Outdoors Away from Home	Outdoors	tewhere=9 & actcode≠0501
Any	Any	Walking	Outdoors	tewhere=14
Any	Any	Biking	Outdoors	tewhere=17
1312	Playing Baseball	Anywhere	Strenuous, Outdoors	
1313	Playing Basketball	Not at Gym	Strenuous, Outdoors	tewhere≠31
1314	Biking	Not at Gym or at Home	Strenuous, Outdoors	tewhere≠31 & tewhere≠1
1318	Climbing/Spenunkling/Caving	Not at Gym	Strenuous, Outdoors	tewhere≠31
1319	Dancing	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13110	Participating in Equestrian Sports	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13113	Playing Football	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13114	Golfing	Anywhere	Strenuous, Outdoors	
13116	Hiking	Anywhere	Strenuous, Outdoors	
13118	Hunting	Anywhere	Strenuous, Outdoors	
13119	Participating in Martial Arts	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13120	Playing Racquet Sports	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13121	Participating in Rodeo Competitions	Not at Gym	Strenuous, Outdoors	tewhere≠31
13122	Rollerblading	Anywhere	Strenuous, Outdoors	
13123	Playing Rugby	Anywhere	Strenuous, Outdoors	
13126	Playing Soccer	Not at Gym	Strenuous, Outdoors	tewhere≠31
13127	Playing Softball	No Restriction	Strenuous, Outdoors	
13130	Playing Volleyball	Not at Gym	Strenuous, Outdoors	tewhere≠31
13131	Walking	Not at Gym or at Home	Strenuous, Outdoors	tewhere≠31 & tewhere≠1
13132	Participating in Water Sports	Not at Gym	Strenuous, Outdoors	tewhere≠31
13124	Running	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13125	Skiing/Ice Skating/Snowboarding	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13128	Using Cardiovascular Equipment	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13133	Weightlifting/Strength Training	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13134	Working Out, Unspecified	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
13199	Playing Other Sports	Outdoors Away from Home	Strenuous, Outdoors	tewhere=9
1531	Building Houses/Wildlife Sites/Other Structures	Anywhere	Strenuous, Outdoors	
1316	Boating	Anywhere	Outdoors	
13112	Fishing	Anywhere	Outdoors	
13136	Yoga	Outdoors Away from Home	Outdoors	tewhere=9

Note: Time spent outdoors during work is not included in our measure (if actcode=05010). The tewhere variable is available from the ATUS data, and takes on only one value per activity. This variable takes a value of 1 if the location is in the home or yard, 9 if the location is outdoors and away from home, 14 if the activity is done while walking, 17 if the activity is done while biking, and 31 if the location is at a gym or health club.

A. Data Collection and Coding

After obtaining the raw weather data from NCDC, we used filters to eliminate a few apparent errors, such as temperatures above 150°F or below -150°F, and negative values for precipitation. Weather station identification numbers were used to match weather stations to counties, and we merged in county FIPS codes for each.[27] The process of assembling data on individual time use began by collecting the ATUS data from bls.gov/atus along with CPS monthly extraction files from: http://www.census.gov/cps/. Individual identifying codes were used to merge demographic characteristics from the CPS to the ATUS diary records from 2003 through 2010. County FIPS codes were reported for all individuals living in counties with over 100,000 residents. Finally, we used the county FIPS codes and observation dates to merge the data on time use, weather, and air quality at the county-day level. The files and code needed to replicate our data construction and results are provided in the folder labeled "replicate".

Table SA1: Total Observations at Each Stage of Data Assembly

Year	(1) ATUS National Sample	(2) Matched to County	(3) Matched to Real or Proxy Weather Data and AQI Data	(4) Matched with Real Weather Data and AQI Data	(5) Matched to Real Weather Data and Real Humidity Data and AQI Data
2003	20,720	8,287	7,233	6,995	3,828
2004	13,973	5,426	4,709	4,557	2,452
2005	13,038	3,995	3,466	3,332	1,819
2006	12,943	4,149	3,582	3,436	2,071
2007	12,248	4,034	3,453	3,313	2,077
2008	12,723	4,237	3,649	3,510	2,219
2009	13,133	4,345	3,684	3,563	2,197
2010	13,260	4,354	3,552	3,396	1,964
Total	112,038	38,827	33,328	32,102	18,627

Note: By construction, these columns are nested left to right. Hence, all observations in (3) are contained in (2), and so on. After 2003, the ATUS sample was reduced by 35%, as reflected in this table.

