

Essays on Environmental Economics

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Abstract

Chapter 1.—This chapter investigates the direct behavioral impact of information-based regulations by examining the effect of ozone alerts on cycling trips in Sydney. Moreover, the dynamics of individuals' response is studied by examining the behavioral impact of two successive day ozone alerts on cycling demand. A common problem in estimating direct avoidance behavior is that an increase in the pollution level could be an endogenous response to alerts. While controlling for the endogenous effect of alerts and air quality, results show that cycling trips decrease by 35 percent in response to a smog alert. When alerts are issued for two successive days, however, individuals appear to neglect the second day alerts. Our findings also indicate that ozone alerts induce one and half times larger impacts on weekends compared to weekdays. These patterns suggest that the cost of cycling substitution for commuter goals is higher than leisure goals. Furthermore, the cost of intertemporally avoiding cycling is increasing over time.

Chapter 2.—If decisions with lasting consequences are influenced by extraneous or transient factors then welfare can be damaged. This chapter investigates the impact of outdoor temperature on high-stakes decisions (immigration adjudications) made by professional decision-makers (US immigration judges). In our preferred specification, which includes spatial, temporal and judge fixed effects, and controls for various potential confounders, a 10 °F degree increase in case-day temperature reduces positive decisions by 6.55%. This is despite judgements being made indoors, 'protected' by climate-control. Results are consistent with established links from temperature to mood and risk appetite and have important

implications for evaluating the welfare-burden of climate change.

Chapter 3.—The carbon tax in the Canadian province of British Columbia is widely-regarded as a ‘poster child’ application of market-based methods to address greenhouse gas emissions. However the implications for local air quality have been ignored. Using synthetic control and difference-in-difference methods, in this chapter we evidence a causal link from carbon tax implementation and level to increased nitrogen oxides (NO_x) and ultra-fine particulates ($PM_{2.5}$) pollution problems in Vancouver, the province’s largest city. We provide evidence consistent with the mechanism working through induced switching from gasoline to diesel vehicles. The results prove highly robust to inclusion of a wide set of controls in various combinations, alternative specifications, and satisfy a set of falsification checks. The analysis points to the possibility of negative secondary effects of climate policies, contrary to the usual presumption that secondary benefits are inevitably positive.

Declaration

All chapters of this thesis are self-containing research articles. Chapters 1 and 2 are from joint research. The first chapter is co-authored with Anthony Heyes and Nicholas Rivers. I acknowledge the contribution of Anthony Heyes for the research associated with the second chapter of this thesis. For this chapter, his contribution is equal to my own. Journal articles based on the research for these chapters are published, the first one in the Journal *Resource and Energy Economics* and the second chapter is revise and resubmit in the *American Economics Journal: Applied*.

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General Introduction

This thesis applies a diverse set of econometric tools drawn from reduced-form methods to synthetic control to explore three different questions in environmental economics. The essays presented in the different chapters intend to also contribute to health and labor economics. Chapter 1 and 3 try to establish a causal link between environmental regulations, individuals' behavior and air quality. The first chapter examines the behavioral impacts of air quality alerts. Chapter 3 investigates the causal impacts of carbon tax on local air quality. Chapter 2 answers different question by exploring the causal effects of outdoor temperature on decision outcomes. Throughout my thesis, I rely on many datasets from different countries including Australia, US and Canada.

Managing the impact of pollution exposure is one of the main key policy priorities in many countries. In addition to reducing pollution levels directly, policy-makers put increasing efforts on designing different information-based programs that enable individuals to engage in avoidance behavior to mitigate the negative effects of pollution. For instance the 'air quality alert' schemes that are in operation in many cities across the world, encourage people to change their behavior in order to reduce pollution exposure.

The first chapter of this thesis uses high frequency administrative data to link air quality alerts to the avoidance of a vigorous outdoor activity. In particular, we use bicycle-count data from the cycle path network of Sydney, Australia to investigate the effect of air quality alerts on cycling behavior in Sydney.

We estimate the causal effect of air quality alerts on cycling behavior using the Ordinary

Least Square method that relates daily cycling counts at each cycling counter on the Sydney cycling network with a dummy variable that takes the value one when an air quality alert was in place. Further, to control for the endogeneity in the pollution exposure, we use bushfires that occur throughout neighboring regions of Australia as an instrument for air quality in Sydney.

Our results suggest that air quality alerts are highly effective in encouraging people to adjust their behavior and get off from their cycles. We find that a behavioral response of alert to be around the 15 to 35% level. In addition, cycling for leisure seems to be much elastic with respect to air quality alerts. There is also a weak evidence of alert fatigue. Cyclists do not respond to the second day alert when alerts are issued in the two consecutive days.

In the second chapter we establish a causal link from same-day outdoor temperature to indoor decisions in a high-stakes setting. A new strand of behavioral research (Weaver and Hadley (2009), Weinreb et al. (2002)) and Ferrarelli (2016)) points to the importance of transitory emotions and mind-states in influencing decisions with long-term consequences. Notably, if decisions are affected by irrelevant factors the potential for welfare loss is obvious. This chapter tests for a causal link from outdoor temperature to indoor decisions using universe of asylum applications evaluated over a four year period by the 266 immigration court judges at the 43 US Federal Immigration Courthouse locations spread across most major US cities.

We identify the causal effect of temperature within judges by assuming that temperature realizations are as good as random after accounting for spatial and temporal fixed effects. Our findings indicate that a 10 °F degree increase in temperature reduces the likelihood of a decision favorable to the applicant by 1.075% which is equivalent to 6.55% decrease in the grant rate. The effect is strong and very robust to variety of robustness checks.

Consistent with some existing studies of temperature susceptibility by gender (Yu et al. (2010), Xiong et al. (2015)), the effect is particularly pronounced for female judges. To allay

concerns that there might be something unique to the immigration setting that is driving the results we repeat the exercise for decisions made in 18,461 Parole Suitability Hearings at the 39 locations of the California Department of Corrections and Rehabilitation (CDCR), arriving at parallel conclusions.

The findings suggest that outdoor temperature may be an important factor for policymakers to consider when allocating public resources, especially in contexts where heat exposure is frequent, high-stakes decisions can deviate from its optimal. This paper also provides empirical support for the view that climate and human capital may interact in a way that contributes to the long-debated relationship between hotter climates and slower growth, though more careful research is needed.

The third chapter provides evidence of a negative causal impact of BC carbon tax implementation (and subsequent increases in level) on local air quality in Vancouver. Although the link between the adoption of carbon reduction policies and emission of local pollutants is often discussed, it is generally an ambiguous empirical question.

There is a large body of cost-benefit analysis (i.e. Tollefsen et al. (2009), Ayres and Walter (1991), Bollen et al. (2009), Kan et al. (2004) and Cifuentes et al. (2001)) of which almost all assume that there exist common sources of emissions of greenhouse gas (GHG) and local air pollutants, and that a climate change action which mitigates GHG emissions goes hand in hand with improved local air quality. This assumption is however problematic since it ignores not only the possibility of non-common sources of various pollutants, but also neglects the important role of meteorological conditions, topography and the existence of local air pollutants regulations in determining the local pollutant levels.

The contention of Chapter 3 would be that evaluating the *actual* effect of carbon policy on local air quality outcomes is one of the most pressing policy questions. This chapter applies synthetic control and difference-in-difference methods to assess the effect of British Columbia carbon tax on the concentrations of primary criteria pollutants NO_x , $PM_{2.5}$ and CO in Vancouver.

The headline result of the study indicates that each five dollar increase in tax per tonne of carbon dioxide caused extra 2.6 and 2.4 days per year that NO_x and $PM_{2.5}$ levels in central Vancouver exceeded their safe standards. The synthetic control analysis indicates that by the year 2013 annual NO_x and $PM_{2.5}$ exceedances in Vancouver were around 8 and 12 days higher than what they would have been in absence of the tax.

Although several mechanisms may explain these results, the substitution from gasoline towards diesel consumption in motoring is a prime candidate. Such a mechanism is consistent with the finding of Pacific Analytic Inc. (2015b) and Antweiler and Gulati (2016) that higher fuel prices due to the BC carbon tax resulted in a larger share of more fuel efficient vehicles (diesel cars are typically more fuel-efficient than their gasoline counterparts).

Chapter 1

Behavioral Impacts of Air Quality Alerts: Cycling and Ozone Alerts in Sydney

1.1 Introduction

Air pollution is one of the major environmental risks to human health. The World Health Organization (WHO 2014) estimates that ambient air pollution caused 3.7 million premature deaths worldwide in 2012. The United Nations Environment Programme (UNEP) estimates that urban air pollution costs roughly 2 and 5 percent of GDP in developed and developing countries, respectively.¹ In addition, the recent Australian burden of disease report estimates that in Australia 1.5% of all deaths are related to long-term exposure to urban air pollution and 0.8% to short-term exposure.² Mitigating the impact of pollution exposure, is a key policy priority in many countries. In addition to efforts to reduce pollution levels directly, policy-makers put increasing efforts in information-based programs that enable individuals

¹Urban Air Quality. United Nations Environment Programme (UNEP). Urban Environment Unit <http://www.unep.org/urban-environment/issues/urban-air.asp>

²Australian Institute of Health and Welfare (AIHW). Burden Disease Unit. <http://www.aihw.gov.au/burden-of-disease/previous-studies/>.

to engage in avoidance behavior to reduce the negative effects of pollution.

Among various types of demand-side regulations, increasing attention is given to information-based regulations, which aim to alter individual choice through behavioral intervention. For instance, air quality alerts provide information to help individuals mitigate pollution exposure by advising behavioral changes during poor air quality episodes.

This chapter distinguishes between direct and indirect avoidance behavior in terms of studies' approach in quantifying avoidance behavior. Indirect avoidance behavior is estimated indirectly through the impact of alerts on the health outcomes whereas direct avoidance behavior is computed by estimating the alerts' impact on the demand for outdoor activities. While a growing body of literature suggests that individuals engage in avoidance behavior in response to publicized health risks,³ few studies investigate the existence of direct avoidance behavior.⁴ This chapter contributes to a small body of literature on the behavioral effects of information-based air pollution regulations by quantifying direct avoidance behavior and investigating the dynamics of individuals' response associated with ozone alerts in Sydney from May 2008 to September 2013.

We measure avoidance behavior and its dynamic using administrative data collected by the City of Sydney that provides counts of bicycle use at daily and hourly⁵ intervals on a number of popular cycling routes in the city. To the best of our knowledge, this is the first study that examines whether physically active individuals value air quality information and avoid being exposed to pollution.

Furthermore, following Graff Zivin and Neidell (2009) the dynamics of alerts' impact is analyzed using two successive day alerts model. Investigating the dynamics of alerts' behavioral impact on cyclists (as opposed to some other activities) is noteworthy since not only is

³For instance, look at Ahituv et al. (1996); Jin and Leslie (2003) ; Bresnahan et al. (1997) ;Mansfield et al. (2006);Wen et al. (2009) and Sexton (2011).

⁴Among previous studies just Graff Zivin and Neidell (2009) and Noonan (2011) examine direct avoidance behavior using revealed preferences data.

⁵The hourly cycling data are only used to define leisure and commuter routes. This is mainly because ozone alerts cover an entire day. Thus choosing a sampling frequency that is commensurate with the treatment length is appropriate.

cycling a popular and extremely intensive cardiovascular activity but it also likely exhibits a different cost of substitution than other activities, while it can be used for transportation and for recreation.

Estimating the effect of air quality alerts on individuals' behavior is challenging for at least three reasons. As argued by Graff Zivin and Neidell (2013), there are four main methodological challenges in the estimation of avoidance behavior: First, because of variation in pollution across regions assigning pollution and weather variables to individuals based on individual and monitor locations could lead to measurement error. Second, air pollution might have a non-linear effect on health. In other words, it might be the case that when air pollution exceeds a particular level the hospitalization rates increases, whereas a lower level of pollution could potentially cause other form of morbidities.

Third, omitted-variable bias could arise due to the environmental confounding factors. In fact, meteorological factors can highly impact the levels of outdoor activities and health and at the same time the level of air quality. Therefore, the estimation may be biased since it is hard to fully control for weather conditions with proper functional form.

Lastly, optimizing individuals might engage in avoidance behavior to reduce air pollution exposure that will lead to endogenous pollution. For instance, endogeneity might arise when individuals shift their outdoor activities toward emission-related substitutes in order to avoid exposure. Although this action reduces exposure, it will increase the level of air pollution. Thus the level of air pollution may be endogenous in this framework. In addition, it is hard to fully account for all sources of avoidance behavior.

It is important to clarify that our focus in the paper is on estimating the impact of air quality alerts on cycling behavior. Air quality alerts are established the day prior to the alert being issued (based on the forecast air quality on the day of the alert), are not revised after being set (to correct for forecast errors), and are city-wide. These conditions ensure that there is no measurement error or endogeneity directly associated with our main variable ? the dummy variable for alerts. However, alerts are correlated with actual air quality, which is

potentially endogenous, and which can also affect cycling behavior. We show that neglecting to address endogeneity in the air quality variable will lead to bias in our estimate of the effect of alerts on cycling behavior, and thus we use bushfires that occur throughout neighboring regions of Australia as an instrument for air quality in Sydney

In order to overcome the mentioned methodological challenges, Moretti and Neidell (2011) use the daily Los Angeles boating traffic as an instrument for ozone level to show that controlling for the endogeneity problem, measurement error and environmental confounders, ozone causes \$44.5 million per year in respiratory hospital cost in Los Angeles. In addition, they estimate that avoidance behavior in response to smog alerts costs at least \$11 million per year.

To address the four methodological challenges described above, we use bushfire as an instrumental variable for level of air quality. Bushfires are mainly characterized as any unconstrained fire that is burning in a grass, bush, or forested area. Because of the weather and geographical condition, bushfires are frequent events in Australia. As indicated by the Australian Bureau of Meteorology, in most instances hot and dry winds gusting from central Australia increase a risk of fire. The bushfire season differs by region. Southern Australia is more vulnerable to the threat of fire during the dry summer months (December to March), whereas northern Australia is most susceptible during winter (April to September).

Using bushfire as an instrument for air quality level not only controls for endogeneity of air pollution but also accounts for measurement error and omitted-variable bias. Two factors suggest that bushfire is a valid instrument for air quality. First, the timing of a bushfires' incidence is random in the short run. Although the hot and dry climate results in bushfires in Australia, their occurrence cannot be timed perfectly.

Second, bushfire smoke contains particulate matter, carbon monoxide and volatile organic compounds and can increase the ground level of ozone in the presence of heat and sunlight. In addition, in order to issue an ozone alert, the emission sources from bushfires are thoroughly assessed by New South Wales Office of Environment and Heritage (NSW OEH). Therefore,

it seems logical to assume that all possible impacts of bushfire smoke on cycling demand is completely absorbed by air quality alerts. It might be also useful to mention that bushfires are typically a long way from Sydney. Bushfires typically occur in the dry, sparsely populated bush areas of Boorowa and Hume, several hundred miles to the south-west of the city. More specifically, because of hot dry conditions, PM from bushfire events in Australia can transport vast distances, and affect the air quality level of areas far from their source (Confalonieri et al. (2007)). The average of total active brushfires' distance from city of Sydney during the period of our study was roughly 947 kilometers. Thus, it can be claimed that the smoke from bushfires are rarely observable from the city of Sydney. Therefore it is reasonable to think that bushfires have an adverse effect on air quality while they are clearly uncorrelated with other unobservable factors determining demand for cycling.

Instrumental variable estimates demonstrate that for a one-time ozone alert, cycling trips reduce by a statistically significant 35 percent. However, when ozone alerts are issued for two successive days, the second day response falls to statistically insignificant 6 percent. These consequences that the cost of avoiding cycling is increasing over time. Therefore, individuals appear relatively unresponsive to the second day alerts.

Our result is quite robust to different specifications for pollutants and weather factors. Excluding weather factors, estimation results suggest that cycling trips reduce by a statistically significant 30 percent in response to ozone alerts. This result clarifies the robustness of our approach in accounting for confounders. Moreover, our finding is insensitive to nonlinear effects of air quality on demand for cycling. Adding the quadratic form of the air quality index variable, cycling trips reduce by statistically significant 26 percent in response to ozone alerts.

In addition, alerts' behavioral impact on weekdays versus weekends and commuter versus leisure routes suggests that cycling is a more inelastic demand on weekdays. Regression results suggest that in response to an alert, there is a statistically significant 31 and 49 percent reduction in the number of cyclists on weekdays and weekends, respectively. Furthermore,

cycling trips decline by a statistically significant 24 and 40 percent for commuter and leisure routes, respectively. The larger value of alert response on weekends and over leisure routes is due to the higher elasticity of cycling demand with respect to air quality over weekends and non-peak hours (i.e., leisure activities). This is because the leisure activities can be substituted more easily. Therefore, individuals seem likely more responsive to ozone alerts for their leisure activities over weekends and non-peak hours.

From a policy perspective, our findings highlight the importance of proper health and environmental education that needs to be coupled with air quality forecast policies. More specifically, the air quality program is usually considered as an effort to ‘optimize’ individuals’ behavior. In fact, the magnitude to which behavior can be optimized depends on whether individuals take proper action while taking into account alert and air quality information. Therefore, more relevant and detailed health and environmental advice (which can target individuals’ perception of ambient air pollution) associated with air quality information might be welfare enhancing. The next section surveys previous literature on behavioral impacts of air quality alerts. Section 3 provides a brief overview of the Air Quality Index Forecast program in Australia. Section 4 describes data. A simple theoretical framework is presented in section 5. The next section describes methodology. Section 7 discusses our results. Section 8 concludes.

1.2 Literature review

Generally, air quality alert policies aim to improve public health by inducing avoidance behavior. In fact, public air quality information helps individuals to maximize the utility of their outdoor activities, accounting for the health risk from air pollution. Investigating the effectiveness of information provision and quantifying avoidance behavior is important since, as indicated by Neidell (2004), ignoring individual avoidance response to pollution information (i.e. air quality alerts) not only can result in biased estimation of the impact of

pollution-related health risks, but also might lead us to underestimate the welfare costs of pollution.

Starting in 1999, the U.S. EPA mandated all jurisdictions with populations more than 350,000 to report the daily level of Air Quality Index (AQI). AQI is a measure of air pollution. It is used both in measuring current air pollution and forecasting future air pollution. In the US jurisdictions with more than 350,000 inhabitants are required to report an air quality alert one day in advance. An alert is issued if the AQI is expected to exceed a particular threshold. Air quality alerts serve different goals:(1) reducing exposure, and (2) reducing pollution. These presumably induce different behavioral impacts, partly by design.

A growing body of literature tries to estimate the behavioral impact of alerts. There are three bodies of literature relevant to this subject. First, there are studies that investigate the existence of indirect avoidance behavior in terms of the alerts' impact on cardiovascular and respiratory hospital admissions. Second, some studies explore transportation choices in response to alerts. Third, there are a few studies that examine direct avoidance behavior by investigating how the level of outdoor activities on days with alerts differs from days without alerts.

1.2.1 Air quality alerts: Indirect avoidance behavior

Since human health risk reduction is the main objective of clean air regulations, economists have begun to quantify the impact of air quality alerts by exploring the effect of alerts on the level of respiratory and cardiovascular hospitalizations. The behavioral impact of alerts estimated by these studies is called indirect avoidance behavior because it is computed indirectly through the impact of alerts on the health outcomes. Neidell (2004) estimates the effect of ozone pollution on child hospital hospitalizations for asthma in California. His findings indicate that the decline in pollution levels from 1992 to 1998 reduced hospital admissions by between 5 to 14 percent. Moreover, he estimates that smog alerts reduce the asthma rate among children aged 6-12 years by 1 percent, which demonstrates the existence

of indirect avoidance behavior.

Neidell (2009) investigates the relationship between ozone levels and asthma hospitalizations in Southern California using a regression discontinuity method. His estimation results show that ozone alerts reduce asthma hospital admissions by a statistically significant 16 percent among individuals aged 5-19 years. He also shows that incorporating the response to information about air quality yields significantly 2.6 times larger impact of pollution levels on asthma rate.

Arceo et al. (2016) explores the relationship between pollution and infant mortality in Mexico. Using fixed effect estimates they find that a 1% increase in annual PM_{10} leads to a 0.40% increase in infant mortality, while a 1% increase in CO results in a 0.33% increase. To control for endogeneity in pollution exposure, they also apply IV estimator using thermal inversions in Mexico and they find 5 to 10 times bigger effect sizes.

1.2.2 Air quality alerts: Transportation choice impact

Several studies investigate the impact of alert policies on transportation patterns to determine whether or not alerts induce any behavioral response. These studies are all focused on the policies that have the intention of shifting individuals from private vehicle into public transport. For instance, Cummings and Walker (2000) develop a model to forecast aggregate daily traffic volumes so that they can compare the forecast volume of traffic with the observed volume on days with an ozone alert. They report no significant effect of ozone alerts on the traffic patterns in Atlanta.

In contrast, Welch et al. (2005) use hourly train ridership data to evaluate the impact of smog alerts in Chicago from 2002 to 2003. They demonstrate that although the aggregate level of train ridership does not change in response to alerts, its hourly patterns significantly differ on days with alerts compared with the days without an alert. Specifically, on smoggy days there are 3 to 4 fewer riders per station between 6 and 7 am and 2 and 3 pm while smog alert increases the demand for train by 6 to 8 riders per station between 10 to 11 am

and 2 to 3 pm.

Cutter and Neidell (2009) investigate how individuals in the San Francisco Bay Area change their transportation choice in response to ‘Spare the Air’ (STAs) policy.⁶ Their results show that while pollution advisories (i.e. STAs) decrease the total volume of daily vehicle traffic by a statistically significant 3 to 3.5 percent, they increase total daily demand for public transportation (i.e. Bay Area Rapid Transit (BART)) by a statistically insignificant 1 percent.

A study by Tribby et al. (2013) uses 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. They conduct an ANOVA analysis to show that in response to alerts, the level of traffic decreases in the city centre by a statistically significant 2.1 percent, but traffic increases by 5.8 percent near the edge of the metropolitan area.

1.2.3 Air quality alerts: Direct avoidance behavior

To quantify direct avoidance behavior, previous studies either use survey data, such as Bresnahan et al. (1997); Mansfield et al. (2006); Wen et al. (2009) and Sexton (2011), or they use outdoor attendance data. For instance, Sexton (2011) uses the American Time Use Survey (ATUS) data to show that individuals avoid being exposure to pollution in response to smog alert by on average 18 minutes reduction in their Vigorous Outdoor Activities (VOAs). Graff Zivin and Neidell (2009) use attendance at the Los Angeles Zoo and Botanical Gardens and Griffith Park Observatory as a measure of outdoor activity to examine how individuals adjust their time spent outdoors in response to a smog alert. They find that smog alerts reduce individuals’ attendance at the zoo and observatory by 15 and 5 percent, respectively. However, if the alerts are issued for two consecutive days, there is no statistically significant reduction on the second day. Noonan (2011) investigates the change in the usage pattern of

⁶‘Spare the Air’ (STAs) required the Bay Area Air Quality Management District (BAAQMD) to issue an alert on days when the ground level of ozone is predicted to exceed National Ambient Air Quality Standards (NAAQS). STAs aimed at reducing ozone level by encouraging the voluntary reductions in vehicle trips and increases use of ride-share and public transit.

Piedmont Park, which is a major Atlanta park, in response to smog alerts. He finds that aggregate park usage does not change on days with alerts compared to days without alerts. However, on smoggy days there is a statistically significant 2 and 25 percent reduction in the proportion of elderly and exercisers, respectively.

It is important to note that the existence of avoidance behavior by a physically active individual can play a crucial role as a source of nonmarket behavior in reducing the health risk associated with air pollution. In particular, previous studies such as Carlisle and Sharp (2001) and Atkinson (1997) find that exercising in poor air quality can increase health risks. The cardiovascular and respiratory effects of air pollution are amplified by exercising since exercisers inhale more pollutants. Cakmak et al. (2011) use the Canadian Health Measure Survey (CHMS)⁷ data for 5000 individuals aged 7 to 69 years to investigate the effect of air pollution on cardiovascular function of exercisers. Their results show that a 17 *ppb* increase in ozone is associated with a 1.5 percent reduction in aerobic fitness score.⁸ In addition, Marr and Ely (2010) gather seven marathon race results to show that 10 $\mu\text{g}/\text{m}^3$ increases in the level of PM₁₀ will reduce the performance of female marathon runners by 1.4 percent.

To the best of our knowledge, not only this study is the first which uses administrative data on vigorous outdoor activities to quantify direct avoidance behavior but also to date there is no study in Australia examining the effectiveness of air quality alerts. Notably, previous works such as Chen et al. (2006), Morgan et al. (2010), Jalaludin et al. (2000) and Smith et al. (1996) mainly investigate the effect of bushfire smoke (particularly PM_{10}) on the respiratory and asthma hospitalizations in Australia.

⁷Starting in 2007, the Canadian Health Measures Survey (CHMS) has been gathering relevant information about Canadians' health by collecting main physical measurements such as blood pressure, height, weight and physical fitness.

⁸Aerobic fitness score computes the volume of oxygen that each individual needs to burn during peak exercise.

1.3 Background on air quality policies in Australia

Information provision about air quality (i.e. alerts) may be more cost-effective at reducing pollution exposure compared to direct regulations. As a result, a number of jurisdictions have implemented air quality alert systems. Air quality alert systems aim to provide timely information to individuals about periods of elevated ambient pollution concentrations to allow individuals to make decisions so as to limit pollution exposure.

The National Environment Protection Council (NEPC) is responsible for regulating air quality in Australia. National standards for six major pollutants (i.e. 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 under the National Environment Protection Measure for Ambient Air Quality (the ‘Air NEPM’) Acts. Air NEPM also defines the methods by which these pollutants need to be measured, distinguished and reported.

The NSW Office of Environment and Heritage (OEH) is responsible for reporting AQI in NSW. Each monitoring station collects hourly measurements of air pollutant concentrations. These measures are then used to construct daily measures of AQI for each site and region. OEH reports daily AQI via media including local newspaper, radio and television or known websites and phone applications. The Air NEPM standards and their averaging period are represented in Table 1.

According to NSW EPA, the air quality index (AQI) can take any value between 0-500. The AQI is classified into six categories: Very Good AQI= (0-33), Good AQI= [34-66), Fair AQI= [67-99), Poor AQI= [100-149), Very Poor AQI= [150-199) and Hazardous is for AQI levels above 200.

Beyond the hourly and daily values of AQI, every day at 4pm the OEH issues a forecast for the next day’s air quality index. If any of the three regions within Sydney (Eastern, North Western and South Western Sydney)⁹ are predicted to have AQI above 100 an air pollution health alert is issued by the NSW Office of Health, typically one day in advance

⁹These three Sydney regions include over 60 percent of the 6.04 million residents of NSW.

at 4pm. An air quality alert is announced with hourly pollution details through the NSW OEH web pages,¹⁰ twitter, e-mail and SMS notifications.

The air quality health alert for the Sydney Region is based on gathering and analyzing information from several sources: (1) the Air Quality Index (AQI) value for the previous 24 hours throughout Sydney, (2) the Bureau of Meteorology (BOM) to assess the meteorological conditions including wind speed, wind direction, rainfall, temperature, temperature inversion and cloud cover, (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.

Due to the hot and dry climate, bushfires are frequent events in Australia. As indicated by the Australian Bureau of Meteorology, in most instances hot and dry winds gusting from central Australia increase a risk of fire. The bushfire season differs by region. Southern Australia is more vulnerable to the threat of fire during the dry summer months (December to March), whereas northern Australia is most susceptible during winter (April to September).

Smoke due to the bushfires usually covers large areas of land and can impact the air quality of regions that are hundreds of kilometers away from the actual location of fires. In fact, bushfire smoke is often part of the Australian urban air pollution. This smoke contains mainly particulate matter, carbon monoxide and volatile organic compounds. Bushfire smoke can also increase the level of ground ozone in the presence of sunlight.

1.4 Data

To quantify ozone alerts' behavioral impact and its dynamics on cyclists in Sydney, this study needs to bring together information about cycling activity, air pollution alerts, ambient air pollutants and weather data across Sydney. The following subsections discuss the data sources and the matching approach for each dataset.

¹⁰Alerts are announced at: <http://www.environment.nsw.gov.au>

1.4.1 Cycling activity

This study uses hourly and daily aggregate numbers of cyclists for 31 routes within the city of Sydney as an index for outdoor activity. The regional location of routes can be categorized into: downtown, inner north, inner west, north, northwest, west central and south. We obtained the daily aggregate number of cyclists from May 2008 to September 2013 for 31 counters within the City of Sydney.¹¹ Figure 1 shows the location of Sydney cycling counters.

Focusing on cycling activity as a measure of outdoor activity provides several advantages over previous studies. First, the exact date of aggregate cycling activity data corresponding to forecast AQI alerts is available. Second, the cycling data are available for more than five years, which allows the study of significant variations in pollutant levels, AQI and alerts. Third, the data are available for commuter and non-commuter routes and for weekdays and weekends. This allows us to perform additional specification of behavioral impact of alerts for cycling activities. Lastly and most importantly, previous studies primarily rely on survey data of outdoor activities, while cycling trip data is not only a revealed preferences measure but also is an accurate measure for high exposure outdoor activity.

