Voluntary Information Programs and Environmental Regulation: Evidence from ‘Spare the Air’[1]

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Voluntary Information Programs and Environmental Regulation: Evidence from ‘Spare the Air’

Abstract: This paper assesses whether individuals change their transportation choices in response to “Spare the Air” (STA) advisories, a public voluntary information program in the San Francisco Bay Area that elicits reductions in ozone producing activities. Since STAs are issued when ozone levels are predicted to exceed a particular threshold, we use a regression discontinuity design to identify the effect of STAs. We also use traffic conditions in Southern California, an area without STAs, to estimate difference-in-differences models. The results suggest that STAs reduce traffic volume and slightly increase the use of public transit, with some intriguing patterns of responses within the day, supporting a potential role for voluntary information programs as part of regulatory policy to improve local air quality.

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Environmental policy makers around the world increasingly rely on voluntary programs to improve environmental quality. The 'Community Right-to-Know Act' that led to the development of the toxic release inventory (TRI) and 'Climate Wise' are examples of landmark efforts to reduce toxic and carbon dioxide emissions, respectively (Morgenstern and Pizer (2007)).[2] Most voluntary programs target firms who, despite the notion of altruism, may respond because it affects profits through changes in consumer demand. Therefore, such programs ultimately hinge on consumers actions to improve environmental quality although there are no direct economic incentives to do so.

While most prior research has focused on firms responses to such policies,[3] the goal of this paper is to assess whether individuals directly respond to information programs by voluntarily forgoing consumption of a commodity that may increase ambient air pollution. We examine "Spare the Air" (STA) advisories, offered in the San Francisco Bay Area, which are issued on days when ground-level ozone is predicted to exceed National Ambient Air Quality Standards (NAAQS). STAs are designed to elicit voluntary reductions in automobile trips by encouraging the public to increase ride-sharing and use of public transit. Since some of the emissions from automobiles are a direct precursor to ozone formation, this program intends to lower ozone levels and improve the chances of attaining NAAQS in order to avoid costly regulations.[4]

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[2] Eco-labeling is another commonly used approach for eliciting voluntary responses, such as the Marine Stewardship Council and the Forest Stewardship Council labels.

[3] See, e.g., Hamilton (1995), Khanna et al. (1998), Konar and Cohen (1997) for evidence of the effect of TRI on stock prices and Bui and Mayer (2003) for evidence of the effect of TRI on housing prices. An exception is Reiss and White (2003), who found that households in San Diego voluntarily decreased electricity consumption in response to media campaigns during the 2000-1 electricity crisis. However, this was a one-time program that arose from a unique situation, so it is not clear how it relates to regularly maintained information programs used for regulatory purposes.

[4] These costs are largely incurred through the development of State Implementation Plans, which typically involve incorporating various technologies to reduce ozone levels.

Understanding responses to STAs serves an important role in informing highly-contested ozone regulation policy.[5] Ozone is widely believed to have significant, negative impacts on respiratory health, such as hospital admissions and mortality (Bell et al. (2004), Dominici et al. (2000), Environmental Protection Agency (2006), Neidell (2008)). Despite this, there is strong opposition to tightening ozone standards, in large part due to the increasing marginal abatement costs associated with lowering ozone from the current, historically low levels (Lieu et al. (2003)). Ozone levels are likely to increase in the future as a result of global climate change (Racherla and Adams (2006)), making this debate more contentious in the future.

Since ozone violations are based on daily concentrations,[6] STAs may be a more efficient method than traditional regulations for achieving ozone AQS because of the influence of underlying natural conditions in the ozone formation process. Ozone is formed from reactions between ozone precursors in the presence of sunlight and heat (Environmental Protection Agency (2006)). Therefore, even if ozone-causing emissions are constant throughout the year, unusually hot and sunny weather leads to high levels of ozone, partially explaining the pervasive ozone levels in California.[7] Traditional regulations that lower emissions by power plants or public vehicle fleets reduce emissions on all days, regardless of meteorological conditions. It may only be necessary to reduce emissions for the limited number of times per year when natural conditions might lead to exceptionally high ozone levels. Therefore, ozone outreach action programs, such as STA, may be less costly than traditional regulations by allowing policymakers

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[5] This debate is recently demonstrated by the lengthy legal battle over the proposed 8-hour ozone standard, which as issued by the EPA in 1997 and finally upheld by the Supreme Court in 2002 (Bergman (2004)).

[6] Current ozone standards require that "the 3-year average of the fourth-highest daily maximum measured at each monitor within an area over each year must not exceed 0.08 ppm" (40 CFR 50.9; see Federal Register of April 30, 2004 (69 FR 23996))

[7] The majority of California air quality districts do not meet national ambient air quality standards for ozone.

to focus regulatory effort only on those days when the effort is needed to avoid exceeding ozone standards.

To assess if people respond to STAs, we use administrative data on highway traffic volumes in the Bay Area and public transit ridership on the Bay Area Rapid Transit (BART). If people respond to STAs by substituting away from higher ozone-producing activities towards lower ones, we expect to see a decline in traffic volume coupled with an increase in public transit use. Whether people respond to this particular program, however, is complicated by counteracting incentives. If STAs result in a reduction in trips by some individuals, then other individuals may respond to the reduction in expected traffic (and hence reduced travel time) by undertaking more trips, resulting in a free-rider problem. In addition, evidence indicates that individuals in Southern California reduce time spent outside in response to “smog alerts”, which are also issued when ozone forecasts exceed a particular threshold (Neidell (2008)). Therefore, it is plausible that STAs signal information about risk so that individuals susceptible to ozone may decrease the use of public transit because it increases time outdoors and thus exposure to ozone. These incentives create an ambiguous prediction of the effect of STAs on transportation choices depending on the nature of the trip.

In addition, STA alerts may have a differential effect depending on the purpose of the trip and availability of alternative options. Discretionary (i.e., leisure) trips may be easier to change than work-related commuting trips because discretionary trips can be cancelled or rescheduled, as they are flexible by definition. On the other hand, most workers have little flexibility in missing a work day, especially if labor supply is fixed in the short run and telecommuting alternatives are unavailable, so commuting trips have a significantly higher cost of cancellation. Since discretionary trips are taken throughout the day, while commuting trips are concentrated in the peak rush hour periods, we examine the STA effect for each hour during the day in order to allow the response to vary throughout the day.

We use a regression discontinuity (RD) design to identify the effect of STAs on transportation choices. Since STAs are issued when ozone levels are predicted to exceed a particular threshold, we compare outcomes on days just above the threshold to outcomes on days just below the threshold. If other factors affecting transportation choices are similar around the threshold, as evidence supports, this design controls for all confounding factors. Therefore, any difference in transit outcomes can be directly attributed to the STA advisory. Furthermore, the threshold used for issuing STAs is not publicized[8] and exogenously changed over the time period we study because of changes in federal air quality standards for ozone, so it is unlikely individuals respond to the underlying index that determines STA status.

In addition, we extend our RD design for the traffic regressions by estimating difference-in-difference models that include a control group that does not have a voluntary alert program. For the control group, we use traffic volumes in the metropolitan Los Angeles area. This area has many similar behavioral and environmental factors as the Bay Area, but does not have a voluntary traffic reduction program, so controlling for changes in traffic conditions in Los Angeles further captures potentially unobserved factors common across the two areas.

