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Alerts Work! Air Quality Warnings and Cycling[*]

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Abstract

Alert programs are central to strategies to reduce the health impacts of air pollution in many jurisdictions. Evidence that they work, however, is sparse - indeed the majority of published studies fail to find a significant impact of alerts on behavior. Alerts particularly seek to influence energetic cardio-vascular outdoor pursuits. This study is the first to use administrative data to show that alerts are effective in reducing participation in such a pursuit (namely cycle use in Sydney, Australia) and, to our knowledge, the first showing alerts to be effective in changing ANY behavior in a non-US setting. The behavioral responses are substantial, generally in the range of 14 to 35%. The results are robust to the inclusion of a battery of controls in various combinations, alternative estimation methods and non-linear specifications. We develop various sub-sample results and also find evidence of alert fatigue.

Key words: *Information-based regulation; averting behavior; urban air quality; health impacts of air pollution.*

JEL Classification: I18, Q53, Q58

Résumé

Les programmes d’alerte sont au cœur des stratégies utilisées pour réduire les impacts de la pollution de l'air sur la santé dans de nombreuses juridictions. Toutefois, la preuve de leur efficacité est rare - la majorité des études publiées ne parvenant pas à trouver un impact significatif des alertes sur le comportement. Les alertes cherchent particulièrement à influencer les activités physiques et cardiovasculaires faites en plein air. Cette étude est la première à utiliser des données administratives pour démontrer que les alertes sont efficaces à réduire la participation d’un tel exercice (notamment, l'utilisation du vélo à Sydney, Australie) et, à notre connaissance, la première étude démontrant l’efficacité à réduire tout comportement du genre dans un contexte non-US. Notre analyse trouve que les réponses comportementales sont réduites de façon substantielle, soit entre 14 à 35 pour cent. Les résultats demeurent résistants à l'inclusion d'une batterie de contrôles utilisant diverses combinaisons, de méthodes alternatives d'estimation et de spécifications non-linéaires.

Mots clés : *La réglementation basée sur l'information; comportement d'évitement; la qualité de l'air en milieu urbain; impacts sanitaires de la pollution de l'air.*

Classification JEL : I18, Q53, Q58

1 Introduction

Air pollution is a major threat to human health. The World Health Organization (WHO (2014)) estimates that air pollution causes 7 million premature deaths per year, leading that organization to label it the world's "single biggest environmental health risk". Air pollution causes more than 200,000 premature deaths per year in the United States alone (Caiazzo et al. (2013)).

Tackling the health implications of air pollution - particularly in big cities - is a key policy priority. In addition to efforts to reduce pollution levels, policymakers are putting more faith in information-based programs that enable individuals to engage in avoidance behavior. In particular, air quality alert schemes are now in operation in many cities around the world.[1] When air quality is forecast to be poor, an alert or advisory is issued and people are encouraged to change behavior to exposure. In particular, alerts encourage people to avoid strenuous outdoor activities.[2]

Our paper is the first to use administrative data to link air quality alerts to the avoidance of a strenuous (cardiovascular) outdoor activity. In particular, fine-grained bicycle-count data from the cycle network of Sydney, Australia allows us to investigate the impact of air quality alerts on cycling behavior in that city. To the best of our knowledge, there are only two existing papers that link alerts to directly-observed avoidance behavior using administrative data. One is Graff Zivin and Neidell (2009) using turnstile data to show that alerts impact attendance at two popular outdoor venues in Los Angeles (Zoo and Griffith Observatory) especially among those with children. The other is Noonan (2014) using data from a small-scale survey of people passing two park benches in a 35 day period in Piedmont Park in Atlanta. Noonan gets mixed results, finding no impact of alerts on aggregate use but evidence consistent with reduced use by older people and joggers.

[1] For two examples amongst many, Toronto started an alert program in 2005 and Hong Kong in 2013.

[2] Avoiding energetic outdoor activity is crucial in reducing the health risk of poor air quality. Carlisle and Sharp (2001) and Atkinson (1997) are among many studies that link exercising in polluted air to a variety of elevated health risks.

Estimating the effect of air quality alerts on individuals' behavior is challenging for at least three reasons. First, because of variation in pollution across regions, assigning pollution and weather variables to individuals based on individual and monitor locations can lead to measurement error. Second, omitted variable bias may arise due to confounding environmental factors. Third, the level of ambient pollution may be endogenous in the sense that individuals may shift their outdoor activities toward emission-producing substitutes in order to avoid exposure.

To account for concerns over potential endogeneity, omitted variable bias and measurement error, we employ instrumental variable (IV) methods. We use rural bushfire activity in New South Wales (NSW) to instrument for air quality. A number of considerations point to bushfire activity being a good instrument for air quality. First, rural bushfires are well-understood to have a significant negative influence on air quality in Sydney. Bushfire emissions include carbon dioxide, carbon monoxide, fine particulate matter, oxides of nitrogen and volatile organic compounds which can increase ozone concentration in the presence of sunlight. The frequently hot and dry conditions of rural NSW mean that smoke from fires can be transported across several thousand miles and have a mean lifetime of hours to weeks (Confalonieri et al. (2007)). Second, the only channel through which the fires be expected to impact cycling in the city is through their impact on air quality. The NSW Office of Environment and Health (NSW OEH) closely monitors bushfire sources in developing forecasts of air quality and the issuing of a health alert. Third, the timing of bushfires is random in the short run. Although periods of hot and dry weather may create preconditions for bushfires, their occurrence cannot be perfectly timed.

In our model, bushfire activity is introduced in a binary form as well as in combination with distance from Sydney and size of fire, although results are similar across all specifications. The instruments prove to be powerful, easily exceeding the conventional benchmark of F=10 in each of the reported specifications (Stock et al. (2002)). The cycling reduction in response to an alert is not just statistically significant but substantial in size - around 14%

under OLS estimation and 35% under the preferred IV specification. We also explore the *dynamics* of the response and find evidence consistent with 'alert fatigue'. Specifically, when alerts are issued for two successive days the second day response is much smaller (5% in the preferred IV specification) and no longer statistically significant, albeit in a much smaller sample.

Our results prove robust in sign - and fairly robust in magnitude - to inclusion of alternative combinations of controls for weather, temporal factors, etc. We also allow for the possibility of nonlinear effects of air quality on the demand for cycling whereby the observed cycling reduction is statistically significant 16% and 26% under OLS and IV estimation, respectively. Response is greater on weekends than weekdays (33% versus 30% in the preferred IV specification). In all specifications, the reduction is statistically significant at the 0.1% level or better.

We present some sub-sample results where we categorize the cycle-counter locations according to two criteria - one a measure of the "relative" density of use of a particular route across days of the week (weekdays versus weekends) and the other the "strength" of the peak usage of a particular route during normal travel-to-work windows on an average weekday. Each criterion is designed to disentangle commuting from non-commuter traffic (counters provide a count of the number of bicycle passing - no information on the purpose of the trip). Across both categorizations, we find evidence consistent with a greater impact of alerts on non-commuter traffic.

The layout of the rest of the paper is as follows. The next section summarizes the pertinent research from a number of streams of research in air quality, behavior and the impact of alerts. Section 3 describes data sources. Section 4 lays out the challenges of estimating avoidance behavior and describes our empirical strategy with results contained in Section 5. Section 6 concludes.

2 Existing research

Alert programs aim to promote public health by giving people needed information to allow them to engage in appropriate avoidance behavior - in particular to avoid outdoor cardiovascular activities when air quality is poor. Alerts are one of a number of information-based or so-called 'third wave' instruments that have becoming increasingly popular amongst environmental regulators in recent years.

Evidence of the effectiveness of such information-based programs is important for at least two reasons: (a) they are increasingly popular instrument amongst health and environmental protection agencies; and (b) failing to take proper account of individual avoidance effort (whether or not stimulated by alerts) will bias downwards the estimate of health risks associated with air pollution.

Three strands of literature provide the relevant context for our analysis. First, studies that use *direct* measures of avoidance behavior by comparing participation in activities on days with and without alerts - this is the strand to which we seek to add. Second, studies that infer something about avoidance behavior *indirectly* by assessing the relationship between air quality and health outcomes (prevalence of asthma, hospital admissions for cardiovascular and respiratory problems) in settings with and without alert programs in place. Third - given that our focus is on cycling - studies that relate how alerts impact transport choice, in particular driving behavior.

2.1 Alerts and direct measures of avoidance behavior

To quantify direct avoidance behavior previous studies use either survey data or outdoor attendance data.

Sexton (2011) uses the American Time Use Survey (ATUS) to show that individuals avoid exposure to pollution by reducing time spent in their vigorous outdoor activities by, on average, 18 minutes on alert days. Bresnahan et al. (1997); Mansfield et al. (2006); Wen et al. (2009) also use survey data.