The average length of each cycling path is 6 km. Most of the routes are commuter paths. However, some of them, such as Sydney Park to Centennial Park, are leisure routes that link two recreational facilities together. Shown in Table 2, the daily average number of cyclists from May 2008 to September 2013 is 353.6 per counter; however, the average number of daily cyclists for commuter routes is 614.5 per counter. Counters are excluded from the data if they count fewer than 10 cyclists per day on average.¹² There were 16 days from May 2008 to September 2013 in which counters did not work properly and all of the counters counted zero cyclists. Those dates with zero cyclists for all counters are dropped out from the regression. After dropping all the missing values for included explanatory variables (which are discussed below), we are left with a total 1831 days.

¹¹Counters belong to NSW Roads and Maritime Services.

¹²Because of this reason 5 out of 31 counters are excluded from our regression.

In order to conduct additional avoidance behavior specifications, the Sydney cycling network is classified into leisure and commuter routes according to two alternative mechanisms: First, by comparing the daily average number of cyclists on the weekend with weekdays routes are classified into leisure and commuter. If the average number of cyclists for a specific route is higher on the weekends than weekdays, a route is classified as leisure. Conversely, if the average number of cyclists is higher on weekdays, the route is classified as a commuter route. Figures 4 and 5 show the average number of cyclists over each day of the week for a typical commuter and leisure route.¹³ Second, to gauge the robustness of our results, routes are classified by investigating the peak hours of cycling demand for each route. In particular, the percentage share of weekday peak hours cycling trips from total weekday trips is calculated for each counter.¹⁴ Figures 6 and 7 represent the hourly pattern of a commuter and a leisure counter. If the share of peak hours trips is more than 85 percent, the route is called commuter. Otherwise, it is categorized as a leisure routes.¹⁵

1.4.2 Ambient air pollutant information

Data on ambient air pollution, air quality index and air quality alerts are obtained from the NSW OEH. Shown in Figure 1, overall there are 21 air quality monitoring stations around Sydney region, of which 14 stations are active corresponding to the period of this study and 6 stations are used according to their distance to the cycling stations. To control for potential omitted variable bias, 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), 1-h particulate matter (PM_{10} and $PM_{2.5}$) are included in our model.¹⁶ All pollutant variables are 24-hour averages deriving from maximum 1-hour averages. To assign a daily pollution level to each cycling counter, the closest air pollution monitoring site station is used based on longitude and

¹³Based on this specification out of 26 active stations, 11 are classified as leisure and 15 are classified as commuter.

¹⁴Peak hours are between 7am-10am and 4pm-7pm.

¹⁵According to this criteria, 4 and 22 stations are classified as leisure and commuter, respectively.

¹⁶Data are available at <http://www.environment.nsw.gov.au/AQMS/search.htm>

latitude coordinates.

It is also important to note that the NSW OEH issues a single air quality alert (based on the air quality forecast) for the entire Sydney region. This study deals only with behavioral impact of ozone alerts, since in most instances the forecast is primarily determined by the forecast value of ozone. In fact, in our period of study 96 percent of air quality alerts are ozone alerts.¹⁷ Particularly, as indicated by NSW EPA 2012, the ambient concentrations of CO , NO_2 , and SO_2 , are generally 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 areas often exceed the standards.

As shown in Table 2, a one-time ozone alerts occurred 1.3 percent while two successive alerts occurred only for 0.4 percent¹⁸ of the days between May 2008 and September 2013. This suggests that an ozone alert is not a very frequent incident in Sydney region.

1.4.3 Weather

This study controls for confounding weather factors. On one hand, short run variations in the weather conditions can impact the ambient level of pollution, such as ground level of ozone. On the other hand, cycling activity is highly affected by weather conditions. In particular, the daily measures of maximum temperature, average air temperature, precipitation, relative humidity, number of hours of bright sun from sunrise to sunset, total global sun exposure and wind speed are included as weather variables in our estimation.

The weather data are obtained from the Australian Bureau of Meteorology (BOM). Data are assigned to all cycling counters using measures from the Sydney Airport Metropolitan monitoring station.¹⁹ Figure 1 shows all weather, pollution stations and cycling counters.

¹⁷For a total of 1831 days, alerts are issued for 25 days, of which 24 are determined by forecast value of ozone. Observed value of AQI was above threshold for 34 days.

¹⁸In period of our study two consecutive alerts issued for 7 days, of which only 2 are occurred on weekends and holidays.

¹⁹The Sydney airport weather station is located around the downtown of Sydney and it has the most complete weather data. Given the fact that this may cause measurement error, we assign weather conditions to cycling stations based on GPS coordinates and find no significant difference. The model is also regressed

1.4.4 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 a very long distance (i.e. over 2000 miles) and has 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, O_3 and CO concentrations over Europe during August 1998. DeBell et al. (2004) find that bushfires in Quebec in early July 2002 had significant influences on O_3 , CO and $PM_{2.5}$ concentrations in both urban and rural areas of the east coast of the United States. Glatthor et al. (2013) show that pollutants from bushfire in early February 2009 in southeast Australia had significant negative impacts on the level of air quality in northeastward of New Zealand after 3 to 4 days.

Bushfires typically occur in the dry, sparsely populated bush areas of Boorowa and Hume, several hundred miles to the south-west of the city. More specifically, because of hot dry conditions, PM from bushfire events in Australia can transport vast distances, and affect the air quality level of areas far from their source (Confalonieri et al. (2007)). Notably, previous works such as Chen et al. (2006), Morgan et al. (2010), Jalaludin et al. (2000) and Smith et al. (1996) provide evidence of the statistically significant causal link between bushfire smoke (particularly O_3 and PM_{10}) and health outcomes in Australian cities. In more recent work, Johnston et al. (2011) show that bushfires in the Eucalypt forests to the west of Sydney significantly increased PM and O_3 concentrations of the city and were associated with a 5% increase in non-accidental mortality for a period of 1994 - 2007.

As mentioned above, this study uses bushfire as an instrumental variable for air quality. Bushfire data are obtained from the NSW Rural Fire Service (RFS), Australian Emergency

excluding weather variables shown in Table 6.

Management Institute (AEMI)²⁰ and Romsey Australia.²¹ Shown in Table 2, there were active fires around Sydney 2.7 percent of the time. Data on active bushfires are gathered from RFS and Romsey Australia. Moreover, each fire size and its distance from the city of Sydney are obtained from AEMI. To give insight into how many fires burn near Sydney, Figure 2 shows all active burning fires around Sydney during 2013.

1.5 Conceptual framework

This section presents a simple economic model to show that how poorer level of air quality (i.e. larger value of air quality index) might lead to a lower level of cycling. Let θ be the type of cyclists. Assume cyclists are distributed on θ according to distribution $F(\theta)$ with density function $f(\theta)$ over the interval $\theta = [0, 1]$. Suppose further F is strictly increasing. The utility function for a type θ of cyclist is denoted by

$$u(q, \theta) = \begin{cases} \theta v - c(q) & \text{if cycles,} \\ 0 & \text{otherwise,} \end{cases} \quad (1.1)$$

where v is the benefit from cycling and $c(q)$ is the cost of cycling as a function of air quality $q \in \mathbb{R}_+$ (i.e., $c(q)$ is the damage from air pollution conditional on cycling). The larger value of q corresponds to poorer air quality. Assume c is strictly increasing in q . In fact $c(q)$ shows damage from air pollution. It is logical to assume that marginal damage is increasing in pollution (i.e., the damage from air pollution is convex). Finally, assume $c(q) < v$ so there is always demand for cycling.

From (1) there will be a type

$$\tilde{\theta}(q) = \frac{c(q)}{v} \in (0, 1) \quad (1.2)$$

²⁰Data were found at: <http://www.emknowledge.gov.au>

²¹Data were found at: <http://home.iprimus.com.au>

such that all types $\theta \geq \tilde{\theta}$ will cycle and all types $\theta < \tilde{\theta}$ do not. Demand for cycling is then given as

$$D(q) = 1 - F(\tilde{\theta}(q)). \quad (1.3)$$

Now assume that q_0 is an initial value of air quality index and air quality increases to q_1 such that air quality exceeds a threshold for alert. It follows from Taylor's theorem that:

$$\begin{aligned} D(q_1) - D(q_0) = & \\ & - f(\tilde{\theta}(q_0)) \frac{c'(q_0)}{v} [q_1 - q_0] \\ & - \frac{1}{2} \left[f'(\tilde{\theta}(q_0)) \frac{c'(q_0)}{v} + f(\tilde{\theta}(q_0)) \frac{c''(q_0)}{v} \right] [q_1 - q_0]^2. \end{aligned} \quad (1.4)$$

Therefore for $q_1 > q_0$ we will have $D(q_1) < D(q_0)$ which implies that demand for cycling decreases as air quality deteriorates.

1.6 Empirical analysis

Quantifying the level of avoidance behavior is challenging. First, individuals might reduce their exposure to pollution by adjusting their time spent doing outdoor activities by choosing to drive instead of cycling. This action by itself will increase the pollution level. Thus, air quality level is potentially endogenous in this framework.

Second, meteorological factors can directly affect the choice for cycling and at the same time they can impact the level of air quality. Previous studies such as De Freitas et al. (2008) and Connolly (2008) demonstrate that for most outdoor activities, meteorological factors have a nonlinear functional relationship, and adding higher polynomial orders of weather conditions (especially maximum air temperature and precipitation) has a substantial effect on the estimates of demand for outdoor activities. Although weather conditions can be observed and controlled, estimation may be biased since it is hard to fully control for all

weather factors with appropriate functional form.

Third, as mentioned by Neidell (2009), assigning pollutants variables to each counter using interpolation techniques might result in measurement error because of two reasons. First, air pollution concentrations are highly variable within regions. Second, individuals can move between region and we often do not know where they spend their time. In particular, 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 the pollutants variable to individuals.

In order to address the above methodological problems, this study implements an instrumental variables estimator using bushfires as an instrument for air quality levels in Sydney. Instrumental variables are a dummy for an active bushfire around Sydney, the size of the bushfire and the distance of the bushfire from Sydney.

To estimate short-run direct avoidance behavior, this study begins by examining the effect of alerts on the number of cyclists each day. Our baseline fixed effect model is:

$$\log(cycling)_{it} = alert_t\beta_1 + aqi_{it}\gamma_1 + W_{it}\delta_1 + \Phi_i + \phi_t + \epsilon_{it} \quad (1.5)$$

where $cycling_{it}$ is the aggregate daily level of cycling at counter i at date t . $alert_t$ is a dummy variable which is one when it is forecasted that ozone level will be higher than the threshold level and zero otherwise. aqi_{it} is air quality index affecting cycling quality.²² W_{it} includes the weather variables that may affect cycling experience: maximum temperature, quadratic form of maximum temperature, air temperature, precipitation, relative humidity, solar exposure, number of hours of bright sun and wind speed.²³

²²The daily level of air quality index is calculated using maximum one hour average of pollutant concentrations that are measured everyday from 1.00 am to 12.00 midnight. Therefore to better control for the actual level of air pollution, in addition to AQI , the average daily level of O_3 , CO , NO_2 , PM_{10} and $PM_{2.5}$ are included in our regression. This might increase the standard error of estimated coefficients which will affect the significance of our results. It is however shown that regression results are insensitive to excluding the pollution variables.

²³All weather data used in this study are measures at 6:00 am since most of the cycling paths are commuter routes, so if individuals want to make a decision for cycling they are likely to consider the 6:00 am weather conditions. It is important to mention that results sustain when we change this to daily average measure.

Φ_i and ϕ_t are respectively cycling routes fixed effects and time fixed effects that might affect cycling quality. Specifically, following Graff Zivin and Neidell (2009), ϕ_t is a vector of time dummies which includes dummies for day of week, holidays and year-month. ϵ_{it} is an error term. All the error terms in this study are clustered at cycling counters to account for serial correlation within counters.²⁴

In order to examine which groups of cyclists engage in avoidance behavior, the model is also regressed for weekends versus weekdays and commuter versus leisure routes. This specification allows an understanding of whether behavioral impacts of alerts are distributed uniformly across individuals. The coefficient β_1 captures differences in daily cycling level between days with an alert and days without an alert. We expect β_1 to be negative, which implies that individuals reduce their level of outdoor activities in response to alerts.

To analyze the dynamics of individuals' response to ozone alerts, following Graff Zivin and Neidell (2009) the model is expanded to a 2-day model as follows:

$$\begin{aligned} \log(cycling)_{it} = & alert_t\beta_1 + alert_{t-1}\beta_2 + alert_{t-1}alert_t\beta_{12} \\ & + aqi_{it}\gamma_1 + aqi_{it-1}\gamma_2 + W_{it}\delta_1 + W_{it-1}\delta_2 + \Phi_i + \phi_t + \epsilon_{it} \end{aligned} \quad (1.6)$$

where $alert_{t-1}$ is lagged alerts. The interaction of current ($alert_t$) and lagged ($alert_{t-1}$) alerts allows estimating the effect of current alert on the cycling demand depending on whether there was an alert yesterday. As argued by Graff Zivin and Neidell (2009) in this framework, if alerts are issued on two successive days, $t - 1$ and t , the effect of the second days' alert in t conditional on cycling in t is $\beta_1 + \beta_{12}$. However the impact of one-day alert is still β_1 since for a one-day alert we have $alert_{t-1} = 0$.

Graff Zivin and Neidell (2009)' results show that for a leisure activity such as zoo attendance, when alerts are issued on two successive days, individuals seem quite non responsive to alerts on the second day. This result obviously depends on the type of activities since the

²⁴ 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. Our results are also insensitive to clustering on date.

cost of avoiding activities differ by the nature of them. Investigating the dynamics of individuals' response for an activity such as cycling is crucial since cycling demand (especially in our dataset) represents a mode of transportation. Hence compared to zoo attendance, cycling seems less likely to be optional. Therefore, it is worthwhile to see how the dynamics response of ozone alerts for a less optional activity such as cycling might look like.

To address the potential endogeneity concern about air quality²⁵ the model is regressed using an instrumental variable estimator. In particular, the following equation is estimated in the first stage:

$$aqi_{it} = bushfire_t \alpha_1 + size_{it} \alpha_2 + distance_{it} \alpha_3 + W_{it} \delta_1 + P_{it} \gamma_1 + \psi_t + \Psi_i + v_{it} \quad (1.7)$$

where $bushfire_t$ is a dummy variable which is one for the date when there was an active bushfire near Sydney and zero otherwise. $size_t$ is a hectare measure of each fire and $distance_{it}$ is the distance between an active fire and city of Sydney.

It might be important to mention that previous literature such as Moretti and Neidell (2011) control for other pollutants while they only instrument for the coefficient of their interest. We choose not to include individual pollution levels (O_3 , CO , NO_2 , PM_{10} and $PM_{2.5}$) since our regressions would end up with multiple endogenous variables. As indicated by Angrist and Pischke (2008), it is not sensible to include an additional endogenous variable as a control because models with multiple endogenous variables face identification problems. Moreover, we do not suspect the omission of individual pollution levels to present a problem for our estimations since our results are insensitive to inclusion of them.²⁶

²⁵As discussed in Section 3, since $alert_t$ is determined by the value of $\mathbb{E}_{t-1}[AQI_t]$ and AQI_{t-1} , it might come to mind that there is no need to control for the endogeneity of AQI_t while the coefficient of interest is $alert_t$. As argued by Angrist and Pischke (2008), the endogeneity of one explanatory variable will affect the consistency of other variables unless the orthogonality condition is satisfied. As AQI_{t-1} , $\mathbb{E}_{t-1}[AQI_t]$ and AQI_t are likely to be highly correlated, it is not sensible to assume that $\mathbb{E}_{t-1}[AQI_t]$ and $alert_t$ are orthogonal. Therefore, it is essential to control for potential endogeneity between the level of air pollution and the transportation choice in the presence of an air quality alert.

²⁶Exclusion of 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 cycling decision is not likely to be based on individual pollutant levels.

Using *bushfire*, *size* and *distance* as instrumental variables first requires that several conditions be satisfied. First, these variables must affect air quality level while they should not directly have any influence on the demand for cycling. This requires that $cov(bushfire_t, AQI_{it}) \neq 0$, $cov(size_t, AQI_{it}) \neq 0$, $cov(distance_t, AQI_{it}) \neq 0$. Second, these variables should be orthogonal to other unobservable factors affecting the daily aggregate number of cyclists. In other words, in order to get an unbiased estimation of avoidance behavior (β_1), the conditions $cov(bushfire_t, \epsilon_{it}) = 0$, $cov(size_t, \epsilon_{it}) = 0$, $cov(distance_t, \epsilon_{it}) = 0$ must be satisfied.

Essentially, two properties imply that these instrumental variables can satisfy the above conditions. First, bushfire smoke represents one of the primary sources of urban pollution in Sydney that can adversely impact the air quality. Indeed, bushfire smoke undoubtedly worsens the level of air quality. In addition, as discussed in section (3), in order to forecast the level of air quality, the emission sources from bushfires is thoroughly assessed by OEH. Likewise, it seems logical to assume that all possible impacts of bushfire smoke on cycling demand is completely absorbed by air quality alerts. It might be also useful to mention that the average of total active brushfires' distance from city of Sydney during the period of our study was roughly 1092 kilometers. Thus, it can be claimed that the smoke from bushfires are rarely observable from the city of Sydney.

Second, although hot and dry climate cause bushfires to be a frequent event in Australia, in fact bushfires are a quasi-random event. Generally, bushfires can be started either naturally or as a result of human activities, and their occurrence cannot be timed perfectly. Thus it is sensible to assume that *bushfire* is uncorrelated with other unobservable factors that might affect the cycling decision. Therefore, it is logical to expect that the bushfire measures are valid instruments for air quality.

1.7 Results

1.7.1 Graphical analysis

Figure 3 shows the preliminary evidence that ozone alerts induce avoidance behavior among cyclists in Australia. The aggregate daily level of cycling trips for all routes, observed value of air quality index and alerts are used to draw this graph. While this Figure does not control for any confounders, it shows a scatter plot and linear fitted value of cycling average against AQI for the air quality index valued between 50 and 200.²⁷ Each dot shows the average number of cyclists for all routes at each specific value of air quality index conditional on alert. In other words, we get the average of all routes' cycling trips for each level of AQI for the days with an alert and without alert. For instance, a grey circular dot corresponds to $AQI = 50$ and $\log(cycling) = 5.5$ shows the logarithm of cycling trips when the observed value of air quality was 50 and alert was not issued.

As depicted, the average number of cyclists on days with an alert is about 15 to 30 percent lower compared with days without alerts. This suggests the existence of avoidance behavior among cyclists in response to ozone alerts. This result is comparable to Graff Zivin and Neidell (2009)'s findings, which focus on Los Angeles zoo attendance to examine direct avoidance behavior, and find a statistically significant 15 percent decline in attendance in response to a smog alert.

1.7.2 Regression results

Estimation results based on Equation (5) are presented in Table 3. Column (1) shows baseline OLS results for all routes. The estimates suggest that cycling activity decreases by a statistically significant 14 percent in response to alerts. This result is consistent with our graphical analysis that illustrates the lower level of cycling trips on days with alert. Columns

²⁷In order to better show the difference between the average number of cyclists on days with an alert and days without alerts, the average number of cyclists are depicted against the alerts' threshold value (i.e., $AQI=100$).

(2) and (3) present regression results for weekdays and weekends. Compared to the baseline model, estimates of alert response for weekdays and weekends show a statistically significant 16 and 26 percent decrease in cycling activity, respectively.

Results for subsamples of commuter and leisure routes are presented in Columns (4) and (5).²⁸ Estimates suggest that cycling falls by a statistically significant 14 percent and 17 percent for commuter and leisure routes, respectively.

Previous studies²⁹ such as Tribby et al. (2013) find a 12 percent increase for weekday daily level of vehicle traffic in response to $PM_{2.5}$ alerts in metropolitan areas in Utah whereas the weekend level of traffic reduces by 2 percent. Hence, the behavioral alerts response might lead to higher vehicle use and therefore higher air pollution. This suggests that to estimate an unbiased direct behavioral impact of alerts, we need to control for endogenous increase in air pollution.

The regression results using a fixed-effect instrumental variable estimator are reported in Table 4. Panel A shows the first stage regression results. In the first stage, we estimate the effect of three instruments (bushfire, size and distance) on the air quality using Equation (6). Column (1) shows regression results when only one instrument (i.e. dummy for active fire) is included in the first stage. Column (2) present estimates when bushfire and size are included in the first stage as instruments. Column (3) shows IV regression results when all three instruments are included in the first stage. The second stage results are reported in Panel B where the dependent variable is cycling.

Shown in Panel C, the F-test for the joint significance of all excluded instruments indicates that all instruments are statistically significant and strong. According to the Hausman test,³⁰

²⁸For Table (3) and (5), routes are specified as commuter and leisure using first criteria which is comparing the average number of cycling on weekdays with weekends. Shown in Table 6, the other criteria (i.e., share of peak hours cycling trips) is used to check the robustness of these results.

²⁹Cutter and Neidell (2009); Welch et al. (2005) and Möser and Bamberg (2008) also investigate the transportation-pattern change in response to alerts.

³⁰Under 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 or bushfire and size has respectively a p-value of 0.000 and 0.000.

when bushfire and bushfire and size are instrumented for air quality, the difference between OLS and IV estimation is statistically significant.

Controlling for the endogenous increase in air pollution and accounting for confounding factors and measurement error, results suggest that 29, 35 and 13 percent of cyclists avoid exposure to air pollution when bushfire, bushfire and size and bushfire, size and distance are instrumented, respectively.

Our results are quite consistent and comparable with previous studies such as Graff Zivin and Neidell (2009) and Noonan (2011). Specifically, Noonan (2011) finds air quality alerts reduce exercising in Atlanta Park by 25 percent.

The fact that alerts are effective among cyclists is crucial. In particular because individuals who choose to cycle are generally healthy and young. Therefore it can be claimed that for high-exposure activities such as cycling, young and healthy individuals (who are not really a vulnerable group) value the air quality information and voluntarily avoid being exposed to pollution.

IV Regression³¹ results for subsamples of weekdays versus weekends and commuter versus leisure routes indicate that the impact of alerts is not uniformly distributed among cyclists. In fact, the behavioral impact of alerts differs across people and context of activity. Regression results for weekdays, weekends, commuter and leisure routes are reported in Table 5. Shown in Panel B, cycling declines by a statistically significant 31 and 49 percent on weekdays and weekends, respectively. In addition, when the sample is broken into commuter and leisure routes, there is statistically significant 23 and 40 percent decrease over commuter and leisure routes, respectively.

To test the robustness of our commuter and leisure results, once again routes are specified into commuter and leisure based on their share of peak hours trips from the total weekdays trips. Shown in Table 6, using a different criteria to define a commuter and leisure route

³¹It is worthwhile to note that for all other IV regressions, bushfire and size are instrumented for air quality since the F-statistic for excluded instruments suggest that bushfire and size are statistically stronger instruments for subsample regression, though the results of other instruments are quite similar to each other.

indicate that our results are robust to their specifications. Doing so, if the peak hour cycling trips share for a route is higher than 85 percent, it is called a commuter route and if it is less than 85 percent, it is called a leisure route.³² Columns (1) and (2) present OLS regression results and Column (4) and (5) show IV regression results using this specification. Shown in Panel A, using OLS regression cycling trips decrease by a statistically insignificant 11 and significant 13 percent for commuter and leisure routes, respectively. However, IV regression results show that the cycling demand fall by statistically significant 20 and 38 percent for commuter and leisure routes, respectively.

Together, these results suggest that accounting for endogenous alerts' response, confounding factors and measurement error, not only are alerts productive over weekends and leisure routes but their weekend and leisure behavioral impacts are larger compare to their weekdays and commuters' impact. This could occur because of two reasons. First, the elasticity of cycling demand with respect to air quality on weekends is higher than on weekdays. This is due to the fact that during the weekend cycling is primarily a leisure activity, which can be substituted more easily since an individual who chooses to cycle on weekends as a leisure activity has more options. Second, cycling on weekdays reflects one commuter-transportation option, while cyclists on weekends are highly likely to be more health conscious. Therefore, a weekend cyclist seems to be more responsive to an alert than a weekday cyclist.

Table 7 shows results for the 2-day model. As presented, when alerts are issued for two successive days, the behavioral impact of second day alert decline to statistically insignificant 5 and 4.9 percent for OLS and IV regression,³³ respectively. These results suggest that individuals' response to alerts is diminishing over time, indicating that the costs of intertemporally avoiding cycling are increasing as alerts are prolonged.

To test the robustness of our approach in controlling confounders, following Moretti

³²These thresholds are selected comparing the hourly patterns of counters with each other. Shown in Figures 6 and 7, more than 85 percent of trips for a commuter route are during peak hours while for a typical leisure route shown in Figure 8 this ratio is 68 percent.

³³As discussed in the empirical section the second day response is $\beta_1 + \beta_{12}$. The significance of this coefficient is tested using a joint test of significance.

and Neidell (2011), the model is regressed by excluding climate and pollutant factors. As discussed, environmental variables might be a potential source of confounders and accounting for their effects with proper functional form is one the main methodological challenges in estimation of pollution cost. Therefore, if our estimation results do not change by excluding these variables, it can be claimed that our approach could properly control for the effect of confounding variables.

Table 8 reports the sensitivity of our estimates to weather and pollutant factors. Column (1) repeats the benchmark estimates. Columns (2) and (3) respectively include pollutants and exclude weather variables. The sensitivity assessment results suggest that our approach is relatively strong in controlling for potential unobserved effects of climate and pollutant factors since results are unaffected by excluding weather factors. To gauge the robustness of our regression results, we also assume a non-linear relation between air quality and cycling. Table 9 reports estimation results for quadratic form of the air quality index variable. For IV regression, we also instrument for the quadratic form of AQI by bushfire and size. As presented, alert impacts are all statistically significant, suggesting our estimates are robust to a non-linear relation between air quality and cycling.

1.8 Conclusion

Air quality alerts are known as one of the eminent information-based regulations that aim to enhance air quality across jurisdictions by indirectly pushing individuals to take proper action to control sources of pollution and health risks associated with air pollution. From the public health perspective, an alert program can be considered as an effective program if it helps individuals (and especially the most sensitive groups) to avoid exposure.

From a social welfare perspective, alerts are cost effective if individuals do not substitute emission-related activities for exposure-related activities. In other words, the net benefit of reduction in pollution exposure should be weighed against the net loss due to increases in

emission-related activities in response to alerts. Thus, to trigger proper response, air quality information should be coupled with appropriate incentives to reduce emissions, since air quality policies do not explicitly ask individuals to voluntarily limit their vehicular trips.

In order to quantify direct avoidance behavior, this chapter analyzes the effect of air quality alerts on the individuals' cycling trips. The cyclists' response to alerts can be in the form of using other modes of transportation or deferring the optional outdoor activity. Using other transportation modes rather than cycling might lead to an unintentional increase in air pollution. Controlling for unintentional air pollution increases, environmental confounding factors and measurement errors, there is a statistically significant 35 percent decrease in cycling trips in response to ozone alerts. However, if alerts are issued for two successive day, cyclists seem to neglect the second day alerts, suggesting that the private costs of avoiding cycling is increasing over time.

As argued by Noonan (2011), we also find that avoidance behavior is not distributed uniformly across individuals. Our results suggest that there is 23 and 40 percent reduction in the cycling trips over commuter and leisure routes, respectively. Whereas the weekdays and weekends decomposition results suggest that the avoidance behavior induced by alerts is statistically significant one and half times larger on weekends than weekdays. This pattern is logical since individuals are more flexible to substitute for their leisure activities on weekends. These results are robust to several sensitivity tests. For instance, our results are clearly insensitive to different pollutants and weather factor specifications. Excluding weather factors, cycling trips reduce by a statistically significant 30 percent in response to ozone alerts. This suggests that our instruments strongly control for environmental confounding factors.

This analysis has the generalizability limitations. In fact, the generalizability of this result to areas other than Sydney and to activities other than cycling is unclear.

In terms of policy implications, regulators need to better understand behavioral response to publicly provided information. The existence of pollution avoidance behaviors is a positive outcome, though achieving the initial air quality alerts goal, which is emission reduction,

necessitates more incentives in terms of policy design. In addition, better understanding the dynamics response of alerts can play a significant role in terms of policy implications. Investigating the individuals' dynamics response shows that individuals do not consider the increasing benefits associated with pollution exposure reduction.

As argued by Semenza et al. (2008), an effective factor that will induce behavioral changes in response to a warning system is the perception of ambient conditions rather than advisory forecasts. Therefore, while alerts' impact seem not uniformly distributed over time and for leisure and commuter routes, if alerts were coupled with proper "health and environmental education" which could target individuals' perception of ambient air quality, not only would alerts produce larger impact, but also their unintended consequences would be mitigated.

