On the road to recovery:

Gasoline content regulations and child health*

Michelle Marcus[†]

Brown University

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Abstract

In an effort to curb pollution and improve health, state and federal governments have enacted gasoline content regulations. However, the impact of these regulations on the environment and population health has not been quantified. I exploit spatial variation in children's exposure to highways to estimate the effect of gasoline regulation on both pollution and child health. Using a difference-in-difference estimation strategy, I compare childhood asthma hospitalizations in high exposure areas to low exposure areas, before and after gasoline regulation. Results show that the introduction of California Air Resource Board (CARB) gasoline in California in 1996 reduced asthma by 8 percent in high exposure areas. A cohort-level analysis shows improvements in health over time, implying a cumulative effect of cleaner-burning gasoline. Moreover, children of low socio-economic status experience a larger health improvement. Therefore, precisely-targeted gasoline content regulations can improve child health, and may help diminish existing health disparities.

1 Introduction

Asthma affects 1 in 10 children and costs the U.S. over $6 billion every year. Motor vehicle exhaust has been identified as an important asthma trigger, and epidemiological research has provided evidence of the correlation between traffic pollution and health outcomes

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[†]Department of Economics, Brown University, 64 Waterman Street, Providence, RI 02912. Email: michelle_marcus@brown.edu.

for children and infants.[1] In an effort to curb pollution and improve health outcomes, state and federal governments have enacted gasoline content regulations designed to reduce pollution from motor vehicle exhaust. Several states, including California, have adopted more stringent gasoline programs than those imposed by the federal government. In March 1996, California Air Resources Board (CARB) gasoline was required throughout the state. The precisely targeted, inflexible regulations of CARB gasoline required the removal of particularly harmful compounds from gasoline.

However, gasoline content regulations are associated with certain economic costs. These regulations can increase the price and price volatility of gasoline, which is costly to consumers (Brown et al., 2008; Muehlegger, 2002).[2] Given the large compliance cost to refineries, over $1 billion per year in California, it is important to identify whether or not gasoline content regulation significantly decreases pollution, improves health, and reduces health expenditures.

Cleaner-burning CARB gasoline is likely to have the largest impact on people living near highways, given the documented relationship between distance from highways and level of traffic-related air pollution (Gilbert et al., 2003). In this paper, I exploit spatial variation in children's exposure to highways to estimate the effect of gasoline regulation on both pollution and child health.[3] However, a cross-sectional comparison of people living near and far from highways will be biased by differences in observable and unobservable characteristics, such as income, education and preference for clean air, which are correlated both with choice of residence and susceptibility to asthma.[4] However, it is not unreasonable to think that the differences between these neighborhoods will remain fairly constant

[1] See English et al. (1999); Weiland et al. (1994); Duhme et al. (1996); McConnell et al. (2006); Ryan et al. (2005); van Vliet et al. (1997); Brunekreef et al. (1997); Ciccone et al. (1998); Friedman et al. (2001); Wilhelm and Ritz (2003).

[2] Brown et al. (2008) estimate that the price to consumers increased by an average of 3 cents/gal in metropolitan areas with gasoline content regulations, relative to a control group. The price effect, however, varied by 8 cents/gal across different regulated markets depending on geographic isolation.

[3] Recent research has suggested that traffic pollution can travel up to 1km from the highway (Hu et al., 2009). Throughout this paper I consider the area of exposure to be within 1km of a highways. However, the results are robust to smaller areas, such as within 300m of highways, as shown in Table 8.

[4] In fact, Table 9 in the appendix shows that census tracts near the highway have a larger percentage of non-white residents, a larger percentage of Hispanics, a larger percentage of single female households with young children, lower levels of educational attainment, a larger percentage of foreign born and non-citizens, higher unemployment, a larger percentage of blue collar workers, and a greater percentage below the poverty level. Clearly, a cross-sectional comparison would be biased by the differences in underlying population characteristics that are known to be related to health outcomes as well.

over time. Neighborhood characteristics are somewhat stable over time since people are not perfectly mobile and the housing market is not perfectly fluid.[5] Therefore, I employ a differences-in-differences framework to examine the between-location difference in both pollution and asthma incidence before and after the CARB regulation goes into effect. As long as the neighborhood level characteristics do not shift discontinuously at the same time as the 1996 CARB regulation, then the difference-in-difference estimates presented below will be unbiased.

Previous literature on the link between pollution and health has exploited natural experiments to avoid inherent endogeneity problems of cross-sectional comparisons (Chay and Greenstone, 2003; Currie and Walker, 2011). Neidell (2004) and Currie and Neidell (2005) have also exploited seasonal variations in pollution within zip codes to identify pollution's impact on child asthma hospitalizations and infant mortality. Although there is a clear link between pollution and child health, the role that gasoline content regulations play in reducing asthma from motor vehicle exhaust is undocumented. Instead, research on gasoline content regulations has focused on the production response of refineries, the impact on price and price volatility, and the improvements in air quality (Auffhammer and Kellogg, 2011; Brown et al., 2008; Muehlegger, 2002). When refiners are granted flexibility in deciding which specific compounds to remove from gasoline, they chose to remove the cheapest, rather than the most harmful pollutants. Auffhammer and Kellogg (2011) find that only the precisely targeted, inflexible CARB regulations improved air quality. However, the health impacts of gasoline content regulations have not yet been quantified.