In the study already mentioned, Graff Zivin and Neidell (2009) find that an alert in Los Angeles reduces attendance at the zoo and observatory by 15% and 5%, respectively. However, if alerts are issued for two consecutive days there is no statistically significant reduction on the second day.[3] Noonan (2014) investigates the change in usage pattern of Piedmont Park in Atlanta in response to smog alerts. He counts people passing two park benches on 35 days in the summer of 2005 of which 35 days 7 were subject to alerts. His findings show that aggregate park usage did not change on days with alerts compared to days without alerts although the evidence is consistent with a fall in usage by the elderly and joggers.[4]

To the best of our knowledge, our study is the first to use administrative data on a strenuous cardiovascular activity to quantify direct avoidance behavior and the second overall in the literature (following the small sample park bench study of Noonan (2014)).

2.2 Alerts and health outcomes

While reducing damage to human health is the primary objective of clean air regulations, it is interesting to quantify the impact of air quality alerts by exploring the effect of alerts on health outcomes.

Neidell (2004) estimates the effect of ozone pollution on hospitalization of children for asthma in California. He estimates that the decline in pollution levels from 1992 to 1998 reduced hospital admissions by between 5 and 14%. Moreover, smog *alerts* reduce the asthma hospitalization rate among children aged 6 to 12 years by 1%, providing indirect evidence of

[3]In an earlier version Neidell (2006) found no statistically significant reduction on attendance at Los Angeles County Arboretum.

[4]Noonan (2014) uses regression discontinuity methods and works with *proportions* of users drawn from different categories so significance is less straightforward to infer. His own summary is that: "(O)verall, smog alerts do not appear to significantly affect the aggregate park usage, even by sensitive subgroups, except the elderly. Individual groups of passers-by, on the other, hand do appear affected by smog alerts - exercisers and elderly compose less of park users" (p.16). Noonan (2011) uses data from the ATUS time-use diaries aggregated across a set of US cities to assess the impact of alerts on the probability of adult participation in evening sports but finds insignificant results.

a behavioral response to alerts. In another study, Neidell (2009) investigates the relationship between ozone levels and asthma hospitalization in Southern California using a regression discontinuity approach. He estimates that ozone alerts reduce asthma hospitalization by a statistically significant 16% among those aged 5 to 19. In contrast, Ward (2015) applies similar methods to data from Ontario, Canada and finds no significant effect of alerts across most age groups. The exception is a significant but small impact for those aged over 65.[5]

2.3 Alerts and transport choice

A small literature on alerts investigates the impact on driving behavior and public transit usage. Cummings and Walker (2000) develop a model to forecast aggregate daily traffic in Atlanta to compare it against the observed traffic volumes on days with an ozone alert. They find no significant effect of alerts on traffic patterns. Henry and Gordon (2003) use telephone survey data to analyze individuals' behavioral response to smog alert program in Atlanta. They find no significant effect of alerts on the number of car trips or mileage driven by non-government employees.

Welch et al. (2005) use hourly turnstile counts from the Chicago Transit Association to evaluate the impact of alerts on public transit ridership from 2002 to 2003. They find no significant impact of alerts on aggregate ridership although the hourly pattern of ridership for both the morning and evening peak were pushed later.

Cutter and Neidell (2009) investigate how individuals in the San Francisco Bay Area change their transportation mode choice in response to pollution alerts.[6] They show that while alerts reduce the volume of daily vehicle traffic by a statistically significant 3 - 3.5%, they do not significantly change demand for public transportation (i.e., Bay Area Rapid Transit (BART)).

[5]However, the threshold for issuing an alert is much higher in California (200 ppb) than Ontario (50 ppb). This can be expected to impact the personal cost-benefit of changing behavior in important ways.

[6]The Bay Area Air Quality Management District (BAAQMD) is required to issue an alert on days when the ground level of ozone is predicted to exceed National Ambient Air Quality Standards (NAAQS).

Tribby et al. (2013) use daily vehicle traffic data over a 10 year period in Salt Lake and Davis counties to investigate the effectiveness of particulate matter and ozone alerts, arriving at mixed results. ANOVA analysis shows that alerts result in a statistically significant 2.1% reduction in vehicle traffic in the city center, but traffic *increases* by 5.8% in areas closer to the edge of the metropolitan area.

3 Data

This study requires data on cycling behavior, air quality, air quality alerts and a variety of potential control variables. These are assembled from a number of governmental administrative sources all judged to be of high quality.

3.1 Cycling

Cycling in Sydney is popular both as a means for getting to and from work and as a leisure pursuit. The city contains an extensive cycle-path network. The regional location of routes are categorized by sector: downtown, inner-north, inner-west, north, northwest, west central and south. As shown in Figure 1, Sydney has 11 regional cycling routes which are equipped with counters. The NSW Department of Roads and Maritime Services operates a network of electronic path-side counters that record the number of cyclists passing at 31 points across the 11 different routes in the city (see Figure 2). We obtain the daily count of cycle movements from May 2008 to September 2013 for each of these counters as well as hourly breakdowns.

In 2013 total daily average number of cyclists was 4400 of which around 2200 use Harbour Bridge (counter number 1), 1400 use Anzac Bridge (counter number 2) and 1000 use the Parade Cycleway (counter number 3).

The average length of each cycle path is 6 km. Many of the routes are regarded locally as 'commuter' routes - primarily used for the purposes of getting to and from work. Others

- such as the path running from Sydney Park to Centennial Park - are more intensively used for leisure. Later in the paper, we investigate two different categorizations of routes.

Focusing on cycle trips as a measure of outdoor activity has several advantages. First, cycling is a widespread, energetic cardiovascular activity that takes place outdoors. As such, it is *precisely* the sort of behavior that those implementing alerts seek to influence. Second, cycling allows the use of administrative rather than survey-derived data and therefore is not subject to the vagaries of memory lapse or misrepresentation inherent in (for example) diary-based approaches. Third, cycling data are available for an extended period (more than five years) which straddles significant variations in pollutant levels and alerts. Fourth, the counters provide reliable data across a range of different *types* of routes and for weekdays and weekends which allows for some interesting analysis of sub-samples.

Table 2 presents summary data on cycle counts and other variables. Between May 2008 and September 2013, the average number of bicycles passing each counter was about 354 with a lot of variation across days and across counters. The system is about 20% more heavily used on weekdays than on weekend-days (an average count of 373 per weekday compared to 305) although again this pattern varies a lot between counters.

Counters are excluded if they count fewer than 10 cyclists per day on average which led us to drop 5 of the 31 counters. There were 16 days from May 2008 to September 2013 when counters did not record properly (more correctly the transmission of data from the remote counters to the central database did not work due to technical problems) so those dates were dropped. After cleaning the data to remove a small number of dates associated with missing values for explanatory variables - none of which we have reason to think would be correlated with air quality - there remain observation from 26 counters for a total of 1831 days.

3.2 Pollution

Data on ambient concentrations of various airborne pollutants, air quality index (AQI) and air quality alerts are obtained from the responsible government body in the state of

New South Wales, the NSW Office of Environment and Heritage (OEH). AQI is a common composite measure of air quality.

There are 21 air quality monitoring stations around the Sydney region of which 14 of were operational throughout our study period. For each cycle counter, we identified the closest air quality station by comparing their GPS coordinates and by this means ended up using data from 6 air quality monitors.

To control for potential omitted variable bias and as a robustness check, the daily measures of (one-hour) 1-h ozone (O_3), 1-h carbon monoxide (CO), 1-h nitrogen dioxide (NO_2) and 1-h particulate matter (PM_{10} and $PM_{2.5}$) are included in our model.[7]

The National Environmental Protection Council (NEPC) is responsible for regulating air quality in Australia. National standards for six major pollutants (namely ozone (O_3), carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), lead and air particles ($PM_{2.5}$ and PM_{10})) are set by legislation which also defines the methods by which these pollutants are measured and recorded. The NSW OEH is tasked with air quality surveillance. Each monitoring station collects hourly measurements of air pollution concentrations which are used to construct daily and hourly AQI measures for each site and region. NSW OEH reports daily and hourly AQI on its website and the daily measure is reported in the local media (for summary data see Table 2.)

The AQI takes a value between 0 and 500 and is categorized into six levels: Very Good AQI = 0 - 33; Good AQI = 34 - 66; Fair AQI = 67 - 99; Poor AQI = 100 - 149; Very Poor AQI = 150 - 199 and Hazardous AQI $>$ 200.

Beyond the hourly and daily values of AQI, each day at 4 pm the OEH issues an AQI forecast for the next day. If any of the three most populous regions within Sydney (Eastern, North Western and South Western divisions) are forecast to have AQI above 100 a health alert is issued by the NSW Office of Health for the whole city at the same time as the forecast. An air quality alert is announced prominently on the OEH web pages

[7] The daily measures of pollutants are the average hourly level and are found at: http://www.environment.nsw.gov.au/AQMS/search.htm.