Our findings indicate people respond to STAs, but this is only detected when we employ the regression discontinuity model. STAs reduce total daily traffic by 2.5 to 3.5 percent, with the largest effect during and just after the morning commuting periods. STAs have no statistically significant effect on total daily public transit use, but borderline statistically significant effects during peak commuting periods. Our results are robust to alternative specifications of the RD

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[8] For example, we contacted the Bay Area AQMD several times until we could locate the correct employee who knew the STA threshold.

and the inclusion of traffic monitor or public transit station fixed effects. Given the robustness of our results, the plausible time of day patterns, and evidence of substitution from driving to public transit, it seems unlikely our results are driven by unobserved heterogeneity. Our results support a potential role for voluntary information programs as a part of regulatory policy to improve local air quality, though a more formal analysis on the ultimate impact on ozone levels is warranted.

1. Background on Ozone and STAs

Ozone (*oz)* is not directly emitted into the atmosphere, but is formed from interactions of nitrogen oxides (*NOx*) and volatile organic compounds (*VOCs*) in the presence of heat, sunlight, and solar radiation (*solrad*):

(1) $oz = f\,(NOx,\ VOC,\ weather,\ solrad).$

Because of this process, ozone levels vary considerably both across and within days – it tends to peak in the summer and middle of the day when heat, sunlight, and/or solar radiation are at their maximum (U.S. EPA (2006)). Ozone levels are particularly high in California because of greater amounts of heat and sunlight that lead to ozone formation, the mountains that help to “trap” pollutants, and the temperature inversion layers that enhance ozone production.

NOx and VOCs, the two primary precursors to ozone, are directly emitted. Both stationary and mobile sources, primarily automobiles, contribute considerably to NOx and VOC emissions. For example, 49 percent of NOx emissions in the San Francisco Bay Area, Sacramento Valley, and San Joaquin Valley are due to on-road mobile sources, with 55 percent of that coming from gasoline vehicles (Air Resources Board (2003)).

Although there are no direct air quality standards for NOx and VOC, NAAQS for ozone are based on measures taken on a daily basis. For example, in order for an area to attain NAAQS for 8-hour ozone, “the 3-year average of the fourth-highest daily maximum measured at each monitor within an area over each year must not exceed 0.08 ppm” (40 CFR 50.9; see Federal Register of April 30, 2004 (69 FR 23996)). Because this is based on a peak observation and not the mean over a period of time, despite extensive efforts to reduce ozone levels, unexpected weather can lead to air quality violations.

Policy makers consider various approaches to achieving NAAQS. One approach is to shift the distribution of NOx and VOCs to the point that the maximum amount of emissions will not result in an ozone violation. Given the inherent fluctuations in weather, ensuring that violations no longer occur even on hot, sunny days can impose extensive costs to firms and individuals, especially if there are increasing marginal abatement costs to reducing ozone levels.

An alternative approach to avoiding NAAQS violations is to respond to forecasted weather conditions by limiting sources of pollution only on days when violations may occur. This can be accomplished by targeting the sources with the lowest cost of shifting pollution generating activities to other days. Since factories face considerable costs to alter their production on a temporary basis, one potential avenue is to target individuals. In particular, individuals who commute by automobile may find it less costly to switch transportation behaviors temporarily, making this a potentially more efficient policy.

The Bay Area Air Quality Management District (BAAQMD), which encompasses all of seven counties - Alameda, Contra Costa, Marin, San Francisco, San Mateo, Santa Clara and Napa - and portions of two others - Solano and Sonoma, has issued STAs since 1991. In order to provide ample notification for people to alter their behavior, STAs are issued one day in advance based on air quality forecasts, typically by noon the day before people are encouraged to limit their contribution to pollution. Since the goal of an STA is to achieve reductions in ozone throughout the region, STAs are widely publicized on the television, radio, email, and newspaper to target all residents in the Bay Area.

STA alerts are issued when the ozone forecast was predicted to exceed .081 ppm in 2003 and 2004 and .084 ppm in 2001 and 2002.[9] This change in the trigger rule is due to changes in federal air quality standard for ozone, and not an endogenous policy change to influence responses to STAs. Importantly, the trigger is not based on particular non-linear changes in ozone concentrations, such as changes in visibility or health effects, so days just at or above this trigger can be viewed as otherwise equivalent to days just below it.

Air quality forecasts are provided for five regions (*r*) within the BAAQMD. An STA, which is disseminated the day before and day of the expected high ozone conditions, is issued based on the maximum ozone forecast across regions according to:

$$(2) \qquad STA_t = 1\{oz^f_t = \max_t (oz_{rt})\};\ oz_{rt} = f\,(oz_{rt-1},\ weather^f_{rt},\ solrad_t) \geq trg\}$$

where oz^f is forecasted ozone and *trg* is the trigger rule for issuing STAs. Note that traffic conditions are not used in the ozone forecast. According to equation (1), however, automobiles contribute to observed ozone levels through NOx and VOC. Therefore, temporarily reduced use of automobiles will lower NOx and VOC levels, which lower expected ozone levels, and increase the probability of attaining NAAQS.

Air quality forecasts are also publicly available through various local news media as required by federal law (U.S. EPA (1999)), regardless of STA status. The air quality forecasts are provided as part of the air quality index, which ranges from 0-500 and is indexed so that a value of 100 corresponds to the National Ambient Air Quality Standards as set forth in the Clean Air Acts. A brief legend summarizing the air quality is also provided: 0-50 good; 51-100

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[9] .081 ppm corresponds to 92 on the air quality index, an alternative scale frequently used for conveying air quality forecasts, and .084 corresponds to 100.

moderate; 101-150 unhealthy for sensitive groups; 151-200 unhealthy; 201-300 very unhealthful; and 301-500 hazardous. This suggests people may generally be aware of air quality levels even on non-STA days, which has two potential implications for our research. One, the level at which an STA is issued also corresponds with reaching the “unhealthy for sensitive groups” category, so STAs may serve as a signal of health risk as well, which we incorporate into our model. Two, given that people may use the continuous forecast in their transportation decisions, this paper assesses responses to the information contained in STAs above and beyond the information contained in the continuous forecast.

Although STAs and other comparable advisory programs have existed for several years, there are only a handful of studies examining whether people respond to them. Schreffler (2003) focused on STAs by conducting a small telephone survey in the Bay Area that requested daily travel activities, and found a statistically significant 4.8 percent reduction in trips. Cummings and Walker (2000) examine a similar voluntary program in the Atlanta, GA area on hourly traffic volumes and found statistically insignificant effects. Welch et al. (2005) examined the impact of ozone advisories on hourly public transit in Chicago, IL and found increases during peak commuting periods and decreases during non-peak hours.

Our study offers several important innovations. One, Schreffler (2003) relies on self-reports of transportation choices, while we use observed reports of such choices. Two, although estimates from Welch et al. (2005) are reported as statistically significant, standard errors were not adjusted to account for observing multiple stations per date despite one advisory applying to the entire region, which leads to under-estimates of standard errors (Moulton (1986)). We account for this Moulton effect by allowing for within day correlations in our error term. Three, Cummings and Walker (2000) and Welch et al. (2005) include traffic or public transit lags from the previous hour, which in effect is comparing whether transportation choices changed within a day. For determining whether these programs have an effect on transportation choices, it is appropriate to examine how transportation patterns change across days, i.e. when an STA is issued vs. when an STA is not issued, so we include lags from the previous day. Four, advisories are often issued on warmer, sunnier days, so that confounding may be a concern. We exploit a regression discontinuity design to confront this and provide several robustness checks that support the validity of our model. Five, we examine the impact of STAs on both traffic and public transit to provide a more comprehensive picture of STAs.