Table

Table 1.1: 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 ($\mu\text{g}/\text{m}^3$)
Particles as PM10	1 day	50 ($\mu\text{g}/\text{m}^3$)
Particles as PM2.5	1 day	25 ($\mu\text{g}/\text{m}^3$)

Source: NSW EPA.

Table 1.2: Summary statistics

	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 ($^{\circ}C$)	22.73	4.97
Daily average of air temperature ($^{\circ}C$)	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 1.3: OLS regression results

	(1)	(2)	(3)	(4)	(5)
	Total	Weekdays	Weekends	Commuter ^(a)	Leisure
Alert	-0.141*** [0.0292]	-0.162*** [0.0422]	-0.265*** [0.0376]	-0.141* [0.0367]	-0.174** [0.0493]
Controls for weather	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y
Cycling routes fixed effect	Y	Y	Y	Y	Y
Observations	28452	20331	8121	16543	11898
R^2	0.261	0.308	0.331	0.308	0.329

Note: (a) Routes are classified into leisure and commuter by comparing their weekdays average of cycling trips with weekends.

Clustered by counters, standard errors in brackets.

* significant at 10% ** significant at 5% *** significant at 1%.

Table 1.4: 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
(P-value)	(0.001)	(0.005)	(0.003)
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 1.5: IV regression results for weekends vs. weekdays and leisure vs. commuter routes

	(1)	(2)	(3)	(4)
	Weekdays	Weekends	Commuter ^(a)	Leisure
A. First stage ^(b)				
Bushfire	2.667	22.413***	6.584	5.918
	[3.014]	[6.207]	[3.498]	[4.938]
Bushfire*Size	-0.0043***	-0.0048*	0.00243	0.0034*
	[0.0013]	[0.0023]	[0.00126]	[0.0021]
B. Second Stage ^(c)				
Alert	-0.309***	-0.495***	-0.237***	-0.401***
	[0.0547]	[0.109]	[0.0676]	[0.0810]
Controls for weather	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Cycling routes fixed effect	Y	Y	Y	Y
F-statistic for excluded instruments ^(d)	22.74	18.32	19.10	17.85
(P-value)	(0.0001)	(0.006)	(0.005)	(0.001)
Observations	20331	8121	16543	11898

Notes: (a) Routes are classified into leisure and commuter by comparing their weekdays averageDependent variable of cycling trips with weekends. is *AQI*. (b) Dependent variable is $\log(\text{cycling})$. (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 1.6: Sensitivity of commuter and leisure routes results to their specification

	(1)	(2)	(3)	(4)
	Commuter	Leisure	Commuter	Leisure
	OLS	OLS	IV	IV
Alert ^(a)	-0.119	-0.133***	-0.200***	-0.386***
	[0.0619]	[0.0337]	[0.0724]	[0.0821]
Controls for weather	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Cycling routes fixed effect	Y	Y	Y	Y
F statistic for excluded instruments ^(b)	-	-	14.31	22.21
(P-value)	-	-	0.001	0.002
Observations	5358	23094	5358	23094

Notes: (a) For this table the share of peak-hours cycling trips is used to specify routes as leisure and commuter. 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 1.7: Impact of two successive day alerts on cycling activity

	(1)	(2)
	OLS	IV
First day response	-0.169*** [0.0315]	-0.247*** [0.0474]
Second day response	-0.05 [0.0256]	-0.049 [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 1.8: Sensitivity of results to weather and pollution factors

	(1)	(2)	(3)
OLS regression ^(a)			
Alert	-0.141***	-0.124**	-0.298***
	[0.0292]	[0.0485]	[0.0361]
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
(P-value)	0.0009	0.000	0.001
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%.

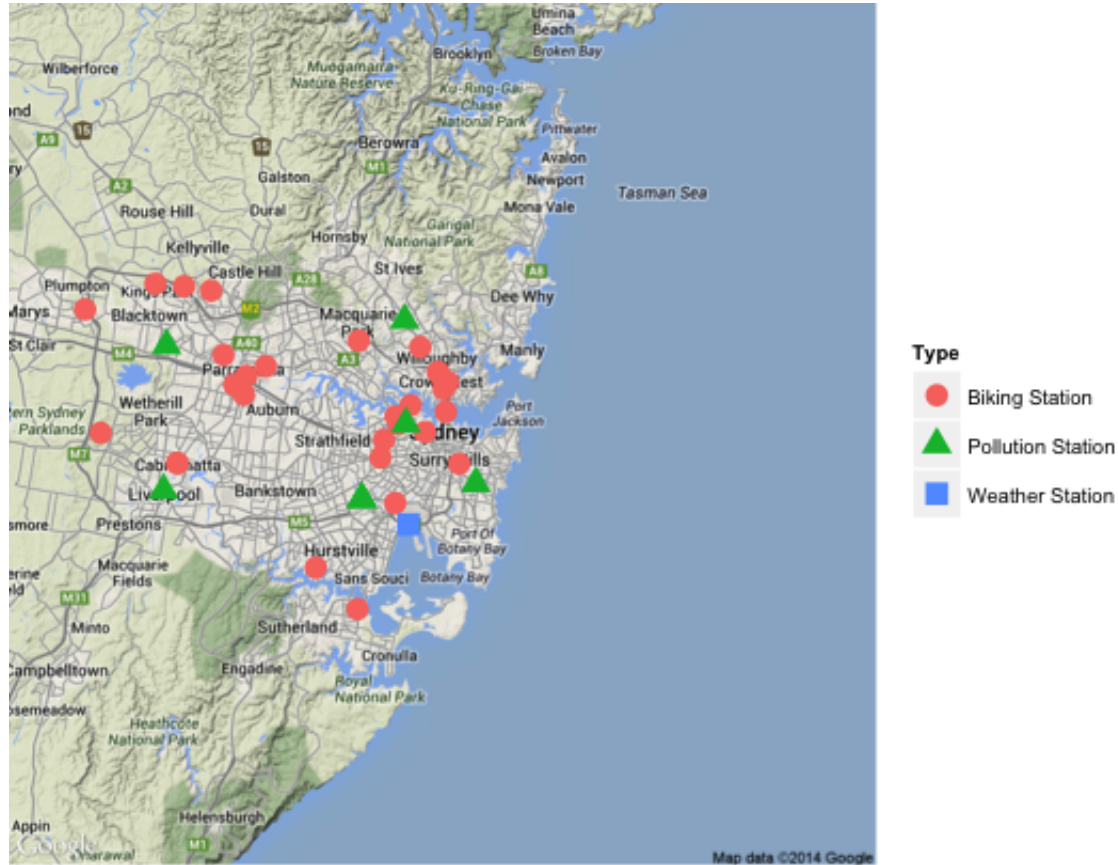
Table 1.9: Robustness to non-linear relations between air quality and cycling

	(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%.

Figure 1.1: Cycling, pollution and weather stations



Notes: 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 1.2: Active bushfires around city of Sydney during 2013

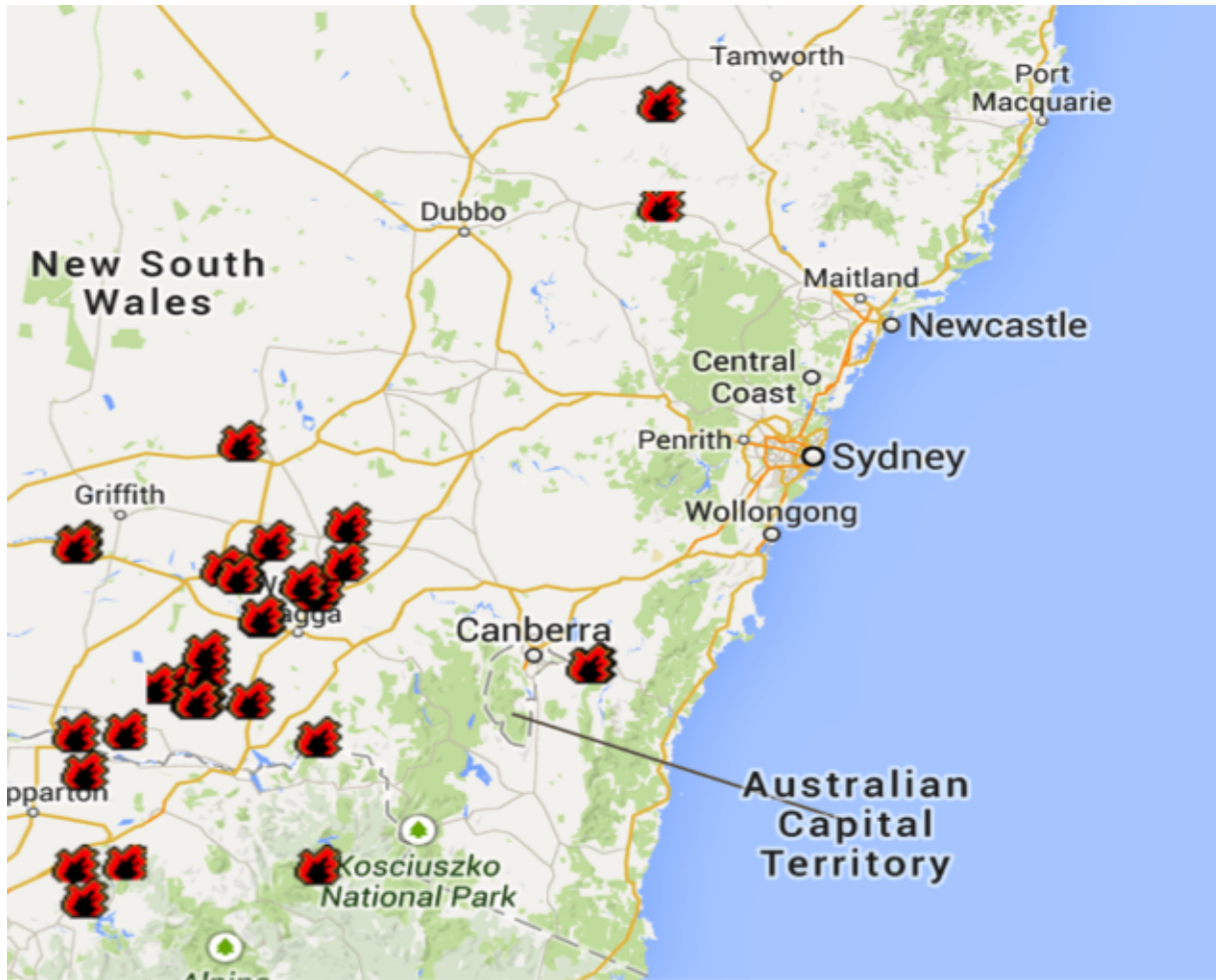
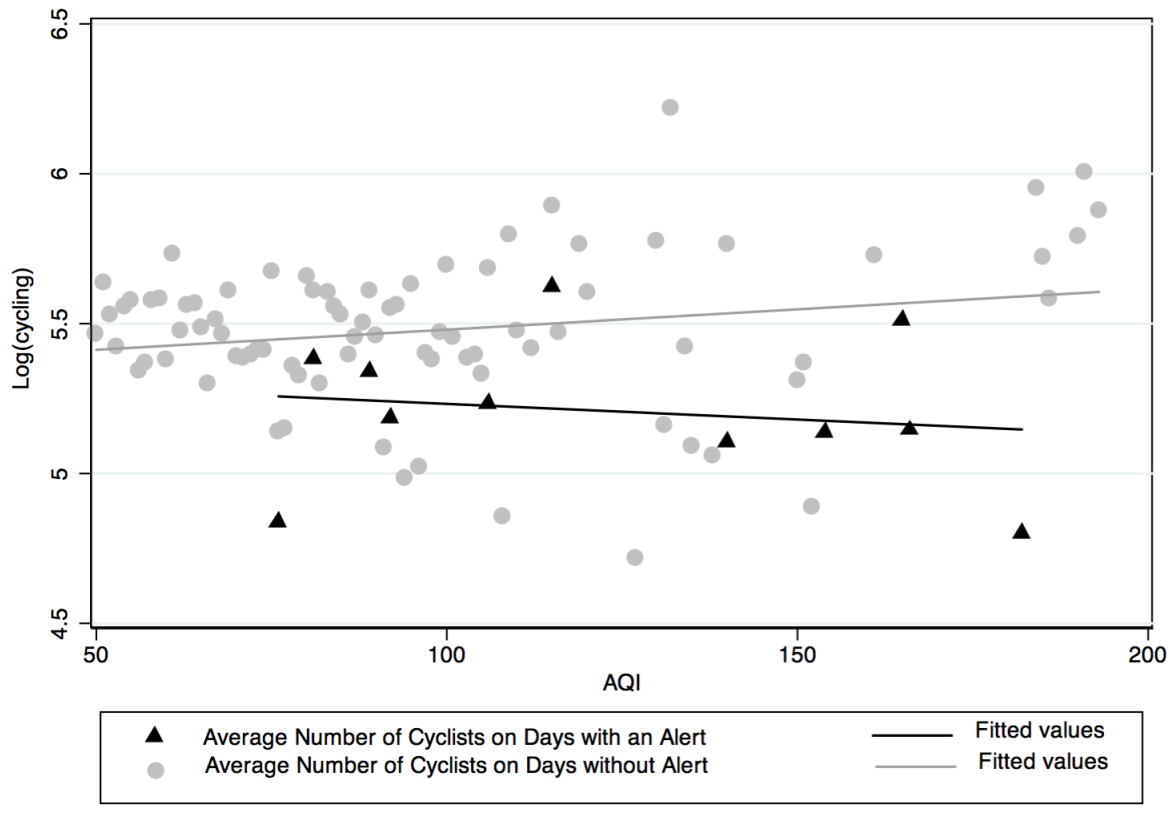


Figure 1.3: Cycling average on days with alerts vs. without alerts



Notes: 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.

Figure 1.4: Average number of cyclists per day of week for a commuter route

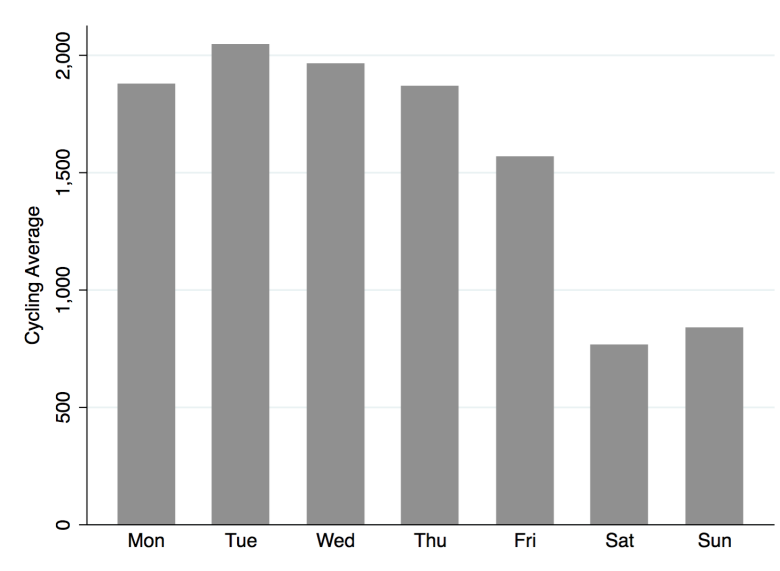
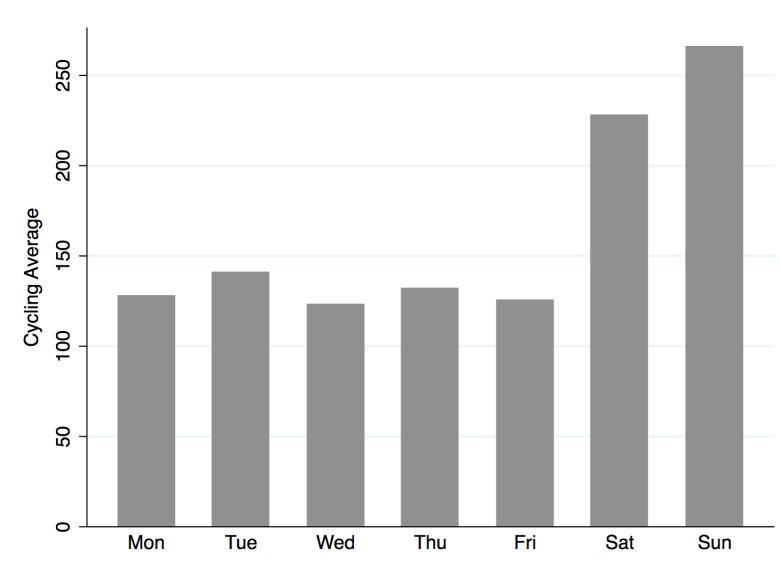


Figure 1.5: Average number of cyclists per day of week for a leisure route



Notes: The Sydney cycling network contains 31 counters. This graph is depicted using first and last counter's data by getting the average number of cyclists per day of the week for the period of May 2008 to September 2013. The counter is called commuter if the average number of cyclist is higher on weekdays.

Figure 1.6: Hourly pattern of cycling for a commuter route

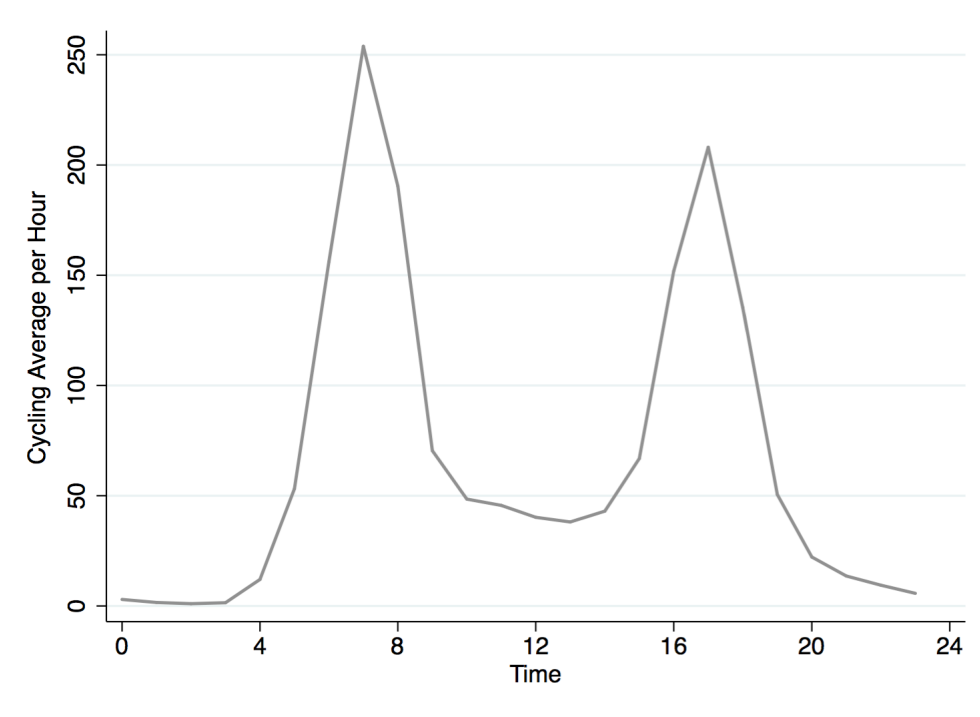
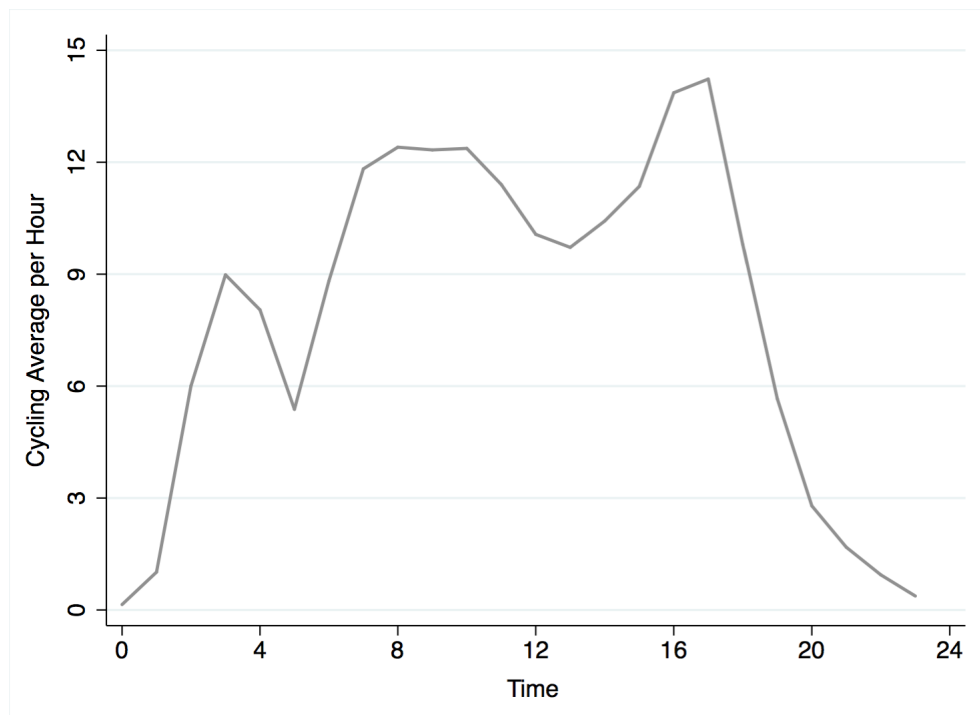


Figure 1.7: Hourly pattern of cycling for a leisure route



Chapter 2

Temperature and Decisions: Evidence from 207,000 Court Cases

2.1 Introduction

Decisions - those made by consumers, managers, investors and other sorts of agent - are pivotal to almost all economically and socially important outcomes. Textbooks are full of agents making judgements and trade-offs. It is therefore not surprising that a central ambition of economics (and other behavioral sciences) has been to understand how individuals make decisions. The canonical model is rationality, and welfare analysis typically assumes that agents successfully ‘solve’ the constrained optimization problems that confront them.

However, this assumption is increasingly challenged by evidence that factors not accounted for, and apparently irrelevant, in standard models can cause decision-making to depart substantially from the optimizing ideal. For examples, Mani et al. (2013) show that poverty, by occupying scarce mental resources or ‘bandwidth’, reduces cognitive function and reduces decision quality. Hunger negatively influences mental function (Weaver and Hadley (2009) and Weinreb et al. (2002)) and perception of risk (Ferrarelli (2016)). Tiredness reduces cognitive function (Tchen et al. (2003), Abd-Elfattah et al. (2015)), increases

risk-taking (Viner et al. (2008)) and reduces self-control (Kahol et al. (2008)).¹ A wider set of behavioral research, consistent with introspection, points to the importance of transitory emotions and mind-states in influencing decisions with long-term consequences (see Loewenstein (1996) for an early survey). For instance, while Ariely and Loewenstein (2006) show that sexual arousal can impact sexual decision-making, Jahedi et al. (2016) show that it can also influence a wider set of economic decisions by temporarily distorting risk attitudes. All of these fit into the ‘biology and economics’ agenda that seeks to model the agents that populate economic textbooks as biological organisms (‘wet machines’) - sensitive to the environment in which they function.

If decisions with durable consequences are systematically influenced by irrelevant or transient factors the potential for welfare loss is obvious. Our focus is on the role of temperature, and fits into this strand of research. Temperature profiles vary across space. Some places are hotter than others, usually cold places sometimes have hot days, etc.. Furthermore, climate change points to temperature patterns changing over time, both in terms of averages and variability (Stern (2007)). The question we investigate is the following: do decision outcomes, the substance of which have nothing to do with contemporaneous temperature, depend causally on how hot it is outside on the day the decision is made? Our answer is a resounding yes - with high significance and robustness, and a substantial effect size. As such we evidence a subtle and pernicious channel through which variations in climate (through space and time) can damage wellbeing: By influencing decisions.

We analyze the universe of files (just under 207 000) evaluated over a four year period by the 266 immigration court judges at the 43 US Federal Immigration Courthouse locations spread across most major US cities. Four things make this an ideal test-bed for the theories that we investigate;

¹There is a philosophical debate about how to conduct welfare analysis in these settings (Diamond and Vartiainen (2012)). Typically preferences (say with respect to risk) are regarded as having some longevity. If a person who has lost a night of sleep due to construction noise acts “as if” they have a higher risk appetite than they otherwise would then emerging practice would be to treat the mis-decisions made as welfare-reducing (O’Brien and Mindell (2005) and Halleröd and Larsson (2008)).

(1) The decisions that we observe are socially and economically significant and the appropriate choice self-evidently has nothing to do with contemporaneous temperature. As such any influence of temperature on decisions necessarily implies inefficiency and welfare burden;

(2) Our subjects are experienced decision-makers. While the precise characteristics of any individual file are unique, the setting in which they work and the broad parameters of case files are not novel. Furthermore, the setting mirrors the sort of repetitive-but-idiosyncratic decisions that agents such as consumers and managers face in the main economic models;

(3) The decision-makers that we observe work *indoors* and protected in their workplace by climate-control at a level typical of good-quality US Federal government buildings in the twenty-first century. In terms of protection, then, close to full application of the most obvious technological solution to mitigate temperature effects is already accounted for in the results. With regard to biological adaptation to prevailing conditions, the judges do not move around - they are attached to a single court location - meaning that they are ‘used to’ the prevailing temperature patterns in the city in which we observe them. Further, because location and dates of work are determined externally and in a way not sensitive to short-term temperature realizations we can ignore issues of displacement that might be important in other settings - the work task is fixed in substance, space and time.²

(4) The quality of data and the procedural details of the immigration system allow us to avoid a plethora of identification challenges, allowing for clean, persuasive causal inference.

Our main approach uses high frequency data to estimate a linear probability model with a variety of fixed effects, though we also provide some non-parametric results. We also develop variants in which (a) the dependent variables of interest are the Heat Index (a measure used by the US National Weather Service that combines temperature and humidity non-linearly into a metric designed to capture how hot it ‘feels’) and, (b) the variation between realized temperature on a particular date and local norms for that date. Our main

²For example, in some professions an employee might choose to defer work from a hot day to a cooler day (or work in the evening), or decide at short notice to work from home on a particular day.

identifying assumption is minimal: That temperature realizations are as good as random after accounting for spatial and temporal fixed effects.

The analysis uncovers a substantial effect of short-term (daily) variations in temperature on decision outcomes. In our preferred specification, which includes year-by-month, location and judge fixed effects, as well as controls for case characteristics and other potential environmental confounders, same-day outdoor temperature has an impact on decision outcomes. Our results suggest that a 10 °F degree increase in temperature reduces the likelihood of a decision favorable to the applicant by 1.075% which is equivalent to 6.55% decrease in the grant rate (the grant rate in the data as a whole is 16.4%). Consistent with some existing studies of temperature susceptibility by gender (Yu et al. (2010), Xiong et al. (2015)), the effect is particularly pronounced for female judges. To allay concerns that there might be something unique to the immigration setting that is driving the results we repeat the exercise for decisions made in 18 461 Parole Suitability Hearings at the 39 locations of the California Department of Corrections and Rehabilitation (CDCR), arriving at parallel conclusions.

Why are these results important? As a straight piece of law and economics the research contributes to an assessment of the consistency of US immigration (and California parole) practices. The Sixth Amendment to the US Constitution lays out ‘fair trial’ as a fundamental right. Administrative Procedure Act (APA) (1946) determines that any adjudication or decision by an agent of the US government should not be “arbitrary or capricious”. Agency decisions should be “... rationally connected to the facts before it” (Committee on Capital Markets Regulation (CCMR), 2016, p.2). The immigration court system is ‘about’ decisions, and natural justice - as well as the law - dictates that decisions on a particular file should be based solely on the merits of the case (“the facts and nothing but the facts”). There is no plausible reason why a particular file should have any different prospect of success if evaluated on a day unusually warmer for that location at that month-of-the-year, than on a day with a different temperature realization.³

³There has been a very long and much broader body of debate on arbitrariness in legal systems in the US and elsewhere. Oakley and Coon (1986), Danziger et al. (2011).

However, as our opening paragraphs suggest, cautiously we propose that the analysis provides a *prima facie* case that temperature may damage decision consistency and quality in a much wider set of settings. If experienced, professional judges, working in an environment in which they are protected from outdoor temperature with high-quality climate control technology, are as subject to influence as our analysis suggests, what should we think might be the impact of temperature on the wider population of agents (consumers, investors, managers, etc.) making diverse decisions with long lasting implications for welfare?

We are careful not to over-interpret the results, but it is tempting to juxtapose the findings with what we know about differences in temperature profiles across locations and through time. That we do not observe ‘right’ and ‘wrong’ decisions, even *ex post*, precludes definitive welfare analysis. Given that the correct arbitration does not depend on contemporaneous temperature *the sensitivity of outcomes to changes in temperature in itself implies inefficiency*. However it is not possible for us to point to particular type 1 and 2 errors.⁴ Notwithstanding this we can develop ballpark estimates for “excess” wrong decisions based on an additional *assumption*, grounded in existing research, that human comfort and performance is optimized at a particular temperature range. Other things equal does the analysis imply that immigration system decisions are on average ‘better’ when made in New York than in Phoenix? Or, to extrapolate further, that consumers, market traders, entrepreneurs and others make better decisions in New York than they do in Delhi? Climate change is expected not only to raise average temperatures in many places - will this diminish through time the quality of myriad decisions made by millions of agents within a city, with concomitant welfare losses? Can this provide a mechanism linking temperature patterns, through decisions, to workplace productivity and economic development?