(http://www.environment.nsw.gov.au), through twitter, e-mail and SMS notifications, and it is widely-reported in the mainstream, popular media.

The process of forecasting air quality is informed by several types of data for different sources including: (1) the Air Quality Index (AQI) value for the previous 24 hours throughout the city, (2) the Bureau of Meteorology (BOM) forecast of weather conditions including wind speed, wind direction, rainfall, temperature, temperature inversion and cloud cover; and (3) Rural Fire Service (RFS) to assess emission sources from bushfires when their presence is likely to cause elevated particle levels for the next day.

In the event a health alert is issued, the OEH also makes a statement about the particular pollutant which is primarily responsible for the alert being triggered. Over period of study 96% of air quality alerts are triggered by ozone.[8] Generally, the ambient concentrations of CO, NO_2, and SO_2, are below the NEPM standards whereas the ground level of O_3 in urban areas and the concentrations of PM_{10} and $PM_{2.5}$ in urban and rural NSW exceed the standards (NSW OEH, 2012). Alerts on two consecutive days are unusual, occurring on only 7 occasions in our 1831 day study period.

3.3 Weather

It is important to control for potential confounding impacts of weather variables. Not only do weather conditions have an important influence on ambient pollution levels, such as ground level ozone, but weather can also have a direct effect on cycling behavior.

We seek to control for daily measures of both average and maximum daytime air temperature, precipitation, relative humidity, number of hours of bright sun between sunrise and sunset, total solar exposure and wind speed in most of our regressions.

Weather data is obtained from the Australian Bureau of Meteorology (BOM).[9] Data are assigned to all cycle counters using measures from the Sydney Airport Metropolitan

[8]For a total of 1831 days, alerts are issued for 25 days of which 24 days are triggered by the forecast value of ozone.

[9]Data are found at: http://www.bom.gov.au/climate/data/

monitoring station.[10]

3.4 Bushfires

Bushfires are frequent events in south-eastern Australia and are acknowledged to contribute significantly to air quality problems in Sydney. Bushfires emit particulate matter, carbon monoxide, carbon dioxide, oxides of nitrogen and volatile organic compounds which, in the presence of sunlight, becomes photochemical smog. It is well-established that, depending on meteorological conditions, smoke from bushfires can travel very long distance (i.e. over 2000 miles) and have a mean lifetime of 8 to 20 days (Glatthor et al. (2013), Wotawa and Trainer (2000)). For instance, Forster et al. (2001) find a clear link between Canadian forest fires and O_3 and CO concentrations in Europe. DeBell et al. (2004) find that bushfires in the province of Quebec have a significant influence on O_3, CO and $PM_{2.5}$ concentrations over a large part of the east coast of the United States.

The bushfires that affect Sydney typically occur in the dry, sparsely populated bush areas of Boorowa and Hume several hundred miles to the south-west of the city. Because of the frequently hot and dry conditions, emissions from bushfires in Australia can be transported vast distances and have a deleterious impact on air quality in areas far away (Confalonieri et al. (2007)). Previous works such as Chen et al. (2006), Morgan et al. (2010), Jalaludin et al. (2000) and Smith et al. (1996) provide detailed statistical and simulation-based evidence of the causal link from bushfire emissions to O_3 levels in Australian cities. In a more recent study, Johnston et al. (2011) show that bushfires in the Eucalypt forests to the west of Sydney significantly increased O_3 concentrations in the city.

In this study, we use bushfire activity as an instrument for air quality. In this way

[10] The Sydney airport weather station is located close to the downtown of Sydney and has the most complete weather data. Given that varying distances between the airport and individual counters may cause measurement error concerns, we also assign weather conditions to stations based on GPS coordinates and find no significant difference in results. To assuage concerns about the possibility of including too many controls in regressions - which could increase the standard error of estimated coefficients and so impact implied significance - we also estimate a stripped-down version of the model excluding weather controls. Results are in Section 5.4.

we endeavour to disentangle the independent effect of alerts on behavior. Bushfire data is obtained from the NSW Rural Fire Service (RFS) and Romsey Australia.[11] For each bushfire, the size and its distance from the city of Sydney were obtained from the records of the Australian Emergency Management Institute (AEMI).[12]

4 Methodology

Quantifying the impact of health alerts on averting behavior (in our case reduced cycling demand) raises a number of empirical challenges.

First, meteorological factors can be expected to affect cycling decisions directly - people may prefer to cycle on days that are warm (but not too warm) and dry, etc.. Connolly (2008) and De Freitas et al. (2008) show that, for a variety of outdoor activities, weather matters. Furthermore, weather can be expected to impact air quality. Ozone is a pollutant that is not directly emitted by any particular source, but arises from the chemical reaction of nitrogen oxides and volatile organic compounds when exposed to sunlight. Moreover, pollutants can be washed from the air by rain and smog once formed, can be dispersed or moved by wind. Although we try to control for weather conditions, it is likely to be difficult to fully control for environmental confounders at sufficient spatial and temporal level (Moretti and Neidell (2011))

Second, individuals may reduce their exposure to pollution by substituting to more emissions-intensive activities (for example by switching from cycling to driving). Therefore, pollution level is potentially endogenous in the framework of our study.

Third, assigning pollution variables to each counter using interpolation techniques may result in measurement error for two reasons: a) air pollution levels may vary between regions and b) individuals may move between regions in the course of a day and we do not know in a sufficiently detailed way *where* they spend their time and therefore the level of pollution

[11]Data are found at: http://home.iprimus.com.au

[12]Data are found at: http://www.emknowledge.gov.au

to which they have been exposed. Previous studies such as Jacquemin et al. (2013), Lleras-Muney (2010) and Schlenker and Walker (2011), find that estimation of the effect of air pollution on health is quite sensitive to the methods used in assigning air pollution exposure variables to individuals.

To address these challenges, we use IV methods using bushfires as our instrument. The IV method controls for endogeneity of air pollution and also accounts for concerns about measurement error and omitted variable bias. Encouragingly, our results prove quite similar (indeed identical in terms of sign and significance) across the IV and OLS methods. In addition, results are robust to a variety of specification checks.

4.1 OLS

To estimate short-run direct avoidance behavior, we begin by examining the effect of alerts on daily cycle counts. The baseline fixed-effects model is:

$$\log(cycling)_{it} = alert_t\beta_1 + aqi_{it}\gamma_1 + \boldsymbol{W_{it}\delta_1} + \Phi_i + \phi_t + \epsilon_{it} \tag{1}$$

The dependent variable, $cycling_{it}$ is the number of bicycle trips counted at counter i on date t. The variable $alert_t$ is a dummy variable which takes the value one on an alert day and zero otherwise. aqi_{it} is the air quality index affecting cycling quality.[13] $\boldsymbol{W_{it}}$ is a vector of daily weather variables that we have already noted might have a direct impact on cycling behavior: maximum temperature, maximum temperature squared, average air temperature, precipitation, relative humidity, solar exposure, number of hours of bright sunshine and wind speed. Counter fixed-effects and time-fixed effects are Φ_i and ϕ_t, respectively. In particular, ϕ_t is a vector that includes dummies for day of week, holidays and year-month. ϵ_{it} is an error

[13]The daily AQI is calculated using maximum 1-h average of pollutant concentrations during the 24 hour period. To better control for the actual level of air pollution, in addition to the AQI composite and as a robustness check, we include the average daily level of O_3, CO, NO_2, PM_{10} and $PM_{2.5}$ in our regressions. Inclusion of these variables could increase the standard error of estimated coefficients and affect the significance of our results. Our results, however, are shown to be quite insensitive to inclusion of these pollution variables.

term. Throughout the paper error terms are clustered on counters.[14]

When alerts are repeated on consecutive days, Graff Zivin and Neidell (2009) show evidence of a strong 'rebound effect' - at least for the leisure activity of visiting a zoo. This sort of result, if more general, could have important implications for the operation of an alert program as the regulator needs to be aware of the possibility of 'alert fatigue'. The extent of the rebound is likely to be sensitive to the activity in question. A zoo visit is an infrequent, and in most cases easy-to-postpone activity whereas getting to work by bicycle, for example, might not be. To see how far their results carry over into our setting, our model is expanded to a 2-day model as follows:

$$\begin{aligned}\log(cycling)_{it} &= alert_t\beta_1 + alert_{t-1}\beta_2 + alert_{t-1} \times alert_t\beta_{12} \\ &\quad + aqi_{it}\gamma_1 + aqi_{it-1}\gamma_2 + \boldsymbol{W_{it}\delta_1} + \boldsymbol{W_{it-1}\delta_2} + \Phi_i + \phi_t + \epsilon_{it} \qquad (2)\end{aligned}$$

where $alert_{t-1}$ is the lagged alert. The interaction of the current ($alert_t$) and lagged ($alert_{t-1}$) alert allows for the possibility that the impact of an alert on date t is sensitive to the presence of an alert on date $t-1$. If alerts are issued on two successive days, $t-1$ and t, the effect of the second day alert in t conditional on cycling at t is $\beta_1 + \beta_{12}$. However, the impact of one-day alert is still β_1 as for a one-day alert we have $alert_{t-1} = 0$.