2. Theory

To determine the conditions under which individuals respond to STAs, we develop a model where individuals receive value from contributions toward environmental goods even if they do not directly benefit from these goods. This is akin to 'existence value' -- individuals value the existence of goods they do not use in any way, such as the preservation of land -- in the environmental economics literature and to the 'warm glow' individuals get from giving to public charities.[10] We generally follow the warm-glow model except we assume individuals receive greater altruism benefits from their actions as pollution problems worsen. That is, the benefits individuals receive when switching from driving to public transit are greater as ozone increases.

To formalize our model, utility is affected by a composite good (z), time spent traveling (t), health effects from exposure during transit (h), and environmental altruism (s), which involves their contribution to ozone levels. People do not enjoy traveling, so utility is decreasing in travel time. Health costs are weakly increasing in ozone level, $h[oz] \geq 0$, but for the vast majority of the population, their health is unaffected by ozone at currently observed levels, as the

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[10] See Freeman (2003) for a review of the concept and Clarke (2003) for a recent example of existence valuation, and Andreoni (1995) for evidence of warm-glow.

"unhealthy for sensitive groups" message indicates. Mass transit may results in health costs because it involves spending more time outdoors as a result of walking to a transit station or waiting for public transit to arrive, which increases exposure to ozone.[11] Individuals spend their exogenously determined earnings[12] (w) less the monetary cost of commuting (c_j) on consumption of z. Since each person's polluting activities make a minimal contribution to overall pollution levels, we consider each person a price-taker in the ozone production market. That is, one individual's mode of transportation has no effect on ozone levels to a first approximation.

Individuals have three main choices (indexed by j) for each possible trip they might take during a day: drive alone (d), use public transit (p), or not take a trip (0). We eliminate a fourth choice of carpooling because we do not observe carpool trips in our data, but this does not impact the hypotheses we test. The associated travel time for each mode j (t_d, t_p, t_0) may be a function of STA because driving time is affected by the number of drivers on the road ($D=\Sigma d$), which is the total number of commuters minus the total number of public transit riders. If some drivers switch from driving alone to public transit, then the equilibrium driving time decreases because there are fewer cars on the road.[13] We assume public transit time is not affected by an STA because fixed time schedules allow increased ridership without delays (as long as there is spare capacity).

Each transportation mode then gives the following utility for individual i:

(3a) $y_{i,0} = \beta_0 X + u[(w)] - t_{i,0} + s_i[oz]$

(3b) $y_{i,d} = \beta_d X + u[(w-c_d)] - t_{i,d}[D[STA]]$

(3c) $y_{i,p} = \beta_p X + u[(w-c_p)] - t_{i,p} + s_i[oz] - h_i[oz]$

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[11] Ozone rapidly breaks down indoors (Chang et al. (2000)), so we assume public transit involves comparable exposure to ozone as driving once people have boarded.

[12] We assume labor supply is fixed in the short-run, but could alternatively let travel time affect time available for work. This does not affect the insights from our model.

[13] This is only true when highway delays exist, which is common in the Bay Area.

where consumption of the composite good is given by $z_j=(w - c_j)$ and X is a vector of transportation mode characteristics that affect the utility from transportation mode j but do not vary with the expected ozone level.[14] We allow health costs (h), travel time (t), and warm-glow (s) to differ by individuals. For instance, individuals who are more susceptible to the effects of ozone may incur greater health costs from using public transit because the additional exposure from walking to a transit station or waiting for transit to arrive has a greater impact on their health than driving. Individuals choose the mode y_j such that $y_j = y_{max} = max[y_0, y_d, y_p]$.

To assess how STAs affect travel modes, we assume an STA functions as a signal of higher ozone levels (i.e., $\delta STA=\delta oz$) for those utility components that are a function of ozone levels. This is a reasonable assumption because an STA is the most easily accessible signal of higher ozone levels in the Bay Area. With this setup, the effect of an STA on the change in utility for each travel mode is given by equations 4a-4c:

(4a) $\delta y_o/\delta STA = \delta s_i/\delta oz \geq 0$

(4b) $\delta y_d/\delta STA = -\delta t_{i,d}/\delta oz \geq 0$

(4c) $\delta y_p/\delta STA = -\delta h_i/\delta oz + \delta s_i/\delta oz$

Equation (4a) indicates that forgoing a trip in response to the STA provides a warm-glow, which increases utility from that choice. Equation (4b) indicates that an STA alert provides no warm-glow for the driving alone alternative but reduces travel time, which also increases utility from that choice. Equation (4c) indicates that an STA alert provides a warm-glow for the public transit mode but may also increases potential health costs, so the net effect on utility is

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[14] Wages (w) could also vary by j if, for example, taking public transit makes someone late to work, but this does not impact our predictions since w is absorbed into z, which already varies by j.

ambiguous.[15] These derivatives alone do not imply that individuals choose a particular travel mode, but instead reflect the change in utility from choosing a particular travel mode when an STA is issued.

We assess the effect of STAs on two distinct transportation trips: commuting trips and discretionary trips. We draw this distinction because labor supply is typically fixed in the short run, so canceling a trip is not an option for commuting trips for the vast majority of individuals. Schreffler (2003) found that for people who identify as reducing trips due to an STA, only 14.8% of trips were work related and the rest were not. Moreover, discretionary trips tend to occur throughout the day, so there is a greater chance that these trips occur during the middle of the day when ozone levels peak.

2.A. Commuting trips

For commuting trips, we rule out the option of canceling a trip because of fixed labor supply and only compare (4b) to (4c). Since ozone levels peak during the middle of the day, they are much lower during typical commuting periods, so any health effects from ozone exposure are minimal. These derivatives imply individuals decrease the probability of driving (increase the probability of using public transit) if the environmental warm-glow outweighs the reduced travel time from emptier highways. Therefore, although STAs are designed to decrease automobile trips, by lowering traffic volumes they also have the perverse effect of providing an incentive to increase driving and reduce public transit use. This perverse incentive only kicks in if people respond to STAs in sufficient volume to improve traffic speeds, so it is likely to attenuate the impact of STAs on traffic volumes rather than lead to a net increase in traffic volume. Schreffler (2003) study finds that divers who were not aware or did not respond to STA

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[15] In the event that there are no health costs, which may arise if an individual is unsusceptible to the effects of ozone or spends limited time outside while taking public transit, $-\delta h_i/\delta oz$ will drop out of equation (4c) and the net impact of STAs on public transit will be unambiguously positive.

alerts actually increased their number of trips on STA alert days; decreased highway congestion could be one reason for this observed increase.

2.B. Discretionary trips

For discretionary trips, we separately compare each of the 3 options (cancel trip, drive, public transit) to assess driving and public transit choices. Individuals decrease the likelihood of driving relative to canceling their trip if the warm glow exceeds their benefit from reduced travel time, the same prediction as above for commuting trips. Alternatively, individuals decrease the likelihood of driving relative to using public transit if the net effect of their warm glow less the expected health costs from public transit exceeds the reduced travel time benefit.

The model suggests that switching to public transit has low potential utility gain for discretionary trips. Canceling a trip weakly dominates public transit since it also entails receiving the warm-glow but has no potential negative health effects, so the probability of canceling increases relative to public transit. And, as just described, individuals increase the probability of public transit relative to driving only if the warm glow net of increased health costs exceeds the reduced travel time. Taken together, STAs have an ambiguous effect on discretionary public transit use, with a greater likelihood of a decrease in public transit during peak ozone periods (when potential health effects are highest).

3. Empirical Methodology

Our goal is to estimate the demand for driving and public transit. Estimation of this equation may be hampered because STAs are not exogenously assigned. The factors that determine when an STA is issued, such as weather conditions, may also affect individual's transportation choices, and it may be difficult to observe all of these factors. For example, STAs are more likely to be issued on particularly hot days when weather conditions are more favorable to ozone production. People may be likely to avoid the heat by staying in air-conditioned cars (rather than walking or bicycling) during these same conditions, leading to an increase in traffic. If we are unable to completely account for weather conditions or other unobservable factors correlated with STA days, then a naïve regression analysis could yield a spurious relationship or fail to find a significant relationship between STAs and transportation choices.

