

**SMOGGY WITH A CHANCE OF ALTRUISM: THE EFFECTS OF OZONE ALERTS ON
OUTDOOR RECREATION AND DRIVING IN ATLANTA**

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Abstract

Metropolitan smog alerts are prominent public information campaigns designed to enhance public health and to curb driving and other emissions. Unlike many other voluntary information-based environmental policies, air quality alerts target household behavior via forecast information about ambient concentrations rather than firm or product characteristics. This paper explores behaviors with high emissions (driving) and with high exposure (outdoor recreation) and underscores the difference between altruistic and risk aversion motivations. Behavioral impacts are identified using the threshold nature of daily air quality forecasts. A regression discontinuity (RD) design finds elderly users and exercisers tend to curtail their use of a major park following smog alerts. The RD design also reveals that households do not drive less on smog alert days. Juxtaposing high emissions behavior with high exposure behavior in the same study highlights how public forecast information may better trigger some responses and struggle to trigger others.

keywords: voluntary environmental policy, public information, air pollution

INTRODUCTION

The purpose of forecasts is often to inform and affect behavior. For instance, metropolitan smog alerts serve as a key element in a public information campaign designed to curb driving and other emission-causing behavior. Environmental forecasts made available to the public are ubiquitous in the United States. Forecasts about snowfall, natural disasters, droughts, pollen, pest and infectious disease outbreaks, and a host of other phenomena range in time horizons from hours to centuries. The behavioral effects of these public forecasts are often taken for granted, assumed, or completely neglected – rarely are they actually measured. Yet behavioral responses to forecast information can be critical to achieving environmental, public health, and other goals.

This article focuses on a specific example of using smog alerts to change behavior in Atlanta. Similar forecast programs exist in over 300 major cities nationwide. This publicly available forecast seeks to affect ozone-producing behavior in a city with severe air quality problems, thus making it of particular interest to policymakers using it as a low-cost tool to improve air quality and influence transportation demand. These forecasts also serve public health goals by informing residents when to take precaution to avoid risks. A better understanding of the behavioral impacts of programs like this can inform environmental, health, and transportation policy as well as those more generally interested in using public information to voluntarily “nudge” behavior. The results indicate that Atlanta households do not drive less under smog alerts on average, despite the aims of the state’s air quality plan. They also indicate mixed effects of smog alerts on park usage, with some sensitive populations reducing exposure in parks following smog alerts.

The next section frames the analysis with some policy background and a review of previous empirical evidence. Key issues are highlighted next in a discussion of activity choice that incorporates private and public interests and distinguishes between air quality and smog alerts. This general framework predicts an ambiguous effect of smog alerts on driving and a negative impact on outdoor activities. The results section reports the findings of an analysis of park usage data using a

regression discontinuity design that leverages the discontinuous or “threshold” nature of the smog alert system. The results suggest that at least the sensitive populations (elderly, exercisers) do seem to reduce their park use on alert days, and likely those who would otherwise do strenuous activities in the park become low-intensity walkers. The analysis employs a similar method to describe the impacts of daily air quality forecasts on driving behavior. The conclusions highlight the complications of using forecasts as part of a public information campaign. There does seem to be some positive effect on informing sensitive populations to avoid air pollution-related health risks, but the overall influence of the public information campaign to switch to alternative travel modes is not evidenced in the Atlanta data.

BACKGROUND

Policy Context

Recent years have seen a rise in information-based and voluntary policies (Niles and Lubell 2012). Following the command-and-control policies typical of the major federal environmental legislation (e.g., CAA, CWA, ESA, RCRA), a second wave of federal environmental legislation and regulatory efforts has emphasized the role of information provision in improving environmental quality and promoting voluntary “green” or healthy behavior. Various informational regulations like the Toxic Release Inventory (TRI) and other voluntary programs (e.g., Project XL, Energy Star, Green Lights, 33/50 Program) have gained prominence in the policy landscape and received considerable attention by researchers (e.g., Alberini and Segerson 2002, OECD 2003, Konar and Cohen 1997, Khanna 2001, Shapiro 2005, Koehler 2007, Shimshack et al. 2007, Darnall and Sides 2008, Innes and Sam 2008, Brouhle et al. 2009, Bae et al. 2010). Some voluntary programs rely more on information provision than others. In a Symposium on Voluntary Environmental Programs in this journal, Lyon and Maxwell (2007) discuss the role of information diffusion even in voluntary

programs targeting firm behavior. The more information-based policies (e.g., ecolabeling, certification) tend to focus on firm behavior or product labeling to drive consumer demand.

This analysis focuses on air quality alerts – a type of voluntary, information-based environmental policy that offers two important departures from this literature. First, they target household-level behavior via public information provision without providing information about product or firm qualities. Second, the information provided is forecast information that describes future environmental quality and may prove inaccurate. Because cost-effective attainment of federal Clean Air Act (CAA) standards involves reducing *peak* air pollution levels¹ rather than *average* air pollution levels, policy mechanisms to reduce emissions during episodes of especially poor air quality become particularly attractive to local policymakers. Being able to forecast such episodes enables policymakers to enact temporary, episode-specific measures that are likely much less costly than permanent emissions reductions.

Air quality advisories target the days when it matters most – those peak pollution days when the National Ambient Air Quality Standards (NAAQS) are violated – in an attempt to reduce polluting behavior.² To achieve compliance with the NAAQS, states must submit their State Implementation Plans (SIPs) that demonstrate how their nonattainment area will achieve compliance by particular deadlines. State regulators must select enough abatement mechanisms so

¹ Technically, it involves the average of the fourth-highest ozone levels in that year and the previous two years' fourth-highest ozone level. Details on the determination of the NAAQS for each pollutant can be found at <http://www.epa.gov/air/criteria.html>.

² Air quality alerts take various forms in the 300-plus U.S. cities offering them. Forecasts are typically issued the day before and accompanied by some background information and possible recommended responses. There is considerable variety across cities in the information provided, pollutants being forecast, and alert threshold used. Some air quality alert programs are coupled with incentive-based policy changes (e.g., discounted transit) or mandates. Atlanta's Clean Air Campaign is predominantly voluntary and advisory.

that their projected air quality levels are in compliance. States frequently opted for voluntary abatement programs in their SIPs, raising the question of how much emission reduction these programs yield. The SIP for Atlanta (Georgia Department of Natural Resources and Environmental Protection Division 2001), for example, noted that its voluntary ozone abatement program would account for at least 3 percent of its emissions reduction needed to demonstrate attainment.³ The alert program is one such program.

Of course, air quality alerts may serve goals other than pollution reduction and compliance with the CAA. Often, air quality alerts serve public health purposes.⁴ Informing residents about bad air quality episodes gives them information so that they can avoid or reduce exposure on those days. Responses that reduce exposure may inadvertently raise emissions. For example, commuters might avoid exposure by trading in their bicycles (with high exposure and low emission) for their cars (with low exposure but high emission) when the alert is sounded. Unexpected or not, the impact of the forecast information is ultimately an empirical question. This paper provides evidence on both kinds of behavioral impacts (emissions reductions, exposure avoidance) in Atlanta.

Literature Review

³ In its summary emissions budget calculations, the SIP includes the voluntary Partnership for a Smog-free Georgia (PSG) as an “off-model” source of motor vehicle emissions reductions that amount to a 5.6% reduction in VOC and 1.8% reduction in NO_x emissions. The SIP goes so far as to refer to a 20% reduction in vehicle miles traveled in the region due to the PSG, expecting mobile source emissions reductions far in excess of the amount used in its calculations (Georgia Department of Natural Resources and Environmental Protection Division 2001).

⁴ An e-mail survey conducted of air quality forecasting agencies revealed that, among the 44 agencies responding (whose alerts cover 81 different regions), roughly half of the areas’ alert messages advised the public to avoid exposure and to reduce emissions; while a fifth only recommended avoidance behavior and a fifth only recommended emissions reduction. Atlanta’s alert program includes both recommendations in its messaging.

Existing evidence on the public's responsiveness to smog alerts suggests that a significant impact may be likely. First, a study of Atlanta's early smog alert program (back when it was the PSG) in 1998 suggests significant impacts of forecasts on driving behavior (Henry and Gordon 2003). They conclude that alert days were associated with 5.5 fewer miles driven per commuter, even more for government employees, and no significant difference in the number of driving trips. They also note several factors such as boredom with public information campaigns and greater elasticity of transportation behavior in the long-run – both of which suggest that an analysis of behavior in 1998, only the first year of the program, might not reflect the more long-term effects of public forecast information. The present analysis uses a broader sample, controls for some rescheduling of trips and substitution of trips within households, and examines forecast effects at a later date, perhaps after the novelty of the alerts has worn off and residents adjusted their travel behavior. Concurrent with Henry and Gordon (2003), Cummings and Walker (2000) examine actual traffic volumes in Atlanta in the summer of 1998. Their fixed-effect approach finds that May ozone action days experienced somewhat less traffic volume (0.2 – 8.9 percent) than was predicted, but this difference may just be noise.

Welch et al. (2005) measure the impacts of a similar smog alert program in Chicago on transportation behavior. They fail to find significant effects of “Ozone Alert Days” on overall ridership on Chicago Transit Authority trains, but they do observe changes consistent with riders shifting their schedules to avoid rail travel during afternoon hours. Their study is limited to public rail turnstile counts, however, lending little insight into individual responses. It does suggest, however, that aggregate measures of forecast impacts may mask subtle and complex shifts in travel behavior.