4.2 IV

To address potential endogeneity, measurement error and omitted variable bias, our results from preferred specifications are estimated using IV method.[15] The first stage estima-

[14] Angrist and Pischke (2008) suggest that, to have a fairly accurate variance formula, one needs at least 42 clusters, while we only have 26 clusters. Therefore, we estimate our regressions using block bootstrapping which deliver similar results.

[15] Since $alert_t$ is forecast-driven and determined by the value of $\mathbb{E}_{t-1}[AQI_t]$ and AQI_{t-1}, it might not seem necessary to control for the endogeneity of AQI_t when the coefficient of interest is $alert_t$. However, as argued by Angrist and Pischke (2008), the endogeneity of one explanatory variable will affect the consistency of other variables estimates unless the orthogonality condition is satisfied. As AQI_{t-1}, $\mathbb{E}_{t-1}[AQI_t]$ and AQI_t are likely correlated, it is not sensible to assume that $\mathbb{E}_{t-1}[AQI_t]$ and $alert_t$ are orthogonal. It is therefore

tion is:

$$
\begin{aligned}
aqi_{it} &= bushfire_t\alpha_1 + (bushfire_t \times size_t)\alpha_2 + (bushfire_t \times distance_t)\alpha_3 \\
&\quad + \boldsymbol{W_{it}\delta_1} + \psi_t + \Psi_i + v_{it} \qquad (3)
\end{aligned}
$$

where $bushfire_t$ is a dummy variable which is one for the date when there was an active bushfire affecting Sydney air quality and zero otherwise. The variable $size_t$ is a hectare measure of the size of the bushfire - which can sensibly be regarded as a proxy for the amount of pollutants it is generating - and $distance_t$ is the distance between an active bushfire and Sydney. The first stage regression is run with different combinations of these elements without changing the qualitative results.

It is worth pointing out that we choose not to control for the levels of individual pollutants (O_3, CO, NO_2, PM_{10} and $PM_{2.5}$) while we control for the general level of air pollution by including AQI since the AQI measure is a linear combination of pollutant measures, and is widely reported by the media.[16] Inclusion of these separate measures would imply multiple potentially endogenous variables on the right-hand side which Angrist and Pischke (2008) recommend against. The risk of omitted variables is obviated by use of the instrument, but as a robustness check, we show that inclusion of individual-pollutant controls makes little difference to our estimates with the sign and significance of our coefficient of interest preserved.

We adopt bushfire activity as an instrument for air quality. In the basic version, we account for the incidence of an active bushfire using a dummy for the date of an active fire interacted with size of bushfire. In another version, we also account for the distance of the

essential to control for potential endogeneity between the level of air pollution and the transportation choice in the presence of an alert.

[16]Exclusion of the individual pollutants raises an issue of whether our instrument satisfies the necessary exclusion restrictions. However, this does not seem to be a major issue since the cycling decision is not likely to be based on the separate individual pollutant levels.

bushfire from the city of Sydney.

Using $bushfire$ as an instrument requires that several conditions be satisfied. Essentially, bushfires must impact air quality ($cov(bushfire_t, AQI_{it}) \neq 0$) without having any *direct* influence on cycling behavior. The exclusion restriction implies that a bushfire should be orthogonal to other unobservable factors affecting the demand for cycling ($cov(bushfire_t, \epsilon_{it}) = 0$).

Various considerations point to bushfires being a good instrument for air quality. First, hot and dry weather provides conditions conducive to bushfire but these are a quasi-random event requiring a trigger - either a natural event or a human action. Thus, bushfire occurrence cannot be timed perfectly and it is sensible to assume that $bushfire$ is uncorrelated with other unobservable factors that might affect the cycling decision. As already discussed, it is well-understood that bushfire activity has a significant negative impact on Sydney air quality. The instruments are statistically strong and pass the conventional benchmark for power of F = 10 (Stock et al. (2002)) in every case. In terms of validity, we require that bushfires have no *direct* impact on cycling behavior, except via their effect on air quality. As outlined above, we have established in personal correspondence with NSW OEH that, in forming forecasts of air quality, they routinely assess emissions from bushfires. This information is incorporated in their forecasts using state-of-the-art modelling methods and publicized through air quality alerts. It is arguably true that *all* impacts of bushfire emissions on cycle use are absorbed by air quality alerts since bushfires typically occur a great distance from the city (an average of 589 miles in this study) and smoke from bushfires is very rarely observable in Sydney. During the period of this study, NSW residents were not systematically provided with bushfire information in relation to air quality (even if they should have wanted it) until the NSW OEH website was updated in September 2014 to incorporate a burn notice explicitly.[17]

[17]The NSW OEH burn notice still does not provide information on emissions from bushfires but rather encourages residents to be alert to air quality information. Of course, we cannot eliminate the possibility that people get information on bushfires directly through other sources such as NSW RFS and respond to that, which would threaten the validity of our instrument. However this seems stretched, and with air quality

4.3 Sub-sample analyses

Leisure cyclists and those who commute to work by bicycle may react to an air quality alert in different ways. In particular, a leisure ride may be easier to substitute or to postpone.

The cycle trip counters extract no information on the *motives* of the riders whose bicycles are counted. However, we may expect to see different reactions in aggregate bicycle trips for different *types* of cycle-path.

In light of this, we categorize the 26 routes on which the counters are located into two types - 'leisure' and 'commuter' - and re-estimate our regressions for each sub-sample. For robustness we categorize routes in two different ways:

First, by comparing the relative density of bicycle traffic on a particular route during the week versus on the weekend. Different counters have very different day-of-the-week patterns. In Figure 3, the upper panel depicts the daily distribution of average number of cyclists by day of week from counter 1 (Harbour Bridge), while the lower panel depicts the patterns for counter 31 (Como Bridge). If the average number of cyclists at a counter is higher on the weekends than the weekdays, we classify that route as 'leisure' and 'commuter' otherwise. Using this criterion, 11 of the 26 active stations are classified as leisure and 15 as commuter.

Second, by comparing the density of traffic at different times of day - in particular the pronouncedness of the peak in cycling trips during the traditional morning and evening commuter peak hours (7am - 10am and 4pm - 7pm). Again, the counters vary substantially in the timing of traffic through the day. In Figure 4, in the upper panel (for counter 1 (Harbour Bridge)) the flows during the morning and afternoon peaks are very strong compared to the lower panel (counter 8 (Falcon Street)). Routes are categorized into 'leisure' and 'commuter' adopting the following criterion: if the peak hour cycling traffic exceeds 85% of total weekday traffic, we classified a route to be 'commuter', and 'leisure' if it is below 85%. Applying this criterion, 4 and 22 stations are classified as leisure and commuter, respectively.

forecasts that already expertly incorporate bushfire effects on air quality, it is not clear why they should want to.

5 Results

Figure 5 provides a plot of some basic results, and in particular, shows the relationship between average cycle counts over all counters/days and AQI on bins of days *with* an alert (black triangles) and *without* (grey circles). There are no controls here for the various confounding factors so it is difficult to infer anything from this plot. However, we can fit by OLS lines through the black triangles (the black line) and through the grey circles (the grey line) and see that the former clearly lies below the latter. This provides initial encouragement for the view that alerts are effective in discouraging cycling activity.

Statistically - and again we emphasize that this is without any controls - the mean number of cyclists on days with an alert is between 15% and 30% lower than days without and alert.[18]

5.1 OLS

Ordinary Least Squares (OLS) estimation results based on Equation (1) are presented in Table 3. We acknowledge a number of well-understood difficulties with using OLS in settings of this sort and provide these only as a baseline.

The specifications in all three columns contain the vector of weather controls specified earlier in addition to route and time fixed effects.

Column 1 provides the 'take away' from this part of the analysis. An alert decreases cycle traffic by 14.1% which is significant at the 0.1% level.

Columns 2 and 3 present results of separate OLS regressions run on weekday and weekend day sub-samples. The independent effect of an alert is substantially larger on weekends and reduces cycle traffic by 26.5% (versus 16% on weekdays) which is significant at the 0.1% level. We return to more careful consideration of the impact of alerts on leisure versus commuter traffic later in the paper.

[18]To better show the difference, Figure 5 is only shown for the observations associated with the AQI value between 50 and 200.

5.2 IV

The regression results using a fixed-effect instrumental variable estimator are reported in Table 4.