This paper asks whether or not CARB gasoline improved health outcomes, measured by childhood asthma, by reducing pollution. Identifying the pollution reduction and associated health benefits from CARB gasoline is especially important given that the U.S. EPA has been moving from less restrictive federal gasoline regulations to regulations that bring the nation closer to stringent California standards (CARB, 2008b). I contribute to the literature in several ways. First, I quantify the first-stage impact of CARB gasoline on three criteria pollutants: NO_2, CO, and SO_2. Whereas Auffhammer and Kellogg (2011) estimate air

[5] In fact, according to census 2000 estimates, about 80% of residents lived in the same county for the previous 5 years, and 50% remained in the same house. Table 9 in the appendix provides some evidence that the difference-in-difference estimates of demographic characteristics remain fairly stable between areas near and far from highways before and after the policy of interest.

quality improvements off of the county-level ozone reductions in California relative to ozone levels in the rest of the U.S., the results presented in this paper exploit within state variation in exposure to highway pollution at the zip code level to identify the impact of CARB gasoline on pollution in California. Estimates show a decline of about 2 percent, 6 percent, and 10 percent in high exposure areas for NO_2, CO, and SO_2, respectively. Second, I quantify the impact of CARB gasoline on childhood asthma hospitalizations. Although cleaner-burning gasoline may impact health along several dimensions, I focus on childhood asthma because it is prevalent, the cost of hospitalization is high, and children are especially vulnerable to air pollution. Zip code level estimates indicate that CARB gasoline caused an 8 percent decline in childhood asthma hospitalizations in high exposure areas. Using confidential data containing a record linkage number that is unique to patients, I am also able to estimate the change in an individual's probability of being admitted to the hospital for asthma after the policy, as well as any change in length of stay. The individual level estimates suggest that CARB gasoline reduced the probability of asthma hospitalization by about 6 percent and decreased length of stay by about 10 percent from the pre-policy level. Third, I present suggestive evidence that CARB gasoline reduced infant deaths in high exposure areas, which translates into large value-of-life cost savings for gasoline content regulation. Fourth, I show that the effects of regulation grow over time as the pollution effects accumulate. I present a cohort level analysis to estimate the cumulative effect of exposure to cleaner-burning CARB gasoline. Fifth, I explore heterogeneous effects and non-linearities in the relationship between pollution and asthma. I explore possible differential effects by race, age, and gender. I also use traffic density data to look for heterogeneous effects by level of congestion. Finally, evidence suggests that families living near highways are more likely to be lower in socio-economic status. Therefore, reductions in highway pollution benefit a disadvantaged population that already suffers disproportionately adverse health outcomes, including asthma. I show that the improvement in asthma was stronger for black children, suggesting that the gasoline regulation may help diminish existing health disparities.

The paper is organized as follows. Section 2 motivates the paper and provides background on asthma, pollution, and the CARB regulations. Section 3 describes the data and defines key variables. Section 4 describes the empirical strategy for estimating the impact of regulation on both pollution and asthma. Section 5 shows the results, and Section 6 tests the robustness of the main results. Section 7 provides some discussion and a cost-benefit analysis, and Section 8 concludes.

2 Motivation and Background

2.1 Asthma and Pollution

Childhood asthma is a prevalent and costly condition affecting millions of children in the United States. Over 10 million U.S. children under the age of 18 (14%) have at one time been diagnosed with asthma, 7 million (10%) still have asthma, and 4 million (55%) of those with asthma experience asthma attacks (CDC, 2012). Asthma is more likely among non-Hispanic black children, children in poor families, and children in fair or poor health (Bloom et al., 2013). According to the California Environmental Protection Agency, nearly 667,000 school-aged children in California have experienced asthma symptoms during the past year (CARB, 2013). One important asthma trigger is outdoor air pollution.

Children are especially vulnerable to air pollution for several reasons. First, early exposure to pollution can alter lung development and function. Second, children spend a considerable amount of time engaging in physical activities outdoors. Increases in breathing rate lead to larger levels of environmental pollutants in the respiratory tract. Finally, children are predominantly oral breathers, meaning that air by-passes the nasal filter and more particles may enter lower airways (Esposito et al., 2014).