A series of recent studies in California investigates the effects of air quality alerts on behavior. Neidell (2004, 2005a, 2009) observes indirect evidence of averting behavior (i.e., avoiding exposure) in response to air quality forecasts by examining how hospital visitation for respiratory

problems differs between days with alerts and days without alerts. Neidell shows a particularly strong effect of alerts in reducing hospital visitation for children. This suggests that people do seem to take precaution on those days to avoid exposure. By tracking attendance at major Los Angeles institutions, Neidell (2005b) finds more direct evidence of behavioral changes in response to air quality alerts. As expected, visitation at attractions associated with more outdoor activity (e.g., LA Zoo, Griffith Park Observatory) fell on alert days. This is primarily due to declined in visitation by youth and elderly patrons, again signaling that more sensitive populations are more responsive to alert information. This is also consistent other survey research showing that parents of asthmatics claiming to be more responsive and to have greater willingness to pay to avoid exposure for their children than others (McDermott et al. 2006, Mansfield et al. 2006). Sensitive populations and those with lower-cost substitute activities (such as locals rather than tourists) may undertake averting behavior in Southern California. Zivin and Neidell (2009) observe forecast fatigue, where behavior changes on the first day of an air quality episode that spans multiple days, but largely resumes its normal pattern by the second day. This provides evidence consistent with the idea that ozone forecasts can promote averting behavior especially among sensitive populations and when substitute activities are low cost. Cutter and Neidell (2009) show how smog alerts in the San Francisco Bay Area affect transportation behavior. They find decreases in total daily traffic flows and insignificant increases in transit ridership following “Spare the Air” (STA) advisories. Sexton’s (2011b) recent working paper attempts to further untangle the impacts from the informational and incentive-based STA program.

The generalizability of these findings may be limited by many factors. The results in the California studies may not extend well to other states and cities, especially those with different

transportation or recreation alternatives.⁵ Moreover, the quality of the forecast and its dissemination may differ in important ways across contexts and over time. Programs themselves may be more than just informational, as the Bay Area’s Spare the Air program included free transit on alert days. The present analysis considers a different city (Atlanta) and, for the first time, assesses the impacts of smog alerts on both emission-causing behavior (driving) and averting behavior (outdoor recreation) in the same study area. This should add more evidence on behavioral impacts of forecast information as well as allow for a direct comparison of the more private-interest responses (to reduce exposure) and the more public-interest responses (to reduce emissions). Because the new case study city’s air quality alert program emphasizes both self-protection and emissions reduction in its messaging, and it does not include any special incentives on alert days (e.g., transit prices do not change), it offers an excellent opportunity to test the relative influences of altruistic and averting responses to these public alerts.

BEHAVIORAL RESPONSES TO AIR QUALITY ALERTS

Travel Mode Choices

For a traveler who must choose a mode of transport, several factors likely play a role – a few of which are especially important in the context of air quality alerts. We might expect a traveler to select a mode by weighing alternative modes’ direct travel costs (including travel time) and indirect costs, which includes differential exposure to environmental risks. The modes might also be more than instrumental means of transport; some modes might be more or less enjoyable. Moreover, a “warm glow” might be enjoyed by travelers who select more environmentally friendly modes. Suppose our hypothetical traveler compares available modes in terms of these costs and benefits.

⁵ Sexton’s (2011) working paper uses a national sample to offer preliminary measures of an average effect in the U.S.

We might then expect their “best” option to depend these factors – potentially each of which might vary with air pollution levels.

Comparing one day with high air pollution levels to a cleaner but otherwise identical day might reveal a behavioral response. Although travel times or intrinsic enjoyment of different modes might vary with air pollution levels, the primary interest here is with two forces affecting the mode decision: risk aversion and altruism. Risk averting preferences would lead travelers to switch away from high-exposure modes on days with high air pollution levels. This avoidance confers a private, internal benefit to the traveler in the form of better personal health. In practice, this might mean avoiding walking, biking, or even waiting outside for public transit on more polluted days. Alternatively, an altruistic motivation might especially lead to “greener,” lower emission mode choices on more polluted days. The altruistic traveler realizes benefits from “going green” and helping (or at least not harming) the public’s air quality. In practice, altruistic travelers might take transit or travel later in the day in order to mitigate their harm to the airshed on those days.

It is possible, or even likely, that risk aversion and altruistic motivations push behavior in opposing directions. Which force is stronger may depend on the relative strength of preferences for private or public gains, or on the individual’s perceived efficacy of their choice in reducing their risk or helping others. As the model in Appendix B shows, the critical issue is how smog alerts alter the marginal costs and marginal benefits of choosing a “greener” mode. Travelers compare how their private (averting) and public (altruistic) net benefits of particular mode choices change when alerts are issued. While private interests might be expected to dominate, at least on average, this analysis focuses on air quality *alerts* rather than pollution levels as such. The public alerts emphasize altruistic responses through messaging that calls for pro-social behavior, and alerts are sounded when emissions reduction produces more of a public good (i.e., attainment of the NAAQS). On balance, how behaviors respond to news of worsened air quality is an empirical question.

For a formal, mathematical version of this discussion, see Appendix B. This economic model offers a transparent and simplified characterization of the mode choice problem in order to highlight the ways in which air quality alerts might affect equilibrium behavior. For decisions that do not involve emissions, such as the choice between running outside or walking outside for exercise, the choice context is much simpler. There is no altruism component as none of the alternatives produce emissions. The averting behavior remains and hypothesized behavioral response is a straightforward reduction in exposure.

AIR QUALITY ALERTS AND REGRESSION DISCONTINUITY DESIGN

Atlanta's ozone alert program lends itself to analysis via a regression discontinuity (RD) design. The treatment – issuing a smog alert – follows clearly from the running variable, ozone level forecasted, exceeding a threshold (85ppb). The forecast variable provides an observable assignment of each observation into either a treated (alert) or nontreated (no alert) status. The outcome variable (e.g., daily miles driven) should be a continuous function of the assignment variable, and the treatment effect on the outcome should be visible as a discontinuity when the forecast exceeds the cutoff. An advantage of the RD design is that other factors influencing behavior (e.g., weather, age, transit options) should vary smoothly around the threshold. This creates an opportunity to identify the effect of policy treatment separate from other confounding factors using an RD design. Lacking a randomized experiment, this RD design functions like a “close cousin” (Lee and Lemieux 2010) and offers an excellent opportunity to identify the effects of an information policy that is otherwise difficult to robustly detect. The possible discontinuity will be observed via visual inspection of the data as well as local regressions and nonparametric RD tests in the next section.

The design of air quality alert programs seem very well suited for evaluating using an RD approach. The power of the RD design in effectively replicating a randomized experiment locally – i.e., for forecast values close around the threshold that triggers the alerts – is a direct consequence of

the assumption that individuals have at best imprecise control over their forecasted levels. Thus, the most important threat to the validity of an RD design is the possibility that an individual can precisely manipulate the assignment variable (Lee and Lemieux 2010). If an individual could control the forecasted ozone level, for instance, the RD approach would not apply. On its face, only the forecasters themselves might be able to exert such direct control, and otherwise households could only imprecisely affect their forecasted ozone levels by manipulating the day they enter the sample. (Even that is minimized in this context given the unit of observation in the park usage analysis, discussed below, and the fact that respondents to the travel survey have their diary day randomly assigned.) But, for values just above and below the threshold, they should appear independently distributed. This kind of sorting around the cutoff discussed by McCrary (2008) is examined below for the driving behavior analysis.

The advantages of using an RD design include its approximating a “local” randomized experiment and that its assumptions can actually be tested. Implementing an RD approach requires the researcher to make some design choices. This includes choices about how to graph the data and how to estimate regressions. The data at hand influence these choices, so they are discussed in more detail below. The general principle involves selecting bandwidths (or bin size for histograms) that balance the need for sufficient data density to obtain locally smooth distributions and the risk of bias from observations far from the threshold. In a sense, this reflects a common between precision and bias. Restricting bandwidths to very small or local values may reduce bias but comes at the expense of greater noise in the analysis. Because the running variable is discrete (only integers are forecast), some of these design choices are simplified in this context (Lee and Lemieux 2010).

EVIDENCE OF SMOG FORECASTS' EFFECTS ON OUTDOOR RECREATION

Data

To assess whether Atlanta's ozone alerts encourage averting behavior and reduced outdoor activity raises questions about the nature of the outdoor activity. Strenuous activities such as running are commonly discouraged on "red alert" days. The analysis here focuses on behavioral change for outdoor activities, measuring both the amount and the intensity of that outdoor activity in an attempt to discern whether people reduce their outdoor recreation time or merely alter their type of outdoor recreation. This analysis combines data on park usage with a dataset of air quality forecasts for Atlanta. Air quality modelers at the Georgia Institute of Technology provide data on the next-day forecasts provided to the Georgia Environmental Protection Division for use in their Clean Air Campaign (Chang 2005). When the forecasted ozone levels exceed 84 parts per billion, an ozone alert is issued to news outlets, sent to other audiences, and posted on highway signs. The alert includes suggestions to both reduce emissions (e.g., carpool, avoid refueling in the morning) and reduce exposure (e.g., limit outdoor exertion).