To account for such confounding, we use a regression discontinuity design to identify the effect of STAs (Cook and Campbell (1979)). This design assumes that all unobservable factors either do not vary around the STA trigger rule or evolve smoothly around the trigger rule in the same manner as the observed covariates. If so, then the discontinuity in transportation choices that occurs at the trigger rule represents the causal effect of STA advisories.

To formalize this method, we estimate the following equation for both total daily volume and separately for each hour of the day:

$$y_{kt} = \beta * STA_t + g(oz_t^f) + \delta_1 * W_t + \delta_2 * y_{kt-1} + \delta_3 * STA_{t-1} + \theta_k + \mu_t + \varepsilon_{kt} \qquad (5)$$

where y is traffic or BART volume, the subscript k represents the traffic monitor or BART station, and the subscript t represents the date. We specify y in levels rather than logs because in the hourly regressions the reduced total daily volume is the relevant factor for STAs. For example, a 5% reduction at 2 a.m. when traffic volumes are low should not have the same impact on air quality as a 5% reduction at 9 a.m. when traffic volumes are high. However, we report the percentage change in traffic from an STA for total daily volume for ease of interpretation. g is a function that relates the air quality forecast for ozone (oz^f) to transportation choices. W are other factors correlated with transportation choices, including contemporaneous and lagged observed and forecasted weather and separate dummy variables for day of week, month, and year. We include 1 lag of the dependent variable to account for any transitory shocks specific to a monitor or station, such as a highway construction project that lasts several days or longer, and lagged STA to account for any serial correlation.[16] In models using hourly measures of traffic, we include lags from the same hour on previous days (rather than previous hours on the same day). θ_k is a monitor/station random effect to account for common shocks to each monitor/station. As a specification check, we also specify θ_k as a fixed effect, which captures all time-invariant observed and unobserved factors at a given monitor or station. μ_t is a date specific random effect to account for the fact that STAs are issued at a daily level but we observe multiple monitors/stations per day.[17] ε is an idiosyncratic error term. Our hypothesis to test is $\beta=0$, that STAs have no effect on transportation choices.

We also extend our model for traffic conditions by including traffic monitors in Los Angeles as a control and estimating difference-in-difference models.[18] Since the Los Angeles area is geographically close, it shares similar air quality and meteorological conditions as the Bay Area. Furthermore, the South Coast Air Quality Management District (SCAQMD), which consists of most of Los Angeles, Orange, Riverside, and San Bernardino counties, provides air quality forecasts but does not provide an STA program.[19] Therefore, we estimate a difference-in-differences (DID) model by including traffic from various monitors in Los Angeles in our main regression:

$$(6) \qquad y_{kta} = \beta_1 * STA_t + \beta_2 * a + \beta_3 * STA_t * a + g(oz_{ta}^{f}) + \delta_1 * W_{ta} + \delta_2 * y_{kt-1a} + \theta_k + \mu_t + \varepsilon_{kta}$$

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[16] Excluding both of these lags or including additional lags had a minimal impact on our estimates, suggesting serial correlation is unlikely to plague our analysis.

[17] When we include monitor or station random effect in addition to date random effects, we estimate two-way mixed effects models (Baltagi (2005)).

[18] For the BART results, we do not estimate a difference-in-differences model because there is no comparable mass transit system in the Los Angeles area in the time period we examine.

[19] Although other metropolitan areas closer to the Bay Area, such as Sacramento, have certain features that may make them a more appropriate control group, they have STA programs.

where *a=1* if the air quality district is the Bay Area and *a=0* if South Coast. β_3 now represents the effect of STAs on traffic conditions.[20]

Using BART is only one of several options for people to alter their commuting behavior and reduce their contribution to pollution. They may carpool, work at home, ride their bicycle or walk to work, or take other forms of public transportation. All of these behaviors can lead to a reduction in traffic volume, but have no effect on BART use. Therefore, we expect a smaller effect on BART than on traffic volume.

To allow for a flexible specification of *g*, we estimate models restricting the sample to observations centered near the trigger rule. To understand how this strategy works, imagine restricting the sample to days with ozone forecast of .083 and .084 parts per million (ppm), where the trigger rule for issuing an STA is .084. We argue that any difference between the days other than the STA is random, as evidence below in Table 2 supports, so $\beta = E[y|STA=1] - E[y|STA=0]$ is the causal effect of STA on transportation choices. Since there are few observations with ozone forecasts of exactly .083 or .084, we instead restrict our sample to days centered on the trigger rule and also include the above mentioned covariates and the ozone forecast to account for any potential differences across the days above and below the trigger. We present estimates from two sample restrictions – within .02 and .01 ppm of the trigger rule – to assess the sensitivity of our estimates to the choice of *g*. Restricting the sample limits the generalizability of our results but is more likely to yield unbiased estimates for the existing policy (Dinardo and Lee (2004)). Since STAs do not need to be issued for ozone levels very

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[20] An important assumption in this DID model is that individuals in SCAQMD do not respond to STAs issued in the Bay Area. We find it unlikely that they would respond because they are served by a different media market and may not receive the warnings. Even if they did receive the warnings there would be little benefit from responding since ozone precursors in SCAQMD are unlikely to impact ozone concentrations in BAAQMD.

different from the current trigger levels for attaining NAAQS, the treatment effect near the ozone levels where STAs are currently issued is most relevant for ozone regulation policy.

4. Data

Data on STAs and ozone forecasts come directly from BAAQMD. Ozone STAs are only issued during the ozone season, which is from June 1 to October 15, when solar radiation, sunlight, and heat are at their peak.[21] Because we observe the ozone forecast for each region within BAAQMD, we follow the decision rule in equation (2) and use the maximum forecast across the regions for each day. Table 1 shows the number of STAs issued by year in the full and RD sample. There are a total of 23 STAs issued over the 4 years and, in our most restrictive RD sample, there are 44 days when the air quality forecast is within .010 ppm of the trigger rule but no STA is issued.

We are unaware of individual level data on transportation choices observed on a daily basis, so instead use daily aggregate measures. For one measure, we use traffic data from the Freeway Performance Measurement System, which is a joint project of the University of California at Berkeley and various California state agencies. This system collects real-time traffic flow and speed from freeways sensors throughout the State of California to generate various performance measures. The traffic monitors measure the number of vehicles passing through a roadway and the speed of each vehicle in five minute intervals. We use data from 92 traffic monitors available in the BAAQMD and 50 monitors available in SCAQMD. We choose Bay Area Monitors so that there is a monitor on every freeway in the San Jose, Oakland, and San Francisco area that is within BAAQMD and hence potentially affected by STAs. Given the large

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[21] During the winter season, ‘Spare the Air Tonight’ may be issued to reduce particulate matter from wood burning stoves and fireplaces and motor vehicles.

amount of monitors available, we use data from randomly selected monitors within these freeway segments. In SCAQMD we select 50 monitors at random from Los Angeles County.