Air pollution is associated with an increased risk of asthma exacerbation and acute respiratory infections. It is thought that SO_2 particles may act as irritants, stimulating sensory nerves in the airways to induce cough, bronchoconstriction, and increased mucus secretion. NO_2 may induce airway inflammatory changes, but the mechanisms through which this occurs are not well understood. In general, existing evidence of the relationship between specific pollutants and asthma is unclear and sometimes conflicting (Barnes, 1995; Esposito et al., 2014). Although there is no consensus on the exact biological mechanisms through which criteria pollutants impact asthma, epidemiological studies have found that patients with asthma are affected by certain criteria air pollutants, such as NO_2, CO, and SO_2 (Sheppard et al., 1980; Huang et al., 1991; Orehek et al., 1976; Kleinman et al., 1983; Bauer et al., 1986; Koenig et al., 1983; Leikauf, 2002).[6]

Prevalence of asthma imposes a great financial burden across the U.S. health care system. Direct costs include payments for ambulatory care visits, hospital outpatient services, hospital inpatient stays, emergency department visits, physician and facility payments, and prescribed medications. Indirect costs can also result from missed work or school, and days with restricted work activity. Smith et al. (1997) estimate that the total costs of asthma (direct and indirect) were $5.8 billion in 1994. Hospital expenditures accounted for over half of all expenditures for asthma. Total costs for childhood asthma were almost $2 billion in 1996 (Wang et al., 2005).[7]

2.2 Gasoline Content Regulation

Prior to cleaner-burning gasoline regulations, gasoline powered vehicles produced about half of all air pollution in California according to the California Environmental Protection Agency. The new stringent state-wide gasoline standard affected all cars simultaneously, unlike restrictions made to engines and vehicles which are implemented only through vehicle turnover.

CARB restricts several harmful pollutants found in gasoline. Specifically, CARB requires an 80 percent reduction in the sulfur content of gasoline to reduce the emission of SO_2 and NO_x. It also calls for added oxygen, which is intended to reduce CO.[8]

California's EPA estimated that CARB gasoline would cause a reduction in the amount

[6] Furthermore, certain Hazardous Air Pollutants (HAPs) may exacerbate asthma because, once sensitized, individuals can respond to remarkably low concentrations, and these irritants can lower the bronchoconstrictive threshold to respiratory antigens. Benzene and 1,3-Butadiene, both restricted by CARB gasoline regulations, appear on a list of the 19 compounds with the highest potential impact on the induction or exacerbation of asthma (Leikauf, 2002). Unfortunately, data on these HAPs are sparse and I will not be able to show a first stage for these pollutants. Although it is not possible to estimate the impact of the CARB restriction on HAPs, reduced form results estimate the impact of CARB on asthma and will include the impact of both the reduction in criteria pollutants and the reduction in HAPs.

[7] Direct medical expenditure was estimated at $1 billion, parents' loss of productivity from asthma-related school absence days was $719.1 million, and lifetime earnings lost from asthma-related death of children was $264.7 million.

[8] CARB gasoline places a cap on the benzene content of gasoline at 1 percent by volume, and applies a 7.0 psi RVP limit. There is also a limit on the concentrations of two other classes of VOCs that are highly reactive: olefins (6 percent by volume) and aromatic hydrocarbons (25 percent by volume).

of on-road pollution from NO_x (11%), CO (11%), and SO_2 (80%).[9] Given that on-road pollution accounts for about 53 percent, 79 percent, and 7 percent of total NO_x, CO, and SO_2 emissions, one would expect to see an overall decline of about 5.8 percent, 8.7 percent, and 5.6 percent, respectively, based on the projections (CARB, 2008a; EPA, 2000). This paper finds evidence to support the expected reduction in air pollution following CARB in areas near highways. Estimates presented in section 5.1 show a decline of about 2, 6, and 10 percent in high exposure areas for NO_2, CO, and SO_2, respectively. It is not surprising that the findings are slightly smaller than projected estimates, because the control group (low exposure to highways) may also experience a small reduction in pollution. Therefore, estimates of total pollution reduction will be understated.

3 Data

Patient Discharge Data

The California Patient Discharge Data is an extensive source of individual health outcomes. This dataset is comprised of a record for each inpatient discharged from a licensed acute care hospital in the state of California. Data are available from 1992 to 2000, and each year contains information on the principal diagnosis of the patient upon release from the hospital, quarter of admission, zip code of the patient's residence, age, sex, race, ethnicity, and the expected principal source of payment. Although hospital data does not include information on all asthma attacks that occur in a given period, hospital discharges are a more objective measure than self-reported surveys which could be subject to reporting biases.[10] Furthermore, this dataset provides a large number of observations across the entire state of California, whereas many surveys are only representative of select MSAs and large counties.

The primary outcome variable of interest, *Asthma*, is defined using the International Classification of Diseases, Ninth Revision, (ICD-9) codes to identify patients admitted to

[9] California's EPA also estimated a reduction in smog-forming gases, volatile organic compounds (17%), benzene, and 1,3-butadiene.

[10] According to the CDC, asthma hospitalizations occur at the rate of about 2 per 100 persons with asthma.

the hospital for asthma related conditions (code 493).[11] [12] The population of interest in this paper will be children under 10 years of age, since this is an especially vulnerable population. Therefore, *Asthma* is defined as the number of childhood discharges for asthma, per 10,000 children under age 10, for each zip code.

$$Asthma_x = \frac{\sum_i \mathbb{1}\{PrimaryDiagnosis_{ix} = Asthma\}}{Population_x} \tag{1}$$

for each x ∈ X, where X is the set of all zip code-year combinations and i indexes individuals.