Usage patterns of a large, central Atlanta park were recorded during the summer of 2005. (The Appendix describes the data collection in more detail.) In short, two observers recorded passersby in Piedmont Park on 35 days, spread across different days of the week and various afternoon hours at two different park locations. Seven of those days had alerts forecasted. These data permit exploring several ways in which ozone levels and alerts might affect park usage. First, aggregate park usage is measured as the count of passersby during a 30-minute observation period (i.e., a "sitting").⁶ Second, the proportions of different subgroups of passersby composing that aggregate are also examined. Aggregate park use variables for each 30-minute sitting are constructed

⁶ The total number of visible park occupants at the beginning of each observation period can also be used to proxy for park usage at the time. No significant results are evident for this measure.

as deviations from the average usage for a given day of the week, time period of day, location in the park, and coder. Measures of aggregate park use are available for 124 instances during the summer of 2005. Finally, characteristics of each group passing by the observer can be used to describe the types of users and uses in the park at that time. Of course, many such groups are singletons. Measures of characteristics of particular groups of passersby are observed 4047 times during the summer.

Given that park usage is unlikely to affect air quality and is not seen as conferring a warm glow effect on poor air quality days, the theoretical model above suggests that avoidance will be the dominant response on days with alerts. Park use is expected to fall, and strenuous activities (e.g., exercise) and sensitive populations (e.g., kids, elderly) are expected to be even more responsive to such alerts. In the absence of a genuine threshold effect in the health impacts of ozone, any effect of alerts most likely represents a behavioral impact of the program's information campaign.

Results

The regression discontinuity research design lends itself well to this empirical application. The forecasted ozone levels serve as the running variable, and the data are examined on either side of the 85ppb cutoff. To explore how the measures of outdoor recreation differ on either side of the cutoff, Figures 1 and 2 display the graphs showing how park usage (on the vertical axis) varies across the ozone forecast level. A treatment effect of alerts would be visible as a sharp discontinuity at the 85 ppb threshold (just to the right of the red vertical line). Panels A, B, and C indicate total park use, share of users exercising, and share of users that are elderly, respectively. Figure 1 shows simple

weighted average values for the outcome variables, while Figure 2 uses a nonparametric smoothing (around a bandwidth of 6 ppb).⁷

These results show that any discontinuous impact of alerts on park usage arises at the individual passerby level rather than the aggregate level. There is no significant discontinuity for the aggregate traffic flow at sittings at the alert threshold (Panel A in Figures 1 and 2). There does appear to be a significant discontinuity for the proportion of passersby that are exercising (Panel B in Figures 1 and 2) and for the proportion of elderly in each group passing by (Panel C in Figures 1 and 2).

[FIGURE 1 ABOUT HERE]

[FIGURE 2 ABOUT HERE]

Formal tests for these discontinuities, as well as several other measures of park usage for subpopulations or specific activities, are presented in Table 1. Following Imbens and Lemieux (2008), local linear regressions are run on either side of the 85ppb cutoff to examine whether or not a discontinuity exists. Nichols (2007) suggests a test for discontinuity by comparing the outcomes at the cutoff predicted by two different local linear regressions, one estimated above and one estimated below the cutoff. This computed difference is bootstrapped (1000 replications) to allow for a test of discontinuity. Alternatively, Ludwig and Miller (2007) suggest a nonparametric RD design that tests

⁷ Other bandwidths were explored, and a bandwidth of 6 is chosen to best illustrate the RD design here. Following Lee and Lemieux (2010), a test for whether the bandwidth is narrow enough fails to reject the hypothesis that there are within-bin trends in the data ($p=0.29$ for the share exercising; higher p -values for other activity measures).

for discontinuity following Hahn, Todd, and Van der Klaauw (2001) and Porter (2003).⁸ Table 1 reports the results of this RD test. Several bandwidths for the local regression are tested to assess the sensitivity of results; smaller bandwidths trade off reduced bias for weaker ability to detect discontinuities. The park data do not support bandwidths of 5 ppb or smaller. Following Lee and Lemieux (2010), an inspection of the graphs and diagnostic tests point to desired bandwidths between 6 and 10 as balancing the improved precision of the estimates against introducing more bias.⁹

The aggregate traffic flow in a given sitting exhibits no significant discontinuity at the cutoff for all users or various subgroups. Elderly traffic flow is one exception, where the composition of elderly in the flow falls by about 2 percentage points following alerts. Even if the aggregate flow remains the same around the cutoff, its make-up changes and reflects some interesting responses by park users. Across many bandwidths (6 and larger), the smog alert “treatment” points to observed passersby being 16 – 33 percentage points less likely to be exercising. This effect is largest when the bandwidth is small, suggesting a strong local impact. To place this in context, the average passerby group is about 43 percent exercisers at the threshold. Runners, a subset of exercisers, exhibit a

⁸ This test arises from kernel-weighted linear regressions to the left and right on the cutoff, with the treatment effect calculated as the difference in the left and right limits of the regressions at the cutoff. The triangle kernel is used because of its preferred boundary properties. The standard errors are computed following Porter (2003).

⁹ Around the cut-off of 85ppb, relatively little curvature is observed for most outcome variables in the park analysis, suggesting bandwidth choice may not matter much. The optimal bandwidth chosen via cross-validation (Lee and Lemieux 2010) is between 7 and 10, depending on the outcome measure. For total passersby, the optimal bandwidth may be much larger, but the conclusions are unaffected as Table 1 demonstrates.

similar effect (approximately 8 – 18 percentage points) from the alerts, although this effect is weakest and insignificant for the small bandwidth of 6.¹⁰

The proportion of kids or elderly might also exhibit some discontinuity at the threshold if these sensitive populations react to the alerts. For smaller bandwidths (≤ 10), the proportion of elderly in each group passing is about 0.05 lower on smog alert days. The effect fades at large bandwidths.¹¹ The proportion of kids is lower on alert days, although the effect size varies substantially as bandwidth varies from 6 (insignificant) to 10 (-0.14) to 20 (-0.03). The effect on the proportion of females is negative 14 percentage points and significant at the smallest bandwidth (6), zero at the middle bandwidth (10), and 11 percentage points and positive at the larger bandwidth (20). These unstable results for kids and females prevent firm conclusions. Overall, smog alerts do not appear to significantly affect the aggregate park usage, even by sensitive subgroups, except for the elderly. Individual groups of passersby, on the other hand, do appear affected by smog alerts – exercisers and elderly compose less of park users.

The validity of the RD approach here depends on other factors that might explain park usage either not varying at all or varying smoothly around the cutoff point of 85ppb. The close

¹⁰ The significant negative effects on exercising and running on a per-passersby basis is consistent with results for aggregate flows per sitting. With far fewer observations at the aggregate level, effect estimates are much less precise. Nonetheless, proportion of elderly in the aggregate traffic flow falls by 10 – 14% on alert days (with p-values less than 0.30). The proportion of runners falls from 3 – 11%. This gives some confirmation of the RD analysis done on a per-passersby basis, although imprecision remains.

¹¹ This negative effect is robust to a variety of bandwidths and model constructions. If the typical group passing by has 5% fewer elderly on smog alert days, and aggregate park usage is unaffected by the alerts, we should expect the count of elderly to also fall significantly on those days. The RD approach finds a discontinuity in counts of elderly per sitting, although estimated much less precisely, with elderly counts falling by -1.4, which is 2.9% of the average flow of 49.03 passersby per sitting.

correlation between temperature and ozone levels, and that weather likely affects park usage, might confound conventional regression approaches. At least when ozone levels are near the 85 ppb threshold, however, weather variables like temperature do little to predict the *alert* treatment. To verify this, the Porter (2003) approach used above finds a difference of less than 1 degree Fahrenheit, a discontinuity that is insignificant at any bandwidth. Similarly, windspeed makes no significant jumps at the 85ppb threshold, while cloud cover is minor in all observations on either side of the cutoff (i.e., no precipitation). Weather cannot explain why behavior changes at the threshold.

In all RD analyses, sorting around the cutoff is a concern. Piedmont Park is quite accessible to nearby residents and many users can easily reschedule their visits. Thus, we might expect to see a lower density of observations on the righthand side of the 85ppb cutoff and more on the lefthand side. This can be taken as evidence of some effectiveness of the public information campaign. To test for this, the Nichols (2007) bootstrapping approach is taken to test for a discontinuity in the density of observations around the cutoff. The results are inconclusive and highly sensitive to the choice of bandwidth. More tellingly, a RD approach indicates that party size is significantly larger after smog alerts are sounded (effect = 1.1, $p < 0.05$). This result is consistent with solo park users being more elastic in response to smog alerts, as they do not have to coordinate with companions. It is also consistent with joggers switching to walking on alert days and walkers tending to cluster in the park (either in fact or in appearance to the observers).

[TABLE 1 ABOUT HERE]

EVIDENCE OF SMOG FORECASTS' EFFECTS ON DRIVING BEHAVIOR

Data

This air quality public information campaign also sought to affect driving behavior to reduce emissions. Assessing drivers' sensitivity to smog alerts requires coupling air quality forecast data with driving behavior data. The driving data come from the Atlanta Regional Commission (ARC). The ARC, the formal metropolitan planning organization for Atlanta, conducted a household travel survey in 2001 and 2002 in order to inform its regional transportation planning. Sampled households were randomly assigned two consecutive days over which each household member was to record their travel information. The data were collected from April 2001 to April 2002, except for July. With a response rate of 66 percent, 8,069 households completed the travel diaries, representing 21,323 persons, 14,449 vehicles, and 126,127 places visited during the two-day sample. See ARC (2003) for further details about the survey administration.