While several performance measures are available from the traffic data, we use “traffic flow” as the dependent variable, which is the number of vehicles passing a detector during a given time period. This variable, aggregated appropriately, measures the total number of vehicles on that segment of the road. Although measures are available at 5 minute intervals, we must be cautious in not defining too narrow of a window that reflects traffic conditions in addition to traffic volume. For example, if heavy traffic congestion from 8:00 a.m. to 8:05 a.m. leads to slower driving speeds for the entire 5 minutes, then flow will indicate fewer vehicles on the road. Therefore, we compute all day traffic (6 a.m. – 12 p.m.) so that all vehicles clear the road and separate hourly measures within that time period.[22]

Although traffic flows are not necessarily an indication of trip reductions (it could reflect automobile accidents, road construction, etc.), our econometric analysis will not be affected as long as these other factors vary smoothly around the discontinuity. That is, if construction delays are similar both above and below the STA trigger level, then changes in traffic volume attributed to the STA will reflect changes in transportation choices.

For another measure of transportation, we use ridership on the Bay Area Rapid Transit (BART), the major commuting rail system in the region. This data, obtained from the San Francisco Metropolitan Transit Authority, consists of hourly station entrances and exits at each of the 43 stations. BART stations are mainly located in the San Francisco and Oakland areas. We compute comparable measures of the dependent variable to the traffic data. To increase responses to STAs, BAAQMD began offering free rides on BART in 2004 to all passengers

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[22] We omit volumes before 5 a.m. because they are considerably smaller than volumes throughout the day.

when an STA is issued. In that year, fare collection gates remained opened on STA days, so entrances and exits were not counted. Therefore we omit this year from the BART analysis.[23]

Table 1 also shows summary statistics for the traffic and BART measures. Monitors in the Bay Area average flows of over 65,000 vehicles per day. BART stations average roughly 6,000 passengers per day. In terms of distribution throughout the day, traffic volumes in the Bay Area are widely dispersed between the hours of 7 a.m. and 7 p.m., while BART volume shows stronger commuting rush hour patterns. These patterns suggest that BART use is more heavily concentrated among regular commuters than road traffic and that discretionary trips are a lower proportion of BART ridership than road traffic.

For the other covariates included in our model, we obtain daily data on weather from the Surface Summary of the Day (TD3200) from the National Climatic Data Center (NCDC). Using the numerous weather stations available in the Bay Area, we assign temperature and precipitation at the county level.[24] Since weather forecasts are an important component of ozone forecasts, we also add data on weather forecasts at the county level, obtained from coded city forecast (FPUS46) provided by the Monterrey station (KMTR), available from the NCDC. The weather forecasts include the predicted high and low temperatures and cloud cover, which we capture by using a set of dummy variables. Given the different sources of data used, we limit the analysis to the years where all data exists, which consists of 2001-2004 for traffic and 2001-2003 for BART.

In Table 2, we present evidence to support the quasi-experimental random assignment the regression discontinuity design affords. In this Table we assess whether the covariates given in W in equation (5) are correlated with STA status. To do this, we present the difference in means

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[23] It is also unclear whether we should include these days because BART use may change because of price changes in addition to warm-glow.

[24] Data from weather stations from some entire counties were missing for several months in 2003. These values were replaced with measures from the nearest county.

on STA versus non-STA days, with the overall means of each variable in column 1.[25] We present this for the entire sample, shown in column 2, and for our RD samples after adjusting for the ozone forecast via linear regression, shown in columns 3 and 4. For example, on STA days the maximum temperature is 14 degrees higher on average than non-STA days using all observations, but is less than 1 degree higher in the sample within .02 ppm of the STA trigger. The covariates do not balance when using the entire sample: differences for 5 of the 11 variables are statistically significant, raising potential confounding concerns. When we employ the regression discontinuity design, however, all of the covariates are balanced. This supports the notion that STAs can be treated as exogenous when exploiting the RD design so that any difference in transportation choices can be causally attributed to STAs.

5. Results

The first set of results, shown in Table 3, presents estimates of the effect of STA on total daily traffic volume in Panel A (based on equation (6)) and BART ridership in Panel B (based on equation (5)), with the only difference between the two equations being that the traffic model includes SCAQMD traffic conditions as a control. For comparison purposes, column 1 presents results using the entire sample and ignoring the ozone forecast. The results indicate a drop in traffic from STAs of approximately 1100 vehicles per monitor, but this is not statistically significant. When we estimate our preferred RD design, which limits observations to within .02 ppm of the STA trigger rule, the estimate doubles in size to over 2300 vehicles and becomes statistically significant. This indicates that naïve regressions that do not properly account for how STA days differ from non-STA days yield biased estimates. Moving to the more restrictive RD sample, which limits observations to within .01 ppm of the STA trigger rule, reveals a

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[25] Although there are multiple stations per date, we use only 1 observation per date in this Table to properly account for the Moulton effect.

comparable estimate to our preferred specification of 2000 vehicles, suggesting our estimates are not particularly sensitive to the functional form of the RD. Overall, these estimates suggest total daily traffic volumes decrease by 3-3.5% when an STA is issued.

Immediately below these results, we also present results using traffic monitor fixed effects. Thus far, we have used a traffic monitor random effect, which assumes that any monitor specific factors are uncorrelated with STAs. The fixed effect accounts for all observed and unobserved time-invariant factors specific to each monitor, so it offers one robustness check for our model. Our coefficients are largely unaffected by including the fixed effect, suggesting total daily traffic decreases in response to STAs.

For the BART results, in Panel B, we find that STAs are associated with an increase in total daily use of about 35 riders per station, which is less than a one percent change in total daily volume, but this estimate is not statistically significant. This estimate is comparable across all specifications, suggesting STAs are not associated with total daily use of public transit as measured by BART volume.

As previously mentioned, responses to STAs may vary by time of day depending on the nature of one's trip. In Figures 1 and 2 we plot the separate estimates of the STA coefficients with confidence intervals for each hour of traffic and BART volumes, respectively. We first focus our discussion on our baseline model, which focuses on the RD sample within .02 ppm of the trigger, includes monitor/station random effects, and includes SCAQMD as a control group for the traffic results only.

Examining the response to STAs by hour of day reveals several interesting patterns. For traffic, we find large, statistically significant decreases in traffic during and immediately after morning hours, statistically insignificant and smaller responses throughout the middle of the day and into the evening rush hour[26], and statistically significant decreases after 8 p.m., though smaller in magnitude than morning decreases. Although we can not empirically distinguish whether a trip is commuting or discretionary, we interpret the evidence of responses outside of rush hour as consistent with discretionary trips responding to STAs (Schreffler (2003)).[27] The decrease in morning but not evening rush hour is generally consistent with responses coming from discretionary trips since commuting involves round trip travel, although an alternative explanation is that we do not observe a significant change in evening commutes because they are smoothed over a longer period of time than morning commutes. Given that ozone concentrations typically peak in the late afternoon and traffic reductions in the day are unlikely to impact ozone levels for that day, it is somewhat surprising to see traffic decreases after 8 pm. A possible explanation for the night response is that people may not be aware of the ozone formation process and peak pollution periods, so they obtain their warm glow when shifting activities is easiest. In support of this, STAs do not specify when people should alter their behavior, only that they should. Furthermore, the Bay Areas also offers the STA tonight program during the winter, which encourages people to reduce PM 2.5 concentrations via reduced driving (and reduced use of fireplaces and woodstoves) at night, so individuals may confuse the two. Overall, these patterns tend to support the hypothesis that a significant proportion in the change in traffic volume comes from discretionary trips, though we can not rule out other explanations.

Turning to the hourly BART results, we find evidence of varying responses throughout the day consistent with model predictions, though they are generally imprecise. The two largest increases in BART use occur at 9 a.m. and 6 p.m., with both estimates borderline statistically

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[26] For example, the 95 percent confidence interval for responses at 6 pm ranges from a -1.4% to +1.2% change in traffic.