The preferred specification also includes all respiratory related discharges for children less than one year old, since diagnosis of asthma among infants is difficult (Martinez et al., 1995).[13]

Another outcome variable, *InfantDeaths*, is defined using the diagnosis related group (DRG) code 385 for "neonate, died or transferred to another acute care facility." The variable *InfantDeaths* is defined analogously to the asthma rate shown above. It is the number of patients with DRG code 385 per 10,000 infants for each zip code, where infant is defined as less than one year old. Although this is not a perfect measure of infant deaths, since it contains some transfers, it is used as a proxy for infant deaths.

Population Data

The 1990 and 2000 U.S. Census data will provide estimates of population counts by age, race, and gender for each zip code. I use linear interpolations of population to estimate the number of children in each zip code for each year between 1990 and 2000.

Highways and Traffic Data

[11] The International Classification of Diseases (ICD) is maintained by the World Health Organization and is designed as the international standard health care classification system. It provides a system of diagnostic codes for classifying diseases, including generic categories together with specific variations.

[12] The results are very similar when DRG codes (DRG code 98 for bronchitis and asthma) are used to identify asthma hospitalizations rather than ICD-9 codes. Diagnosis-related group (DRG) is a system used to classify hospital cases into different groups. Because patients within each classification are clinically similar, DRGs have been used in the U.S. since 1982 in order to determine Medicare reimbursement to hospitals.

[13] The results have been estimated for an outcome variable that restricted the under 1 age category to only those with asthma diagnoses, excluding infants with a diagnosis of any other respiratory condition. These results are similar, although less well identified for the youngest age group for whom it is difficult to diagnose asthma.

Information on the location of highways comes from combining data on U.S. and State Highways from the U.S. Census Bureau's 2000 TIGER/Line geographical information systems (GIS) shapefiles, available through the Californian Spatial Information Library. The highway data is spatially linked to Cartographic Boundary files for census tracts and zip codes using ArcMap 10.1. For the purposes of this paper, a highway refers to either a U.S. or State highway, as defined by the U.S. Census Bureau (see Appendix A).

Traffic volume data comes from California's Department of Transportation, Division of Traffic Operations for 2011. Although traffic volume data is not available for the study period 1992-2000, traffic volumes from 2011 should be strongly correlated with past volumes. Annual average daily traffic (AADT) is recorded for 6,926 count locations on Californian highways. Using ArcMap 10.1 to determine zip code proximity to highways and AADT count locations, I calculated the average AADT level for each zip code. For the purposes of this paper, I consider high traffic roads to have an average AADT of at least 60,000 vehicles per day, which is consistent with the literature.