The outcome variable of interest here is daily vehicle-miles-traveled (VMT) by households. The hypothesis tested is that daily VMT falls on alert days, corresponding to a primary goal of the alert program and a prominent metric in transportation planning. Of course, smog alerts might affect other aspects of driving in Atlanta (e.g., frequency, timing, destinations). For brevity and because it is the best proxy for the emitting behavior of policy interest, this analysis focuses on mileage of trips. VMT is aggregated to the household level to control for within-household substitutions and, except where noted, the ARC's sample weights are used. Aggregating driving behavior to the household level and restricting the sample to the 2001 ozone season (May – September) reduces the effective sample to 991.

Results

Using the log of the household's daily miles driven as the outcome variable, the data look noisily distributed across ozone prediction levels. In Figure 3, there does not appear to be an obvious pattern in driving and ozone predictions. More importantly, there does not appear to be a

significant discontinuity at the cutoff point, indicated with a vertical line. If anything, perhaps, there is an increase in driving on alert days. Figure 4 shows a similar story with histograms of average outcome variables across forecast levels for a variety of binwidths. The results in Panel A of Figure 4 differ from Figure 3 somewhat because the sample-weighted averages are used in Figure 4. The results do not appear sensitive to binwidth choice.

[FIGURE 3 ABOUT HERE]

[FIGURE 4 ABOUT HERE]

Several tests for discontinuity are performed. The results of the bootstrapped tests from Nichols (2007), for bandwidths ranging from 3 to 10 and for local mean smoothing or for local linear regression, all fail to reject the hypothesis that VMT is different above the threshold. Depending on the bandwidth and smoothing, (unweighted) household VMTs appear 3 – 18 percent higher with alerts – though none of these effects are remotely significant. Porter’s (2003) nonparametric tests generally reveal similar results, except at small bandwidths (e.g., ≤ 5). Regardless, the discontinuity is never significant at conventional levels. The insignificant but positive effects at the cutoff appear very sensitive to the sample weighting. Using the sample weighting provided by ARC and examining bandwidths from 3 to 12, the nonparametric smoothing shows 0 – 17 percent lower household VMTs with smog alerts – though again none of these effects are remotely significant. Figure 5 shows the nonparametric curves for a representative set of bandwidths (3, 6, and 12). The drop-off in VMT evident at high forecasted ozone levels results from few observations in that range. At the least, that drop-off and variation at lower ozone levels are not the result of the smog alert issued at the 85ppb threshold.

[FIGURE 5 ABOUT HERE]

Table 2 summarizes the results across different bandwidth selections. It shows that household miles driven may fall once the 85ppb threshold is passed, but this effect is very noisy and indistinguishable from zero. This conclusion is not sensitive to the choice of bandwidth. A more focused analysis excludes evening driving, when emissions will not affect that day's ozone levels. This RD analysis is similar, with no significant treatment effects.

While the smog alerts may not have a significant impact when measured log-miles, perhaps the effect exists in linear miles. The results across the bandwidth range also fail to reject the hypothesis of no treatment effect. There are a few influential observations, however, and when the two households traveling over 500 miles that day are dropped (perhaps reasonable considering these miles are unlikely to be predominantly in the Atlanta airshed), the evidence of discontinuity becomes much stronger and is now statistically significant at the 10 percent level. The ozone alerts here appear to cause a significant reduction in household VMTs. This significant effect is only found in linear VMT with outliers dropped. It disappears if the analysis is restricted to daytime VMTs this might affect peak ozone. The insignificant threshold effects hold for log-VMT regardless of restricting the time of day or dropping the two influential observations.

Table 2 also reports a test for discontinuity in household size. This variable is not expected to exhibit discontinuities around the 85ppb threshold, and if it did it would call into question the attribution of any treatment effect to the alerts. Household size does not appear discontinuous at the threshold. Other household demographic variables (e.g., age, years of schooling, income) are also tested for discontinuities around the 85ppb threshold. The results generally support the use of the alerts as an exogenous treatment as observations on either side of the threshold closely resemble each other. As in the park usage analysis, weather variables can be tested for whether they show a discontinuity at the forecast alert cutoff. Rainfall in particular may affect driving. Here, again,

precipitation shows no discontinuity, as it shows no variation whatsoever around the threshold. (In the sample, as is typical in Atlanta, precipitation prevents ozone from reaching high levels.)

[TABLE 2 ABOUT HERE]

The possibility of sorting around the 85ppb threshold is of some importance here. Sampled households cannot choose which side of the threshold they are on. Yet the sampling design of the ARC travel diary survey leads to observations being dropped if that household took no trips on a given day. This might lead to observations clustering on the lefthand side of the threshold *if* households responded to smog alerts by taking no trips when ozone forecasts reached 85ppb. Alternatively, if households tended to respond by taking at least one trip on smog alert days, there might be sorting to the righthand side of the threshold. Given that non-travelers were not sampled, sorting by households onto one side of the cutoff or the other has substantive implications as it suggests the smog alert is affecting driving behavior. This possibility is explored graphically in Figure 6, where the share of observations falling into each ppb 'bin' is plotted against local mean-smoothed curves on the right and left of the cutoff (triangle kernel, width of 6). The discontinuity is robust to different constructions (e.g., other width, local linear regression). It appears that some sorting may be occurring where the threshold marks a discontinuous jump in the frequency of observations. A test from Nichols (2007) shows that the density of observations is greater at the threshold. The bootstrap procedure with 1000 replications to test whether local linear regressions (width of 6, triangle kernel) on the left and right side of the cutoff yield different density values, indicates a statistically significant 0.013 difference. At different bandwidths, the density of observations appears 0.01 higher to the right of the cutoff. This modest sorting is consistent with an increased tendency to take at least one trip on alert days, relative to similar days without an alert. Again, it does not support the hypothesis that the smog alert discourages trip-taking.

[FIGURE 6 ABOUT HERE]

In summary, there does not appear to be strong evidence of a negative effect on household VMTs of smog alerts in Atlanta in the summer of 2001. There could be many reasons for this, including offsetting effects of private interests (i.e., driving to avoid exposure) and public interests (i.e., taking transit to contribute to the public good) as described in the theoretical model above.¹² Alternatively, the smog alerts may have low salience and low dissemination, or travelers may simply be very inelastic in their short-run travel demand. Perhaps the strongest evidence of a treatment effect comes in the discontinuity in the density at the cutoff. Sorting appears somewhat likely, consistent with households being more likely to take a driving trip on the righthand side of the cutoff than the left.

The results for both the park visitation and the household driving analyses are subject to some important limitations. Both datasets rely heavily on measures of behavior that could include error or even bias. Student observers in the park may mistakenly code some passersby. Travel diary respondents may incorrectly recall their daily activity. In both cases, this approach assumes measurement error in the outcome variables is independent of that day's air quality level. For the travel diary analysis, this dataset – with all its limitations – has been frequently used by Atlanta's regional transportation planners. The park use data, conversely, is a novel observational approach to collecting data inexpensively. Accordingly, it lacks a richer set of demographic control variables

¹² If the alerts triggered different behavioral responses in different households such that they offset and the average response appeared minimal (i.e., some households altruistically reduced VMT while others drove more to avoid exposure), then the variance in the VMT measure should exhibit a discontinuity at the threshold. For this sample, the standard deviation of household VMT actually falls from 1.23 below the threshold (and above 83ppb) to 1.06 above the threshold (and below 87ppb). Offsetting appears unlikely to account for this.

(making the RD design even more appealing) and lacks external validity checks. In both cases, as the original datasets had no overt connection or design features related to air quality whatsoever, the threat of air quality issues biasing the data is minimized.

DISCUSSION

The impact of public forecasts on decisions and behavior has been demonstrated in sectors like the environment, transportation, and health. Air quality forecasts operate at the nexus of all three sectors. Smog alerts' impact on many behaviors (e.g., jogging, walking, driving) in Atlanta are complex and results are mixed. The RD approach offers substantial improvements in research design over previous research in Atlanta. Juxtaposing high emissions behavior (driving) with high exposure behavior (park use) in the same study area highlights how public forecast information may better trigger some responses and struggle to trigger others. This is especially likely when private and public interests may appear incompatible for some behaviors (commuting) and not for others (exercising). Thus, the failure find robust evidence of negative impacts of smog alerts on VMT in Atlanta comes as little surprise, despite the aims of the Clean Air Campaign. The RD approach does show, on the other hand, that the elderly and exercisers may be quite responsive in terms of avoiding outdoor recreation. Responsiveness by subgroups may be masked when looking at aggregate measures.

The role of forecasts as a policy may be more nuanced than some imagine, especially when forecasts are used to affect the outcome being forecast. Assumptions that “more information is better” or that public forecasts represent neutral information provision may not hold up in practice. Forecast information may not have the desired or even intuitive effects. Smog alerts may inadvertently encourage pedestrians to seek shelter in cars. Moreover, these public forecasts may have dramatically different effects in different contexts. Some areas or activities may have few ‘marginal’ decisionmakers, for whom new public forecast information pushes them past a tipping

point and into a new behavior. This might partly explain why these results depart from previous work. Fewer or more costly alternative travel modes in Atlanta relative to San Francisco could help account for the difference in driving responses. Future research would do well to provide evidence explaining the regional variation in responsiveness.