The upper part (Panel A) shows the relationship between AQI and bushfire from the first-stage regression results based on Equation (3). Estimates in the second Column show that a bushfire increases on average, the level of AQI by a statistically significant 11.1 units. The magnitude F-statistic from the first-stage show that our instruments are statistically strong and relevant. Panel B provides coefficient estimates on the *alert* variable from the second-stage estimation using a full suite of controls.

We report three variations to help provide a sense of robustness (we actually ran a host of other variants obtaining similar results throughout) and in each case we estimate - as expected - a larger impact of alerts than the 14.1% reduction in use implied by OLS.

In Column 1, air quality is instrumented with the bushfire dummy and the issuance of an alert is estimated to reduce cycle traffic by 29.3% which is significant at the 0.1% level.

Column 2 and 3 adjust the first-stage estimation to allow for the size of the fire in hectares, and then for the distance of the fire from the city. The implied impact of an alert is to reduce cycle traffic by a statistically significant 35.1% and 13.2% in the two cases, respectively. The difference between our OLS and IV estimates is statistically insignificant when we instrument for AQI by bushfire, size and distance.

The statistics in Panel C point to the quality of the instrument used.[19]

[19] Under the null hypothesis of the Hausman test, the specified endogenous regressors can be treated as exogenous and the test statistic is distributed as chi-squared with degrees of freedom equal to the number of regressors tested. The Hausman test for bushfire, bushfire and size, and bushfire, size and distance has respectively a p-value of 0.000, 0.000 and 0.4126. This implies that the difference between the OLS and IV estimation is statistically significant when bushfire and bushfire and size are instrumented for air quality. Furthermore, the F-statistics from the first stage for excluded instruments are calculated to test the hypothesis of the excluded instruments as irrelevant. The magnitude of F-statistics indicate that all our instruments are statistically strong and relevant.

5.3 2-day model: Alert fatigue

There is concern among policy-makers of the possibility of alert fatigue - whereby the impact on behavior may be substantial on the first day that an alert is issued, but declines if alerts are issued on subsequent days.

Table 5 shows the OLS and IV results for a 2-day model. In our preferred IV specification, the alert on the second day is estimated to reduce cycle traffic by only 5% (statistically insignificant at the 5% level).[20] It should be noted, however, that the number of consecutive-day alerts in our data set is very small - occurring on only seven occasions in the five year period covered by this study. As such, we need to be wary about reading too much into either the value of our coefficient or its lack of significance.

5.4 OLS and IV robustness

We conduct two robustness checks on our results. First,to control for confounders, we re-estimate our preferred specifications excluding weather controls. Second, we include daily measures of specific air pollutants information (O_3, NO_2, CO, PM_{10}, $PM_{2.5}$) and re-estimate our regression.[21]

As already noted, pollution and weather variables are likely sources of confounding and accounting properly for their impacts on cycling demand is one of the main empirical challenges in this context. Insofar as the main coefficient estimates do not change excessively when controls for these variable are excluded, it can be claimed that the approach taken does a good job controlling for the effect of confounding variables (following Moretti and Neidell (2011)). We can conclude that omitted variable bias is unlikely to be a substantial concern in our estimation.

[20] The second day response is $\beta_1 + \beta_{12}$ and the significance of this composite is tested by means of a joint test.

[21] Although excluding these variables might lead to omitted variable bias, we did not include them in our regressions because this could lead to multiple endogenous variables in the reduced form regression. Omitted variable bias is not likely to be an issue for us when using IV as this method overcomes the potential omitted variable bias.

Table 6 reports the results of six separate regressions (three OLS and three IV). In assessing our results, the primary focus is on the stability of the IV estimates. Column 1 reproduces coefficient estimates from the preferred specifications in Tables 3 and 4.

In Column 2, we re-estimate our regressions including individual pollutant levels. In Column 3, we re-estimate excluding weather controls. The absolute value of the estimated coefficient on alerts using our preferred IV approach falls from 0.35 to 0.14 or 0.30 in the two cases. Together, these results suggest that our approach controls well for potential unobserved effects of pollution and weather factors since the coefficient estimates remain the same in sign and significance and similar in magnitude.

We explore robustness of the regression results to the potential non-linearity in the relationship between air quality and the demand for cycling. Table 7 reports results allowing for quadratic form of the air quality index variable. For IV, we also instrument for the quadratic form of AQI by bushfire and size. In the benchmark OLS estimation, controlling for the quadratic formulation leaves the estimated coefficient almost unchanged whilst in the IV estimation the coefficient changes from -0.35 to -0.26, unchanged in sign and significance.

5.5 Sub-sample analyses

Results for sub-sample analyses are presented in Table 8. Each column summarizes the key outputs from IV estimation for a sub-sample of the data.[22]

We might expect different behavioral responses depending on the trip purpose, in particular a leisure ride versus a commuter ride to work. The opportunities for modal or inter-temporal substitution may vary substantially between these purposes.

We divide the sample in three different ways. The underlying difficulty is that the counter measures only cycle trips while the purpose of the journey is unobserved. Our categorizations will provide indicative evidence but can not provide a 'clean' separation of

[22]It is worthwhile to note that, for all IV regressions, bushfire and size are instruments for air quality since the F-statistics for excluded instruments suggest that bushfire and size are statistically stronger instruments for sub-sample regressions. Other combinations of the instruments generated very similar results which we do not report.

leisure from commuter trips. As usual, what we are looking for is consistency of results across the various sub-sample treatments.

Columns 1 and 2 summarize analyses of weekday and weekend cycle use. The results of the second-stage regression are reported in Panel B and show that alert issuance reduces cycle use by 32.9% on weekends, but only 30.9% on weekdays. This is consistent with our hypothesis that a leisure trip is easier to cancel or postpone than is a commuter trip to work.

Instead of the divisions of the data-set by time, we provide two different ways in which we categorize *routes* into commuter and leisure-intensive routes. In Columns 3 and 4 of Table 8, the cycle routes are divided according to the pattern of cycle movements *across days of the week* with those routes more heavily used on weekdays being categorized as 'commuter'. The coefficient estimates in Panel B show the effect of an alert is to reduce cycle use by a statistically significant 40.1% on leisure routes and 23.7% on commuter routes which is consistent with our hypothesis.

In columns 5 and 6, the cycle routes are divided according to the pattern of cycle trips *within each day*, with those experiencing more than 85% of their usage during peak hours on weekdays being categorized as commuter routes. The coefficient estimates in Panel B show the effect of an alert is to reduce cycle use by a statistically significant 38.2% on leisure routes and 18.2% on commuter routes.

None of our leisure/commuter categorizations are perfect in distinguishing trip purpose, so we take this evidence as indicative only. A person riding on a Saturday may be on her way to work, for example, though that is less likely than would be the case if observed on a Monday. However, the striking similarity in estimated coefficients across the three categorizations indicates the robustness with the reduction in leisure ridership induced by an alert being in the range 24 to 38%, and for commuting ridership being in the range 18 to 24%.

6 Conclusion

Our empirical analysis provides compelling evidence that air quality alerts issued in Sydney, Australia are highly effective in encouraging people to reduce cycling activity. Estimates have varied across specification and sub-samples in terms of cycling trip reduction but the results consistently point to a response in the range of 18 to 40% level. Cycling for leisure appears to be much easier to discourage than cycling to work. There is some evidence of alert fatigue based on a very small sample.

That people react - by adjusting their behavior when provided with pertinent information - is central to the effectiveness of information-based policy interventions. In particular, it is vital that, when air pollution levels are elevated, people reduce or eliminate participation in vigorous outdoor activities and limit their exposure to air pollution. This is the first study to use administrative data to show that people do engage in avoidance behavior (and indeed only the second overall following a small-scale study carried over just 35 days in Atlanta). Estimating the health benefits of the change in behavior is beyond the scope of the paper and would pose an additional challenge of determining the activity which people substitute when they reduce cycling.

Naturally, a study of this sort involves a particular application which in our case is cycling in Sydney. As such there are obvious questions as to how far the results may generalize to other settings and activities - maybe an Australian will heed a public health warning where as a German wouldn't. This points to the utility of further empirical work in other contexts. Given the increasing reliance placed on alert schemes and other information-provision interventions, evidence that they work - and work well - in discouraging vigorous outdoor activity in at least *one* setting is encouraging.

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Table 1: New South Wales Air NEPM Standards

	Average period	Maximum concentration
Carbon monoxide	8 hours	9.0 (ppm)
Nitrogen dioxide	1 hours	0.12 (ppm)
Photochemical oxidants (as ozone)	1 year	0.03 (ppm)
	1 hour	0.10 (ppm)
	4 hours	0.08 (ppm)
Sulfur dioxide	1 hour	0.20 (ppm)
	1 day	0.08 (ppm)
Lead	1 year	0.50 ($\mu g/m^3$)
Particles as PM10	1 day	50 ($\mu g/m^3$)
Particles as PM2.5	1 day	25 ($\mu g/m^3$)

Source: NSW EPA.