Air Pollution Data

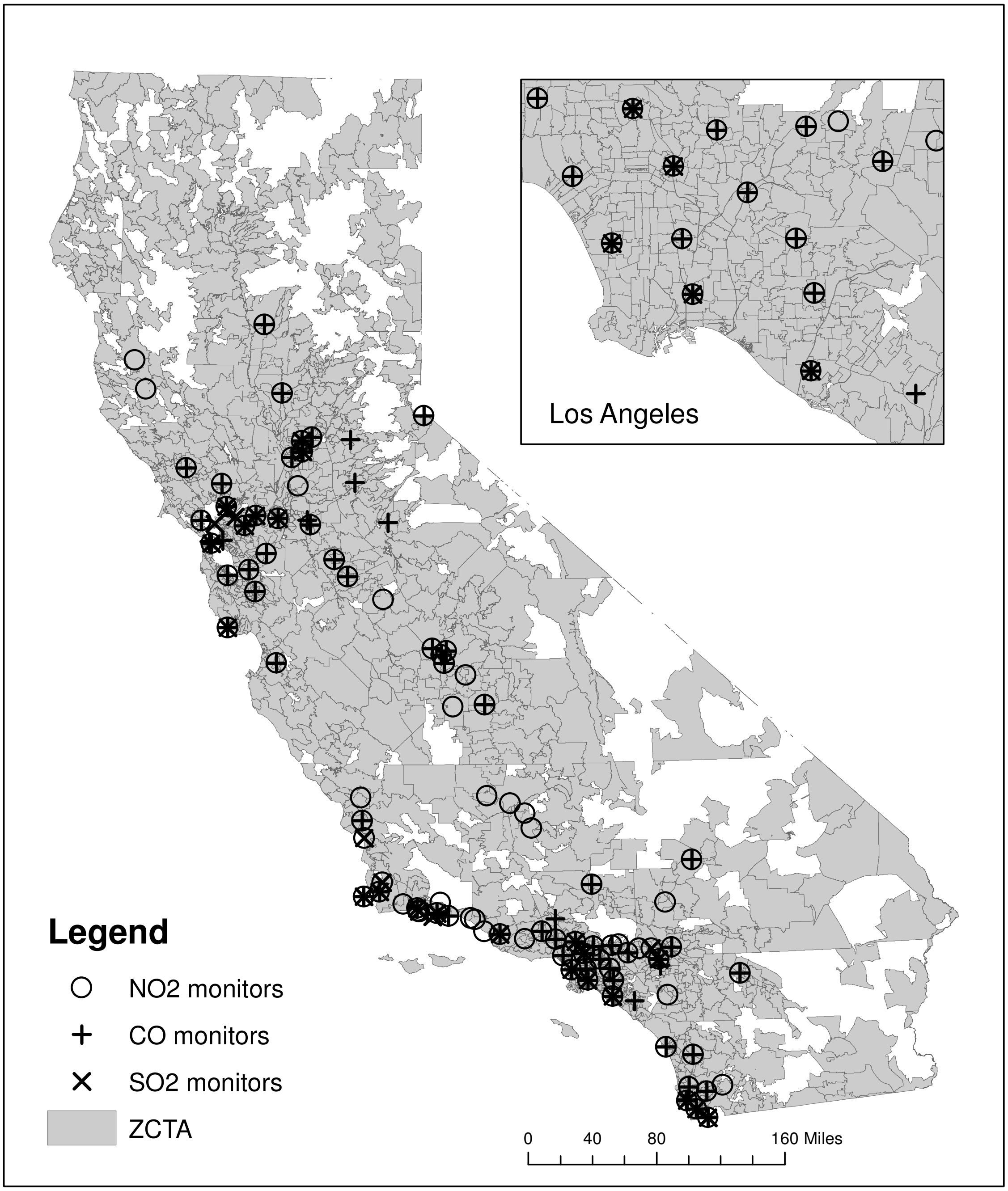
Daily data on air pollution comes from the EPA's Air Quality System (AQS) Data Mart through AirData. Daily air quality summary statistics are available for the criteria pollutants NO_2, CO, and SO_2 by monitor for the state of California.[14] There are 275 monitors throughout California that have readings during the sample period of 1992 to 2000. There may be some concern about endogenous placement of monitors during the sample period if the placement of new monitors coincides with locations that experience an unusually large change in pollution. Therefore, the main specifications limit the sample to consistently observed monitors, which are monitors observed for at least 3 months in every year of the sample period. Pollution monitors record different types of criteria pollutants. For the sample of consistently observed monitors, 90 record NO_2, 74 record CO, and 30 record SO_2. Results are similar for the full sample of monitors.

Air quality monitors are located throughout California, as shown in Figure 1. Generally, monitors are more likely to be located in areas with higher population density. Although

[14] NO2 and SO2 are measured as the mean daily maximum 1-hour concentration, while CO is measured as the mean daily maximum 8-hour concentration, following EPA standards.

there are many monitors recording NO_2 and CO levels, a sparsity of monitors for SO_2 will cause more noise in estimates for this pollutant.

Figure 1: Air quality monitors: Consistently observed



Notes: Air quality monitors are shown for all monitors consistently observed from 1992 to 2000 with measurements for pollution recorded for at least 3 months in every year of the study period.

To link Californian air quality monitors with zip codes, I follow the methodology used in Neidell (2004) and Currie and Neidell (2005). First, I calculate the monthly average measure of pollution for each air quality monitor. I find the centroid of each zip code and create a weighted average of all monitors within 20 miles of the centroid, using the inverse of distance to the centroid as the weight.[15]

4 Empirical strategy

4.1 Treatment Designation

Research has shown that traffic pollution can travel up to 1km from highways in California (Hu et al., 2009). Ideally, patient addresses would identify whether or not an individual lived within 1km of a highway. However, due to patient confidentiality constraints, only zip code of residence is available in the data.[16] Using data on the location of highways in California and census tract population data from the 2000 Census to determine within zip code density of population, I calculate the percentage of the population of a zip code that is living within 1km of a highway, τ.[17] With this measure, I classify zip codes into a treatment group and a control group, using the median value as a cutoff.[18]

$$Treat_{(T1)} = \mathbb{1}\{\tau > median(\tau)\} \tag{2}$$

Figure 2 shows the location of treatment and control zip codes in California, based on

[15]The results were estimated using a weighted average of all monitors within alternative distances from the centroid with similar results. Neidell (2004); Currie and Neidell (2005) also test the validity of these weighted averages by comparing the actual level of pollution at each monitor location in California with the level of pollution that would be assigned using their method if the monitor in question was not located there. These correlations between actual and predicted levels of pollution were very high (0.77-0.92).

[16]I have made some assumptions about where people spend the majority of their time. For children, school location may matter, since school attendance may encompass a significant portion of their time. Epidemiological research suggests that asthma risk increases with traffic-related pollution exposure near both homes and near schools, and that a disproportionate number of economically disadvantaged and nonwhite children attend high-exposure schools in California (McConnell et al., 2010; Green et al., 2004). However, given the current assumptions, as long as children are likely to attend school within their own residential zip code, the results should be unaffected by this distinction.