[27] We would ideally liked to have estimated models separately for weekend vs. weekday as a further attempt to distinguish between discretionary and commuting trips, but only 4 STAs occurred on weekends for the time period studied.

significant.[28] Both occur during rush hour, in the hour immediately after peak hourly entrances occur. Given that we estimate an effect for those who do not typically use BART, this just off-peak response could represent the increased marginal time associated with switching to public transit. Although statistically insignificant, we can not rule out potentially large impacts for other hours of the day, with the upper confidence interval typically the largest also during rush hour. These results are generally consistent with our prediction that the largest response for BART occurs during commuting hours.

We also find instances of decreases in BART use from 2-4 p.m., with the 3 p.m. estimate statistically significant in certain specifications. Since STAs provide information about expected air quality at a level where health concerns may arise, people may respond to STAs by reducing public transit trips in order to lower their exposure to pollution. Ozone levels peak around 3 p.m., so the decrease in BART during these hours coupled with no change in traffic volumes suggests the cancellation of public transit trips is consistent with evidence of avoidance behavior. Although the potential health benefits from the information contained in STAs are important to consider, the goal of STAs from a regulatory perspective is to reduce ozone concentrations.[29]

Our estimates are generally larger than those from other studies. Cummings and Walker (2000) found statistically insignificant effects on traffic volume in Atlanta, GA. Welch et al. (2005) found considerably smaller impacts of ozone advisories on public transit in Chicago, IL, though a similar pattern of increases during peak commuting periods and decreases during non-peak hours. Given that these findings are comparable to results from our regressions that exclude ozone forecasts and thus do not leverage the regression discontinuity, we contend that the larger impacts we find is likely due to better control for confounding factors.

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[28] The effect at 9 am is statistically significant with a window of +/- .01 ppm of the STA trigger, though the point estimate is comparable to the .02 ppm window.

[29] See Neidell (2008) for a more complete analysis of the effect of air quality information on avoidance behavior.

We also present in Figures 1 and 2 results from several alternative specifications akin to those in Table 3 as further robustness checks for our model. First, we show results with monitor/station fixed effects, which control for a large amount of variation specific to each monitor/station, and find nearly indistinguishable coefficients from those with random effects. Second, we further restrict our sample to observations within .01 ppm of the trigger, and again our coefficients are largely insensitive to this change in specification. Third, for the traffic results only, we exclude SCAQMD as a control group, and the results again show a very comparable pattern to our baseline model.

As a final robustness check for our model, we perform a falsification test by testing for a discontinuity in hourly traffic volume where one should not exist. Following Imbens and Lemiuex (2008), we use the sub-sample without an STA, which avoids estimating a regression where a known discontinuity exists, and create an artificial discontinuity at the median ozone forecast, which maximizes the power of the test to find jumps. The results, shown in Figure 3, reveal that only one of the 19 coefficients is statistically significant, which is as expected using a significance level of .05. Furthermore, the estimates are much smaller in magnitude than the main traffic results (also shown as a reference). These results provide support for the internal validity of the regression discontinuity model we employ.

6. Conclusion

As policy makers discuss ways to improve environmental quality, the adoption of voluntary programs is a potentially useful mechanism. In this paper, we evaluate the impact of the ‘Spare the Air’ program offered in the San Francisco Bay Area on individual transportation choices. Given that numerous areas throughout the country offer similar voluntary programs, such as Sacramento, CA, Atlanta, GA, Charlotte, NC, Houston, TX, and Pittsburgh, PA, to name a few, evaluating their impact is necessary to determine how these programs can best be incorporated into state and local efforts to meet air quality standards.

Using a regression discontinuity design that compares days where an STA was issued to days that were close to having an STA issued, we find that individuals respond to STAs by reducing ozone-causing activities. In terms of the generalizability of our results, although our RD estimates only identify a local average treatment effect (LATE) and may not generalize to advisories issued at other levels, the LATE we identify is of direct policy interest since it is the level at which air quality standards are violated. However, the Bay Area has well-developed alternative transportation modes and an environmentally aware population, so how well the results generalize to other areas will greatly hinge on local conditions.

Whether the change in transportation patterns as a result of STAs can cause a change in ozone concentrations, the ultimate goal of program, depends upon two factors. The first relates to the ozone formation process. The time from which NOx emissions leads to ozone formation is rapid -- within minutes -- so ozone chemistry suggests this is possible, which is why the program is offered in the first place (Chameides et al. (1992)).[30] However, the highly non-linear relationship between NOx and VOCs in ozone formation suggests that a decrease in NOx may not necessarily lead to a decrease in ozone, and may even increase ozone formation depending on the VOC/NOx ratio.[31]

The second factor for assessing whether the changes in transportation patterns can reduce ozone concentrations is whether magnitude of the response is large enough to cause a change. A basic statistical model, because it does not account for the complexity of ozone formation, is

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[30] This explains the strongly diurnal patterns in ozone levels, particularly in the summer months, where peak ozone concentrations typically range from .02 to .12 ppm but evenings ozone levels typically drop below .01 ppm.

[31] This is the leading theory behind the ozone weekend effect in Southern California whereby ozone levels increase on the weekends despite decreases in both NOx and VOC emissions.

unlikely to produce meaningful estimates.[32] The use of a model that simulates chemical and physical interactions, such as the Community Multiscale Air Quality (CMAQ) model,[33] is unfortunately beyond the scope of this paper.

A necessary component of this analysis that policymakers must also consider is the costs to individuals from changing behavior. Carpooling, delayed or cancelled trips, and taking public transit impose time costs to consumers that policy makers must acknowledge. Although these costs are voluntarily absorbed by consumers, the STA responses are based on a government signal that altruism is particularly valuable on certain dates. Therefore, policymakers need to know these costs and weigh them in its decisions, making this a priority for future research.

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[32] Furthermore, regional transport of NOx can lead to air quality improvements in neighboring air quality districts that must be recognized (U.S. EPA (1998)). In fact, the Sacramento Air Quality Districts automatically issues a STA if the BAAQMD issues once regardless of local conditions. However, improving air quality in neighboring districts is not part of the objective of the BAAQMD.

[33] For more information on CMAQ, see www.epa.gov/asmdnerl/CMAQ/.