[27] Each station has a combination of Cooperative Station ID (coopid) and Weather Bureau Army/Navy ID (wbnid) unique to it. The file matching these numbers to counties is available here: http://cdo.ncdc.noaa.gov/cdo/sodstn.txt.

Table SA1 summarizes how observations were lost when we merged the different data sets. An individual observation corresponds to all of the activities done by one individual over a calendar day, or an 'activity-day.' For example, 2003 starts with 20,720 activity-days. After matching observations to the county level, this number is reduced to 8,287. The other 12,433 observations were lost because the ATUS identifies an individual's county only if it contains over 100,000 residents. Merging in county level data on weather (excluding humidity) and air quality left us with 7,233 observations, of which 6,995 have real, rather than proxy, weather data. Further limiting the sample based on the availability of humidity yields the 3,828 observations shown in the first row of (5). Except for 2003, which used a 35% larger sample than 2004-2010, we have a similar number of observations each year. This is consistent with the ATUS sample sizes reported, meaning that data cuts are uncorrelated with time.

B. Supplementary Tables and Figures

Table SA2: AQI Color Ratings by Year

Year	% Green	% Yellow	% Orange	% Red and Above	N
2003	77.10	19.31	3.14	0.45	298,220
2004	79.99	17.56	2.22	0.23	304,728
2005	75.87	20.51	3.36	0.27	307,457
2006	77.92	19.17	2.60	0.31	307,428
2007	76.31	20.45	2.96	0.27	311,427
2008	80.97	17.03	1.71	0.29	311,411
2009	85.88	12.95	1.02	0.15	315,338
2010	82.70	15.90	1.27	0.14	298,426

Note: This table reports the percentage of days with green, yellow, orange, or red and above AQI ratings per year from 2003-2010. An individual observation is an AQI rating for a particular county on a given day.

Table SA3: Spatial Heterogeneity in the Correlation Between Air Quality and Weather: 2003-2010

	(1)	(2)	(3)	(4)
Percentiles	Max Temp	Min Temp	Precipitation	Snowfall
min	-0.56	-0.59	-0.50	-0.33
1%	-0.42	-0.48	-0.29	-0.17
5%	-0.18	-0.28	-0.24	-0.13
10%	-0.04	-0.13	-0.21	-0.10
25%	0.14	0.04	-0.18	-0.07
50%	0.31	0.20	-0.15	-0.04
75%	0.42	0.33	-0.10	-0.02
90%	0.51	0.43	-0.06	0.01
95%	0.56	0.47	-0.04	0.04
99%	0.68	0.62	0.02	0.11
max	0.86	0.77	0.18	0.33

Note: This table reports the distribution of correlation coefficients calculated between daily AQI and weather variables within each county between 2003 and 2010. For example, the 50th percentile for Col. (1) shows that the median county (Berks County, PA) had a correlation coefficient of 0.31 between AQI and maximum temperature. The AQI data are from the EPA and the weather data are from the National Climatic Data Center.

Table SA4: Time Use for People with Some or No Minutes Outdoors

	(1)	(2)	(3)	(4)
Average Minutes Spent	Outdoors>0	Outdoors = 0	Difference	p value
Attending Religious Services	7	10	-3	0.0000
Eating & Drinking	72	67	6	0.0000
Food & Drink Preparation	27	26	1	0.0027
Household Activities	75	77	-2	0.0432
Indoor Exercise/Recreation	8	7	1	0.0220
Other	168	176	-8	0.0588
Other Relaxing/Leisure	53	59	-6	0.0000
Outdoor Exercise	106	.	.	.
Physical Care for Children	11	13	-2	0.0000
Reading for Personal Interest	27	23	4	0.0000
Shopping, Except Food or Groceries	18	19	-1	0.0010
Sleep	517	527	-11	0.0313
Socializing With Others	41	43	-2	0.0133
Washing/Grooming	40	40	0	0.3110
Watching Television	149	170	-21	0.0000
Work	114	174	-59	0.0000
Work-Related Activities	7	9	-2	0.0000
Total Minutes	1440	1440	-106	
Total People	19784	13544		

Note: This table reports average time allocations for the subsets of people who do and do not report spending any leisure time outdoors.