The rest of the chapter is laid out as follows. In Section 2 we provide a sketch of some

⁴We do not have access to decision appeals which, at least superficially, might help identify errors. However, the rights to appeal and review in this area are much less developed than in those areas of law that relate to US citizens (which be construction immigration law does not). In addition, this is an area in which judges have very wide discretion in interpreting case circumstances, and there is no right to appeal purely against how that discretion is exercised. Appeals (as in most areas of law) relate to procedural mistakes.

existing research on the effect of temperature on humans, and the mechanisms that might underpin a link from outdoor temperature to indoor decision-making. Sections 3 and 4 detail data sources and methods. Section 5 presents the results of the main analysis and a series of robustness and falsification checks. Section 6 concludes.

2.2 Literature

While mechanism is not going to be our central focus it is worth highlighting several strands of research that link temperature to mental function, decision-making, risk attitudes and mood.

Several studies have examined the role of *indoor* temperature on some measure of mental or cognitive acuity. The temperature in a space is manipulated by the researcher, who then observes some measure of performance. For example, Hedge (2004) and Fang et al. (2004) examine performance on simple visual tasks and abstract problem solving in a laboratory. Wyon et al. (1996) assess vigilance, again in a temperature-manipulated laboratory setting. Chao et al. (2003) measure a set of more complex tasks in an office. Allen and Fischer (1978) measure student learning in classrooms. Seppanen et al. (2006) conduct a meta-analysis of the 24 papers that a particular search protocol elicits on this topic (including those just listed). Of these, 9 take place in the lab, the rest are in offices or schools, and between them they generate just over 100 effect size estimates. Their systematic review of the literature generates an estimate of the indoor temperature associated with highest productivity being at 21.75 °C (71.5 °F) with a decrement of performance of around 9% when temperature is 30 °C (86.1 °F).⁵ In general heat stress has a much greater influence than does cold stress on the performance of cognitive tasks (see Hancock and Vasmatazidis (2003) for a review).

⁵The first of these numbers accords with anecdotal introspection. In a more recent review (Cheema and Patrick, 2012, page 985) note that: “Prior studies find that an ambient temperature of 72 °F, one at which most people appear comfortable, may be most conducive for automatic tasks”. For instance, Allan et al. (1979) find that performance on a paired-association memory task peaks at 72 °F. Other evidence suggests a difference between temperatures that are optimal for comfort and those that are optimal for performance. Specifically, Pepler and Warner (1968) show that people perform office work best at 68 °F, although they report feeling cold.”

Turning to decision-making, Cheema and Patrick (2012) present five studies of consumer behavior in which they manipulate laboratory temperatures. In higher temperatures subjects are; (a) less likely to engage in gambles (particularly complex gambles); (b) less likely to choose innovative products over established ones, and; (b) more likely to rely on “system 1” (heuristic or habit-based) processing (Pocheptsova et al. (2009)). In our setting - in which the rejection rate of immigration applications is around 83% such that the granting an applicant leave to stay can plausibly be regarded as the less-habitual, more innovative and more risky choice - this would point to a negative relation between high temperatures and grant rates.

While evidence of the effect of contemporaneous indoor temperature on brain-intensive tasks is suggestive for us, none of it is directly relatable. Studies that cast light on the impact of how daily *outdoor* temperature effects indoor mental performance are rare. Graff Zivin et al. (2015) find that (outdoor) temperature above 79 °F on a particular day damages performance of children on math (but not reading) tasks. Park (2016) investigates the relationship between daily outdoor temperature and high school exit exams in New York city and finds that compare to a 72 °F day, taking exam on a 90 °F day reduces students’ performance by 0.19 standard deviation.

Turning away from cognition, separate strands of research evidence; (a) a causal link from ambient temperature (and other dimensions of weather) to ‘mood’, broadly defined, and then; (b) a causal link from mood to decision-making. Baylis (2015) links temperature to measures of hedonic state (mood) using geo-located Twitter activity. His four sentiment metrics based on phraseology, emoticon use and profanity each become more negative once outdoor temperatures exceed 70 °F (with little to no effect for colder temperatures). Denissen et al. (2008) find a similar effect when they analyze online diary entries of 1233 students. Relatedly, a number of behavioral finance papers (for examples Hirshleifer and Shumway (2003), Cao and Wei (2005), Floros (2011)) link daily variations in weather - typically cloud cover and sunshine, but also temperature and humidity - to stock price movements via

changes in emotional state.⁶

It is well-established that emotions inform judgment and regulate thought in a variety of different ways (Clore and Huntsinger (2007) provide an accessible introduction to that literature). In addition, various studies find that extraneous factors may have meaningful effects on judicial decisions. For instance, Guthrie et al. (2007) discuss that unlike the best efforts of judges to make decision based on facts and legal criteria, arbitrary factors such as results of National Football League (NFL) game and cognitive overload of a judge can affect judicial outcomes substantially. As such Chen (2017) finds that the probability of grant decision by US immigration judges increases by 1.4% the day after winning of home NFL team. Eren and Mocan (2017) find that judges assign roughly 6.4% longer sentences on Louisiana juvenile defendants when Louisiana State University (LSU) football team loses. Danziger et al. (2011) find that the likelihood of a favorable judgment is higher after a food break or at the beginning of working day since judges are less fatigue. There are also various experimental papers identifying the unwanted influence of mood, cognition fatigue and emotion on judgment (Englich and Soder (2009), Simon (2012) Dijksterhuis et al. (1996) and Wyer and Carlston (1979)).

Turning to the question of this chapter, the decision-maker in our setting is protected from outdoor temperature by climate control, but may ‘import’ the effect of exposure to, for example, an extreme outdoor temperature when they move inside, coming in from the morning commute, or after a break.⁷ Determining the physiological mechanisms through which this happens is beyond the scope of this chapter, but competition for glucose in

⁶Again physiological processes are not well-understood, but Lambert et al. (2002), for example, point to weather (particularly sunshine) influencing the production of serotonin, an important neurotransmitter which is generally thought to be a contributor to well-being. Temperature and other weather variables have been linked to a variety of emotional and behavioral outcomes including aggression (Baron and Bell (1976)), impatience (Ahn et al. (2010)), generosity (Williams and Bargh (2008)), depression (Pflug et al. (1976)) and suicidal tendencies (Page et al. (2007)). However this remains an ill-understood area which deserves further empirical research.

⁷Danziger et al. (2011) identify the effect of decision fatigue in sequential parole decisions made by Israeli judges and discuss that the time of day that a case is heard can affect its outcome. Unfortunately we do not observe the time at which a particular file is heard, or know the movements of the judge during the day, which might have allowed us to investigate intra-day or mental fatigue effects - for example larger effects just after a period outdoors.

the body is a popular theory. There is a much larger literature on the effect of ambient temperature on a variety of animal behaviors. We do not survey it here. However - for one example among many - Mathot et al. (2015) find that birds are less likely to engage in risky choices at higher-than-familiar temperatures. Importantly glucose depletion can have sustained effects.⁸ Outdoor conditions may also condition a judge’s behavior in a way that makes him fatigue, or influences his mood. For example, if external temperature is very high he may not venture outside during breaks ‘for fresh air’. Anyone who has spent time in a city like Houston or Atlanta during a heat-wave should understand that possibility. Lack of fresh air has been linked to reduced cognitive function (Chen and Schwartz (2009)) and depressive mood (Cunningham (1979)). In this way outdoor temperature could in principle affect the output of the subject even *if she never went outside and was exposed to it*.

2.3 Data

Our central analysis links US-wide data on outcomes of asylum applications with what we know about environmental conditions at the location of decision on the date in question. We also use state-wide parole decisions from California to probe external validity.

2.3.1 Immigration

We use case-level administrative data on US asylum applications made to immigration courts from January 2000 through September 2004. Our final dataset includes the universe of 206 924 decisions made over this 58 month period by all 266 immigration judges across the 43 US cities in which courts are located (see Figure 2.1). Each court serves a specific geographical region. Decision data is merged with hand-collected data on judge gender. In our dataset, 34% of judges are female. The mean grant rate (the rate at which a decision is made that favors the applicant) in the database as a whole is 16%.

⁸Elsewhere, Graff Zivin et al. (2015), p.2 note the existence of a more general “.. neurological literature that documents the brain’s sensitivity to temperature”.

Our data comes from asylumlaw.org. Asylumlaw no longer operates but was: “A website run by an international consortium of agencies that helps asylum seekers in Australia, Canada, the United States and several countries in Europe. It provides links to legal and human rights resources, experts, and other information valuable for asylum seekers.”⁹ The data contains date of hearing, identity of judge, nationality of applicant and category of application.¹⁰

Asylum decisions made by immigration judges are decisive and those that are denied asylum are subject to removal. Judges sit alone, and there are no formal quotas with respect to their grant rate. While the activities of judges are subject to the overall supervision of the US Attorney General, this is an area of law in which individual judges are commonly regarded as having a high degree of personal discretion and independence in the way in which they evaluate files (see Ramji-Nogales et al. (2007) and Chen et al. (2016)). Though the characteristics of cases that judges in different locations are likely to see will of course vary, the degree of discretion is supported anecdotally by the wide variation in grant rates of judges both between and within particular courthouses. For instance, over the study period in the Los Angeles courthouse there are five judges that granted asylum to fewer than 4% while three others granted in over 67%.

Judges typically determine multiple cases on a given day. The judge is presented with a file, may (or may not) ask questions of the applicant and/or his legal representatives, then enters an adjudication. Within a court all cases are in principle randomly assigned to the judges (Ramji-Nogales et al. (2007)), however we do not test for random assignment on observables, neither does our approach to identification rely on it. The setting of dates for cases and the rostering of judges is done well in advance. For instance, as of December 2016 more than 533 000 immigration cases had hearing dates scheduled, with the average delay from scheduling to hearing being over a year.

⁹The dataset was provided by Professor Kelly Shue of the University of Chicago Booth School of Business.

¹⁰There are two types of cases in immigration courts: affirmative cases in which the applicant presents in the courts on her/his own and defensive cases in which the applicant is referred by the immigration authorities.

An important question in the evaluation of climate change is the extent to which adaptation might allow the impacts of temperature variations to be mitigated. The most obvious protective measures are building design and climate-control. As such it is useful to note in passing the context in which our subjects work. No data is available regarding internal temperatures, nor the precise engineering and thermal properties of buildings. However, all of the courtrooms represented in the study are contained within climate-controlled buildings, as would be expected for important operational spaces of the US Federal government. Figure 2.2 presents pictures of the 16 biggest locations ranked by contribution of cases to sample - contributing between them 86.4% of the total. While the buildings vary, taken as a set it is apparent that the judges work in good quality space, of the sort experienced by many North American professionals.¹¹ The effects of external temperature on internal behavior that we identify in this chapter should be taken as already being adjusted for that level of adaptation embodied in buildings typical of this class.¹²

2.3.2 Parole

Data on all parole hearings conducted by the Board of Parole Hearing (BPH) between 3 January 2012 and 18 December 2015 is obtained from the California Department of Corrections and Rehabilitation (CDCR).¹³ The dataset includes 18 461 hearing decisions made by 12 BPH commissioners across the 39 venues in California. Figure 2.3 maps venue locations.

The Board of Parole is responsible for evaluating the risk to public safety from the release of inmates incarcerated for serious crimes. An affirmative decision by the BPH means that a prisoner is returned to the community, so these are high stakes decisions. Parole hearings are conducted in-person with the inmate and his attorney at the inmate's prison. Sessions

¹¹In an unreported robustness check we dropped each venue one at a time and re-ran the preferred specification on the remaining sample. In no case did this substantially disturb the resulting estimates.

¹²According to the Administrative Office of the United States Courts (AOC) that develops standard level of features for U.S. courts facilities, indoor temperature of courtrooms, judge's chamber suites, and jury deliberation should be set at 75 °F degree in summertime and rooms should be pre-cooled to 70 °F degree before scheduled cases (Administrative Office of the United States Courts (AOC) (1996)). AOC mandates all regional offices to satisfy these standards. This confirms that courthouses are air conditioned.

¹³The data can be obtained from: <http://www.cdcr.ca.gov/>.

are scheduled one year before an inmate becomes eligible for parole and conducted by a panel of two members, a Board Commissioner and Deputy Commissioner (Kathryne et al. (2016)). The former is a non-expert appointed from a variety of professional backgrounds (law enforcement, academia, the military, politics) while the latter is a civil servant and expert in legal process. Formally the Commissioner is responsible for running the hearing and exercising discretion in determining outcome, while the Deputy Commissioner for legalities and post-release management of successful applicants. Despite this, that the panel comprises two members potentially complicates inference, obscuring *individual* decision-making. The grant rate in the dataset - the fraction of cases in which a decision is made that is favorable to the applicant - is 16.48%.

Our data contains the date of hearing, identity of panel members, inmate unique identifier, location of hearing, hearing type and outcome.¹⁴

2.3.3 Environment

Our main research question is whether the adjudication on a file responds to the outdoor temperature on the day on which it is evaluated. To accomplish this, we combine our decision dataset with temperature and a variety of other environmental controls.

The location of asylum decisions from which we construct our dependent variable is drawn from the 43 US cities in which the US Department of Justice operates immigration courthouses. These are widely dispersed (see Figure 2.1) and subject to diverse weather conditions.

The exact date and location of each decision is known which allows us to assign environmental measures (pollution and weather) to each. Temperature and other weather data is obtained from two sources. Hourly observations for air temperature, dew point, air pressure, precipitation and wind speed are retrieved from the National Oceanic and Atmospheric Ad-

¹⁴There are two types of hearing that we consider: (1) Initial parole (which is scheduled one year before eligibility), (2) Subsequent parole that is scheduled if there is any consideration in the initial session.

ministration (NOAA).¹⁵ Data for cloud cover comes from the Northeast Regional Climate Center (NRCC).¹⁶ Weather information is assigned to each courthouse location from the closest monitoring stations, in no case further than 20 miles away. The average distance between weather monitoring stations and courthouses is 9.35 miles with standard deviation of 6.33.

For our central specifications we work with averages computed for the period 6 AM to 4 PM each day. This is the period over which decision-makers are likely “up and about” - including travel to work, and work day. It excludes exposure that arise after courts close, which logically can have no effect on proceedings. Figure 2.4 summarizes the annual distribution of 6 AM to 4 PM mean temperatures across ten temperature-day categories over the study period (2000 to 2004) across locations in 10 °F bins. Most existing research on the effects of short-term temperature and pollution on a variety of outcome variables work with calendar-day data and, while we believe this to be an inferior approach, for purpose of comparison we also present analysis on that basis. In a further variant, that we do not report, we also conduct the exercise using 8-hour blocks (Midnight to 6 AM, 6 AM to 4 PM, 4 PM to midnight).

We will also be controlling for air quality conditions. Daily pollution data is published online by United States Environmental Protection Agency (USEPA).¹⁷ The dataset includes daily measures of particulate matter less than 2.5 microns in width ($PM_{2.5}$), carbon monoxide (CO) and ozone (O_3) throughout the United States for the period of 2000 to 2004.

Table 2.1 presents summary statistics for all variables.

¹⁵The data is obtained from: <https://www.ncdc.noaa.gov/>.

¹⁶The data is retrieved from: <http://www.nrcc.cornell.edu/>.

¹⁷The data is available at: <https://aq5.epa.gov/api>.

2.4 Methods

2.4.1 Empirical strategy

We estimate the following linear probability¹⁸ model:

$$g_{it} = \beta_0 + \beta_1 temp_{it} + W_{it}\beta_2 + P_{it}\beta_3 + X_{it}\beta_4 + \gamma_i + \Psi_{ct} + \theta_t + \epsilon_{it} \quad (2.1)$$

where g_{it} is a binary variable that takes the value one if the judge's decision in asylum application i on date t is granted, zero otherwise.

The key independent variable is the mean 6 AM to 4 PM temperature on the date the case is considered, $temp_{it}$. For most of our discussion β_1 is the coefficient of interest.

To allow for the possibility that other dimensions of weather rather than temperature might impact decisions, we include a vector of weather controls, W_{it} . It contains dew point temperature (a standard measure of humidity), precipitation, wind speed, air pressure and sky cover on date t , in the vicinity of the courthouse in which application i is adjudicated, all calculated on a 6 AM to 4 PM average basis. Pollution exposure can also influence cognitive function, mood and/or decision-making (Archsmith et al. (2016), Chang et al. (2016), Lavy et al. (2016)). To allow for this possibility we include P_{it} which is a vector of pollution controls. It comprises mean daily measures of ozone (O_3), carbon monoxide (CO) and ultra fine particulate matter ($PM_{2.5}$).

Court and case context can be expected to impact case outcomes (Chen et al. (2016)). We include a vector X_{it} of controls for a number of additional court and application characteristics. More specifically, we control for category of application and nationality of applicants.¹⁹ γ_i is a vector of judges fixed effects which controls for all time invariant characteristics of

¹⁸Our results sustain when we estimate the same equation using logit and probit methods.

¹⁹The case characteristics that we observe are limited in the dataset. It is clear that other unobserved characteristics are important determinants of case outcomes such that we have omitted variables. However, once we have controlled for location and time fixed effects it is plausible that those omitted characteristics would be uncorrelated with case-day temperature such that the OLS estimate of β_1 would be unbiased and the associated standard error remains undisturbed.

a judge and allows us to identify the within-judge effects of temperature.²⁰ The vector θ_t includes time fixed effects; day of week to account for possible changes in decision patterns across the day of week and year fixed effects to control for aggregate trend in the data and also to account for the likelihood of hotter work days due, for instance, to climate change. Finally, Ψ_{ct} is a vector of city-by-month fixed effects to control for any time-invariant unobservables common to each city in each month that might impact immigration outcomes. City-by-month fixed effects ensure that we are comparing the effect of temperature on probability of favorable decision by judges within the same city across different days within the same month.

Error terms may be spatially- and serially-correlated. In our preferred specification standard errors are clustered by city-month which serves two purposes: to account for spatial correlation across cities and to allow for autocorrelation in decisions in each month. For the purposes of robustness we establish later that the results are robust to a variety of other ways of calculating standard errors.²¹

As noted we include a rich set of fixed effects. In particular we are identifying off within-location, within-month variation. Our identifying assumption is that once location and time effects are controlled for, the realization of outdoor temperature on any *particular* day - and therefore the assignment of a temperature treatment to any particular decision - is as good as random.²² That is to say, we can examine cases heard in Atlanta, in the first week of June. Sometimes a case adjudicated on day in the first week of June in Atlanta can be assigned a

²⁰Judges are appointed to a specific court and would change their cities once a while. According to our dataset around 95% of the time judges have stayed in one city. However, in very rare occasions judges need to go to other cities to investigate a specific case. That being said in our dataset 168 judges have moved to other cities for total 12 245 cases out of 206 924.

²¹In Table 2.4 we present standard errors from nine alternative clustering strategies (columns (1) through (7)) and heteroscedasticity-consistent Eicker-White and Newey-west standard errors (columns (8) and (9)). In all cases the level of significance of the estimated coefficient is unchanged. While alternative clustering makes little difference the Eicker-White and Newey-west standard errors can be seen to be around 30% smaller.

²²We test our exogeneity assumption by separately regressing the probability that an application is affirmative, a judge is female, an applicant is from middle east and total number of cases heard by a judge on each specific day on temperature and full suit of controls as our preferred specification for both asylum and parole hearings (results are presented in Table 2.5.). We find no significant patterns (except for column (6) of parole analysis) of selection by these observables with respect to temperature on the day of the hearing.

temperature treatment of 60 °F, other times 90 °F. It is that variation, plausibly exogenous, that we exploit for identification.

2.5 Results

2.5.1 Linear

The base results are summarized in Table 2.2. Column (1) is the preferred specification, incorporating the full suite of controls - time fixed effects, weather and pollution controls.²³

The coefficient in column (1) is -1.075 implies that a one standard deviation increase in 6 AM - 4 PM temperature on the day a decision is made reduces the likelihood of a grant decision by 1.68%. Recall that the average grant rate in the sample is 16.4%, so this implies a 10.29% decrease in grant rate. Notably our effect sizes are as the same order of magnitude as those found in Chen (2017) and Eren and Mocan (2017).

Columns (2) and (3) of Table 2.2 reports the results of including a lag or a lead. In each case the point estimates on the lagged terms are much smaller in absolute value than those on the main measure, mixed in sign, and never approach significance at conventional levels. Column (4) includes both lead and lag terms. Figure 2.5 plots results when we add three lags and three leads simultaneously. As can be seen, none of the lags or leads achieve significance. The F-statistic of joint significance of weather variables reported at the bottom panel of Table 2.2 rejects the null hypothesis of no effect for weather covariates.

Our main specification incorporates what we believe to be the most natural set of fixed effects (year and city-month). However Table 2.3 reports the results of other approaches. In columns (1) to (6), we build up to the preferred specification by gradually adding fixed effects while columns (7) to (10) present three other plausible alternatives. Column (11)

²³All of our main specifications are estimated on the whole 58 months of data. The terrorist attacks of 11 September 2001 fall during our study period and can be expected to have impacted on the operation of the immigration system in the US. While we do not report them here, we have run the main specifications on the pre- and post-9/11 portions of the data-set, observing consistent patterns across them.

repeats the preferred specification for purposes of comparison.

As shown when we add the first set of controls (nationality fixed effects), the point estimate on temperature falls (in absolute value) to -0.717 which is suggestive that the nationality fixed effects can explain a fair amount of the raw difference in the grant rate. This effect is still meaningful considering that the mean of grant rate is 16.4% in our sample. The point estimate of temperature increases slightly to -0.727 when we add day of week fixed effects in column (3) and increases to -0.806 when we add type of application and judge fixed effects in column (5). Adding city-by-month fixed effects in column (6) produces point estimate that is closer in magnitude (-1.037 compare to -1.075) to our preferred specification, suggesting that a seasonal trend in temperature may have driven our result. In column (7) we replace city-by-month fixed effects with city and year-month fixed effects. These fixed effects account for both time and location unobservables but assume that time trends are the same in each city. Point estimate falls to -0.893 but is still significant at 5%.

To facilitate comparison, in the lower panel of Table 2.3 we also present Hausman test for equivalency of the estimated coefficient of temperature with preferred specification. Importantly, in all cases (except for column (8)), we find no evidence that there is substantial difference in estimated coefficient of temperature across these specifications. The stability of the estimated coefficient of temperature is remarkable suggesting that selection on the unobservable is likely to be less strong than selection on the observables.

Table 2.6 explores the sensitivity of results to some alternative but plausible specifications.

Much of the related literature on short-term effects of weather and air quality on human outcomes has used the calendar day as its unit of analysis (for examples, Hirshleifer and Shumway (2003), Lavy et al. (2016) and Park (2016)). While this is not our preferred approach - a substantial portion of each calendar day occurs after the court is closed - for comparability we report in Table 2.6 column (2) the results of repeating the exercise on a calendar day basis. As would be expected given the introduction of additional imprecision into the way in which the regressor of interest is measured, the estimated coefficients

are attenuated somewhat, but retain sign and significance and are similar in magnitude to Table 2.2 (-0.750 instead of -1.075 for the preferred specifications).²⁴

Decision locations are dispersed widely across the country and in places that exhibit very different weather patterns. This implies that a 90 °F degree day in Phoenix may not have the same effect as such a day in Boston. The inclusion of city-month and year fixed effects should control for unobservable characteristics of that location at that time of year (such as “normal” weather conditions). However to probe this further we estimate a variant in which the independent variable of interest is the deviation of 6 AM - 4 PM temperature on decision day from the average 6 AM - 4 PM temperature for that location in that week of the year. The results of this exercise are summarized in column (3). The point estimate on same-day temperature deviation is negative and significant at 5%.

The results of an additional exercise to address the concern that the impact of a given temperature treatment may vary by location is reported in column (4). Here we re-estimate the preferred specification but now incorporating a vector of *city* and *temperature* interaction terms, with New York chosen as our reference city. Point estimates on 40 out of the 44 interaction terms are insignificant (the exceptions are San Fransisco, Los Angeles, Philadelphia and New Orleans). As can be seen, the coefficient of interest is little changed.

Most of the evidence that we present points to the depressing effect of hot days on affirmative decisions (this will be confirmed in the non-parametric results that follow). Much of the US is cold during the winter months, while the whole mainland is mild to hot during the rest of the year. Column (5) reports the results of re-estimating the preferred specification but excluding the winter months. Again, the coefficient on temperature retains sign and significance, though it is now somewhat larger in absolute value.

To further confirm the mechanism of influence, in column (6) we perform another robustness check by including interaction term of *precipitation* and *temperature* into our preferred specification. As shown the point estimate on temperature is negative and significant at 5%

²⁴In a further variant we conducted the exercise using 8-hour blocks (Midnight - 8 AM, 8 AM - 4 PM, 4 PM - midnight). We do not report the results of this here, but they parallel those just presented.

while the interaction term is statistically insignificant. This implies that the marginal effect of temperature on likelihood of favorable decision does not vary with rain and therefore there is no difference in the impact of temperature on grant rate in wet and dry days.

2.5.2 Non-linear

In addition to the conventional linear estimate we also examine possible of non-linearity in the relationship between temperature and decision outcomes by re-estimating using temperature bins 5 °F in width, with the 50 - 55 °F bin as the reference category.

The results of this non-parametric exercise from this analysis are illustrated in Figure 2.6. Point estimates are statistically significant and positive when temperature is in the range of 25-30 and 40-45 and negative when it exceeds 55 °F. They are also meaningful in size. Other things equal, taking a case heard on a day where outdoor temperature is between 50 - 55 °F and dropping it instead into a day where the temperature exceeds 85 °F reduces the likelihood of a favorable decision by 6.31%.²⁵

The negative effects of temperature appear close-to-linear and most of the robustness checks and other exercises that we conduct below will be centred on the linear results.

2.5.3 Heterogeneity by gender of judge

Table 2.7 reports a test of the hypothesis that temperature-sensitivity is particularly pronounced amongst females (Yu et al. (2010), Xiong et al. (2015)).

For this exercise we re-estimate the preferred regression specifications on the sub-sample of decisions made by female judges (72 229 decisions made by 95 individuals) and male judges (134 695 decisions made by 171 individuals) separately. In Table 2.7 the results of these exercises are summarized in columns (2) and (3) respectively. In each case the point estimate is negative and significant at the 5% level. However the female coefficient is around

²⁵Around 12% of decisions are made on days above 80°F. Figure 2.6 shows that the change in marginal effect of temperature is non-linear.

6% bigger in absolute value. The Hausman test (reported in the lower panel of Table 2.7) confirms that the coefficient values are significantly different at the 5% level (p-value 0.0325).

In addition to showing consistency with the literature on gender and temperature-sensitivity already cited, the result also goes some way to address a concern that the patterns that we observe are driven not by the effect of temperature on judgement, but that temperature is instead influencing outcomes by impacting (for example) the comportment of the applicant or his lawyer. If that (or other external-to-judge mechanisms) were the channel we would not expect to see differences based on gender of judge.

2.5.4 Robustness

Table 2.8 reports the results of a battery of robustness tests.

Pollution

Recent research points to a possible link from short-term pollution exposure to mood and cognitive function, either of which might influence decision outcomes (Heyes et al. (2016) and Szyszkowicz et al. (2010)). While our main specifications include controls for ambient levels of the main pollutants (O_3 , $PM_{2.5}$ and CO), concern may remain that we have failed to control adequately for air quality effects, and that these are confounding our results. If that were the case then we would expect dropping the whole set of pollution controls to substantially affect our estimate of β_1 . In column (2) we report the result of re-estimating the preferred specification but omitting the vector of pollution controls. The estimated coefficient on temperature retains sign and significance and value changes only a little (-0.910 instead of -1.075).

California

Of our 43 venues 6 are located in California (accounting for around 32% of all decisions). To rule out that what we are picking up something idiosyncratic to California - particularly

since our external validity exercise is going to rely on Californian parole data - we re-estimate our preferred specification excluding decisions made at courts in that state. This excludes around 71 000 of the 207 000 decisions in sample. The result of this exercise are reported in column (3) of Table 2.8. Again, when estimated on the restricted sample the estimate of β_1 retains sign and significance and is little-changed in value (-1.159 instead of -1.075). So the pattern that we observed in the data is not being ‘driven’ by anything particular to California.

Weather

Columns (4), (5) and (6) probe further the potential confounding role of rain and cloud.

Existing research points to cloud cover as influencing mood (Lambert et al. (2002), Kent et al. (2009) and Hirshleifer and Shumway (2003)). We include a continuous variable that captures extent of cloud cover in our main specification to control for this. However, as a further test we re-estimate the central specification on those decisions made on “clear sky” days - the subset of days when daily cloud cover is less than 5% (results in column (4)). The point estimate of β_1 for the subsample estimation remains negative and significant. Though larger in absolute value (-2.738 instead of -1.075) the difference between the two values is not significant at the 5% level.