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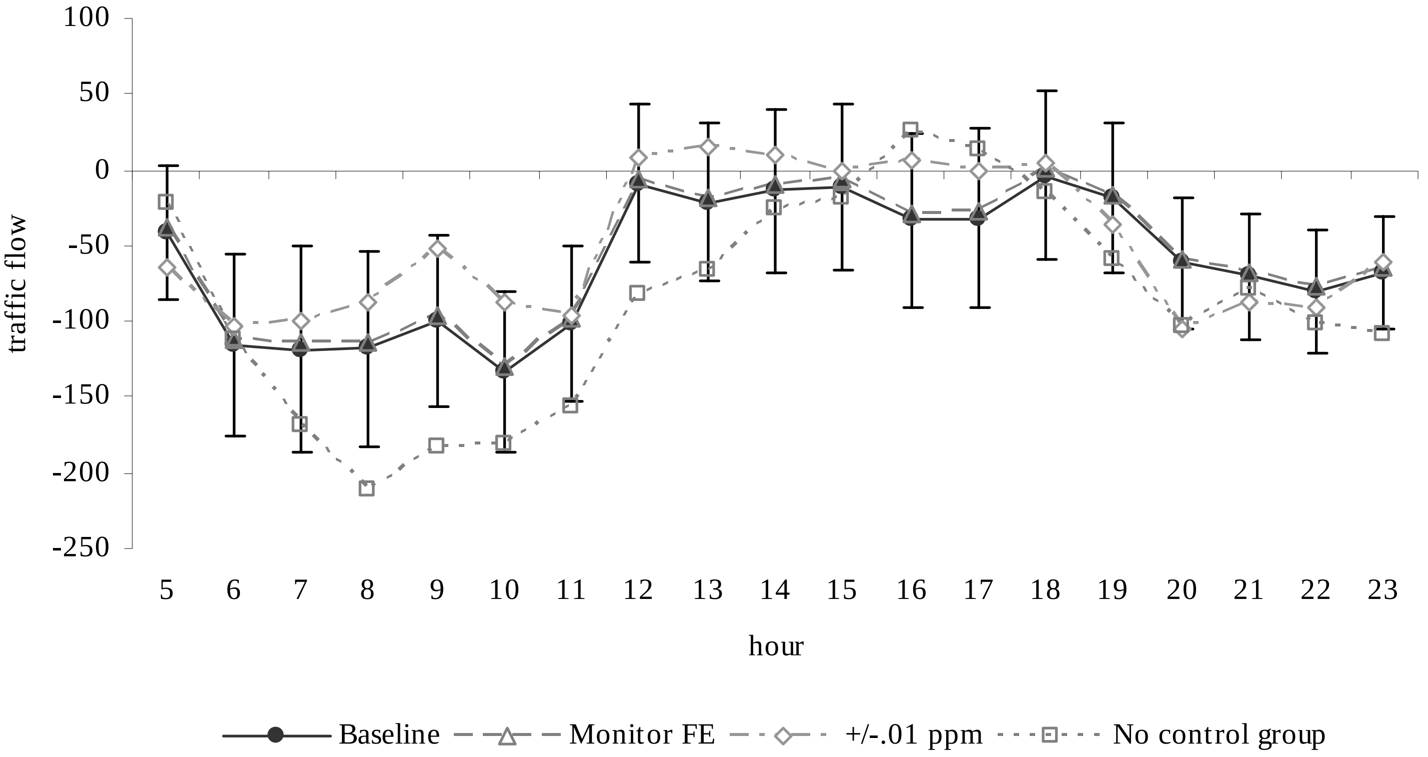
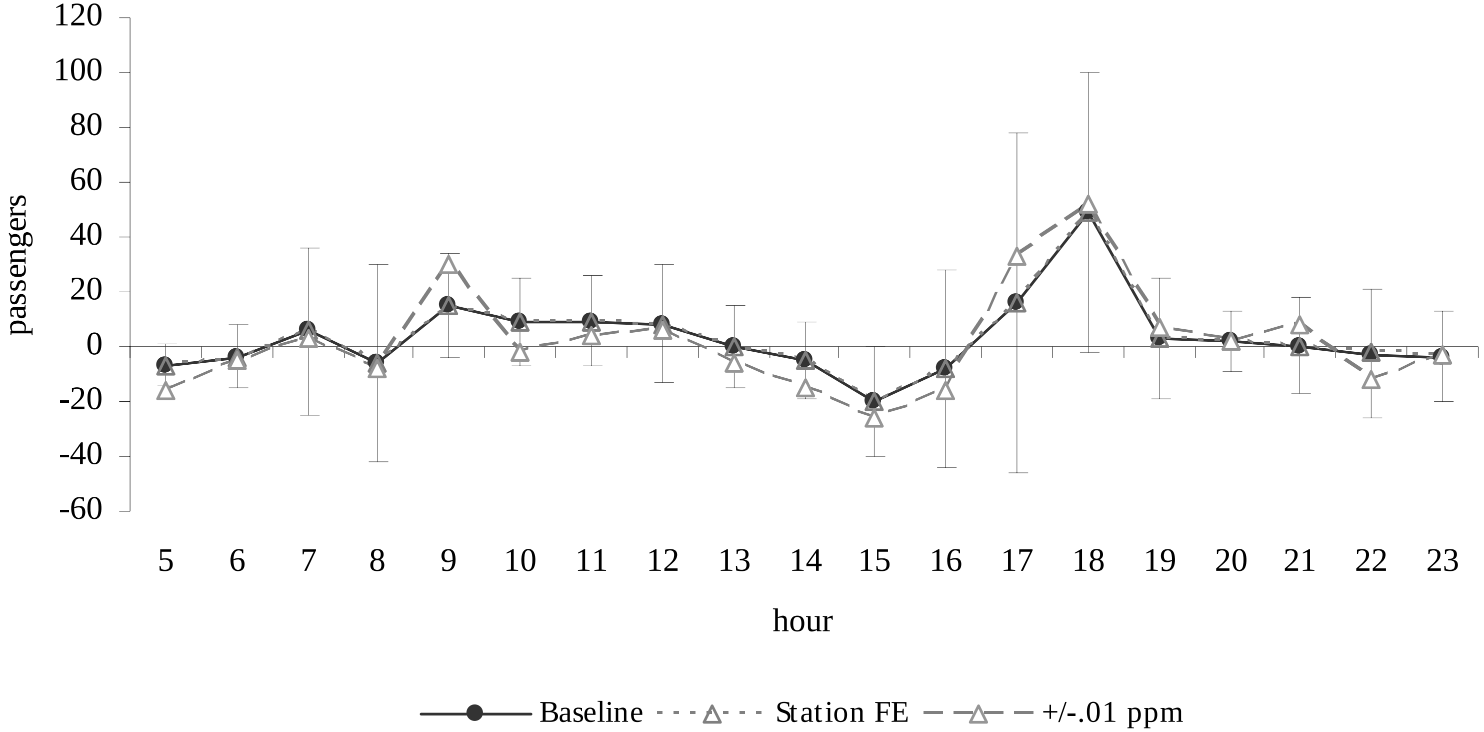
Figure 1. Effect of STA on Traffic Flow by Hour, +/- .02 ppm of trigger