[17]Figure 10 in Appendix A shows the map of U.S. and state highways in California. Figure 9 in Appendix A shows the distribution of τ across zip codes in CA.

[18]The choice of a cutoff value is somewhat arbitrary, but the results are robust to alternative choices of a cutoff value. These results are shown in Table 10 of the Appendix C.

this definition. Treated zip codes are dispersed across the entire state and do not represent any specific region. Even within Los Angeles, a densely populated area, there are zip codes assigned to both the treatment and control groups.

While the designation of a treatment and control group provides for an easier interpretation of results, there is no sharp discontinuity in the exposure to the policy at this cutoff. Therefore, results are also shown using the continuous measure of τ, the percent of the population living within 1km of a highway.

4.2 First Stage Strategy: Pollution

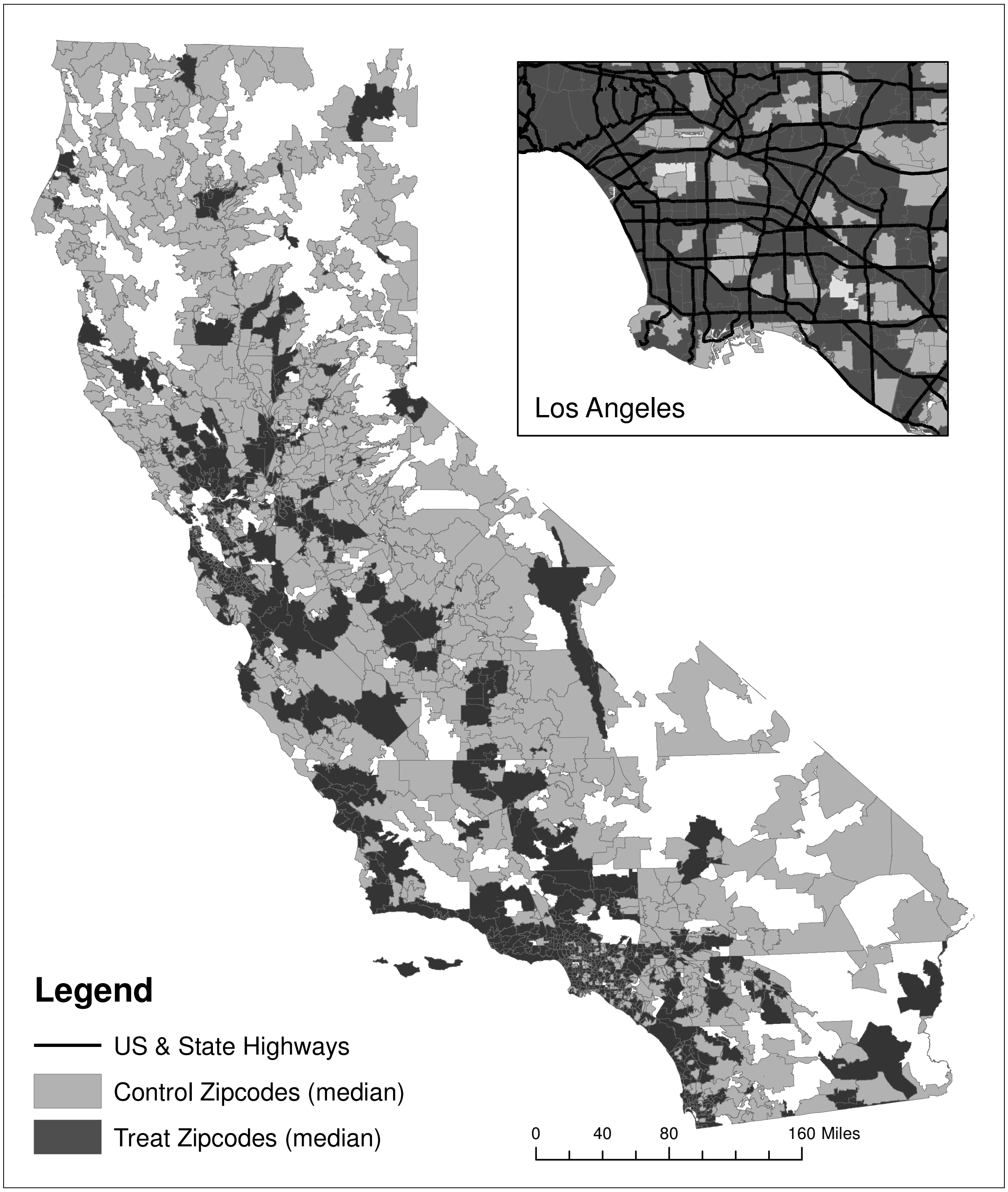
Summary statistics for the criteria pollutants and raw difference-in-difference estimates are shown in Table 1. All three pollutants are higher in the treatment zip codes relative to the control, which is to be expected. The final column shows that pollution gap between treatment and control zip codes is narrowing after the policy. This raw difference-in-difference estimate is significant for each pollutant.