Table 2: Summary Statistics for May 2008 - September 2013

	Mean	Std. Dev.
Cycling	353.7	474.4
Weekdays	373.0	533.2
Weekends	305.3	270.5
Alert Frequency (%)	0.013	0.114
Two Successive Alerts Frequency (%)	0.0038	0.013
Bushfire Frequency (%)	0.027	0.163
Bushfire size (ha)	1988.78	866.64
Bushfire distance (km)	1092.56	1296.94
Explanatory Variables		
AQI	55.58	38.80
Carbon monoxide 1-h (pphm)	0.349	0.170
Ozone 1-h (pphm)	0.032	0.014
Nitrogen dioxide 1-h (pphm)	0.967	0.455
Particles as PM10 1-h ($^{\mu g}/_{m^3}$)	19.17	8.69
Particles as PM2.5 1-h ($^{\mu g}/_{m^3}$)	5.944	3.6
Total Daily Solar Exposure ($^{MJ}/_{m^2}$)	15.99	7.6
Precipitation (mm)	0.33	1.78
Maximum temperature (°C)	22.73	4.97
Daily Average of Air temperature (°C)	15.2	4.72
Relative Humidity (%)	77.65	13.3
Wind speed ($^{km}/_{h}$)	16.41	8.61

Sources: Cycling data obtained from NSW Department of Roads and Maritime Services. Alert and pollutant data collected from the NSW Office of Environment and Heritage. Weather data collected from Australia Bureau of Meteorology.

Table 3: OLS Regression Results

	(1) Total	(2) Weekdays	(3) Weekends
Alert	-0.141***	-0.162***	-0.265***
	[0.0292]	[0.0422]	[0.0376]
Controls for Weather	Y	Y	Y
Time Fixed Effect	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y
Observations	28452	20331	8121
R^2	0.261	0.308	0.331

Clustered by counters, standard errors in brackets.
* significant at 5% ** significant at 1% *** significant at 0.1%.

Table 4: Instrumental Variable Regression Results

	(1)	(2)	(3)
A.First Stage $^{(a)}$			
Bushfire	11.0445***	5.315**	-4.063
	[1.4546]	[2.7167]	[3.1347]
Bushfire*Size	-	0.00287***	0.00463***
	-	[0.0011]	[0.00109]
Bushfire*Distance	-	-	0.0044***
	-	-	[0.0008]
B.Second Stage $^{(b)}$			
Alert	-0.293***	-0.351***	-0.132***
	[0.0575]	[0.0600]	[0.0476]
Controls for Weather	Y	Y	Y
Time Fixed Effect	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y
C. F-Statistic for Excluded Instruments $^{(c)}$	57.65	33.20	32.17
Wu-Hausman	10.822	19.794	0.671
(P-value)	(0.0010)	(0.000)	(0.4126)
Observations	28452	28452	28452

Note: (a) Dependent variable is AQI. (b) Dependent variable is $log(cycling)$. (c) The values reported are the Angrist-Pischke multivariate F-statistics (Angrist and Pischke (2009)). Clustered by counters, standard errors in brackets.
* significant at 5% ** significant at 1% *** significant at 0.1%

Table 5: Impact of Two Successive Day Alerts on Cycling Activity

	(1) OLS	(2) IV
First day response	-0.169***	-0.247***
	[0.0315]	[0.0474]
Second day response	-0.05	-0.049
	[0.0256]	[0.0492]
Controls for Weather	Y	Y
Time Fixed Effect	Y	Y
Cycling Routes Fixed Effect	Y	Y
Observations	28076	28076

Notes: Dependent variable is $log(cycling)$. Lag of AQI is also instrumented by bushfire and size. Clustered by counters, standard errors in brackets.
* significant at 5% ** significant at 1% *** significant at 0.1%

Table 6: Sensitivity of Results to Weather and Pollution Factors

	(1)	(2)	(3)
A. OLS Regression[(a)]			
Alert	-0.141***	-0.124**	-0.298***
	[0.0292]	[0.0485]	[0.0361]
B. IV Regression[(b)]			
Alert	-0.351***	-0.143***	-0.303***
	[0.0600]	[0.0382]	[0.0452]
Controls for Weather	Y	Y	N
Controls for Pollution	N	Y	Y
Time Fixed Effect	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y
F- Statistic for Excluded Instruments [(c)]	184.09	102.03	100.93
Observations	28452	23384	23797

Notes: (a) and (b) Dependent variable is $log(cycling)$. (c) The values reported are the Angrist-Pischke multivariate F-statistics (Angrist and Pischke(2009)). Clustered by counters, standard errors in brackets.
* significant at 5% ** significant at 1% *** significant at 0.1%.

Table 7: Robustness to Non-linear Relations Between Air Quality and Cycling

	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
Alert	-0.141***	-0.155***	-0.351***	-0.260***
	[0.0292]	[0.0307]	[0.0600]	[0.0397]
Controls for Weather	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y	Y
Functional Form	Linear	Quadratic	Linear	Quadratic
Observation	28452	28452	28452	28452

Notes: Dependent variable is $log(cycling)$. Quadratic form of AQI is also instrumented by bushfire and size. We are unable to estimate cubic and quartic form of AQI using IV regression since our model becomes under-identified. Clustered by counters, standard errors in brackets.
* significant at 5% ** significant at 1% *** significant at 0.1%.

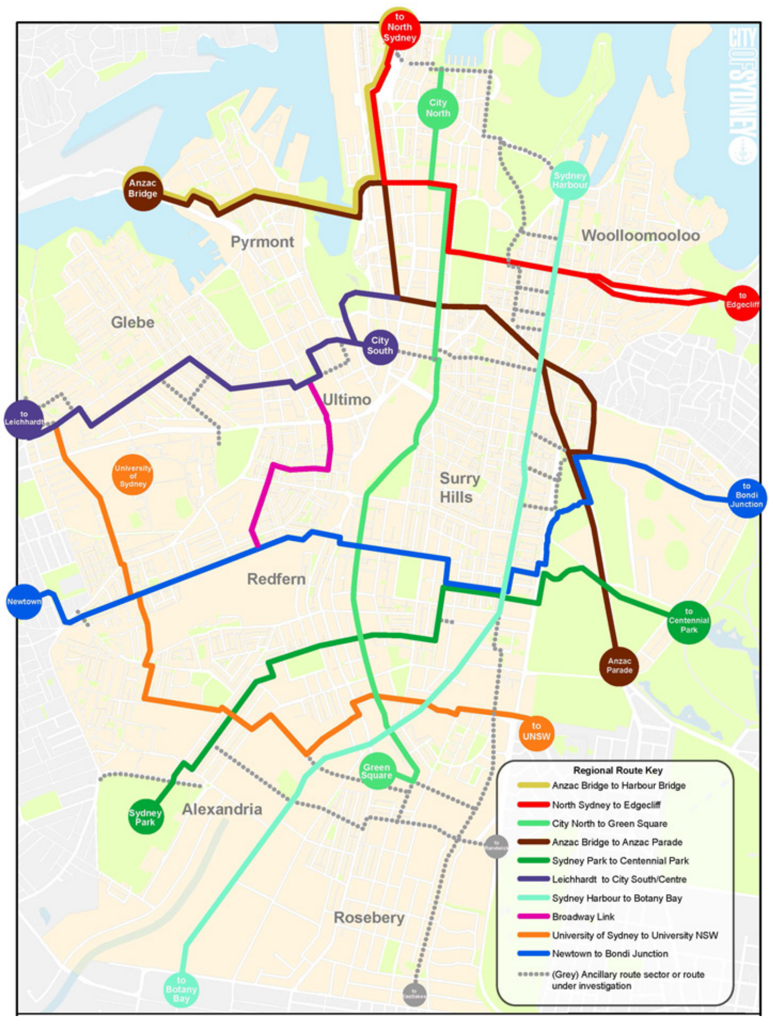
Table 8: IV Regression Results for Weekends vs. Weekdays and Leisure vs. Commuter routes

			Weekday density		Peak hour density	
	(1)	(2)	(3)	(4)	(5)	(6)
	Weekdays	Weekends	Commuter	Leisure	Commuter	Leisure
A. First Stage $^{(a)}$						
Bushfire	2.667	22.413***	6.584	5.918	18.927**	2.464
	[3.014]	[6.207]	[3.498]	[4.938]	[7.000]	[2.954]
Bushfire*Size	-0.0043***	-0.0048*	0.00243	0.0034*	- 0.00008	0.0034***
	[0.0013]	[0.0023]	[0.00126]	[0.0021]	[0.003]	[0.0011]
B. Second Stage $^{(b)}$						
Alert	-0.309***	-0.495***	-0.237***	-0.401***	-0.200**	-0.386***
	[0.0547]	[0.109]	[0.0676]	[0.0810]	[0.0724]	[0.0821]
Controls for Weather	Y	Y	Y	Y	Y	Y
Time Fixed Effect	Y	Y	Y	Y	Y	Y
Cycling Routes Fixed Effect	Y	Y	Y	Y	Y	Y
F-statistic for Excluded Instruments $^{(c)}$	22.74	18.32	19.10	17.85	14.31	22.21
Wu-Hausman	16.408	2.490	3.764	17.816	8.147	15.469
(P-value)	(0.0001)	(0.1146)	(0.0524)	(0.000)	(0.0043)	(0.0001)
Observations	20331	8121	16543	11898	5358	23094

Notes: (a) Dependent variable is AQI. (b) Dependent variable is $log(cycling)$. (c) The values reported are the Angrist-Pischke multivariate F-statistics (Angrist and Pischke (2009)). Clustered by counters, standard errors in brackets.