Similarly rain can influence mood (Denissen et al. (2008)). While a continuous measure of precipitation is included in the vector of weather controls, column (5) reports the result of re-estimating the preferred specification on the subset of decisions (133 890 of them) made on days in which local recorded precipitation is zero. On such days rain cannot plausibly be argued to have influenced outcomes. The estimated coefficient retains sign and significance and is changed slightly in absolute value (-1.304 compare to -1.075). Column (6) reports the results of pushing this further by repeating the same exercise this time excluding days on which recorded precipitation on either the day of decision or the day before were non-zero (111 361 decisions). Again the point estimate on the coefficient of interest is somewhat larger

in absolute value (-1.281 instead of -1.075) but retains sign and significance.

Heat Index (HI)

The way in which temperature is experienced by the human body can itself depend on the water content of the air. Humidity is known to affect both mood and labor productivity (Howarth and Hoffman (1984), Tsutsumi et al. (2007) and Wan et al. (2009)). We therefore investigate the joint effect of temperature and humidity in our setting by dropping temperature and dew point from our preferred specification and replacing it with the Heat Index (HI). The HI is used by the US National Weather Service and combines air temperature and relative humidity, via a non-linear algorithm, into a single metric designed to capture how hot it ‘feels’. It effectively adjusts upwards the dry air temperature for moisture content to provide an index of the discomfort associated with a particular temperature/humidity combination.²⁶

Column (7) reports the results of re-estimating our preferred specification but with HI added, temperature and dew point dropped. Consistent with earlier results we find a negative and significant effect of heat index on decision outcomes. Though the coefficient here is not directly comparable to those from the various other specifications, the point estimate implies that a one standard deviation increase in HI reduces the probability of grant decision by 0.44% (recall that this is against an average grant rate in the sample of 16.4%). However, since HI is primarily regarded as a reliable measure of discomfort only in warm conditions, we also conduct this exercise once more on the subsample of days on which the local heat index exceeds 75 °F in column (8). The estimated coefficient on heat index is negative and significant with an absolute value larger than in column (7), though estimated on a much smaller sample.

In Figure 2.7a we repeat this exercise for the HI variant of the analysis - with dew point

²⁶Countries including the UK and France have an alternative index - called Humidex - that has the same intention, and is highly correlated with HI, but is calculated by a slightly different formula. HI and Humidex references are often heard on media weather broadcasts during warmer times of year. The HI is typically seen as relevant or reliable measure only in warm conditions.

temperature and temperature omitted as regressors but HI added. As noted, this provides a plausible way for allowing for the combined effects of temperature and humidity on how heat ‘feels’. Since HI is only regarded as reliable on warmer days, Figure 2.7b repeats the same exercise for the subsample of days on which HI exceeds 65 °F, with the 65 - 70 °F bin as the reference category. Again the negative impacts of HI exhibit a close to linear pattern with the negative effect become significant for values of HI exceeding 80 °F.

Outlier judges

We note in the data section that judges do not have specific quotas with respect to what their grant rates should be - indeed this is an area of the legal system in which judges, sitting alone, are regarded as exercising a very high degree of personal discretion (Ramji-Nogales et al. (2007)). To convince ourselves that the result that we are claiming is not being driven by ‘extreme’ judges we conduct two outlier analyses.²⁷ In the first we exclude those decisions made by judges who have a grant rate across the whole study period in either the top or the bottom quartile (just retaining the ‘middle half’ of judges when ranked in terms of moderation).²⁸ Column (9) reports the results of this exercise - again sign and significance is retained and the value of the coefficient is little disturbed (-0.707 instead of -1.075). In the second we conduct the same exercise but exclude the top and bottom deciles of judges.²⁹ The results of this is reported in column (10). Again the sign and significance is retained and the value of the coefficient is little disturbed (-1.064 instead of -1.075).

²⁷For example, suppose there existed a judge who is so extreme that he never found in favor of the applicant (his grant rate was 0%). The grant rate of that judge could not go lower upon exposure to high temperature because he is already at the lower bound. Recall that we already have judge fixed effects in all of our main specifications.

²⁸This excludes decisions made by judges who have overall grant rates below 8.1% or above 22%.

²⁹This excludes decisions made by judges who have overall grant rates below 4.7% or above 31%. Note that while we exclude the top and bottom decile of judges we do not lose exactly 20% of our sample of decisions. This is because different judges are associated with different numbers of decisions across the study period.

2.5.5 Placebos

As further falsification tests we perform three placebo exercises.³⁰ First, we replace the decision-day temperature series with the temperature at the same location 100 days after decision-day, and 100 days before. Second we replace the decision-day temperature in the vicinity of the courthouse in which the decision was made with the temperature on the same day, but taken from the weather monitoring station *most distant from it* “as the crow flies”. For example, for Hartford (Connecticut) the placebo temperature is taken from the NOAA measuring station at Davenport (California) 4238.72 miles away; for Dallas (Texas) the placebo temperature values are taken from Port Angeles (Washington) 2792.42 miles away.

The results of these exercises are reported in Table 2.9. In each case the absolute value of the estimate of the coefficient of interest is several times smaller, signs are mixed and in no case is statistical significance achieved.

2.5.6 Parole

Until now we have focused on judges evaluating immigration files. We are not going to claim broad generality of results, though we believe they are highly suggestive of what is likely to be a wider phenomenon. However to probe at least a little into whether the effects that we have identified are unique to the immigration setting we repeat the central linear and non-parametric analysis for decisions made by parole commissioners in the context of Californian parole hearings.

Table 2.10 presents results that repeat the main part of our analysis on a calendar day basis using results from the universe of hearings for the period of 3 January 2012 to 18 December 2015 (18 461 in total) as dependent variable. More concretely the dependent variable is a dummy that takes the value one if a parole applicant is granted release, zero

³⁰For this exercise we limit analysis to mainland US locations (exclude weather stations in Puerto Rico and Hawaii). We ran a wide variety of other placebos with similar (insignificant) results.

otherwise.

The pattern of results presented in Table 2.10 proves similar to those earlier. Decision-day outdoor temperature has a significant, negative effect on likelihood of a decision to release the applicant. The effect is similar in magnitude to the immigration setting. In the preferred specification (column (1)) a 10 °F degree increase in outdoor temperature reduces the probability of a grant release decision by 1.56%. Against an average grant rate in the data-set of 16.48% this implies a 9.5% decrease in the rate of affirmative decisions. We also test the implications of adding a single lag or lead, both individually and concurrently (columns (2), (3) and (4)), again finding coefficients on these that are much smaller, mixed in sign, and never achieve significance. That their inclusion or exclusion disturbs the estimated coefficient of interest more than in the immigration case likely reflects the lower day-to-day variation in the mid to southern Californian locations of the hearing venues.

Figure 2.8 depicts the results of non-parametric analysis for Californian parole hearing decisions. Point estimates are negative and statistically significant at 5% for temperatures exceeding 65 °F. Consistent with the results from the immigration setting, there is close to linear effect of temperature on decision outcomes. Results suggest that compared to a day with average temperature in the 50 to 55 °F bin, the likelihood of releasing an inmate is 2.6% lower on a day when temperature is higher than 85 °F. In the context of an overall grant rate of 16.48% this corresponds to a 9.46% fall in the rate of decisions favoring the applicant - a substantial effect.

2.6 Conclusions

Temperature patterns are changing - in much of the world average temperatures are rising, as are the frequency of very hot and very cold days. Understanding how such changes are likely to influence a variety of social and economic outcomes is crucial to forming a measured view of the implications of such change.

We present what we believe to be the first evidence - in either a naturally-occurring or artificial setting - that same-day outdoor temperature influences indoor decisions. Effect sizes are large and robust. That we study a naturally-occurring, high-stakes setting populated by experienced subjects adds to the likelihood that the effects identified reflect a broader phenomenon.³¹ While the evaluation of a file may be sensitive to the case-day behavior of the applicant, and we cannot rule out that part of the effect that we uncover works through induced changes in that, the heterogeneity of effect between male and female judges points to an internal-to-judge effect. If this was purely a story about over-heated applicants changing their comportment, we would not expect the gender of judge in a particular case to matter.

While we don't observe their precise movements nor the particularities of the indoor conditions in which they work, we can say that these professionals work in good quality, climate-controlled environments. Also, presumably, they travel to work and move around their cities in a manner consistent with better off professional workers (have air conditioning in their cars, *etc.*). In other words, the subjects that we study are offered a level of protection against weather variations that most people, even office-based professionals, would find quite comprehensive. That despite this we still observe substantial and robust effects of ambient temperatures outdoors to how these individuals are going about their business indoors, causes us to be sceptical of claims that climate control is likely to be fully-effective in ameliorating climate impacts.

There are different ways to think about the implications of the results. At the broadest, we provide a bridge from local climate to what is happening indoors - where most high value employment is based, and where most important work and non-work decisions are taken - even when the agents, and the buildings in which they work, are adapted to local conditions.

As such we can, amongst other things, provide a plausible link from local climate to workplace productivity. Of course we rarely have persuasive measures of individual, daily productivity in high value employment settings (which is why existing research has focussed

³¹The parole results provided some 'out of sample' testing, and reassurance that the patterns that we see in the immigration data are not unique to that setting.

on low-grade jobs such as picking fruit and answering routine calls in a job center). Our setting shares that shortcoming since the job of a judge is quality-driven and we do not observe ‘right’ and ‘wrong’ decisions, even ex post. However, given that the correct arbitration self-evidently does not depend on contemporaneous temperature *the sensitivity of outcomes to changes in temperature in itself implies welfare inefficiency*. Insofar as the correct arbitration matters - in other words that this is from a societal perspective of a high-stakes setting - the large effect sizes imply that the welfare losses are, in turn, large.

Away from the world of work, decisions are central to human well-being. We all routinely make decisions about what to buy, how to invest, how to vote, when to quit our jobs, etc. If decisions with durable impacts are systematically affected by irrelevant, transient factors then the potential for individual and welfare loss across many settings is obvious.

One area in which we have been agnostic throughout this chapter is channels. Pinning down the mechanism(s) from outdoor temperature to indoor decision processes would be a useful ambition of future work, and probably initially best suited to laboratory or laboratory-in-the-field methods. The two broad channels that we noted in the introductory review that are consistent with the results relate to (1) mood and (2) cognitive acuity. High temperatures may stimulate temper, irritability (for example in Baylis (2015) Twitter users are more likely to use profanity) and other emotions that might induce a judge to be less well-disposed towards a typical applicant. In addition depressive mood has been linked to reduced risk appetite. In both the immigration and parole settings denying a request can be plausibly be regarded as the risk averse course of action. Mental fatigue and other effects of heat can reduce mental acuity which can increase mistakes, and also themselves induce transient increases in risk aversion.

Just as we have sought not to over-sell the results, neither should we over-state the limitations. That outdoor temperature can have a large, significant and apparently robust effect on indoor decisions, even when subjects operate in a climate-controlled setting, has potentially huge ramifications for how we think about the links from climate to human well-

being. The bounds on those effects, and the mechanisms underpinning them, are important foci of ongoing research.

2.7 Tables

Table 2.1: Summary Statistics

	Mean	Std. Dev.
Grant indicator	0.164	0.371
Temperature (°F)	57.37	15.721
Heat index (°F)	57.77	16.423
Air pressure (pa)	29.688	0.759
Dew point (°F)	49.372	17.202
Precipitation (mm)	0.003	0.014
Wind speed (km/h)	4.557	3.441
Sky cover (percent)	55.44	0.276
Ozone (ppm)	0.0220	0.0120
CO (ppm)	0.917	0.496
PM _{2.5} (μ/m^3)	14.957	11.569

Table 2.2: Fixed effect estimates: 6 AM - 4 PM average

	(1)	(2)	(3)	(4)
	Preferred	1-Day lag	1-Day lead	All
$Temperature_t/1000$	-1.075*** [0.274]	-1.454*** [0.406]	-1.208*** [0.382]	-1.617*** [0.486]
$Temperature_{t-1}/1000$	- -	0.361 [0.278]	- -	0.372 [0.277]
$Temperature_{t+1}/1000$	- -	- -	0.139 [0.260]	0.159 [0.260]
F-statistic of joint significance	3.41	3.07	2.99	2.73
P-value	0.0026	0.0036	0.0044	0.0059
Observations	206,924	206,924	206,924	206,924

Notes: Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Standard errors clustered on city-month in brackets. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. All weather covariates are 6 AM to 4 PM average. Pollutant covariates include controls for ozone, carbon monoxide and PM25. All pollutant variables are the mean of daily values. Time fixed effects include day of week and year dummies. Regressions also control for city-month fixed effects, judge name, type of application and nationality of applicant. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.3: Alternative fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Temperature_t/1000</i>	-1.470*** [0.355]	-0.717*** [0.270]	-0.727*** [0.273]	-0.780*** [0.269]	-0.806*** [0.249]	-1.037*** [0.278]	-0.893*** [0.215]	-0.652** [0.262]	-1.082*** [0.271]	-0.939*** [0.285]	-1.075*** [0.274]
Hausman-test	1.40	0.76	0.69	0.44	0.63	0.40	0.36	5.24	0.90	0.09	-
P-value	0.236	0.384	0.406	0.506	0.426	0.528	0.549	0.022	0.343	0.760	-
Observations	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924
Nationality FEs	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day of week FEs	N	N	Y	Y	Y	Y	Y	Y	Y	N	Y
Type of application FEs	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y
Judge FEs	N	N	N	N	Y	Y	Y	Y	N	Y	Y
City-month FEs	N	N	N	N	N	Y	N	N	N	Y	Y
Judge-month FEs	N	N	N	N	N	N	N	N	Y	N	N
City FEs	N	N	N	N	N	N	Y	N	Y	N	N
Year FEs	N	N	N	N	N	N	N	N	Y	Y	Y
Year-month FEs	N	N	N	N	N	N	Y	N	N	N	N
City-year-month FEs	N	N	N	N	N	N	N	Y	N	N	N
Date FEs	N	N	N	N	N	N	N	N	N	Y	N

Notes: Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Standard errors clustered on city-month in brackets. All regressions control for weather and pollution. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. All weather covariates are 6 AM to 4 PM average. Pollutant covariates include controls for ozone, carbon monoxide and PM25. All pollutant variables are the mean of daily values. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.4: Alternative standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	City-week	Year-month	City-year	City	Judge	Judge-month	City and week	Eicker-White	Newey-West
$Temperature_t/1000$	-1.075*** [0.297]	-1.075*** [0.242]	-1.075*** [0.313]	-1.075*** [0.306]	-1.075*** [0.271]	-1.075*** [0.273]	-1.075*** [0.320]	-1.075*** [0.197]	-1.075*** [0.196]
Observations	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924

Notes: Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. All weather covariates are 6 AM to 4 PM average. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25} . All pollutant variables are the mean of daily values. Time fixed effects include day of week and year dummies. Regressions also control for city-month fixed effects, judge name, type of application and nationality of applicant. Newey-West standard errors allowing for arbitrary serial correlation within 15 days. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.5: Randomization test

	Immigration				Parole		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Type	Middle East	Female	Number	Type	Female	Number
	of app.	applicant	judge	of cases	of app.	judge	of cases
<i>Temperature_t/1000</i>	0.241	0.131	-0.0216	0.747	0.901	-0.505	5.284**
	[0.233]	[0.136]	[0.358]	[1.350]	[0.681]	[1.584]	[1.688]
Judge FE	Y	Y	N	Y	Y	N	Y
Nationality FE	Y	N	Y	N	N	N	N
Type of application FE	N	Y	Y	N	N	Y	N
Observations	168,794	168,794	168,794	74,929	18,461	18,461	9,472

Notes: Dependent variable in columns (1) and (5) is a dummy for type of application, in column (2) is a dummy for middle eastern applicants in columns (3) and (6) is a dummy for female judges and in columns (4) and (7) is total number of cases heard by each judge in each day. Standard errors clustered on city-month in brackets. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25} . All environmental covariates are daily mean. Time fixed effects include day of week and year dummies. Regressions also control for city-month fixed effects, judge name, type of application and nationality of applicant unless otherwise stated. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.6: Sensitivity analyses

	(1)	(2)	(3)	(4)	(5)	(6)
	Preferred	Calendar	Deviation	City	Winter	Rain and temp
	spec.	day	from weekly avg.	interaction	exclusion	interaction
$Temperature_t/1000$	-1.075*** [0.274]	-0.750*** [0.256]	-0.618** [0.309]	-1.520*** [0.466]	-1.160*** [0.330]	-1.238*** [0.276]
$Temperature_t/1000 \times Rain_t$	-	-	-	-	-	-0.336 [0.274]
Observations	206,924	168,794	206,924	206,924	156,951	206,924
City*Temperature	N	N	N	Y	N	N
Temperature*Rain	N	N	N	N	N	Y

Notes: Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Standard errors clustered on city-month in brackets. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. All weather covariates are 6 AM to 4 PM average. Pollutant covariates include controls for ozone, carbon monoxide and PM25. All pollutant variables are the mean of daily values. Time fixed effects include day of week and year dummies. Regressions also control for city-month fixed effects, judge name, type of application and nationality of applicant. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.7: Heterogeneity gender of judge

	(1)	(2)	(3)
	Whole sample	Female	Male
<i>Temperature_t</i> /1000	-1.075*** [0.274]	-1.128** [0.494]	-1.064*** [0.330]
Observations	206,924	72,229	134,695
Hausman test	3.65**		
P-value	0.0325		

Notes: Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Standard errors clustered on city-month in brackets. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. All weather covariates are 6 AM to 4 PM average. Pollutant covariates include controls for ozone, carbon monoxide and PM25. All pollutant variables are the mean of daily values. Time fixed effects include day of week and year dummies. Regressions also control for city-month fixed effects, judge name, type of application and nationality of applicant. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.8: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Preferred	Pollution	CA	Clear sky	Zero	Zero precipitation	HI	HI	Quartiles	Deciles
		exclusion	exclusion	days	precipitation	including lag		(>75)	exclusion	exclusion
<i>Temperature_t/1000</i>	-1.075*** [0.274]	-0.910*** [0.269]	-1.159*** [0.384]	-2.738** [1.144]	-1.304*** [0.318]	-1.281*** [0.328]	- -	- -	-0.707* [0.424]	-1.064*** [0.299]
<i>Heatindex_t/1000</i>	- -	- -	- -	- -	- -	- -	-0.437** [0.195]	-1.991** [0.772]	-	- -
Observations	206,924	206,924	135,184	13,981	133,890	111,361	206,921	29,659	102,408	163,890

Notes: Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Standard errors clustered on city-month in brackets. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. All weather covariates are 6 AM to 4 PM average. Pollutant covariates include controls for ozone, carbon monoxide and PM25. All pollutant variables are the mean of daily values. Time fixed effects include day of week and year dummies. Regressions also control for city-month fixed effects, judge name, type of application and nationality of applicant. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.9: Placebos

	(1)	(2)	(3)	(4)
	Preferred	+100	-100	Furthest
		days	days	monitor
<i>Temperature_t/1000</i>	-1.075***	-0.000237	0.0000730	-0.00000945
	[0.274]	[0.000148]	[0.000157]	[0.000230]
Observations	206,924	206,924	206,924	206,924

Notes: Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Standard errors clustered on city-month in brackets. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover. All weather covariates are 6 AM to 4 PM average. Pollutant covariates include controls for ozone, carbon monoxide and PM25. All pollutant variables are the mean of daily values. Time fixed effects include day of week and year dummies. Regressions also control for city-month fixed effects, judge name, type of application and nationality of applicant. * significant at 10% ** significant at 5% *** significant at 1%.

Table 2.10: Parole estimates: Calendar day

	(1)	(2)	(3)	(4)
	Preferred	1-Day lag	1-Day lead	All
$Temperature_t/1000$	-1.560*** [0.468]	-2.188*** [0.779]	-1.586** [0.746]	-2.378** [1.116]
$Temperature_{t-1}/1000$	- -	0.763 [0.720]	- -	0.802 [0.752]
$Temperature_{t+1}/1000$	- -	- -	0.0319 [0.762]	0.194 [0.793]
Observations	18,461	18,461	18,461	18,461

Notes: Dependent variable is a dummy for favourable judgment. Standard errors clustered on institution-month in brackets. All regressions control for weather, pollution and time fixed effects. Weather covariates include controls for humidity, air pressure, wind speed and precipitation. Co-pollutant covariates include controls for ozone, carbon monoxide and nitrogen dioxide. Time fixed effects include day of week and year dummies. Regressions also control for institution-month fixed effect, judge name, other panel members name, type of application and inmate's name. All environmental variables are the mean of daily values. * significant at 10% ** significant at 5% *** significant at 1%

Figures

Figure 2.1: Location of immigration courts (excluding Honolulu)



Figure 2.2: US immigration courts



Note: Buildings that house the 16 largest courts ranked by contribution to sample. From left-to-right, top row: New York, Los Angeles, Miami, San Francisco, Chicago, Arlington, Orlando, Baltimore, Boston, Detroit, Philadelphia, Memphis, Atlanta, Houston, San Diego, Seattle.

Figure 2.3: Location of hearing institutions

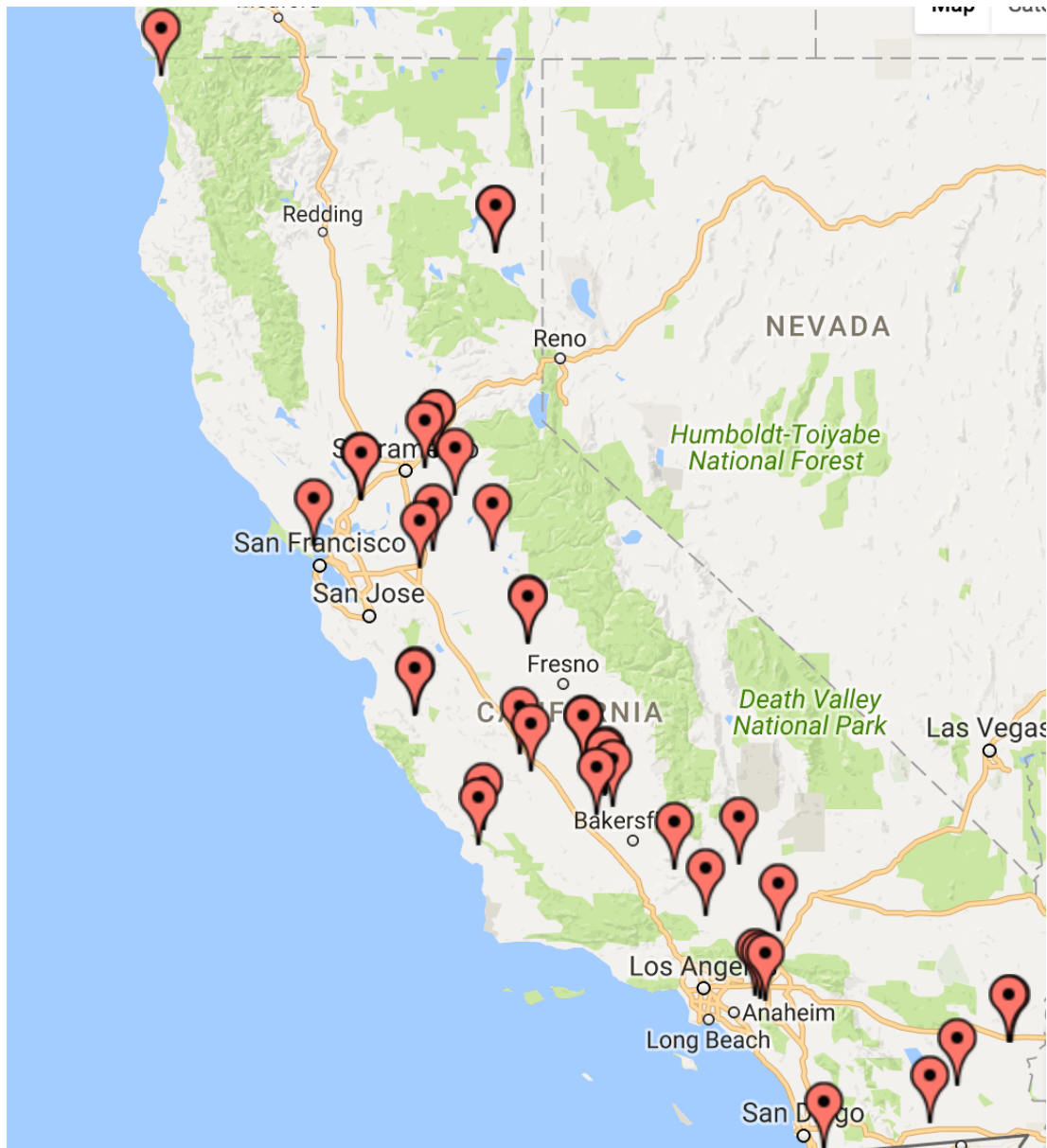


Figure 2.4: Distribution of 6 AM - 4 PM temperature, 2000-2004

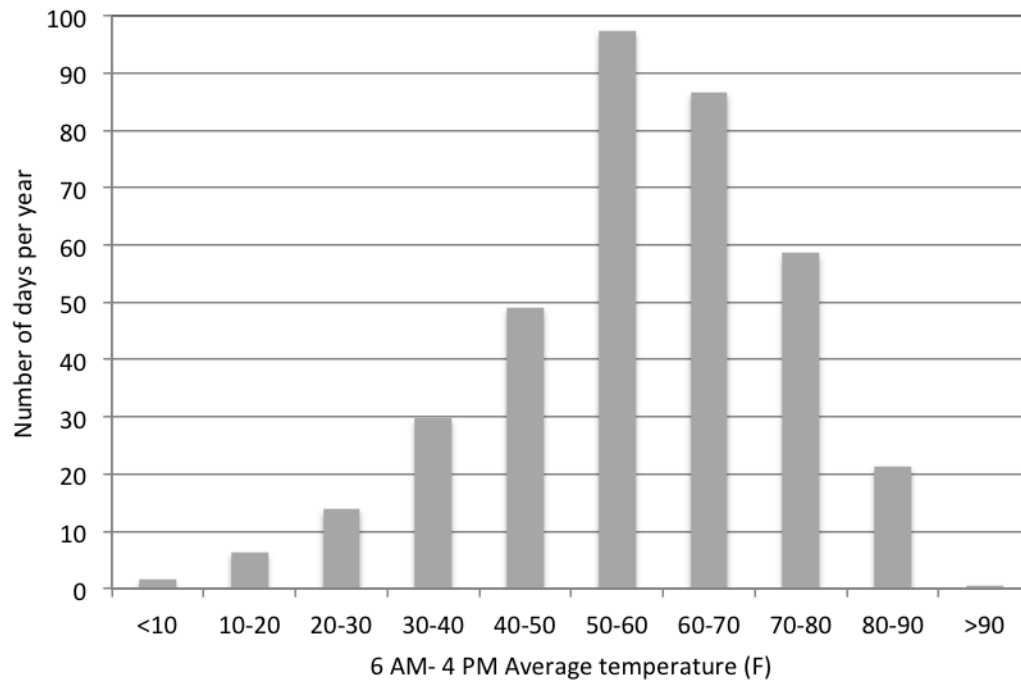
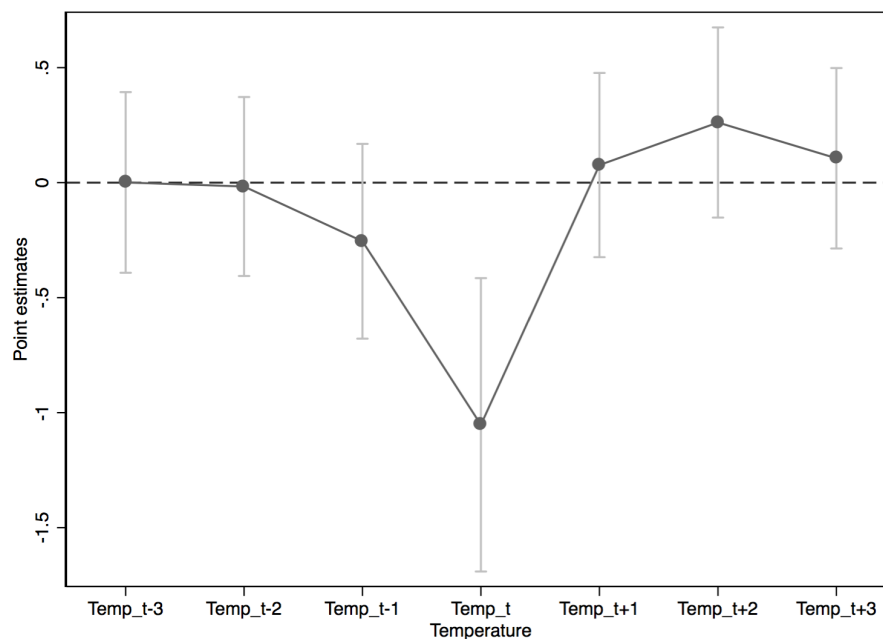
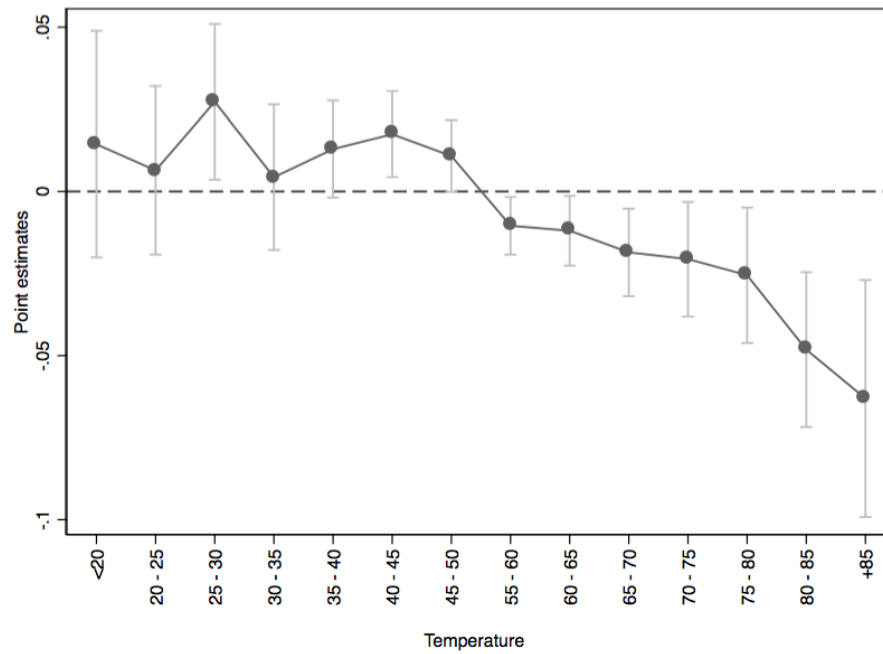


Figure 2.5: Timing of exposure: 6 AM - 4 PM



This figure plots the coefficients for the temperature. Gray lines show the 95 percent confidence interval based on standard errors clustered on city-month. The dependent variable is favourable judgement. The regression includes controls for temperature, sky cover, dew point, air pressure, wind speed, precipitation, ozone, carbon monoxide, $PM_{2.5}$, year, city-month, day of week, judge name, type of application and nationality of applicant dummies.