This empirical analysis takes advantage of the discontinuous or threshold nature of the ozone alert program. This allows the effect of the forecast or alert to be disentangled from the effect of the ozone levels themselves. While this peculiar design feature of the public policy is a boon for program evaluation researchers, it may not make for good policy. It raises interesting questions for policy design. The color-coded air quality alert system, not unlike other public information campaigns like the former Homeland Security Advisory System, simplifies the messages and converts continuous risk or safety information into a categorical signal. Preprocessing the data may substantially affect behavior. Simpler messages have important consequences for public use of the information, one possible implication being that worsening air quality will only affect behavior if it crosses some threshold. This entails lost opportunities for averting behavior for air quality changes that do not cross thresholds. Conversely, time and cognitive costs of more information may imply that less information elicits more reaction. When there is no special health effect associated with the threshold, this begs a question of whether the forecast information is being optimized to promote public health (or, perhaps, to elicit volunteers to help achieve compliance with the NAAQS). Given cognitive limits, a significant behavioral response at an arbitrary point may be better than a muted response across a wider range of circumstances.

The results from the RD approach suggest that ozone alerts have little influence on emitting behavior like driving – in contrast to some earlier work in Atlanta and to recent results for San Francisco. The variation in forecast impacts over space and time warrant systematic research efforts to progress our understanding of this prevalent policy tool beyond single-city case studies. One novel aspect of this study is the application of an RD approach in the same city to activities that

likely have tensions between private and public interests, such as driving, and also to activities with predominantly private interests, such as park use. The results offer more evidence that forecasts effectively foster averting behavior but have limited stimulation of altruistic responses from drivers at least in Atlanta. That averting behavior is facilitated in both Atlanta and the California settings may be heartening for proponents of information-based policies, whereas the absence of similar impacts on driving behavior in Atlanta may owe to paucity of alternative transit options in this setting. Other explanations worth examining include differences in alert awareness, in content and dissemination of the alerts, in alert program longevity and incentives, and in population characteristics. Further research is needed to explore how forecast information affects different choice settings and different decisionmakers.

REFERENCES

- Alberini, Anna and Kathleen Segerson. 2002. "Assessing Voluntary Programs to Improve Environmental Quality." *Environmental and Resource Economics* 22(1): 157–184.
- ARC. 2003. *2001 Atlanta Household Travel Survey: Final Report*. Atlanta: Atlanta Regional Commission.
- Bae, Hyunhoe, Peter Wilcoxon, and David Popp. 2010. "Information Disclosure Policy: Do State Data Processing Efforts Help More Than the Information Disclosure Itself?" *Journal of Policy Analysis and Management* 29(1): 163-182.
- Brouhle, Keith, Charles Griffiths, and Ann Wolverton. 2009. "Evaluating the Role of EPA Policy Levers: An Examination of a Voluntary Program and Regulatory Threat in the Metal-Finishing Industry." *Journal of Environmental Economics and Management* 57 (2): 166-181.
- Chang, Michael. 2005. "Forecasting Ground-level Ozone in Atlanta, Georgia." Website. <http://cure.eas.gatech.edu/~chang/docs/forecast/index.html>
- Cummings, Ronald and Mary Beth Walker. 2000. "Measuring the Effectiveness of Voluntary Emission Reduction Programs." *Applied Economics* 32(13): 1719-1726.
- Cutter, W. Bowman and Matthew Neidell. 2009. "Voluntary Information Programs and Environmental Regulation: Evidence from 'Spare the Air.'" *Journal of Environmental Economics and Management* 58(3): 253-265.
- Darnall, Nicole and Stephen Sides. 2008. "Assessing the Performance of Voluntary Environmental Programs: Does Certification Matter?" *Policy Studies Journal* 36(1): 95-117.
- Georgia Department of Natural Resources and Environmental Protection Division. 2001. *Georgia's State Implementation Plan for the Atlanta Ozone Non-attainment Area*. Georgia Department of Natural Resources. Available at: http://www.gaepd.org/Files_PDF/plans/sip_narrative.pdf
- Hahn, J., P. Todd and W. Van der Klaauw. 2001. "Identification and Estimation of Treatment Effects with a Regression Discontinuity Design." *Econometrica* 69: 201-209.

- Henry, Gary T. and Craig S. Gordon. 2003. "Driving Less for Better Air: Impacts of a Public Information Campaign." *Journal of Policy Analysis and Management* 22(1): 45-63.
- Imbens, Guido and Thomas Lemieux. 2008. "Regression Discontinuity Designs: A Guide to Practice." *Journal of Econometrics* 142(2): 615-635.
- Innes, Robert and Abdoul G. Sam. 2008. "Voluntary Pollution Reductions and the Enforcement of Environmental Law: An Empirical Study of the 33/50 Program." *Journal of Law and Economics* 51 (2): 271-296.
- Khanna, M. 2001. "Non-mandatory Approaches to Environmental Protection." *Journal of Economic Surveys* 15 (3): 291-324.
- Koehler, Dinah A. 2007. "The Effectiveness of Voluntary Environmental Programs – A Policy at a Crossroads?" *Policy Studies Journal* 35(4): 689-722.
- Konar, S. and M. A. Cohen. 1997. "Information as Regulation: The Effect of Community Right to Know Laws on Toxic Emissions." *Journal of Environmental Economics and Management* 32 (1): 109-124.
- Lee, David S. and Thomas Lemieux. 2010. "Regression Discontinuity Designs in Economics." *Journal of Economic Literature* 48: 281-355.
- Ludwig, Jens and Douglas L. Miller. 2007. "Does Head Start Improve Children's Life Chances? Evidence from a Regression Discontinuity Design." *Quarterly Journal of Economics* 122(1): 159-208.
- Lyon, Thomas P. and John W. Maxwell. 2007. "Environmental Public Voluntary Programs Reconsidered." *Policy Studies Journal* 35(4): 723-750.
- Mansfield, Carol, F. Reed Johnson, and George Van Houtven. 2006. "The Missing Piece: Valuing Averting Behavior for Children's Ozone Exposures." *Resource and Energy Economics* 28: 215-228.

- McCrary, Justin. 2008. "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test." *Journal of Econometrics*. 142(2): 698-714.
- McDermott, Marc, M. Rajendu Srivastava, and Sarah Croskell. 2006. "Awareness of and Compliance with Air Pollution Advisories: A Comparison of Parents of Asthmatics with Other Parents." *Journal of Asthma* 43: 235-239.
- Neidell, Matthew. 2004. "Air Pollution, Health and Socio-Economic Status: The Effect of Outdoor Air Quality on Childhood Asthma." *Journal of Health Economics* 23 (6): 1209-1236.
- Neidell, Matthew. 2005a. "Incorporating Behavior into Biological Models: Understanding the Health Effects of Ozone." Center for Integrating Statistical and Environmental Science Technical Report No. 25, available at: <http://www.stat.uchicago.edu/~cises/research/cises-tr25.pdf>
- Neidell, Matthew. 2005b. "Public Information and Avoidance Behavior: Do People Respond to Smog Alerts?" Center for Integrating Statistical and Environmental Science Technical Report No. 24, available at: <http://www.stat.uchicago.edu/~cises/research/cises-tr24.pdf>
- Neidell, Matthew. 2009. "Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations." *Journal of Human Resources* 44 (2): 450-478.
- Nichols, Austin. 2007. "Causal Inference with Observational Data: Regression Discontinuity and Related Methods in Stata." Presented at 2007 North American Stata Users' Group Meetings. Available at: <http://repec.org/nasug2007/causal.pdf> Last accessed 27 July 2012.
- Niles, Meredith T. and Mark Lubell. 2012. "Integrative Frontiers in Environmental Policy Theory and Research." *Policy Studies Journal* 40(S1): 41-64.
- OECD (Organisation for Economic Co-operation and Development). 2003. Voluntary Approaches for Environmental Policy: Effectiveness, Efficiency and Usage in Policy Mixes. Paris: OECD Publications. Available at: <http://www1.oecd.org/publications/e-book/9703091E.PDF>

- Porter, Jack. 2003. "Estimation in the Regression Discontinuity Model." Working paper.
Department of Economics, University of Wisconsin.
http://www.ssc.wisc.edu/~jrporter/reg_discont_2003.pdf. Last accessed 27 July 2012.
- Sexton, Alison. 2011a. "Responses to Air Quality Alerts: Do Americans Spend Less Time Outdoors?" 7 December 2011 working paper. Available online at:
<http://www.tc.umn.edu/~sexto060/workingPapers/Air Quality Alerts.pdf>
- Sexton, Steve. 2011b. "Paying for Pollution? How General Equilibrium Effects Undermine the 'Spare the Air' Program." March 2011 working paper. Available online at:
<http://works.bepress.com/sexton/12>
- Shapiro, Marc D. 2005. "Equity and Information: Information Regulation, Environmental Justice, and Risks from Toxic Chemicals." *Journal of Policy Analysis and Management* 24(2): 373-398.
- Shimshack, Jay P., Michael B. Ward, Timothy K. M. Beatty. 2007. "Mercury Advisories: Information, Education, and Fish Consumption." *Journal of Environmental Economics and Management* 53(2): 158-179.
- Welch, Eric, Xiaohua Gu, and Lisa Kramer. 2005. "The Effects of Ozone Action Day Public Advisories on Train Ridership in Chicago." *Transportation Research. Part D: Transport and Environment* 10(6): 445-458.
- Zivin, Joshua Graff and Matthew Neidell. 2009. "Days of haze: Environmental Information Disclosure and Intertemporal Avoidance Behavior." *Journal of Environmental Economics and Management* 58: 119-128.