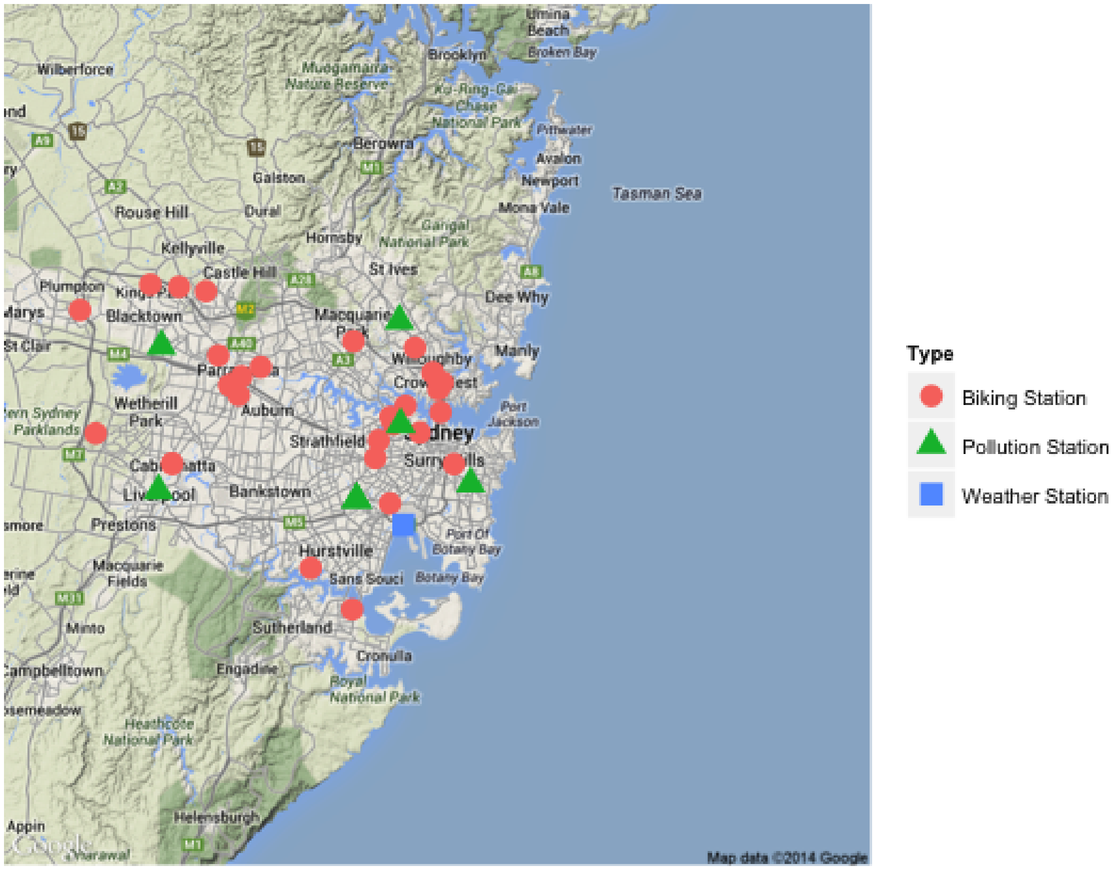
* significant at 5% ** significant at 1% *** significant at 0.1%.

Figure 1: Sydney Regional Cycling Path



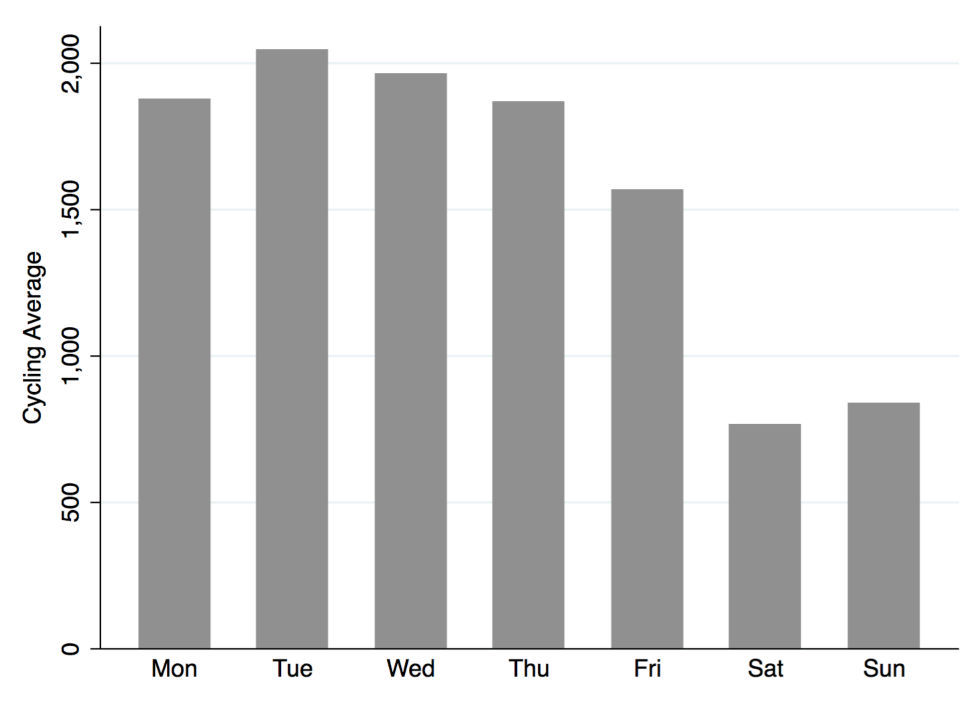
Source: City of Sydney

Figure 2: Cycling, Pollution and Weather, Stations

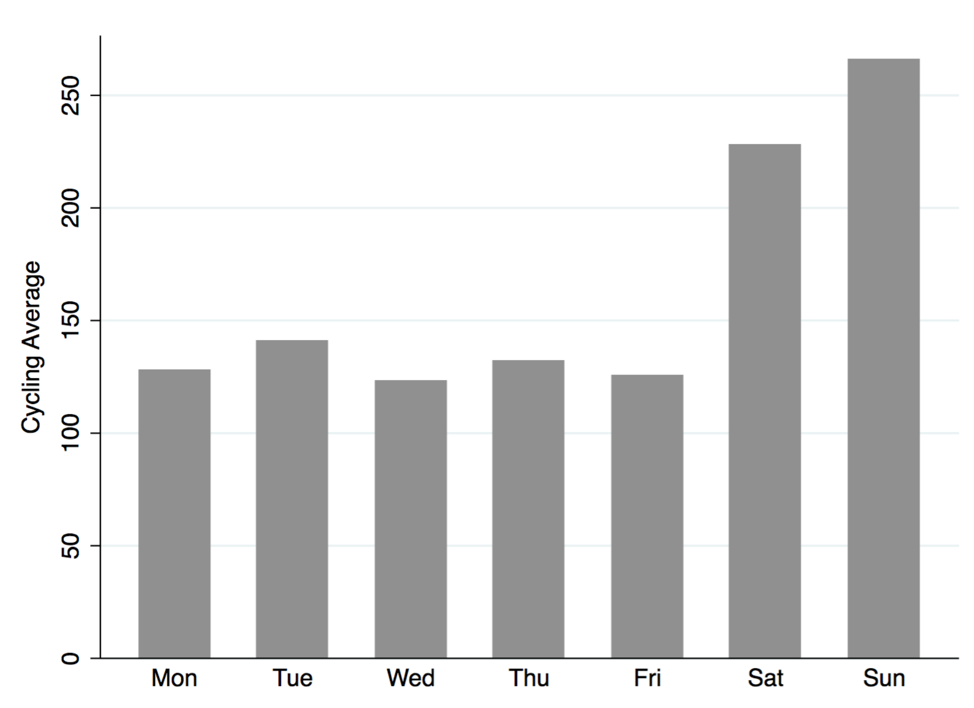


Note: The GPS coordinates of Cycling, Pollution and Weather Station are respectively obtained from the city of Sydney, NSW Office of Environment and Heritage and NSW Bureau of Meteorology. This figure shows all 31 cycling counters while 26 counters are used for our regression.