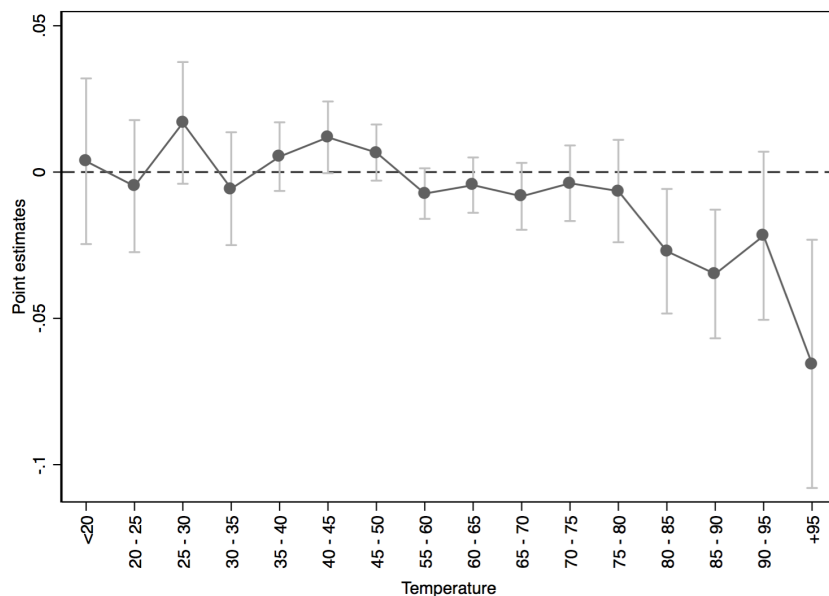
Figure 2.6: Non-linear estimates: Temperature, 6 AM - 4 PM



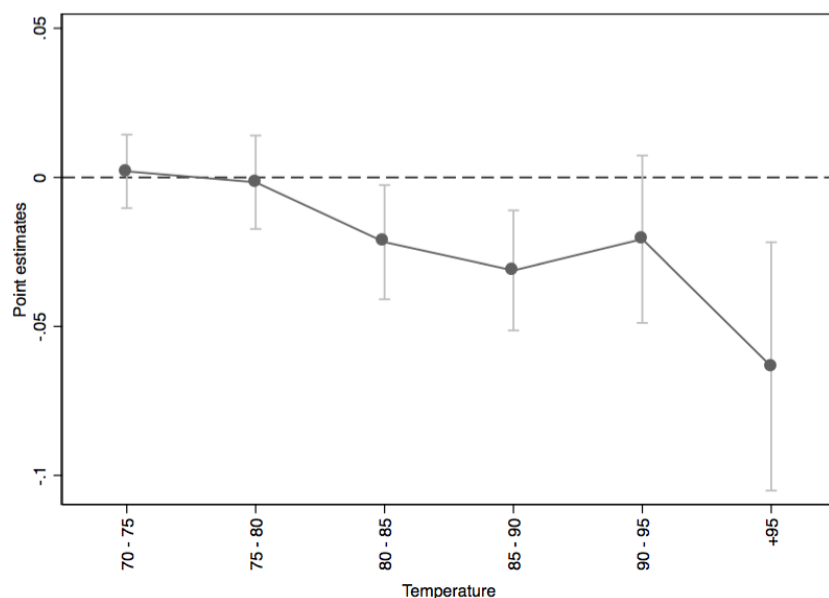
Note: This figure plots the coefficients for the temperature indicator variables. Gray lines show the 95 percent confidence interval based on standard errors clustered on city-month. The dependent variable is favourable judgement. The regression includes controls for sky cover, dew point (5 degree F indicators), air pressure, wind speed, precipitation, ozone, carbon monoxide, $PM_{2.5}$, year, city-month, day of week, judge name, type of application and nationality of applicant dummies.

Figure 2.7: Non-linear estimates: Heat index, 6 AM - 4 PM

(a) Whole sample

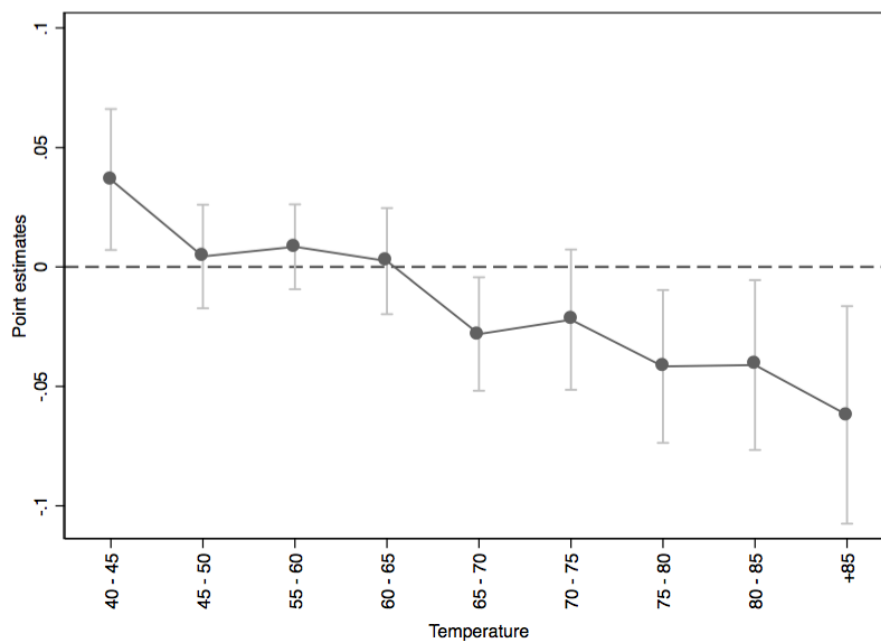


(b) HI > 65



Note: These figures plot the coefficients for the heat index indicator variables, Panel (a) depicts the whole sample and Panel (b) shows the subsample of HI $\geq$ 65. Gray lines show the 95 percent confidence interval based on standard errors clustered on city-month. The dependent variable is favourable judgement. The regression includes controls for sky cover, air pressure, wind speed, precipitation, ozone, carbon monoxide, $PM_{2.5}$, year, city-month, day of week, judge name, type of application and nationality of applicant dummies.

Figure 2.8: Non-linear estimates: Parole, temperature, calendar day



Note: This figure plots the coefficients for temperature. Gray lines show the 95 percent confidence interval based on standard errors clustered on institution-month. The dependent variable is favourable judgement. The regression includes controls for sky cover, humidity (5 degree F indicators), air pressure, wind speed, precipitation, ozone, carbon monoxide, nitrogen dioxide, year, institution-month, day of week, judge name, other panel's member name and type of application dummies.

Chapter 3

The Negative Effect of the BC Carbon Tax on Vancouver Air Quality: A Good Climate for Bad Air?

3.1 Introduction

In July 2008, the Canadian province of British Columbia was the first jurisdiction in North America that implemented a carbon tax on the consumption of all fossil fuels. The tax was initially set at \$10 per tonne of carbon dioxide and increased \$5 per year to reached its maximum level of \$30 per tonne in 2012 (see Table 1). It is applied more or less across the board, in fact by 2013 coverage was estimated to be around 80%.

A number of studies have explored the impact of BC carbon tax on CO_2 emissions (Antweiler and Gulati (2016), Rivers and Schaufele (2015), Gulati and Gholami (2015) and Elgie and McClay (2013)) - the stated objective of the policy. We provide evidence of a negative causal impact of its implementation (and subsequent increases in level) on local air quality in Vancouver. In particular the frequency of days in the city in which the levels of two key local pollutants - nitrogen oxides and ultra-fine particulates - exceeded safe thresholds.

We believe this to be the first empirical evidence of the negative environmental side effects of a carbon reduction policy.

Although empirical evidence of the impact of carbon policies on concentrations of local air pollutants is rare, there is a large body of cost-benefit analysis¹ of which almost all assume that there exist common sources of emissions of greenhouse gas (GHG) and local air pollutants, and that a climate change action which mitigates GHG emissions goes hand in hand with improved local air quality. However this can be problematic since it first ignores not only the possibility of non-common sources of various pollutants, but also neglects the important role of meteorological conditions, topography and the existence of local air pollutants regulations in determining the local pollutant levels (Gaffney and Marley (2009), Brown et al. (2006) and Jacob and Winner (2009)).

Second, difference between the tax rates on different fossil fuels (i.e. according to their carbon density) can shift consumption in a way that despite the overall reduced fuel use, a policy such as carbon tax can have an ambiguous effect on local air quality. Fuels vary very significantly in the particular mixture of pollutants generated by their use. For example, compared to unleaded gasoline, the use of one litre of diesel emits 35 times *less* carbon monoxide but 33 times *more* particulate matter.

Third, the relationship between *emissions* of various pollutants and resulting ambient pollutant *concentrations* in a particular location is determined by a complex set of often highly non-linear functions (Sillman (1999), Pappin et al. (2016) and McKendry (2002)). For example, other things equal the relationship between ozone formation and NO_x is described by an inverse U-shaped (Auffhammer and Kellogg (2011)) - up to some critical value ozone formation is associated with reduced level of NO_x , after that point small *decreases* in the level of NO_x lead to *increased* ground level of ozone (Sillman (1999)). That critical value, and the strength of the relationship on either side of that value, is itself sensitive to the availabilities of other pollutants - which can act as catalysts or inhibitors - and a host of

¹Among many for instance look at: Tollefsen et al. (2009), Ayres and Walter (1991), Bollen et al. (2009), Kan et al. (2004) and Cifuentes et al. (2001).

other environmental factors such as temperature level, rate of change of temperature level, sunlight intensity, etc.. An over-arching theme of the natural scientific research on local air quality - though one essentially ignored by almost all economic analyses in this area - is that it is the precise “cocktail” of pollutants, interacted with weather conditions, that drives outcomes (Jacob and Winner (2009), Pope III and Kalkstein (1996) and Samet et al. (1998)).

Recognizing this, it is apparent that in principle the direction of the effect of the adoption of carbon reduction policies on local air quality is an ambiguous empirical question. Although the link between emissions of local pollutants and climate change is often discussed, the design of policies that might achieve a ‘win-win’ outcome is still a point of debate (Tiwarly et al. (2014), Salon et al. (2010), Burtraw et al. (2003) and Naiker et al. (2012)). Indeed, our contention would be that evaluating the *actual* effect of carbon policy on local air quality outcomes - identifying synergies or trade-offs - is one of the most pressing policy questions. To the best of our knowledge we offer the first analysis of the effect of an economy-wide carbon policy on local air quality outcomes. We do this by assessing the effects of British Columbia carbon tax on the concentrations of primary criteria pollutants NO_x , $PM_{2.5}$ and CO in Vancouver.²

Vancouver is the largest city in British Columbia with a population of 2.4 million in its metropolitan area which is the second largest Canadian city (after Toronto). As a measure of local air quality, we focus on the monthly number of pollutant-specific exceedances:³ Those days in a particular month on which the concentrations of NO_x , $PM_{2.5}$ and CO exceeded their respective air quality standards as measured in in the city centre.⁴ We focus on the primary pollutants.⁵ Except for $PM_{2.5}$, NO_x and CO are mainly emitted from fuel

²Criteria pollutants are pollutants that are regulated under the Clean Air Act (CAA) including particulate matter, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides, and lead.

³As a robustness check we look at monthly average of pollutant concentrations, with similar results.

⁴According to British Columbia Air Quality Objectives (AQOs), NO_x , $PM_{2.5}$ and CO are considered harmful to public health if their 24-hour averages pass 100 ppb, 25 $\mu g/m^3$ and 9 ppm, respectively (British Columbia Ambient Air Quality Objectives 2015). These thresholds define the exceedances that are the focus of our analysis.

⁵Primary pollutants are directly emitted from sources while secondary pollutants are formed from the

combustion. A recent Air Pollutant Emission Inventory report (APEI 2014) indicates that around 55%, 59% and 2% of total NO_x , CO and $PM_{2.5}$ emissions respectively are from the transport sector.⁶ Diesel vehicles are the largest contributor of total NO_x emissions, accounting for about 34% of aggregate emissions, and particularly important contributors to emissions in urban centres. However, 28% of total CO emissions are from light-duty gasoline vehicles (Environment Canada (2015)).

The headline result of the study is that the carbon tax has caused a sharp increase in air quality problems in Vancouver. Central estimates from the difference-in-difference part of the study suggest that each five dollar increase in tax per tonne of carbon dioxide caused extra 2.6 and 2.4 days per year that NO_x and $PM_{2.5}$ levels in central Vancouver exceeded their safe standards. Consistent with this - though differently estimated - synthetic control analysis indicates that by the year 2013 (when the tax reached its highest level) annual NO_x and $PM_{2.5}$ exceedances in Vancouver were around 8 and 12 days higher than what they would have been in absence of the tax. The result proves remarkably robust to a variety of different robustness checks.

Although several mechanisms - either singly or, more likely, in combination - may explain the results, the substitution from gasoline towards diesel consumption in motoring is a prime candidate. Such a mechanism is consistent with the finding of Pacific Analytic Inc. (2015b) and Antweiler and Gulati (2016) that higher fuel prices due to the BC carbon tax resulted in a larger share of more fuel efficient vehicles (diesel cars are typically more fuel-efficient than their gasoline counterparts). More specifically, Pacific Analytic Inc. (2015b) finds that the share of diesel and electric vehicles increased in response to the tax. Although the tax imposed an additional charge per litre of diesel that was marginally *higher* than that on a litre of gasoline, converting the per-litre rates to effective tax rates on an energy basis (per-kilometre driven) provides a substantial tax preference for diesel.

chemical reactions between primary pollutants. Working with primary pollutants reduces the challenges associated with weather confounding, though these remain substantial.

⁶Although $PM_{2.5}$ is mainly emitted from non-combustion sources, NO_x is one of the main precursor of secondary $PM_{2.5}$.

One other possible mechanism behind the rise in diesel emissions is the evolution in the composition of the public transportation fleet. According to the statistics from Canadian Urban Transit Association, in 2013 Vancouver has experienced a 7.5% increase in the number of buses and a 3.5% increase in HandyDART service. These two modes of public transportation in Vancouver are mainly diesel fueled and can contribute to the increased level of NO_x and $PM_{2.5}$.

The remainder of the chapter is organized as follows. Section 2 identifies and describes some related literature. Section 3 outlines the data we will exploit in our study and using some simple time series plots provides suggestive visual evidence. Section 3 describes the difference-in-difference identification strategy that we use as our first method, reports results and some robustness checks. Section 4 describes the synthetic control approach that we use as our second identification strategy, reports main results and robustness checks. Section 5 concludes.

3.2 Related literature

As background to what follows we provide a rapid tour of; (1) studies that investigate the effect of BC carbon tax on fuel consumption and CO_2 emissions; (2) studies that examine the effect of carbon policies on local pollutants.⁷

3.2.1 BC carbon tax, fuel consumption and CO_2 emissions

A small number of studies exist that estimate the effects of BC carbon tax on GHG emissions and fuel consumption. The conclusion of this work is that the tax has been successful in

⁷There is a small number of studies that investigate the effect of local air pollution regulations on GHG emissions. For instance, Brunel and Johnson (2016) examines the effects of US National Ambient Air Quality Standards (NAAQS) on GHG emissions. Their findings indicate that local pollution policy did not contribute in current reduced level of GHG emissions in the US manufacturing industries. Holland (2010) estimates the effect of changes in attainment status under the Clean Air Act Attainments (CAAAAs) on the emission of CO_2 and shows that while there exists output effects, there is no substitution effect resulting in the reduced level of CO_2 .

reducing carbon emissions. On its own terms the tax has worked. This is not at all surprising - demand curves slope downwards.

Antweiler and Gulati (2016) examine the effect of BC tax on gasoline consumption and car purchase by estimating the elasticity of gasoline demand with respect to fuel and carbon taxes for all Canadian provinces from 2007 to 2014. They estimate that gasoline consumption fell 1.3% in response to a 1% increase in fuel and carbon taxes. In addition, their simulation results show that in the absence of the tax, per capita gasoline demand would be 7% higher and the average of fleet fuel consumption would be roughly 0.4 L/100km higher.

Applying a difference-in-difference method and controlling for relevant covariates such as income, prices and public transit investments, Rivers and Schaufele (2015) show that the BC carbon tax leads to a 11 to 17% reduction in gasoline sales for the period of 1990 to 2011.

Using monthly data Bernard et al. (2014) conduct a time series analysis for the period of 1997 to 2012 to estimate the effect of fuel tax (comprising both excise and carbon tax) on gasoline and diesel consumption. Their results suggest that there is a 7% and 3% reduction in per capita gasoline and diesel sales due to the carbon tax, respectively. They conclude that for gasoline demand consumer response to the carbon tax is ten times larger than the response to the price changes. However, for diesel there is no significant difference in consumer responses between the other components of diesel price and taxes.

Conducting a computable general equilibrium model for the period of 2008 to 2014, Beck et al. (2015) show that the carbon tax reduces GHG emission by 8.5%. Using a difference-in-difference approach Elgie and McClay (2013) indicate that there is a roughly 19.5% reduction in per capita sales of fuels subject to tax during the period of 2008 to 2012. Although their results are suggestive, their analysis omits several important controls which have significant effects on fuel sales such as oil price.

3.2.2 Local air pollutants

A large number of studies have sought to investigate the air quality co-benefits of climate change mitigation policies using theoretical models, cost-benefit analysis, systems approaches and a variety of simulation-based models.⁸

For instance, focusing on O_3 and $PM_{2.5}$, Thompson et al. (2014) simulate the co-benefits of three different US carbon policies.⁹ They monetarized the human mortality and morbidity benefits of these programs finding that (depending on the flexibility of each carbon policy) such benefits can offset 26 to 1050% of compliance costs. Parry et al. (2015) use data on consumption of coal, natural gas, gasoline, and motor diesel for the top twenty CO_2 emitters and find that the co-benefits of efficient CO_2 pricing reduces global CO_2 emissions by around 11%. It is however important to mention that Parry et al. (2015) do not directly estimate the co-benefits of CO_2 pricing instead they assume that the co-benefits exist because of the reduced use of coal, natural gas, and petroleum products.

The underlying assumption of this - and to the best of our knowledge *all* other of these co-benefits studies - is the existence of common sources of emissions of GHGs and local pollutants. However, as already noted, even a cursory reading of the atmospheric modelling literature points to the fact that it is naive to assume that the quality of air is determined only - or even primarily - by *emission rates*. As discussed by Gaffney and Marley (2009) and others, meteorological conditions, topography, and a host of other considerations interact with the precise mixture or cocktail of pollutants to deliver ambient outcomes.

Furthermore, depending on policy design the differential effects of a carbon tax on the motoring cost per kilometre driven can induce changes in the pattern of fuel purchases

⁸Nemet et al. (2010) survey 37 peer-reviewed of such studies, reflecting economic value of co-benefits of climate policies across different technologies, time horizon, spatial scales and societies. Among many for instance look at Boyce and Pastor (2013), Bollen et al. (2009), Haines et al. (2006), Nemet et al. (2010), Burtraw et al. (2003), Aunan et al. (2004), Pittel and Rübhelke (2008), Syri et al. (2001) and Thompson et al. (2014).

⁹Three policies include Cap-and-Trade (CAT), Clean Energy Standard (CES) and Transportation(TRN). CAT is an economy wide policy that put constraints on total carbon emissions. CES and TRN target electricity sector and on-road light and heavy duty vehicles.

leading to an overall ambiguous effect on local air quality. Harding (2014) discuss not only how differences in tax rates do not reflect the different environmental costs of fuels, but also how they can influence both the level of fuel consumption (specifically in transport - but more widely) and its *composition*. In fact, because of the high substitutability between gasoline and diesel fuels in the medium term, the behavioral responses to the difference in the tax rates might have a significant effect on individuals' fuel-type choice in the passenger car market.¹⁰ This is while fuel composition plays an important role in determining local air quality since fuels vary very significantly in the particular mixture of pollutants generated by their use.

This sort of problem (especially with regard to NO_x) has already been noted by regulators. European authorities used to encourage light-duty diesel engines as a more environmentally friendly alternative to gasoline engines since they emit less CO_2 . The following summary from Washington Post bears repeating; 'A fateful bet on diesel has brought it back with a vengeance. Governments across Europe have aggressively promoted diesel vehicles, reasoning that diesel's lower carbon-dioxide output makes it gentler on the planet than gasoline. In London, the streets are filled with diesel-powered buses and taxis. Continent-wide, diesel accounts for about half the car market. But diesel has one glaring disadvantage: It is a major source of NO_2 , a pollutant that stunts lung growth and has been linked to a range of respiratory and cardiovascular diseases.'(Witte (2016)).

However long debate over diesel engines came to a head after Volkswagen emissions scandal concerning NO_x emissions from diesel cars in Europe. In a sign of hardening attitudes across the world to diesel cars and in order to better control local air pollution problems, European governments are now taking emergency actions to rebalance the road's fuel mix. For instance, effective January 2017 Oslo has banned diesel cars from the city centre. Paris, Madrid, Athens and Mexico City plan to ban diesel engines cars from their roads by year

¹⁰The impact is less likely to be significant in the heavy vehicle market, which is almost exclusively comprised of diesel vehicles. However, in the passenger car market the presence of taxes on the purchase of vehicles and on vehicle fuels is shown to be significant in influencing ownership decisions between gasoline or diesel vehicles (Mayeres and Proost (2001), Parry and Small (2005) and Schipper (2011)).

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This is remarkable since despite the wide range of co-benefits literature, studies that estimate empirically the impact of a carbon policy on concentrations of local pollutants is sparse. Indeed to the best of our knowledge ours is the first study to analyze the effect of an economy-wide carbon policy on *concentrations* of local air pollutants.

Brännlund and Kriström (2001) investigate the effect of Sweden’s carbon and sulfur tax in the heating sector on emissions of NO_x and particulates. Their simulation results suggest that in big cities NO_x and $PM_{2.5}$ emissions increase respectively by 4.5 and 6.2%, mainly because of the substitution between biofuel and fossil fuels. Using a Swedish heat and power plants dataset Bonilla et al. (2015) find that the most obvious effect of the carbon tax is an increase in the demand for biomass fuel which reduces carbon but increases NO_x emissions in Sweden.

3.3 Data

The empirical analysis uses data from several sources. Air pollution data are obtained from Canada’s National Air Pollution Surveillance Program (NAPS).¹¹The NAPS was set up to provide long-term air quality data at a uniform standard. The network was originally established in 1969 with 36 air quality monitoring stations and now encompasses almost 300 monitoring stations spread across Canada. Our dataset spans the years 1998 through 2013.¹²

The NAPS monitoring stations measure ambient pollution levels of a large number of substances. Most stations continuously monitor and report emissions of carbon monoxide (CO), oxides of nitrogen (NO , NO_2 , NO_x), ground level ozone (O_3), sulfur dioxide (SO_2) and particulate matter (PM_{10} and $PM_{2.5}$). In addition, air samples are periodically collected and analyzed at a central facility and allow identification of cumulative levels of over

¹¹A description of NAPS is available at Environment Canada’s website: <http://www.ec.gc.ca/rnsps-naps/Default.asp?lang=En&n=5C0D33CF-1>.

¹²In order to remain consistent in our sample size, we start from 1998 which is the earliest year that $PM_{2.5}$ is measured.

100 additional substances. We focus on CO , NO_x and $PM_{2.5}$ since these are the primary pollutants resulting from fuel combustion.

We assign the closest pollution monitoring stations to the city centres.¹³ In addition to Vancouver we collect data for the 15 largest municipalities in Canada (as of 2013).¹⁴ For each pollutant in the database we extract data for the monitoring station geographically closest to the urban city centre. None of these moved during the period of the study. The closest monitoring station to the city centre of Vancouver is located at intersection of Robson and Hornby Street with naps-id of 100112. Figure 1 maps the location of all active monitoring stations in Vancouver.

Data on meteorological conditions are obtained from historical daily Canadian Climate Data maintained by Environment Canada.¹⁵ To control for the effect of weather conditions on the ambient air pollution concentration, we collect daily data on maximum temperature, minimum temperature, wind speed and precipitation. The meteorological conditions are assigned to city centres using information from the closest monitoring stations to the city centre of each urban area.

Aggregate monthly data on litres of fuel sold within each Canadian province is derived from Statistics Canada. Gasoline price and tax data are taken from Kent Marketing Services Limited. All nominal prices and taxes are transformed into real using the provincial consumer price index. Carbon tax information is retrieved from the BC government’s announcement on the carbon tax and from the update as a result of the biofuel mandate.¹⁶ Additional data such as population, after-tax income, unemployment rate and number of building permits issuance are also obtained from Statistics Canada.¹⁷ Summary statistics are presented in

¹³Results shown to be insensitive when we change this to the average of three closest monitoring stations.

¹⁴These include Toronto, Vancouver, Ottawa, Calgary, Edmonton, Hamilton, Kitchener-Waterloo, London, St. Catharines, Halifax, Oshawa, Windsor, Saskatoon, Regina, and St. John’s. Cities range in size from about 5 million inhabitants (Toronto) to about 0.2 million (St. John’s). Note that Montreal and Quebec are excluded from our analysis since there is no record of NO_x emissions in these cities.

¹⁵Climate data is available at Environment Canada’s website: <http://climate.weather.gc.ca/>.

¹⁶Data is available at: http://www.sbr.gov.bc.ca/documents_library/bulletins/mft-ct_005.pdf.

¹⁷Data on fuel consumption are obtained from ‘Supply and Disposition of Refined Petroleum Products (CANSIM 134-004)’. Data on population and unemployment rate are obtained from ‘Labour force survey estimates (LFS), by sex and age group, seasonally adjusted and unadjusted (CANSIM 282-0087)’. Income

Table 3.

3.3.1 Graphical analysis

Our interest here is in the potential impact of the carbon tax implementation on level of air quality in Vancouver. In Figures 2, 3 and 4 we plot trends of the maximum NO_x , $PM_{2.5}$ and CO concentrations in Vancouver and the 14 other largest Canadian cities for the periods before and after the introduction of tax.¹⁸ As can be seen NO_x and $PM_{2.5}$ concentrations have increased since 2010 while CO has a generally decreasing trend, suggesting that the benefit of reduction in CO emissions might be offset by increased concentrations of NO_x and $PM_{2.5}$.

Although there is no control in all of these graphs, the comparison with the rest of Canada average is quite suggestive - marked relative increase in NO_x and $PM_{2.5}$ concentrations after implementation of the carbon tax.