Table SA5: Extensive Margin Robustness Checks

	with parents and/or children; humidity variables excluded	with children only	with parents only	ATUS respondents over age 65
Moderate	0.07**	0.07*	-0.05	0.05
Unhealthy sensitive	-0.01	0.00	-0.24*	-0.11
Unhealthy	0.01	0.02	-0.20**	-0.11
Very unhealthy	-0.26	-0.22	-0.66	-0.15
Pseudo R^2	0.136	0.155	0.3	0.086
observations	25,434	15,128	8,052	2,879

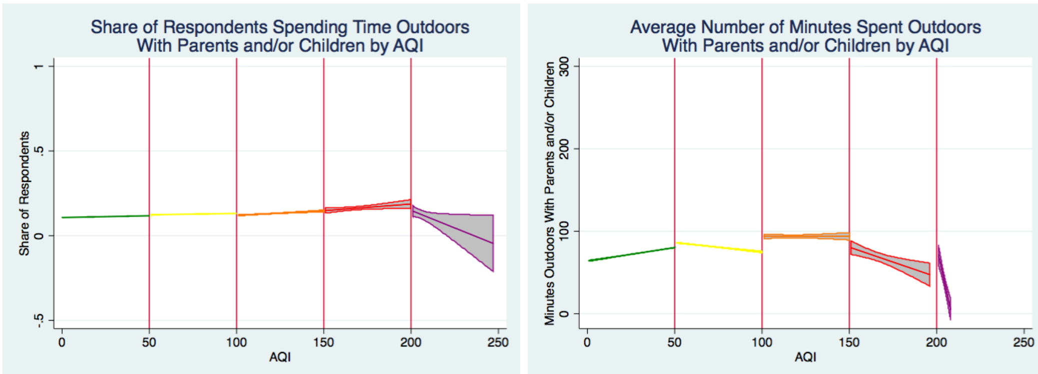
Note: These results are based on probit models comparable to those summarized in table 5. All specifications use county-by-month fixed effects and controls for weather, day of the week, and demographic characteristics of respondents. See the main text for additional details.

Table SA6: Intensive Margin Robustness Checks

	Parents / Children			Parents only		Children only		ATUS Respondant ≥ 65		
Moderate	-6.65*	-6.54	-1.98	1.87	-1.85	-6.25*	-5.31	10.13*	7.44	3.03
Unhealthy sensitive	1.83	6.53	8.81	-2.64	-8.63	3.42	11.15	-7.37	-6.80	-17.89
Unhealthy	6.35	11.36	20.89*	-4.80	-10.87	10.01	16.75	28.94	35.02	31.69
Very unhealthy	-63.20***	-60.42***	-47.48***	-91.84***	-95.83*	-63.04***	-58.23***	-36.93***	-36.70***	-38.28***
observations	4,007	3,377	2,141	586	495	3,503	2,957	2,406	2,202	1,331
state-month dummies	X	X	X	X	X	X	X	X	X	X
humidity constructed		X			X		X		X	
humidity actual			X							X

Note: The table reports results from probit models of the decision for whether or not to spend any leisure time outdoors. The control variables for weather, day, and demographics include minimum and maximum temperature, minimum and maximum humidity, precipitation, snowfall, age, age^2, wage, and indicators for day of the week, holiday, college degree, advanced degree, race, occupation, student, lives with a partner, and ill or disabled. Measures of statistical significance are based on robust standard errors clustered at the county level: *p<.1, **p<.05, ***p<.01.

Figure SA1: Outdoor Leisure with Parents / Children and the AQI



Note: The figure on the left displays a fitted linear trend to raw data on the share of respondents who report spending time with parents and/or children, by AQI category. The figure on the right fits linear trends to the average number of minutes spent outdoors. 95% confidence bands around these trends are also displayed. Five data points with AQI values greater than 250 are truncated to improve clarity.