APPENDIX A: DATA COLLECTION IN PIEDMONT PARK

During the summer of 2005, two undergraduate students were trained to make observations in a prominent, central Atlanta park (www.piedmontpark.org). At each sitting, the observer would sit on a park bench and look ahead at a fixed point across the path. He would record the characteristics of each group passing in front of him for a 30-minute spell. Then, he would move to another location in the park for another similar sitting. The seating location and fixed point was identical across all sittings for each of the two locations. One park location, at the main (western) pedestrian entrance, was selected for maximum traffic. The other park location, near the other (southwestern) primary pedestrian entrance, was selected to capture predominantly exercisers and those taking laps around Lake Clara Meer. Their unit of observation was a “group passing by”. Each group was coded for the time of observation, the size of the party (mean = 1.92, median = 1) as well as several other characteristics (e.g., mode of travel, activity, dogs, age, gender). Multiple activities were coded according to whether the passersby were observed to be exercising, socializing, playing, taking care of children, etc. Age codes were limited to how many passerby were clearly over age 60, how many were clearly under age 15, and how many were toddlers or younger. Because there was no interaction whatsoever with park users, and given the difficulty of estimating ages of people passing by, the age observations may be inaccurate. (For purposes of this study, this might not systematically bias the results, or it might introduce measurement error that serves to attenuate the estimated effects.) At the beginning and end of each sitting, the observer would record the total number of people visible from their position (whether they were passing by or not).

The sittings were scheduled for Mondays, Wednesdays, Fridays, and Saturday. (The Monday, July 4 date was switched to July 5.) On each weekday, four sittings were scheduled. The first began at one location around noon, the second commenced at the other location approximately 38 minutes later. The third sitting began at one location around 5:00pm, followed about 38 minutes later by the fourth sitting at the other location. On weekend dates, only two sittings were scheduled

(one for each location) with a start time at approximately 2:00pm. (The start times for the first sitting ranged from 11:00am to 1:45pm with an average of 12:04. The start times for the third sitting ranged from 3:40 to 5:30 with an average of 4:45pm.) The dates ranged from May 27 to August 1.

[TABLE 3 ABOUT HERE]

APPENDIX B: A BEHAVIORAL MODEL OF MODE CHOICE AND AIR QUALITY

Consider a model of a traveler who must choose a mode of transport. For simplicity, variables will be presented here in continuous form, although reality likely constrains many to be discrete choices. The advantage to presenting the decision model in mathematical form is in its transparency and precision. This lets the analyst clarify which and how factors influence choices and strips away nonessential elements. Let the actor's utility (U) depends on travel time (T), exposure to environmental risks (E), and a "warm glow" (G) feeling from making an environmentally friendly choice. Assume that $U = U(T, E, G)$ is increasing in G and decreasing in T and E . Let M describe the mode choice. In a discrete setting, $M = 0$ for drivers, and $M = 1$ for those taking public transit or walking. In a continuous setting, M might span a continuum from driving alone ($M = 0$) to walking ($M = 1$), with other modes such as rail, bus, and biking ranging in between. As M increases, travel times T increase as well as exposure E (i.e., $T_M > 0$, $E_M > 0$). Let environmental exposure $E = E(M; P)$ where P is ambient pollution concentrations and $E_p \geq 0$. Let travel time $T = T(M; A, M_{-i})$, where A is a binary "smog alert" and M_{-i} represents congestion or the average amount of M chosen by other travelers. Assume that $T_{MA} \geq 0$ as the additional travel time of "going green" is unlikely to be less on smog alert days and may even be more (Niedell and Cutter 2007). Further, assume the marginal exposure penalty of greener travel does not fall on alert days. E_{MA} should be positive if exposure is effectively zero when $M = 0$, regardless of pollution levels, and alerts correlate with P . The warm glow $G = G(M; A)$ such that $G_M \geq 0$ and $G_{MA} > 0$ as "going green" contributes to a warm glow feeling, and this marginal utility increases when an alert has been sounded.¹³ Finally, assume that the individual decisionmaker is inconsequential as far as affecting congestion (i.e.,

¹³ The essential assumption here is that the effect of A on the marginal utility of G be positive (i.e., $\partial U_G / \partial A > 0$).

This is done by assuming $G_{MA} > 0$ and $U_{GA} = 0$. Alternatively, this could be modeled as $G = G(M)$ such that $G_M \geq 0$ and $U_{GA} > 0$. In that case, the $U_G G_{MA}$ term in equation (1) can be replaced by $U_{GA} G_M$ with equivalent effect.

$\partial M_{-i}/\partial M \equiv M_{-iM} = 0$) and affecting air pollution (i.e., $\partial P/\partial M \equiv P_M = 0$). Of course, in the aggregate, these trivial impacts of individuals might amount to significant impacts. The traveler thus takes A , P , and M_{-i} as given.

The actor chooses M to maximize U , leading to first-order conditions that:

$$U_M = U_T T_M + U_E E_M + U_G G_M \geq 0$$

The second-order conditions ($U_{MM} < 0$) are likely to hold unless $U_{TM} \gg 0$.¹⁴ For a traveler who has selected an optimal mode M^* in equilibrium, the policy question is how exogenous shocks to P and A affect M^* . For alerts:

$$U_{MA} = U_{TA} T_M + U_T T_{MA} + U_{EA} E_M + U_E E_{MA} + U_G G_{MA}$$

As long as alerts do not affect the marginal disutility of travel time and exposure, this expression reduces to:

$$U_{MA} = U_T T_{MA} + U_E E_{MA} + U_G G_{MA}$$

The first two terms are nonpositive while the last one ($U_G G_{MA}$) is positive. Thus, whether drivers switch to higher or lower M values depends on whether the alert has a greater effect on the disutility of travel time and exposure or a greater effect on the warm glow of contributing to the public good.

The inequality condition is:

$$(1) \quad -\left[U_T T_{MA} + U_E E_{MA} \right] \begin{matrix} > \\ < \end{matrix} U_G G_{MA} \Rightarrow \frac{\partial M^*}{\partial A} \equiv M_A^* \begin{matrix} < \\ > \end{matrix} 0$$

¹⁴ That “going green” effects a much smaller disutility of time is an important point of emphasis in many marketing campaigns for public transit, including Atlanta’s. This model supports this marketing strategy, as a decision-maker convinced that U_{TM} is very large will tend in equilibrium to eschew driving in favor of greener alternatives.

Assuming that $U_{GM} = U_{EM} = 0$, $U_{MM} = U_{TM} T_M + U_T T_{MM} + U_E E_{MM} + U_G G_{MM}$. It seems reasonable to expect that $T_{MM} \geq 0$ and $G_{MM} \leq 0$, as there is probably declining warm glow returns to greener modes just as travel times rise at an increasing rate with greener modes.

When an alert sounds, drivers who perceive greater altruistic impacts of taking an alternative model and lesser adverse effects of not driving on their travel times and exposure will tend to switch. Conversely, those travelers not driving may begin driving when an alert is sounded if they perceive greater health or congestion costs associated with their alternative modes and relatively minor warm glow losses from driving on alert days.

The relative magnitudes of T_{MA} , E_{MA} , and G_{MA} are obviously important in understanding mode switching behavior – whether the traveler undertakes averting behavior (and drives) or altruistic behavior (and takes transit). This is the most important insight from this model. The magnitude that matter most are the impacts of alerts on the marginal (time-saving, exposure-reducing, or glow-generating) effects of mode choice and *not* the direct marginal impact of alerts on travel time, exposure, or warm glow. Public officials might seek to influence these critical factors via advertising or, for T_{MA} , reducing congestion in alternative modes on alert days. Arguably, $E_{MA} = 0$ because there is no special threshold effect of pollution exposure associated with the alert. (For the 8-hour average ozone level with an alert sounded at 85ppb, E_M is virtually the same at 84ppb and 85ppb.) This makes $M_A^* > 0$ more likely to hold in condition (1). Yet if travelers are generally unaware of P and use A to proxy for it, then E_{MA} is quite likely to be nonzero (and likely positive as air pollution disproportionately affects travelers in alternative modes). Moreover, U_{EA} may be negative as travelers perceive greater marginal health risks during a smog alert. It follows that

$$(2) \quad -\left[U_T T_{MA} + U_E E_{MA} + U_{EA} E_M \right] \begin{matrix} > \\ < \end{matrix} U_G G_{MA} \Rightarrow \frac{\partial M^*}{\partial A} \equiv M_A^* \begin{matrix} < \\ > \end{matrix} 0$$

In equation (1) or (2), compared to $E_{MA} = 0$, the circumstances when A proxies for P appear less favorable to $M_A^* > 0$. Disseminating the crude indicator with an impression that threshold effects

exist can undermine the effectiveness of the alert program. There is still ambiguity in the prediction, however.¹⁵

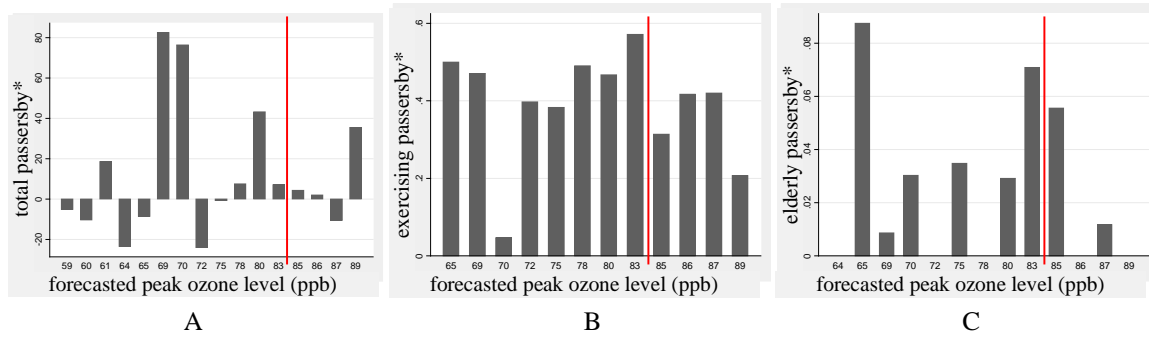
Modeling Other Exposure Choices

The economic model developed here describes a particular choice – which mode of transportation to use for a given trip – but speaks to a more general sort of decision. This approach might apply to any decision that affects the decisionmaker’s exposure or risk and garners the decisionmaker some warm glow under certain conditions.¹⁶ Here, a tradeoff exists between what is selfishly desirable (driving to reduce risk and travel time) and publicly desirable (not driving to reduce emissions). Whether altruistic actors opt for the “green” behavior in response to a public alert depends on the relative weights of this tradeoff – some of which policymakers can directly influence. The model shows some ambiguous results, especially when the alert is also the decisionmaker’s sole proxy for environmental risk.