Figure 3: Average Number of Cyclists Per Day of Week, May 2008 - September 2013.

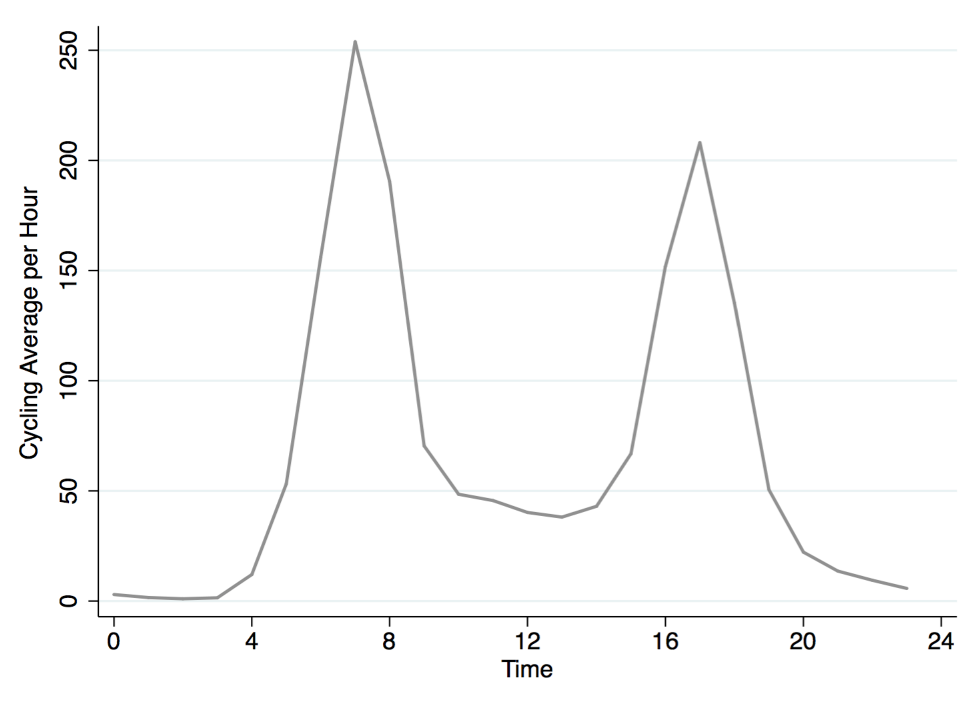


(a) Counter 1 (Harbour Bridge)

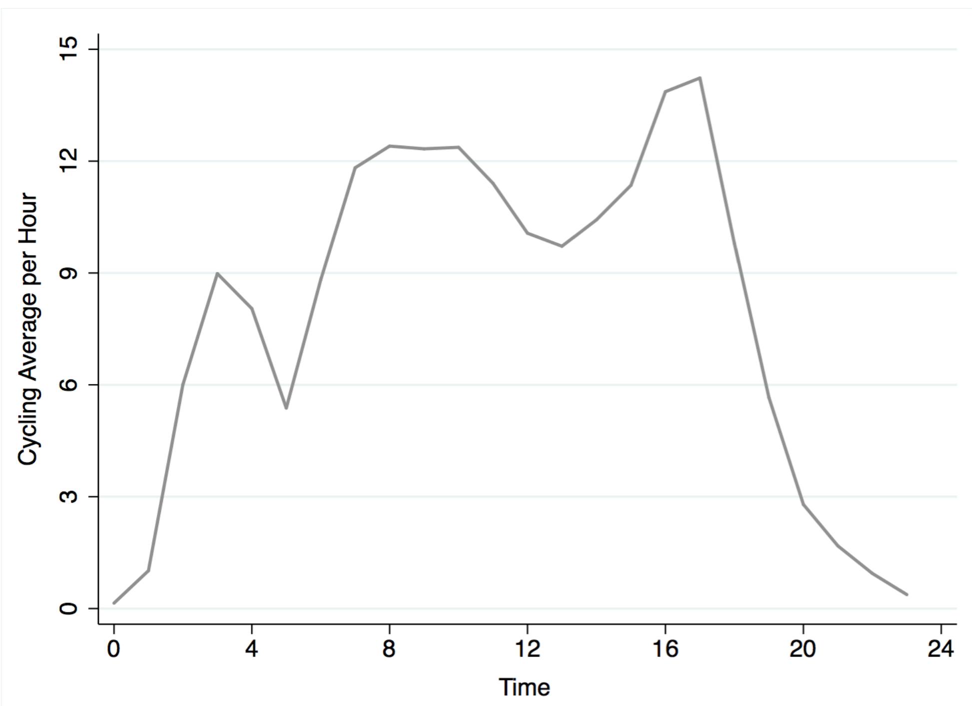


(b) Counter 31 (Como Bridge Cycleway)

Figure 4: Hourly Pattern of Cycling, May 2008 - September 2013.

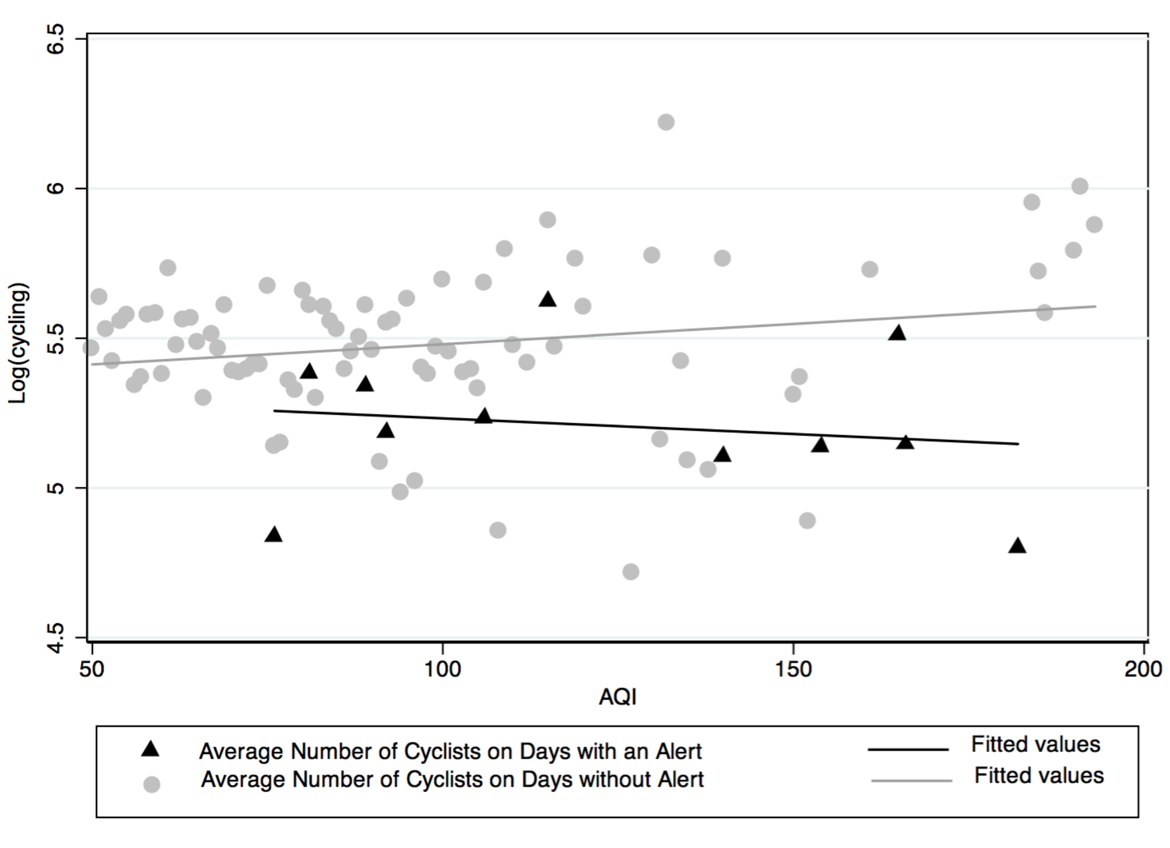


(a) Counter 1 (Harbour Bridge)



(b) Counter 8 (Falcon Street)

Figure 5: Cycling Average On Days With and Without Alerts, No Controls.



Note: Each bin shows the average number of cyclists for the specific observed value of AQI conditional on whether an alert is issued or not. For instance, the black triangle for the AQI=160 shows that the logarithm of average number of cyclists were 5.2 when the observed value of AQI was 160 and an alert was issued.