3.4 Method 1: Differences-in-differences

To investigate the effect of carbon tax on the local pollutants concentrations we estimate the following equation using OLS:

$$y_{ct} = \alpha_{c0} + \alpha_1 \tau_{ct} BC_{ct} + W_{ct} \alpha_2 + X_{ct} \alpha_3 + \phi_c + \gamma_t + \epsilon_{ct}. \quad (3.1)$$

The dependent variable y_{ct} is the number of exceedances of the pollutant in city c during month t . Equation (1) is regressed separately for three different pollutants including NO_x , $PM_{2.5}$ and CO . According to British Columbia Air Quality Objectives (AQOs) $NO_x, PM_{2.5}$

data are retrieved from ‘Average after-tax income, by economic family type, 2011 constant dollars (CANSIM 202-0603)’. Data on building permits are taken from ‘Building permits, residential values and number of units, by type of dwelling (CANSIM 026-0001)’.

¹⁸Cities include Calgary, Halifax, Hamilton, Kitchener, London Ontario, Oshawa, Ottawa, Regina, Saskatoon, St. Catharines, St. John’s, Toronto and Windsor. Cities in Quebec are excluded since the Quebec pollution monitoring network does not measure NO_x . For each city the closest pollution monitoring station to the city centre is used.

and CO are considered harmful to public health and the environment if their 24-hour averages pass 100 ppb, $25 \mu g/m^3$ and 9 ppm, respectively (British Columbia Ambient Air Quality Objectives 2015). Therefore, monthly number of exceedances is defined as the number of days in a specific month that surpass these levels. They are a good measure of the frequency with which a particular type of pollution becomes a problem in the city.

The independent variable of interest $\tau_{ct} \times BC_{ct}$. τ_{ct} is the inflation-adjusted carbon tax per tonne of carbon in city c during month t . BC_{ct} is a dummy variable which takes value one if city is Vancouver and for all months after July 2008 (BC tax implementation) and zero otherwise. W_{ct} is a vector of weather controls and it contains minimum and maximum temperature, precipitation and wind speed.

The carbon tax was enforced at the same time as the occurrence of the financial crisis of 2008. Since the difference-in-difference identification requires an assumption of common trend in Vancouver with other Canadian cities as a control group, any heterogeneous responses to the recession within cities might confound the estimation of the effect of the carbon tax. Therefore, X_{ct} is a vector of potentially pertinent variables that might vary at the city level and it includes after-tax income, unemployment rate, building permit issuance, gasoline and diesel price. Unemployment rate and building permit issuance are used as proxies for economic activities at the city level which can have direct effects on ambient air pollutant concentrations. It is also important to control for gasoline and diesel price as they affect fuel demand and therefore can directly impact local air quality.

ϕ_c is a vector of city-specific fixed effect that absorbs time invariant unobservable characteristics of each city, while γ_t , a vector of time fixed effect captures time-specific unobserved factors that may influence pollutant concentrations. γ_t includes year-month and 2010 Winter Vancouver Olympics dummies. We also include a dummy which takes the value one from August 2009 to control for the potential effect of the Canada Line opening of the SkyTrain rail system on fuel consumptions.¹⁹ Finally, ϵ_{ct} is a city and period specific error term. All

¹⁹SkyTrain is the rapid transit metropolitan rail system of Greater Vancouver. SkyTrain has 68.7 km of track running on underground and elevated guideways. The Canada Line added 15 stations and 19.2 km to

standard errors are clustered at the city level to account for spatial serial correlation within error terms.²⁰

To properly estimate the effect of a carbon tax on local air quality, the underlying identification assumption requires that there would not be any other factors rather than BC carbon tax which generates the differences in level of air quality between Vancouver and other cities. This assumption will be violated if the government of BC concurrently implements other policy induced by the carbon tax that affects air quality in Vancouver differently while no other cities implement a similar policy.

Another important identifying assumption is the common trend. This assumption requires that the changes in local air quality between treatment city (Vancouver) and others (control group) would follow the same time trend in the absence of the carbon tax. To verify the common trend assumption, we follow Martin et al. (2014) approach by comparing the mean of changes in NO_x , $PM_{2.5}$ and CO concentrations in Vancouver and other cities in the pre-treatment period. To do so, we perform a t-test on the difference in mean of monthly number of exceedances during the pre-treatment period between Vancouver and other cities. This test allows us to check if there is a systematic difference in local air quality between control and treatment group. The results are reported in Panel B of Table 3. As shown, the tests fail to reject the null hypothesis of common trends suggesting that there is no significant difference in pre-treatment air quality levels between treatment and control group.

3.4.1 Results

The base difference-in-difference results are presented in Table 4. Each column presents the results for exceedances of a specific pollutant. Columns (1), (2) and (3) report the estimation results for NO_x , $PM_{2.5}$ and CO . A full suite of controls are included in regressions. Columns 4 to 6 repeat the same estimation for the average of three closest air quality monitoring the SkyTrain network.

²⁰Our results are insensitive to alternate ways of clustering including year-month, city-month and city and month.

stations to the city centre.

The coefficient of interest is carbon tax per tonne of carbon. The estimated coefficient on carbon tax for NO_x and $PM_{2.5}$ is positive and statistically significant at the 1% level. The coefficient implies that a five dollar increase in tax per tonne of carbon (the amount by which the tax was increased annually from 2008 until 2013) increases the monthly number of NO_x and $PM_{2.5}$ exceedances by 0.22 and 0.21. The carbon tax point estimate for CO is negative and statistically significant at the 5%, but very small in magnitude. It implies that a five dollars increase in tax per tonne of carbon tax causes a decrease of the monthly number of CO exceedances by 0.07.

Air pollution is linked to various health and non-health outcomes including asthma and cardiovascular disease (Graff Zivin and Neidell (2013) and Moretti and Neidell (2011)), premature death (Currie and Neidell (2005)), increased hospital admissions (Graff Zivin and Neidell (2009)), more emergency room visits (Currie et al. (2009b)), and higher rates of worker absenteeism (Currie et al. (2009a)). Therefore increased number of NO_x and $PM_{2.5}$ exceedances, as suggested by the analysis of this study can have potentially large impacts on welfare cost analysis of air pollution.

We expect co-pollutants and weather factors to be potentially important confounders. If we failed to control appropriately for weather variables, then we would expect that dropping all of those controls would substantially disturb the estimated value of the coefficient of interest. In Table 5, we present the results of re-estimating the base specification but omitting all weather controls. Omission of weather covariates only slightly changes the estimated coefficients on carbon tax suggesting our results do not suffer from potential confounding from environmental factors.

To put these results into perspective, while carbon tax successfully reduces the concentration of CO emissions, each five dollar increase in tax per tonne of carbon leads to 2.6 and 2.4 more days in a year that NO_x and $PM_{2.5}$ concentrations exceed the provincial standards in the city centre of Vancouver. This is equivalent to a roughly 50% increase in the annual

number of poor air quality days in Vancouver.

A possible mechanism underlying this result is substitution of diesel for gasoline in response to a carbon tax. Diesel engines are known as inherently more efficient engines than gasoline. Indeed, diesel engines obtain up to 40% higher fuel efficiency per litre of fuel than gasoline engines of the same power (Heavenrich (2005)). This is while type of fuel plays a substantial role in determining the quality of local air. Table 2 shows the per litre emission rates of different pollutants for a diesel and gasoline engine. As shown, Per litre gasoline emits more CO and VOC and less NO_x , $PM_{2.5}$ and CO_2 .

This mechanism is also consistent with the findings of a report by Pacific Analytic Inc. (2015a) and Antweiler and Gulati (2016). Particularly, the Pacific Analytic Inc. (2015a)'s report investigates the evolution in changes in vehicle stock, fuel efficiencies and average Vehicle Kilometres Travelled (VKT) in Metro Vancouver, suggesting that from 2008 to 2013 the average VKT increased by 2%, average fuel efficiencies increased by 6 to 7% and vehicle stock in MetroVancouver grew by 7.4%. More interestingly, the report argues that while improvements in average fuel efficiency were experienced by all types of passenger vehicles (about 2% improvement in light duty vehicles) much of the improvement (roughly 9.5%) was due to the relatively large number of more efficient diesel SUVs being purchased.

Further evidence in support of the claim of this as a primary mechanism is provided in Figures 5 and 6. Figure 5 compares gasoline and diesel sales in British Columbia to those in the other provinces for the periods before and after the introduction of the tax. As shown in Panel (a), while the rest of Canada has an increasing demand, there was a decreasing trend in gasoline demand in BC until 2012 with no clear pattern thereafter. Panel (b) shows that the BC carbon tax has a significant downward effect on diesel consumption in the first year but demand started to increase from 2012. This can also explain the increasing trends in NO_x and $PM_{2.5}$ concentrations since, as already noted, diesel fuel emits relatively more NO_x and $PM_{2.5}$. Figure 6 shows the British Columbia relative (July 2008=100) evolution of Google search in the BC carbon tax and diesel car for the period of 2004 to 2014. As

illustrated, while the interest indicator for carbon tax jumped with the announcement of the carbon tax in February 2008, starting in July 2010 there was a spike in public interest or research into diesel cars.

3.4.2 Robustness

We have seen that the coefficient of interest is robust in sign and significance to a variety of specifications. In this section we present the results of a further set of robustness checks. Taken together, these specifications reinforce the main conclusions. They also point to consumers having substituted diesel for gasoline.

Averages rather than exceedances

The analysis already presented is based on monthly frequency of exceedances. This seems to us the most natural dependent variable of interest - an exceedance captures a day on which the pollutant in question became a health "problem". It is an outcome variable to which health scientists who study air pollution and health effects attach particular importance.

However, an alternative would have been to work with monthly average pollutant levels as dependent variable. Table 6 presents the results of re-estimation of Equation 1 using monthly average level of pollutants as dependent variable. As shown point estimates on carbon tax remain positive and significant for NO_x and $PM_{2.5}$ and negative and significant (but again small) for CO .

Storage capacity effect

Considering the existence of inventory possibilities, Marion and Muehlegger (2011) compute the elasticity of on-road gasoline and diesel consumption with respect to the fuel tax in the US market for the period of 1983 to 2003. Their results suggest that the existence of capacity storage does not have any significant influences on the gasoline and diesel consumptions. Indeed, they find that low storage levels are associated with higher tax inclusive prices for

both gasoline and diesel fuel.

In a similar study Borenstein et al. (2004) analyze the effect of existence of storage capacity on the periodic price spikes in California’s gasoline market for the period of 1995 to 2002. They argue that to some extent, storage capacity can mitigate the tight supply conditions by effectively shifting consumption across time. However, according to the availability and cost of that storage capacity in California’s gasoline market, the inventory does not extend for more than a month specifically for end-users.

In the same sense and following Rivers and Schaufele (2015), Table 7 distinguishes between temporary and permanent effects of the carbon tax by dropping (a) the three months of June, July and August 2008 (Column (1) to (3)) and (b) April through to September 2008 (Column (4) to (6)). This should mitigate any problem associated with some people having stored fuel, and in addition control for any short-lived ‘announcement effect’ (Rivers and Schaufele (2015)).²¹ As can be seen the point estimates on the carbon tax are slightly smaller for NO_x and $PM_{2.5}$ and larger for CO , however even with this limited sub-samples, estimates remain consistent, assuaging concerns that the effect of tax air quality is not driven by fuel inventory or announcement effect considerations.

Revenue recycling

Revenue neutrality of the carbon tax meant that carbon tax income was recycled into reduction in personal income tax liabilities (higher disposable income). While associated income effects might be expected to be very small in an ideal world we would control for the level of average household income. After-tax real income is included in Table 8.

We did not control for income in our base specification because data on income are only available on an annual basis until 2011. Monthly income is computed by dividing annual income by twelve. As shown, the reduction in sample size to the period of 1998- 2011 does not substantially change the estimation results but also the implied tax effects are insensitive

²¹As argued by Rivers and Schaufele (2015), consumers might temporarily alter their fuel consumption levels since they might be more sensitive in the first one or two months of tax introduction.

to the inclusion of household income.

3.5 Method 2 : Synthetic control

The difference-in-difference method, though widely-used - both in general and in particular in studies of the effects of the carbon tax in British Columbia - has limitations. Difference-in-difference method is feasible when there is enough variations in key variables across multiple treatment units (Donald and Lang (2007)). Therefore, when only one observation (in this case province) within a population receives the treatment, results might be biased. In addition, while the difference-in-difference model allows for the presence of unobserved confounders, it assumes that these effects are constant over time (Abadie et al. (2010)). Such an assumption is by its nature untestable and can generate concerns for the identification claimed above.

To overcome these problems we address the same question applying the synthetic control method, with the annual number of NO_x and $PM_{2.5}$ exceedances as dependent variables.²² The synthetic control method can be applied to evaluate the causal effect of policy interventions and since its invention has been used in many settings, including health economics (Kreif et al. (2015)), political economics (Abadie et al. (2015)) and labor economics (Peri and Yasenov (2015)).

Synthetic control model is built in the same setting as the standard difference-in-difference model but first allows for time varying individual-specific heterogeneity and second takes data driven approach to construct the counterfactual outcome for the treated unit using a weighted combination of untreated units (Robbins et al. (2015), Abadie et al. (2010)) and Abadie et al. (2015)). In other words, the main distinction between difference-in-difference and synthetic control method is the ability to deal with omitted variable biased that raises

²²To be able to run the synthetic control model, we need to have a strongly balanced panel dataset. Hence, all cities that are missing data on a monthly basis are excluded from our sample. This reduces our control cities to Calgary, Edmonton, Halifax, Hamilton, Ottawa, Saskatoon, St.John's, Toronto, Windsor and Winnipeg.

because of the possibility of existence of other coincidental unobserved confounders, assuming that a close fit between the actual and synthetic outcome variable in pre-treatment period is achieved (Fremeth et al. (2016)). As emphasized by Abadie et al. (2010), if a synthetic outcome variable tracks its actual trend closely, the omission of unobserved variables is not a concern since it does not biased estimates. This is mainly because only control units that have similar observed and unobserved attributes are used to construct a synthetic outcome variable.

Therefore, as long as a synthetic outcome could follow the actual behavior of an outcome variable over a sufficiently extended pre-treatment period, any post-treatment discrepancy can fairly be attributed to the treatment itself.

3.5.1 Results

Tables 9 and 10 provide summary statistics of the predictors of the synthetic NO_x and $PM_{2.5}$ constructed using actual data on NO_x and $PM_{2.5}$ exceedances. Both tables illustrate that the synthetic NO_x and $PM_{2.5}$ compare well to the actual NO_x and $PM_{2.5}$ in the pre-treatment period.

Table 11 presents the related weights allocated to control cities in construction of the synthetic variables. Recall that these weights are determined by mathematical optimization in how well they can replicate actual NO_x and $PM_{2.5}$ behavior in the pre-treatment period. When these weights are allocated to post-treatment data, they in fact produce counterfactual performance. As shown, among the remaining ten control cities which could comprise the synthetic NO_x and $PM_{2.5}$, four receive positive weightings. A zero weight in control units is common since they do not make good individual matches and none of their attributes are sufficiently similar to the actual unit's (Fremeth et al. (2016)). The six variables that contribute in calculating weights are: pollutant concentrations before and after carbon tax, gasoline price, diesel price, minimum temperature and building issuance.²³

²³Our results are robust to alternative model specifications and to including and excluding specific other

Figures 7 and 8 plot the synthetic annual number exceedances of NO_x and $PM_{2.5}$ trends in Vancouver compared to actual outcomes. These figures also illustrate how the synthetic outcome variables would have performed relative to the actual annual number of NO_x and $PM_{2.5}$ exceedances. As shown, both the synthetic NO_x and $PM_{2.5}$ and the Vancouver's actual emissions track each other quite well. The most striking point in both Figures 7 and 8 is that in the post-treatment the annual number of emissions exceedances is significantly higher than its synthetic counterfactual, suggesting that Vancouver would have had less poor air quality days if it did not enforce carbon tax.

3.5.2 Robustness

To conduct a robustness check for our synthetic control method, we run a placebo test among untreated cities. The purpose is to check if the carbon tax had been imposed in each of the control cities, rather than Vancouver, would the same gap between the synthetic and actual outcome variable have appeared. If the effect of the treatment on the focal unit is causal, then we would expect to observe completely different gap trends in other untreated cities.

Figure 9 illustrates the gap in NO_x and $PM_{2.5}$ exceedances between the actual and the synthetic versions of each of ten control cities. To construct this figure, we replicate synthetics for each control cities assuming that the carbon tax had instead been imposed in these cities and compare the trend of each with the actual trend. The solid black line represents the gap in emission exceedances between the actual and synthetic trend in Vancouver while solid gray lines plot gaps in the emission exceedances between the actual and synthetic in other control cities. As shown, the estimated gap in Vancouver's emissions is unusually larger than the gaps for placebo cities that did not enforce carbon tax, implying a causal effect of carbon tax on concentration of NO_x and $PM_{2.5}$ in Vancouver.

control variables.

3.6 Conclusion

We provide the first evidence that the BC carbon tax has worsen Vancouver air quality by increasing the level of nitrogen oxides and ultra-fine particulate pollutants. The difference-in-difference results suggest that each five dollar increase in tax per tonne of carbon leads Vancouver to have 2.6 and 2.4 more days in a year that NO_x and $PM_{2.5}$ levels exceed their provincial standards.

The synthetic control estimation results suggest that by year 2013 annual NO_x and $PM_{2.5}$ exceedances in Vancouver were significantly about 8 and 12 days higher than what they would have been in the absence of carbon tax.

The analysis points to the possibility of change in fuel's mix because of carbon tax. In other words, in response to an increase in fuel prices consumers who tend to buy more fuel efficient vehicles might substitute a diesel engine vehicle for gasoline. It is important to mention that the environmental costs from the use of gasoline and diesel fuels include their contribution to both climate change through emissions of greenhouse gases, particularly carbon dioxide, and emissions of other local air pollutants, such as nitrogen oxides and particulate matter.

The key conclusion of this chapter is that there is an essential need to view greenhouse gas mitigation strategies in an integrated fashion which includes other local air pollutant concentration shifts. Thus far, most of GHG regulations have focused solely on GHG emissions. But in principle, local pollutants can be substitutes or complements to global pollutants implying that GHG regulations can have ambiguous effect on local air quality. This is while the costs of local air pollution are largely paid by the local inhabitants whereas the benefits of mitigating GHG emissions are spread diffusely. Our results suggests that BC carbon tax has resulted in a poorer local air quality in Vancouver. This result is robust to many specifications and different estimation methods.

Table

Table 3.1: British Columbia carbon tax level

	Carbon Tax (\$/tonne)	Carbon Tax (cents/litre)	
		Gasoline	Diesel
July 1, 2007	0	0	0
July 1, 2008	10	2.34	3.34
July 1, 2009	15	3.33	4.33
July 1, 2010	20	4.45	5.45
July 1, 2011	25	5.56	6.56
July 1, 2012	30	6.67	7.67
July 1, 2013	30	6.67	7.67

Source: British Columbia Ministry of Finance (2015), Tax Bulletin MFT-CT 005, 'Tax Rates on Fuels,' revised July 2015.

Table 3.2: Range of pollutants emitted per Litre of gasoline and diesel

	Gasoline	Diesel
Carbon dioxide	2,263	2,289
Carbon monoxide	71.42	2.47
Nitrogen oxide	7.36	29.60
Particulate matter	0.025	0.82
Volatile Organic Compounds	8.47	0.52

Source: OECD calculations.

Table 3.3: Summary statistics

	Before 2008		After 2008		t-test
	Mean	Std. Dev.	Mean	Std. Dev.	
<i>A. Overall (N = 2880 J = 15)</i>					
Monthly number of exceedances of NO_x	0.76	3.02	0.59	2.48	-
Monthly number of exceedances CO	0.11	0.83	0.024	0.29	-
Monthly number of exceedances $PM_{2.5}$	0.45	1.73	0.37	1.42	-
Monthly average level of NO_x	31.13	17.84	21.11	0.13	-
Monthly average level of CO	0.46	0.29	0.26	0.13	-
Monthly average level of $PM_{2.5}$	7.94	3.79	10.01	10.58	-
Monthly gasoline consumption	144.37	29.87	150.18	48.79	-
Monthly diesel consumption per capita	97.01	56.12	104.41	75.23	-
Market price of gasoline	75.87	16.78	113.47	16.10	-
Market price of diesel	73.89	17.98	114.52	17.40	-
Monthly real income	1901.48	203.82	2151.92	171.66	-
Monthly unemployment	6.99	2.72	7.50	2.29	-
Monthly labor force	3967.69	2775.02	4421.72	3036.465	-
Monthly number of building permit	611.49	873.81	570.21	783.39	-
Maximum temperature($^{\circ}C$)	12.07	10.32	11.96	10.35	-
Minimum temperature ($^{\circ}C$)	2.02	9.39	2.09	9.46	-
Precipitation (mm)	65.05	20.11	70.25	55.78	-
Wind speed (km/h)	65.51	20.11	66.01	19.17	-
<i>B. Vancouver</i>					
Monthly number of exceedances of NO_x	0.13	0.79	0.92	0.83	0.35
Monthly number of exceedances CO	0.59	1.96	0.069	0.59	0.74
Monthly number of exceedances $PM_{2.5}$	0.076	0.47	0.72	0.28	1.09
Monthly average level of NO_x	46.29	14.51	52.16	16.67	0.63
Monthly average level of CO	0.61	0.17	0.28	0.09	0.14
Monthly average level of $PM_{2.5}$	5.71	1.38	7.05	1.62	1.17
<i>C. Rest of Canada</i>					
Monthly number of exceedances of NO_x	0.47	1.79	0.57	2.56	-
Monthly number of exceedances CO	0.81	3.12	0.021	0.26	-
Monthly number of exceedances $PM_{2.5}$	0.47	1.79	0.33	1.46	-
Monthly average level of NO_x	19.17	14.51	29.51	16.88	-
Monthly average level of CO	0.45	0.30	0.25	0.13	-
Monthly average level of $PM_{2.5}$	8.11	3.86	7.75	4.23	-

Notes: N and J refer to the number of observations and group, respectively. Gasoline and diesel consumption are in litres per capita. Prices are inflation-adjusted and tax-inclusive. Price and excise tax information is retrieved from Kent Marketing Services Limited. Gasoline and diesel consumption are obtained from Statistics Canada for each province. Building permit issuance is obtained from Statistics Canada. Air pollution data are obtained from Canada's National Air Pollution Surveillance Program (NAPS). Weather data came from the Environment Canada. A t-statistic reported in the last column of Panel B is t test of difference in mean of pollutant exceedances and level between Vancouver and rest of Canada. A null hypothesis is that the difference in group means is zero. * significant at 10% ** significant at 5% *** significant at 1%

Table 3.4: Effect of carbon taxes on level of local air pollutants

	Nearest AQS			Average of Three AQSs		
	(1)	(2)	(3)	(4)	(5)	(6)
	NO_x	$PM_{2.5}$	CO	NO_x	$PM_{2.5}$	CO
Carbon tax*Vancouver	0.0430*** [0.00798]	0.0409*** [0.00511]	-0.0129* [0.00498]	0.0156** [0.00631]	0.0000383 [0.000441]	-0.000569 [0.000709]
Gas price	-0.0344 [0.0200]	-0.0171 [0.00991]	-0.00660 [0.00673]	-0.00682 [0.00772]	-0.000215 [0.000756]	0.000521* [0.000178]
Diesel price	0.0270 [0.0137]	0.0136 [0.00756]	-0.00568 [0.00544]	-0.00643 [0.00620]	-0.00113 [0.000903]	-0.00908 [0.000650]
Unemployment	-0.000224 [0.000148]	-0.000196* [0.0000985]	0.0000335 [0.0000596]	0.0000319 [0.0000666]	-0.0000143 [0.00000884]	-0.0000790 [0.00000974]
Building permit	-0.000303* [0.000132]	-0.000164* [0.0000731]	-0.000133** [0.0000430]	-0.000155** [0.0000498]	0.00000926 [0.0000263]	0.00000126 [0.0000440]
Maximum temperature	0.111* [0.0434]	0.0641** [0.0242]	0.0297* [0.0140]	0.0354* [0.0163]	0.00324 [0.00365]	0.00224 [0.00325]
Precipitation	0.000402 [0.00134]	0.000140 [0.000769]	-0.0000351 [0.000432]	-0.0000406 [0.000507]	-0.0000169 [0.0000829]	-0.0000693 [0.000029]
Minimum temperature	-0.0789 [0.0479]	-0.0406 [0.0267]	-0.0167 [0.0192]	-0.0200 [0.0222]	-0.00280 [0.00310]	-0.0731 [0.00150]
Wind speed	0.00254 [0.00287]	0.000446 [0.00200]	-0.00127 [0.000650]	-0.00166* [0.000770]	-0.000127 [0.000291]	-0.000178 [0.000768]
Observations	2,663	2,663	2,663	2,663	2,663	2,663
City fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y

Notes: The dependent variable is monthly number of emissions' exceedances . Standard errors clustered on city in brackets. Time fixed effects include year-month and 2010 winter Vancouver olympics dummies. * significant at 10% ** significant at 5% *** significant at 1%

Table 3.5: Sensitivity of result to exclusion of weather variable

	(1)	(2)	(3)
	NO_x	$PM_{2.5}$	CO
Carbon tax*Vancouver	0.0420***	0.0402***	-0.0132**
	[0.00880]	[0.00498]	[0.00486]
Observations	2,663	2,663	2,663
City fixed effect	Y	Y	Y
Time fixed effect	Y	Y	Y
Weather covariates	N	N	N
Relevant covariates	Y	Y	Y

Notes: The dependent variable is monthly number of emissions' exceedances. Standard errors clustered on city in brackets. All regressions control for maximum and minimum temperature, wind speed and precipitation. Relevant covariates include controls for gasoline price, diesel price, unemployment and building permit. Time fixed effects include year-month and 2010 winter Vancouver olympic dummies. * significant at 10% ** significant at 5% *** significant at 1%.

Table 3.6: Effect of carbon taxes on emissions: Monthly average level of pollutants

	(1)	(2)	(3)
	NO_x	$PM_{2.5}$	CO
Carbon tax*Vancouver	0.214**	0.131***	-0.00766***
	[0.0842]	[0.0342]	[0.00141]
Observations	2,663	2,663	2,663
City fixed effect	Y	Y	Y
Time fixed effect	Y	Y	Y
Weather covariates	N	Y	Y
Relevant covariates	Y	Y	Y

Notes: The dependent variable is monthly number of emissions' exceedances. Standard errors clustered on city in brackets. All regressions control for maximum and minimum temperature, wind speed and precipitation. Relevant covariates include controls for gasoline price, diesel price, unemployment and building permit. Time fixed effects include year-month and 2010 winter Vancouver olympic dummies. * significant at 10% ** significant at 5% *** significant at 1%.

Table 3.7: Effect of carbon tax on emission: Announcement and capacity effect

	(1)	(2)	(3)	(4)	(5)	(6)
	NO_x	$PM_{2.5}$	CO	NO_x	$PM_{2.5}$	CO
Carbon tax*Vancouver	0.0397**	0.0384***	-0.0172**	0.0413***	0.0389***	-0.0256**
	[0.0106]	[0.00632]	[0.00536]	[0.00927]	[0.00557]	[0.00791]
Observations	2,362	2,362	2,362	1,648	1,648	1,648
City fixed effect	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
Weather covariates	Y	Y	Y	Y	Y	Y
Relevant covariates	Y	Y	Y	Y	Y	Y

Notes: The dependent variable is monthly number of emissions' exceedances. All regressions control for maximum and minimum temperature, wind speed and precipitation. Relevant covariates include controls for gasoline price, diesel price, unemployment and building permit. Time fixed effects include year-month and 2010 winter Vancouver olympic dummies. Column 1 to 3 exclude the three months of June, July and August 2008, column 4 to 6 exclude April through to September 2008. * significant at 10% ** significant at 5% *** significant at 1%..

Table 3.8: Effect of carbon tax on emission: After-tax teal income inclusion

	(1)	(2)	(3)
	NO_x	$PM_{2.5}$	CO
Carbon tax*Vancouver	0.0425*** [0.00969]	0.0398*** [0.00591]	-0.0135** [0.00529]
Observations	2,855	2,855	2,855
City fixed effect	Y	Y	Y
Time fixed effect	Y	Y	Y
Weather covariates	Y	Y	Y
Relevant covariates	Y	Y	Y

Notes: The dependent variable is monthly number of emissions' exceedances. Standard errors clustered on city in brackets. All regressions control for maximum and minimum temperature, wind speed and precipitation. Relevant covariates include controls for gasoline price, diesel price, unemployment and building permit. Time fixed effects include year-month and 2010 winter Vancouver olympic dummies. * significant at 10% ** significant at 5% *** significant at 1%.

Table 3.9: NO_x exceedances predictor means

	Vancouver		Average of 10 control cities
	Real	Synthetic	
NO_x Exceedance 1998	8	8.44	7
NO_x Exceedance 2003	7	7.83	6.4
NO_x Exceedance 2005	9	9.71	6.8
Unemployment	7.05	8.10	7.6
Gas price	77.32	76.75	80.04
Diesel price	74.86	75.01	77.9
Maximum temperature	14.07	15.8	11.74
Precipitation	3.11	3.18	2.29
Wind speed	34.82	35.45	40.2

Notes: All variables except for NO_x exceedance are averaged for the 1998-2013 period.