¹⁵ From a public information campaign perspective, this model highlights a tension around the current, binary “red alert” system. Portraying a threshold effect in the alert system may encourage driving on bad days to protect one’s health, but such a threshold may be necessary to spur altruists to action on those days. An incremental signal of pollution might prove too weak a signal to trigger U_G to rise.

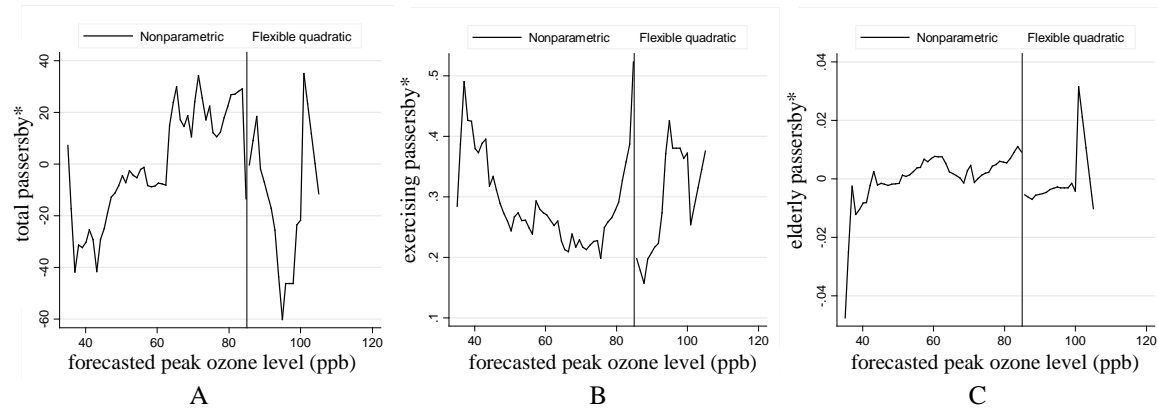
¹⁶ Suppose that M describes the location of a non-emitting activity, like exercise, whether it is exclusively indoors (0) or outdoors (1). The first-order condition above has $U_G G_M = 0$, and assume that $U_T T_M = 0$. This leaves the inequality condition in equation (1) as merely $U_E E_{MA} < 0 \Rightarrow M_A^* < 0$. The alert unambiguously leads to less outdoor (high-exposure) activity. Relaxing the assumption that $U_T T_M = 0$ might alter this, if we allow for differential travel costs for indoor activities. Suppose that the alternative to jogging outside is to exercise in a gym, which might charge or be less convenient (i.e., $T_M < 0$). If the inconvenience of indoor activities increases with alerts (i.e., $T_{MA} > 0$), the equation (2) returns to ambiguity as the decision-maker weighs the additional exposure against the addition inconvenience associated with alerts. This inconvenience might arise if gyms become congested or charge extra on alert days.

Figure 1: Mean (for binwidth=1) of total passersby, exercising passersby, elderly passersby



* Note: Means are shown at various ozone forecast levels. The *total passersby* outcome variable is measured per sitting, as a deviation from the mean as described in the text. The shares of *exercising passersby* and *elderly passersby* variables are measured on a per party passing by basis, with means weighted by party size. See the Appendix for more data details.

Figure 2: Nonparametric discontinuity (bandwidth = 6) of total passersby, exercising passersby, elderly passersby



* Note: Means are shown at various ozone forecast levels. The *total passersby* outcome variable is measured per sitting, as a deviation from the mean as described in the text. The shares of *exercising passersby* and *elderly passersby* variables are measured on a per party passing by basis, with means weighted by party size. See the Appendix for more data details.

Table 1: Estimation results from RD analysis of Piedmont Park data

			Estimated treatment effect (std. err.) N receiving positive weight		
Variable	# of obs.	mean at cutoff	Bandwidth		
			6	10	20
Total passersby per 30-minute sitting (measured in deviations from mean)	124	23.0846	7.320 (30.1895) N=24	-7.423 (23.3713) N=32	-4.518 (20.9861) N=62
Proportion of total passersby <i>exercising</i> per 30-min. sitting (measured in deviations)	124	0.0561	-0.136 (0.1277) N=24	-0.129 (0.0926) N=32	-0.100 (0.0694) N=62
Proportion of total passersby as <i>kids</i> per 30-minute sitting (measured in deviations)	124	0.0278	0.082 (0.0896) N=24	-0.019 (0.0645) N=32	-0.018 (0.0419) N=62
Proportion of total passersby as <i>elderly</i> per 30-min. sitting (measured in deviations)	124	0.0137	-0.014 (0.0119) N=24	-0.020** (0.0086) N=32	-0.017** (0.0066) N=62
Group passing by is <i>exercising</i> (weighted by group size)	4256	0.4260	-0.327** (0.0579) N=1123	-0.265** (0.0450) N=1410	-0.156** (0.0337) N=2426
Group passing by is <i>running</i> (weighted by group size)	3683	0.2427	-0.078 (0.0538) N=914	-0.169** (0.0433) N=1185	-0.177** (0.0308) N=2130
Proportion of <i>kids</i> in group passing by (weighted by group size)	4258	0.1982	0.010 (0.0315) N=1124	-0.138** (0.0217) N=1409	-0.027** (0.0164) N=2412
Proportion of <i>elderly</i> in group passing by (weighted by group size)	4258	0.0584	-0.053** (0.0132) N=1124	-0.048** (0.0089) N=1412	-0.014** (0.0063) N=2412
Proportion of <i>females</i> in group passing by (weighted by group size)	4258	0.2275	-0.142** (0.0431) N=1124	0.010 (0.0335) N=1412	0.113** (0.0268) N=2412

*, ** indicates significance at the 10%, 5% level, respectively.