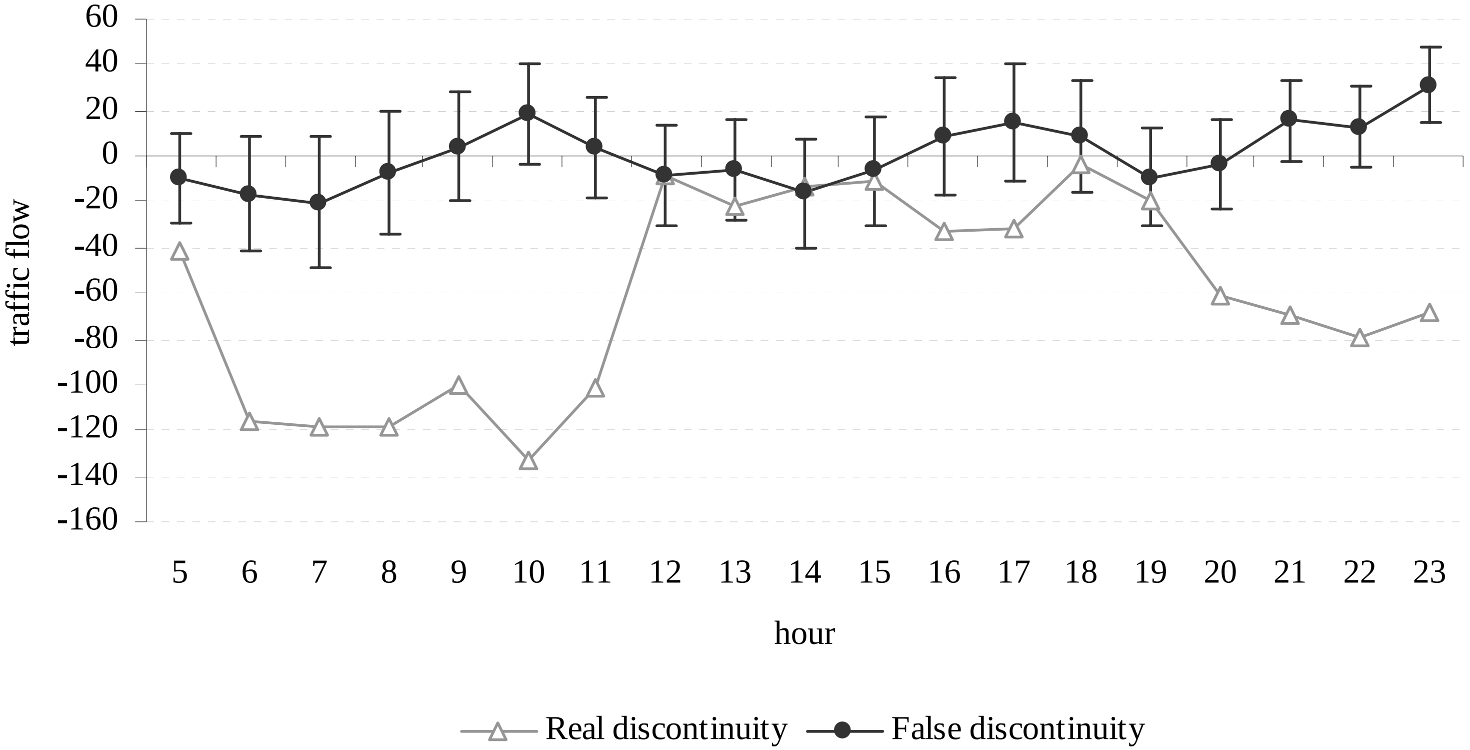
Notes: This figure contains coefficient estimates of STA on traffic conditions for each hour. All regressions include dummy variables for lagged holiday, lagged STA, month, year, day of week, and forecast outlook, controls for contemporaneous and once lagged precipitation, contemporaneous and once lagged quadratic in temperature, forecasted maximum temperature, and date random effects. 'Baseline' is estimates of equation (6) in text (along with 95% confidence intervals), which includes traffic monitor random effects, limits the sample to observations within .02 ppm of the STA trigger rule, and includes SCAQMD traffic conditions as a control group. 'Monitor FE' includes monitor fixed effects instead of random effects. 'No control group' excludes SCAQMD traffic conditions. '+/-.01 ppm' limits the sample to observations within .01 ppm of the STA trigger rule.

Figure 2. Effect of STA on BART Ridership by Hour, +/- .02 ppm of trigger



Notes: This figure contains coefficient estimates of STA on BART ridership for each hour. All regressions include dummy variables for lagged holiday, lagged STA, month, year, day of week, and forecast outlook, controls for contemporaneous and once lagged precipitation, contemporaneous and once lagged quadratic in temperature, forecasted maximum temperature, and date random effects. ‘Baseline’ is estimates of equation (5) in text (along with 95% confidence intervals), which includes BART station random effects and limits the sample to observations within .02 ppm of the STA trigger rule. ‘Station FE’ includes station fixed effects instead of random effects. ‘+/- .01 ppm’ limits the sample to observations within .01 ppm of the STA trigger rule.

Figure 3. Regression Discontinuity Falsification Test



Notes: ‘Real discontinuity’ repeats the ‘baseline’ results from Figure 1. ‘False discontinuity’ estimates the same model as the baseline model except it uses observations within .02 ppm of a false STA issued at the median ozone forecast of the sub-sample without an STA.

Table 1. Summary Statistics

A. Number of STAs by Year

year	STA=1	All observations STA=0	+/- 20 ppb of trigger STA=0	+/- 10 ppb of trigger STA=0
2001	4	130	23	7
2002	7	127	32	8
2003	9	125	63	21
2004	3	131	38	8
Total	23	513	156	44

B. Means of Dependent Variables

	Bay Area Traffic		BART	
Hour	mean	std. dev.	mean	std. dev.
5	1,664	989	70	69
6	2,792	1,608	216	194
7	3,760	2,016	518	445
8	3,896	1,824	631	477
9	3,870	1,570	375	246
10	3,803	1,423	250	141
11	3,903	1,433	237	146
12	4,013	1,457	256	193
13	4,074	1,473	257	229
14	4,298	1,542	271	296
15	4,423	1,606	333	445
16	4,520	1,660	476	754
17	4,604	1,706	696	1,310
18	4,277	1,611	582	1,108
19	3,684	1,395	313	533
20	3,058	1,222	177	286
21	2,780	1,167	144	241
22	2,351	1,116	137	299
23	1,715	952	102	238
all day	65,856	23,755	6,057	5,912

Table 2. Difference in means of covariates across STA status

	1 mean	2 All observations	3 +/- .02 ppm of trigger	4 +/- .01 ppm of trigger
precipitation	0.184	-0.069	0.024	0.023
		[0.75]	[0.61]	[0.78]
max. temperature	81.92	2.115	0.148	-0.255
		[0.00]	[0.60]	[0.52]
precipitation (in.) (lag)	0.184	-0.096	-0.009	-0.006
		[0.65]	[0.83]	[0.94]
max. temperature (lag)	82.015	1.733	0.13	-0.082
		[0.00]	[0.68]	[0.86]
forecast max. temperature	81.524	2.079	0.286	0.262
		[0.00]	[0.29]	[0.54]
forecasted sunny outlook	0.637	0.865	-0.035	-0.257
		[0.00]	[0.90]	[0.44]
forecasted partly cloudy outlook	0.326	-0.8	0.036	0.268
		[0.00]	[0.90]	[0.44]
holiday (lag)	0.024	0.13	0.221	-0.091
		[0.54]	[0.61]	[0.87]
weekday	0.707	0.273	0.16	0.017
		[0.20]	[0.64]	[0.97]
month	7.754	0.163	-0.014	0.27
		[0.45]	[0.97]	[0.54]
year	2002.5	-0.02	0.339	0.373
		[0.92]	[0.25]	[0.35]

Note: Values in each cell of columns (2)-(4) are the difference in standardized values across STA status. Columns 3 and 4 adjust for ozone forecast via linear regression. P-value that variable equal across STA status in brackets.

Table 3. Effect of STA on all day traffic and BART

	1 all observations	2 +/- .02 ppm of trigger	3 +/- .01 ppm of trigger
A. Traffic			
monitor random effect	-1105.965	-2332.260**	-2009.982*
	[823.082]	[857.489]	[1010.082]
	-{0.017}	-{0.035}	-{0.031}
monitor fixed effect	-995.185	-2111.731*	-1683.411
	[822.683]	[856.634]	[1008.854]
	-{0.015}	-{0.032}	-{0.026}
Observations	70805	24073	8768
# of days	536	179	67
# of monitors	142	142	142
B. BART			
station random effect	34.584	40.273	29.448
	[86.777]	[114.965]	[173.317]
	{0.006}	{0.007}	{0.005}
station fixed effect	32.496	41.398	39.162
	[86.697]	[114.636]	[171.911]
	{0.005}	{0.007}	{0.006}
Observations	21391	7160	2520
# of days	536	179	67
# of stations	43	43	43

* significant at 10%; ** significant at 5%; *** significant at 1%. Value in each cell represents the STA coefficient from a separate regression. Standard errors in brackets. All traffic estimates are based on equation (6), which includes SCAQMD traffic conditions as a control, and all BART estimates are based on equation (5). All regressions include dummy variables for lagged holiday, lagged STA, month, year, day of week, and forecast outlook, controls for contemporaneous and once lagged precipitation, contemporaneous and once lagged quadratic in temperature, forecasted maximum temperature, and date random effects. Numbers in braces represent the percent change in traffic from STA, obtained by dividing the estimated coefficient by the corresponding mean from Table 1.