Table 3.10: $PM_{2.5}$ exceedances predictor means

	Vancouver		Average of 10 control cities
	Real	Synthetic	
$PM_{2.5}$ Exceedance 1998	8	9.63	9
$PM_{2.5}$ Exceedance 2003	15	15.61	14
$PM_{2.5}$ Exceedance 2005	5	4.28	6
Unemployment	7.05	7.96	7.6
Gas price	77.32	76.75	80.04
Diesel price	74.86	75.01	77.9
Maximum temperature	14.07	15.8	11.74
Precipitation	3.11	3.18	2.29
Wind speed	34.82	35.45	40.2

Notes: All variables except for $PM_{2.5}$ exceedance are averaged for the 1998-2013 period.

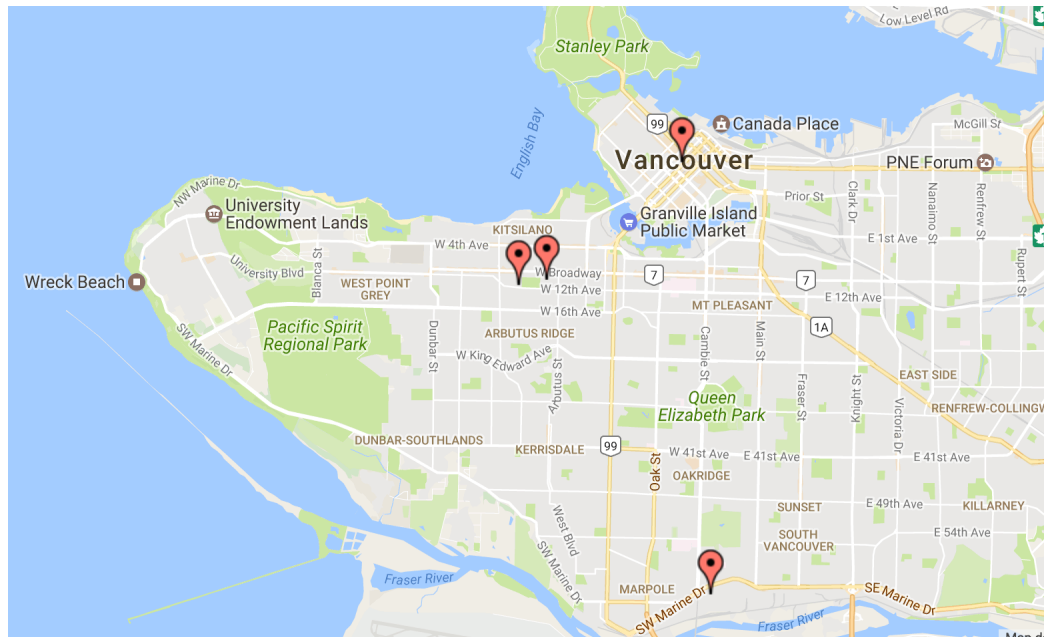
Table 3.11: City weights in the synthetic Vancouver

City	Weight		City	Weight	
	NO_x	$PM_{2.5}$		NO_x	$PM_{2.5}$
Calgary	0.26	0.23	Saskatoon	0	0.34
Edmonton	0.19	0.07	St. John's	0	0
Halifax	0	0.12	Toronto	0.32	0.24
Hamilton	0	0	Windsor	0	0
Ottawa	0.23	0	Winnipeg	0	0

This table shows the weights of each control city in the synthetic NO_x and $PM_{2.5}$ in Vancouver. All other cities in the donor pool are assigned zero weights. Recall that these weights are calculated by how well these cities replicate actual pollutant concentrations in Vancouver before implementation of carbon tax to create a match. The six variables that contribute in calculating weights are: pollutant concentrations before and after carbon tax, gasoline price, diesel price, minimum temperature and building issuance.

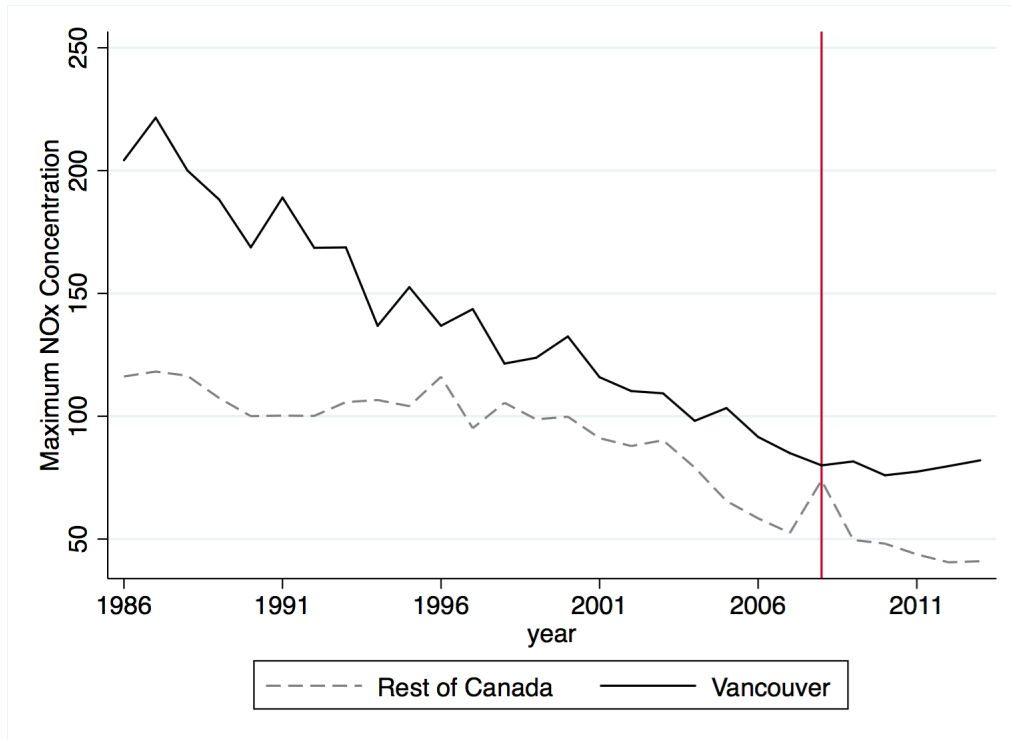
Figures

Figure 3.1: Location of air quality stations in Vancouver



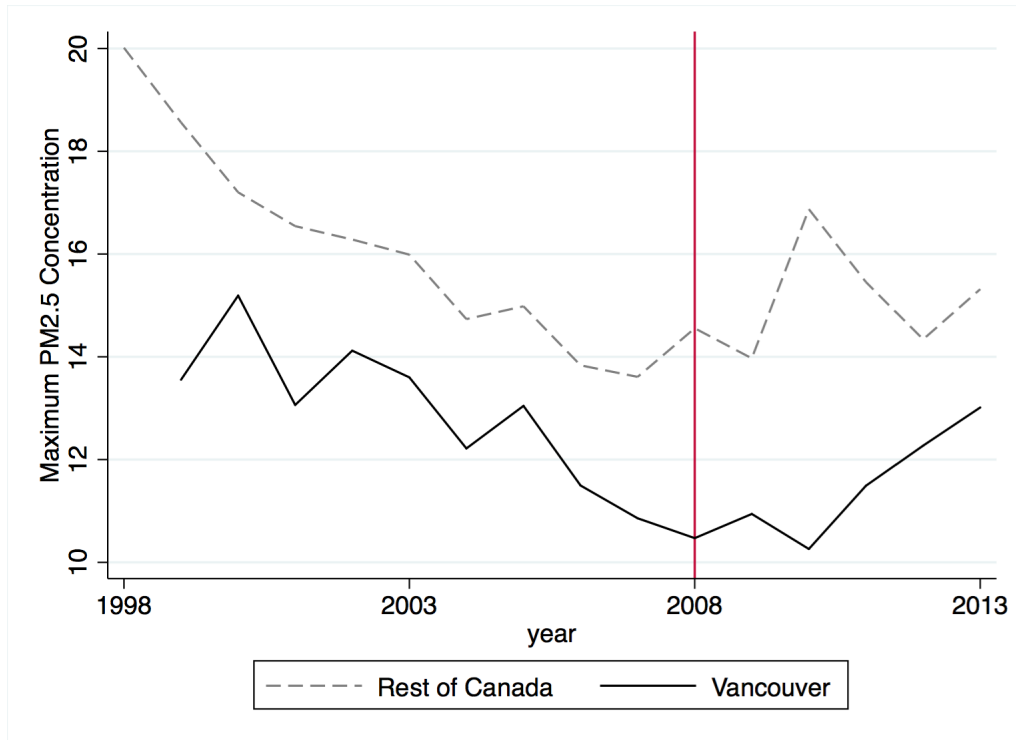
Source: National Air Pollution Surveillance Program (NAPS).

Figure 3.2: NO_x concentration: Vancouver vs. the rest of Canada



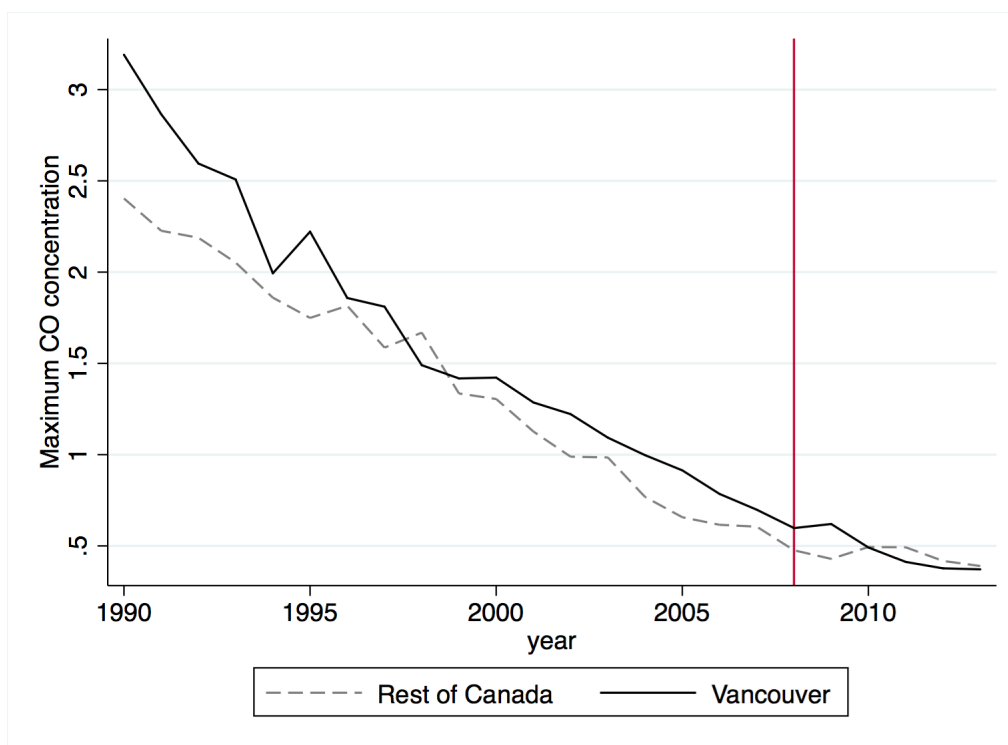
Source: National Air Pollution Surveillance Program (NAPS). This figure plots the trend in maximum $PM_{2.5}$ concentration for the period of 1986 to 2013.

Figure 3.3: $PM_{2.5}$ concentration: Vancouver vs. the rest of Canada



Source: National Air Pollution Surveillance Program (NAPS). This figure plots the trend in maximum $PM_{2.5}$ concentration for the period of 1998 to 2013.

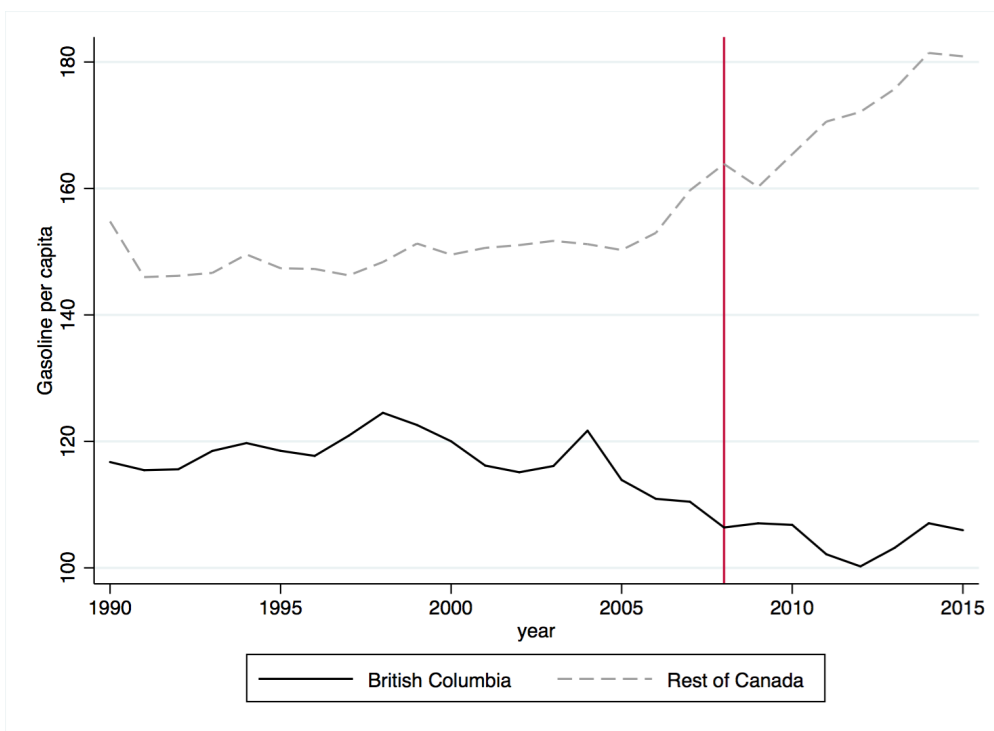
Figure 3.4: CO concentration: Vancouver vs. the rest of Canada



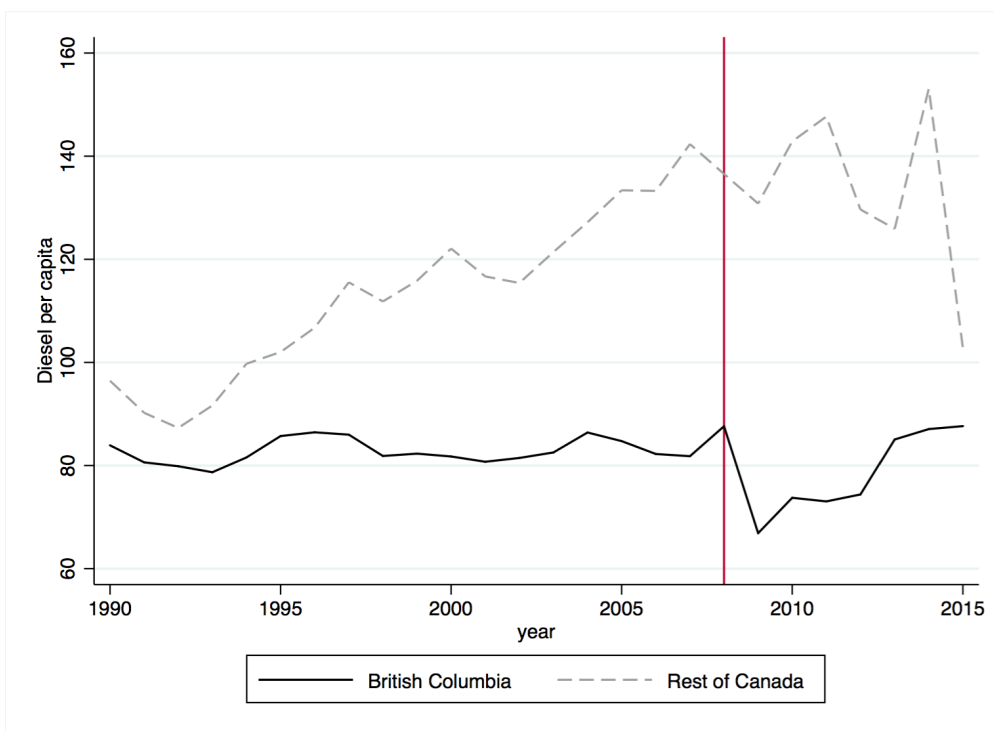
Source: National Air Pollution Surveillance Program (NAPS). This figure plots the trend in maximum $PM_{2.5}$ concentration for the period of 1990 to 2013.

Figure 3.5: Fuel sales: British Columbia vs. the rest of Canada

(a) Gasoline

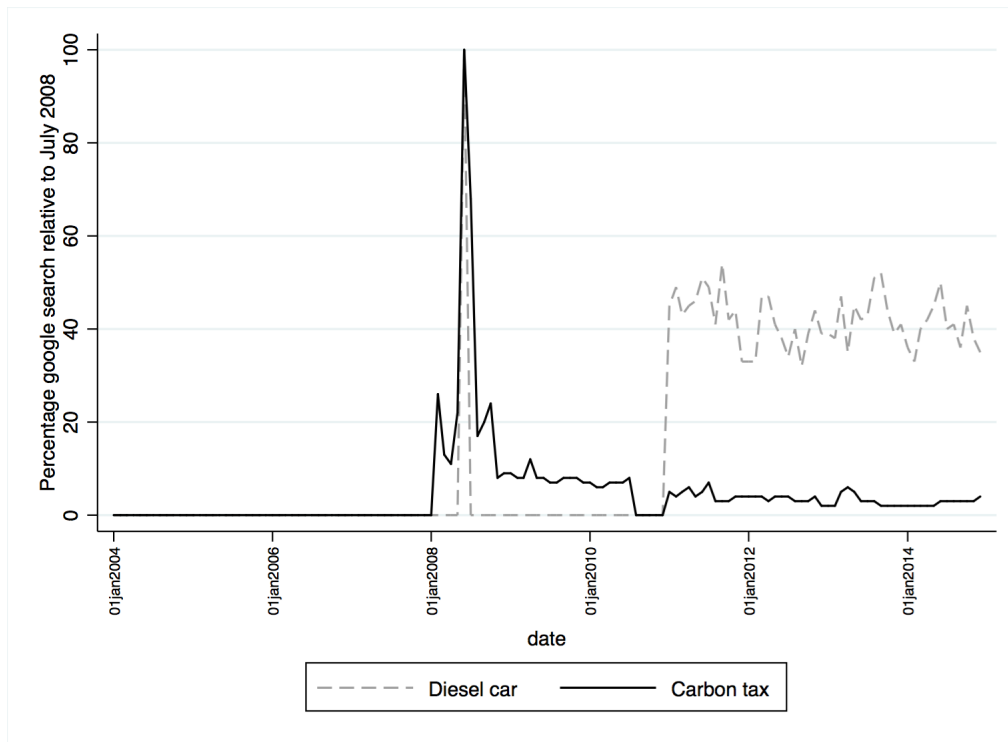


(b) Diesel



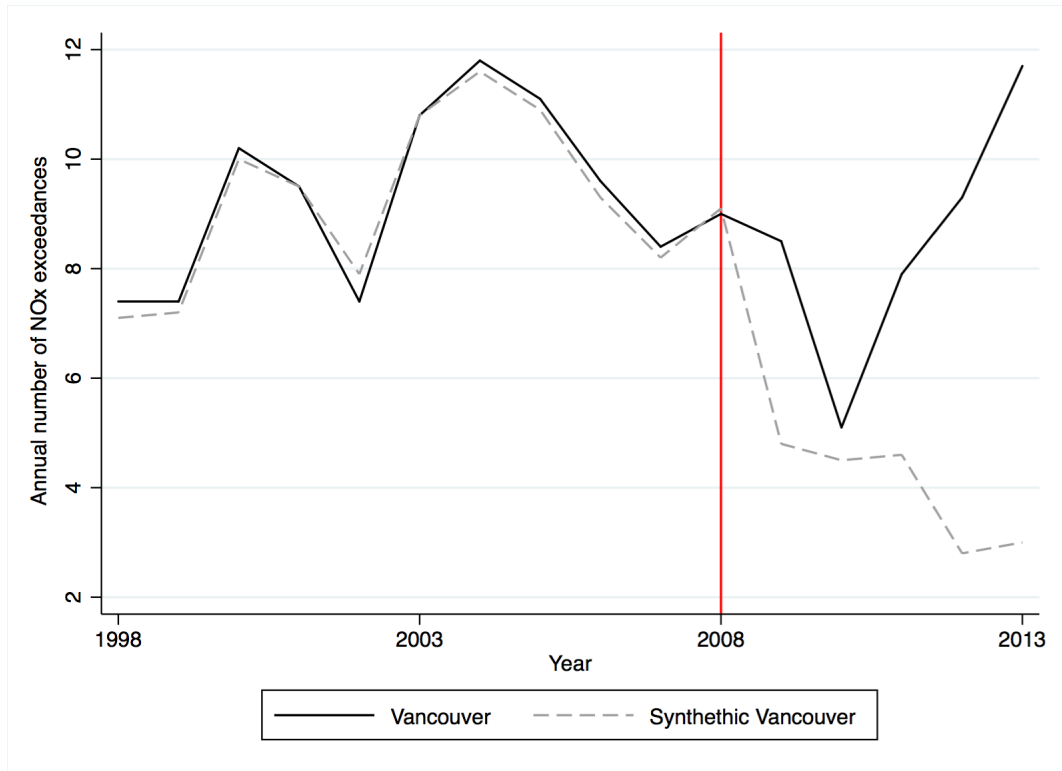
Source: Supply and Disposition of Refined Petroleum Products (CANSIM 134-004) and labour force (CANSIM 282-0087).

Figure 3.6: Public interest in the BC carbon tax and diesel cars over time



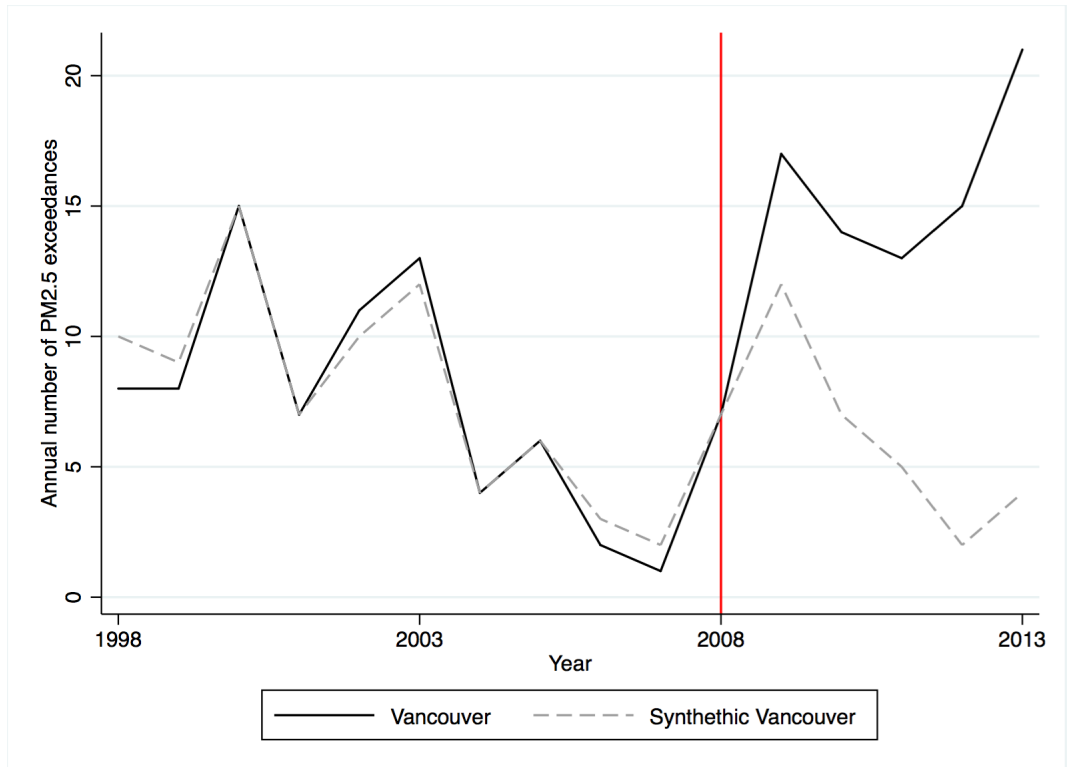
Note: This figure shows the British Columbia relative (July 2008=100) evolution of Google search in the BC carbon tax and diesel car for the period of 2004 to 2014.

Figure 3.7: NO_x exceedances: Vancouver vs. synthetic Vancouver



Note: This figure plots the gap between synthetic versus actual trend in annual number of NO_x exceedances using the weights on the cities presented in Table 3.11.

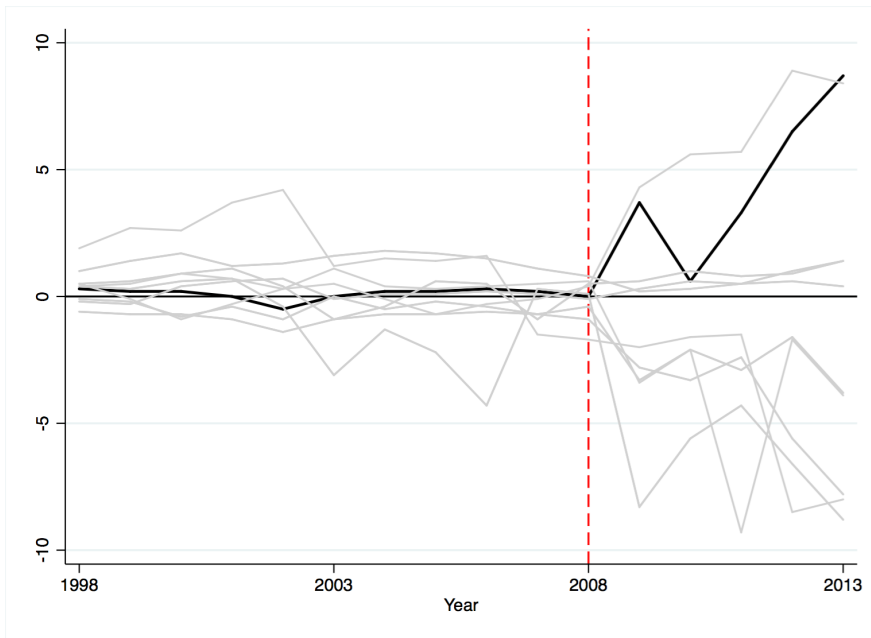
Figure 3.8: $PM_{2.5}$ exceedances: Vancouver vs. synthetic Vancouver



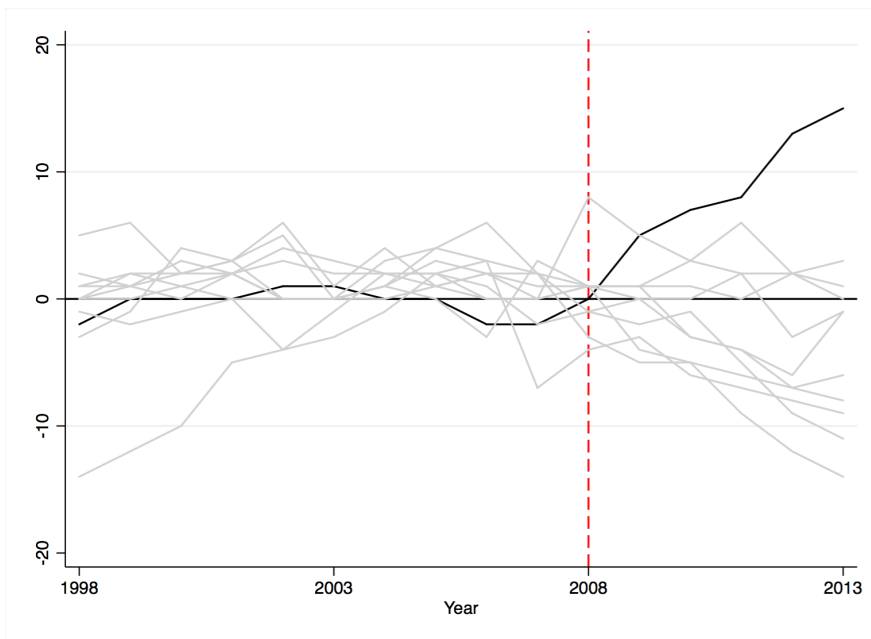
Note: This figure plots the gap between synthetic versus actual trend in annual number of $PM_{2.5}$ exceedances using the weights on the cities presented in Table 3.11.

Figure 3.9: Placebo gaps

(a) NO_x



(b) $PM_{2.5}$



Note: This figure illustrates the gap between the actual and the synthetic versions of each of the 10 control cities. Synthetics for each control city are created as if they had implemented carbon tax in July 2008 just as Vancouver did. The solid line represents the gap in pollutant concentrations between the actual and synthetic Vancouver.

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