With pollution measures linked to zip codes, I can calculate the difference-in-difference estimates of the implicit first stage effects of CARB regulation on pollution. The preferred specification will be as follows:

$$Pollution_{zt} = B_0 + B_1 Treat^{*} After_{zt} + Z_z + \Theta_y + Q_q + B_2 time_t + \nu_{zt} \tag{3}$$

where z indexes zip codes and t indexes time, in months. $Treat$ is equal to one if the zip code is considered treated. $After$ is equal to one after CARB takes effect in March 1996. The results are estimated with zip code fixed effects, Z_z, year dummies, Θ_y, quarter dummies, Q_q, and a linear time trend, $time_t$. The parameter of interest is B_1, which estimates the change in pollution concentration in treatment relative to control zip codes following the implementation of CARB gasoline. The results presented in the next section provide evidence that pollution dropped significantly in zip codes with many people living close to the highway after the CARB regulations.

Figure 2: Treatment and control zip codes



Notes: Treated (control) zip codes are those with at least (less than) the median percentage, 42.5%, of the zip code population living within 1km of a highway. Some areas of California are not covered by zip codes and these areas are left blank.

Table 1: Summary statistics and raw diff-in-diff: pollution and asthma

	Before			After			Diff-in-diff
	Control	Treat	Diff	Control	Treat	Diff	
Pollution							
NO2 (ppb)	41.80	46.02	-4.220***	37.01	40.70	-3.688***	0.679***
CO (ppm)	1.57	1.86	-0.285***	1.19	1.43	-0.237***	0.064***
SO2 (ppb)	4.79	5.62	-0.829***	4.61	4.93	-0.319***	0.533***
Asthma	44.98	56.53	-11.544***	42.08	49.18	-7.105***	3.799**

Notes: Treated (control) zip codes are those with at least (less than) the median percentage, 42.5%, of the zip code population living within 1km of a highway. NO2 and SO2 are measured as the mean daily maximum 1-hour concentration, while CO is measured as the mean daily maximum 8-hour concentration, following EPA standards. Asthma is the number of hospitalizations for asthma per 10,000 children, as defined in section 3.

4.3 Reduced Form Strategy: Asthma

Table 1 shows the overall level of asthma admissions in both treatment and control zip codes before and after the policy. The raw difference-in-difference estimate suggests a reduction in hospitalizations following CARB of about 3.8 per 10,000 children.

The reduced form effect of CARB on child health at the zip code level is estimated with the following specification:

$$Outcome_{zy} = \delta_0 + \delta_1 Treat^{*} After_{zy} + Z_z + \Theta_y + \epsilon_{zy} \tag{4}$$

where z indexes zip code and y indexes time, in years. The main outcome variable, $Asthma_{zy}$, is the number of childhood asthma admissions per 10,000 children. $InfantDeaths_{zy}$ is a secondary outcome variable of interest (see section 3 for definitions). $Treat$ is equal to one if the zip code is considered treated. $After$ is equal to one after CARB takes effect in 1996. The results are estimated with zip code fixed effects, Z_z, and year dummies, Θ_y. The main parameter of interest is δ_1, which estimates the change in asthma in treatment relative to control zip codes following the implementation of CARB gasoline.

Using confidential data containing a record linkage number that is unique to patients, I am also able to estimate the change in an individual's probability of being admitted to the hospital for asthma after the policy, as well as any change in the length of stay. The individual level analysis is estimated in the following linear probability model:

$$Outcome_{iy} = \omega_0 + \omega_1 Treat^{*} After_{iy} + I_i + \Theta_y + \epsilon_{iy} \tag{5}$$

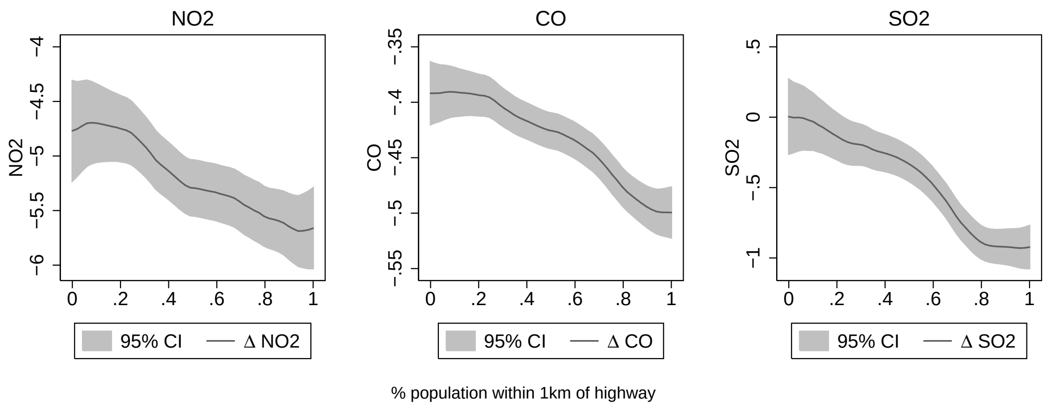
where i indexes individuals and y indexes time, in years. The first outcome variable, $BinaryAsthma_{iy}$ is equal to one if a child has been admitted to the hospital for asthma at least once during that year, and zero otherwise. Secondly, I estimate the impact on $LengthofStay_{iy}$ as a proxy for severity, to see if there are any changes in the intensive margin following the policy. Individual fixed effects, I_i, and year dummies, Θ_y are included. These individual level estimates are based only on individuals who have been admitted to the hospital for asthma at least once during the study period and therefore may not be representative for the general population. However, children who have been admitted to the hospital are an important and expensive patient group. Any change in the probability of asthma admission or length of stay for this group would be important for policy considerations.