Figure 3: ln(household miles driven) by ozone prediction

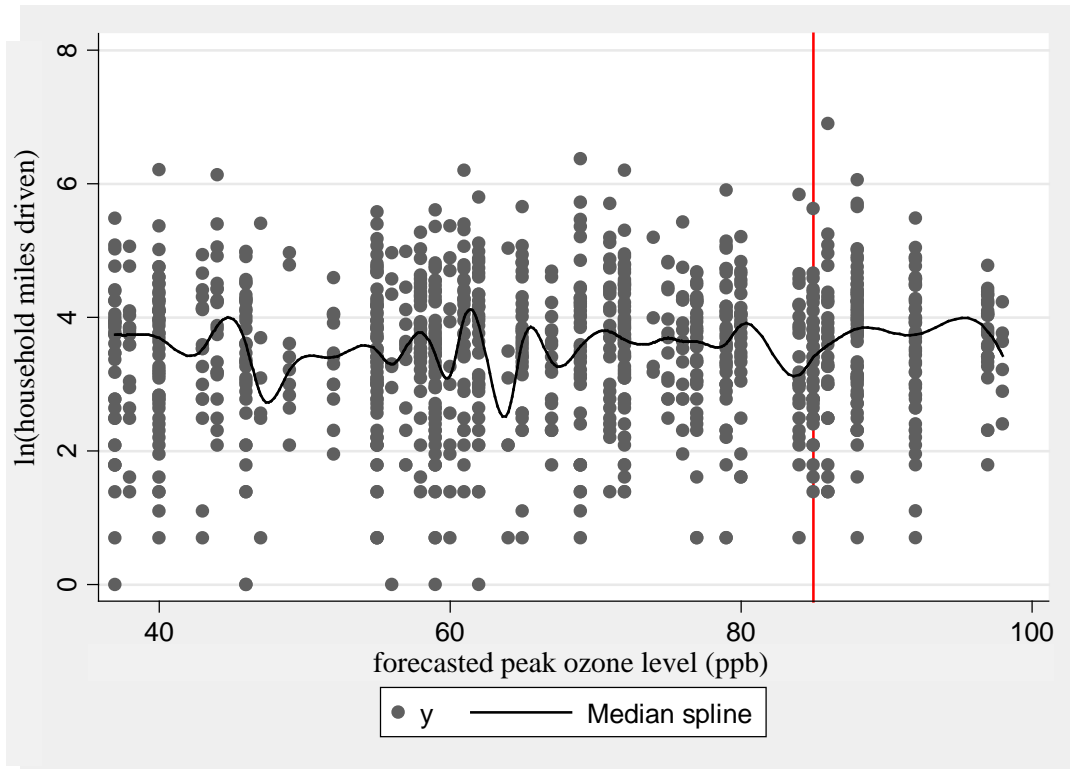


Figure 4: Weighted average of $\ln(\text{VMT})$, for binwidth=1, 2, 3

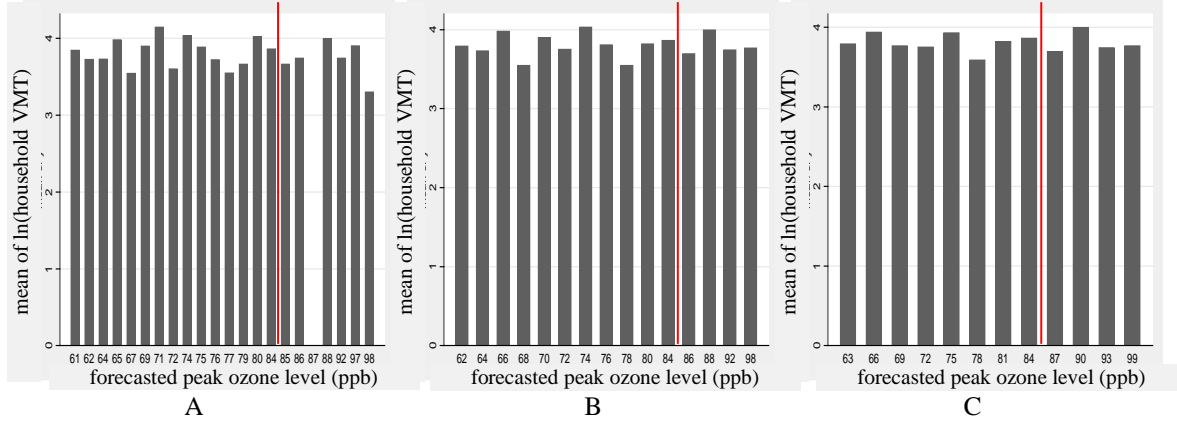


Figure 5: Nonparametric discontinuity in $\ln(\text{VMT})$, bandwidth = 3, 6, 12

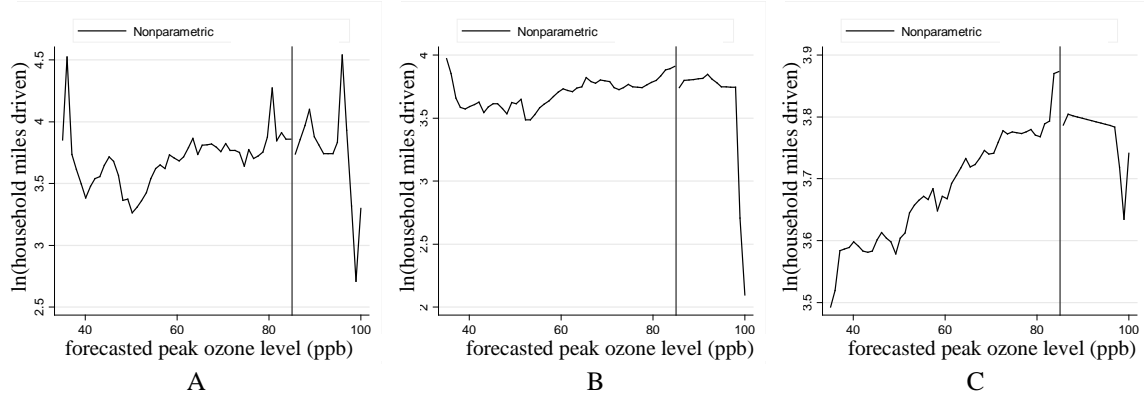


Table 2: Estimation results from RD analysis of travel diary data

Variable	# of obs.	mean at cutoff	Estimated treatment effect (std. err.) N receiving positive weight		
			Bandwidth		
			3	6	12
ln(household miles driven that day), weighted	1023	3.8204	-0.275 (0.3970) N=155	-0.169 (0.2773) N=183	-0.088 (0.2050) N=372
ln(household miles driven before 5pm that day), weighted	931	3.0302	-0.247 (0.3425) N=139	0.159 (0.2675) N=165	0.277 (0.2220) N=338
ln(household miles driven that day), weighted; miles>500 dropped	1021	3.8204	-0.121 (0.3855) N=154	-0.216 (0.2724) N=182	-0.129 (0.2022) N=371
household miles driven that day, weighted	1200	83.0679	. (38.9423) N=181	-25.227 (24.9093) N=211	-16.254 (15.9073) N=431
household miles driven that day, weighted; miles>500 dropped	1198	83.0679	-50.676* (28.2787) N=180	-37.640* (19.3224) N=210	-27.260** (12.5004) N=430
household miles driven before 5pm that day, weighted	1145	22.4691	-45.143 (29.8319) N=175	12.185 (18.6179) N=203	12.117 (12.6389) N=414
household miles driven before 5pm that day, weighted; miles>500 dropped	1143	22.4691	. (9.1062) N=174	-0.565 (7.7584) N=202	0.464 (6.8999) N=413
household size, weighted	1200	2.7439	0.248 (0.4682) N=181	-0.194 (0.3422) N=211	-0.162 (0.2687) N=431

*, ** indicates significance at the 10%, 5% level, respectively.

Figure 6: Density of observations (i.e., “share”) across ozone forecast levels

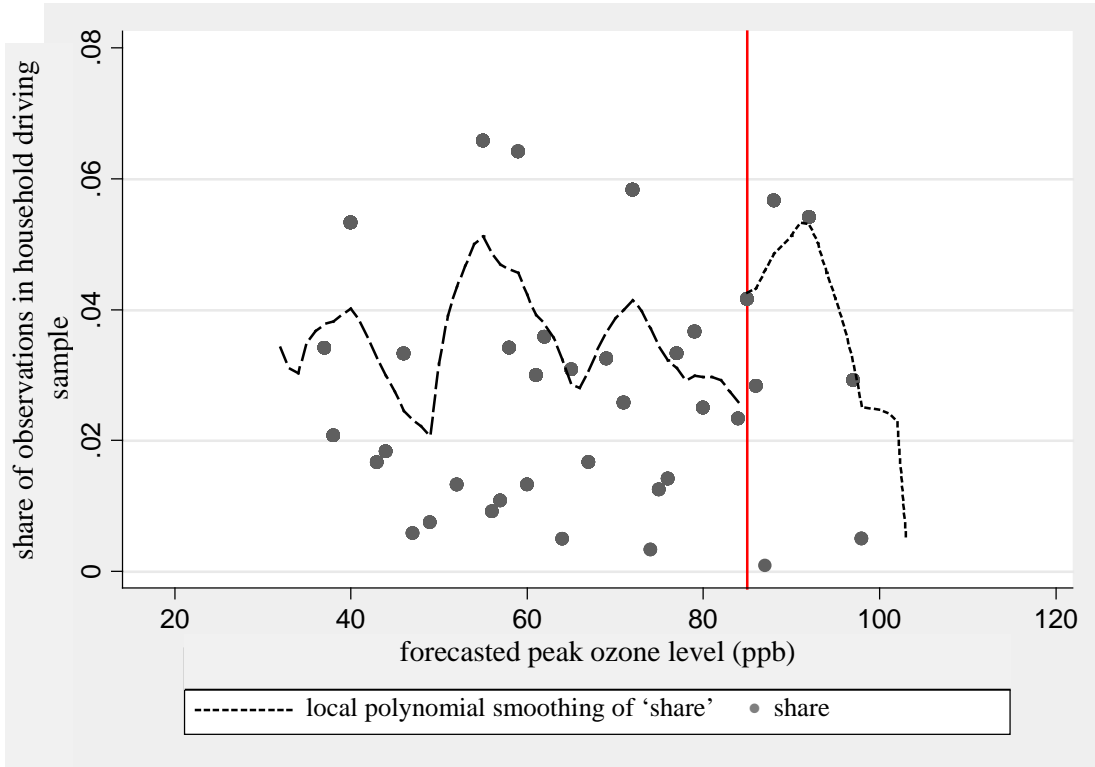


Table 3: Descriptive Statistics from Piedmont Park Sample

Variable	# obs.	mean	std. dev.	min	max
(per sitting)					
Total passersby	124	49.03	39.92	4	230
Total exercising passersby	124	16.55	12.92	0	67
Total running passersby	124	12.46	9.34	0	52
Total kid passersby	124	4.72	10.40	0	77
Total elderly passersby	124	0.89	1.41	0	6
(per party)					
Time of day	4047	15.18	2.25	11.02	18.6
Day of week (Mon.= 1)	4047	3.29	1.97	1	6
Number of people	4047	1.50	1.39	1	46
Number of elderly (over 60)	4047	0.03	0.20	0	3
Number of toddlers or younger	4047	0.03	0.21	0	4
Number of kids	4047	0.14	1.13	0	43
Number of females	3933	0.32	0.65	0	5
Exercising?	4045	0.42	0.49	0	1
Strolling?	4045	0.56	0.50	0	1
Relaxing?	4045	0.02	0.12	0	1
Childcare?	4045	0.05	0.22	0	1
Socializing?	4045	0.24	0.43	0	1
Primary mode: walk	3683	0.60	0.49	0	1
Primary mode: run	3683	0.20	0.40	0	1
Primary mode: bike	3683	0.14	0.35	0	1
Primary mode: skate	3683	0.05	0.21	0	1
Primary mode: other	3683	0.01	0.09	0	1
Forecasted ozone alert?	4047	0.17	0.37	0	1
Forecasted ozone level	4047	68.52	15.44	36	105