5 Results

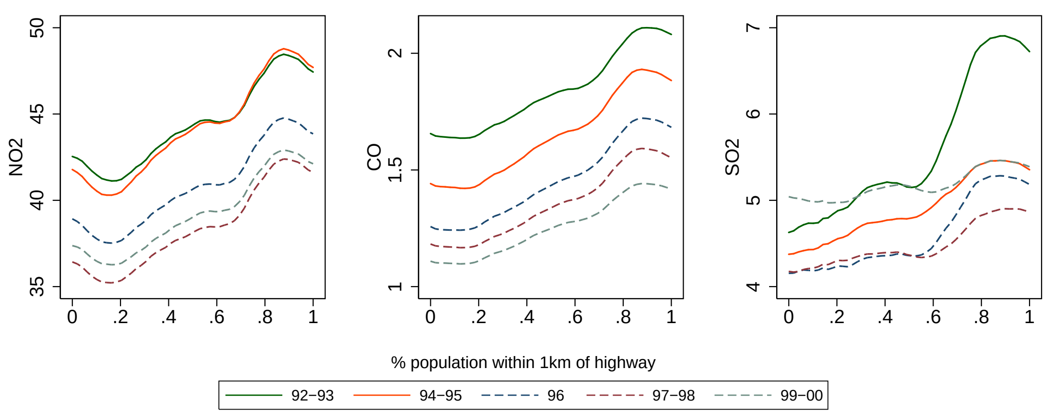
5.1 First Stage Results: Pollution

Graphical evidence of the reduction in pollution following CARB is shown in Figure 3. Figure 3a shows the relationship between the change in pollution after the policy and the percent of the population living within 1km of a highway, τ. The change in pollution following the policy was calculated for each zip code and local mean smoothing over exposure to highways shows that the decrease in pollution is largest for zip codes with the highest values of τ, as expected. Figure 3b shows the smoothed relationship between each criteria pollutant and τ over time. There appears to be an overall downward trend in pollution and a large drop in pollution at the time of the policy. If the CARB gasoline regulation caused a reduction in pollution near highways, one might expect to see a larger decrease in pollution for zip codes with high values of τ in years after the policy. If this is the case, the pollution gradients should become less steep after the policy. Looking at the Figure 3b for NO_2, pollution is actually increasing for the highest values of τ prior to CARB, and following the policy this level drops and the gradient becomes less steep. The gradient for CO is also steepening prior to CARB, and then becomes less steep afterward. The pattern is less clear for SO_2, which is likely due to the fact that SO_2 monitors are sparse and that traffic pollution accounts for a much smaller percentage of overall ambient SO_2 levels.

Figure 3: Pollution changes before and after CARB



(a) Change in pollution following CARB



(b) Pollution gradients over time

Notes: Figure 3a shows the change in pollution levels from before to after the policy. The level change is calculated by zip code for NO2, CO, and SO2. Figures show the local mean smoothed relationship between the change in pollution and the percentage of the population living within 1km of a highway, τ. Zip codes nearer to the highway (i.e. values of τ near 1) experienced the largest decreases in pollution after the policy. Lines show local mean smoothing using "lpoly," with degree zero and a 0.1 bandwidth. Figure 3b shows the smoothed relationship between each pollutant level and τ for different years. Dashed and solid lines indicate years after and before the policy, respectively. Lines are smoothed using "lowess" and a 0.8 bandwidth. Flattening of gradients after the policy indicate that pollution decreased more near highways, for τ nearer to 1.

Table 2 shows the results from the estimation of equation (3) for each of the criteria pollutants, NO_2, CO, and SO_2. Panel A shows estimates based on the binary treatment status indicator and Panel B shows estimates based on the continuous measure of treatment status, τ. The regression results support the graphical evidence that pollution decreased in zip codes with a large percentage of the population exposed to traffic after the implementation of the CARB regulation. Estimates indicate that NO_2 pollution decreased by about 2 percent from the pre-policy, treated zip code level. Similarly, CO pollution decreased by about 6 percent, and SO_2 pollution decreased by about 10 percent. These estimates are in line with the expected reductions in pollution predicted by California's EPA, although their estimates were slightly larger for NO_2 and CO, and slightly smaller for SO_2.

Table 2: First stage: difference-in-difference estimates

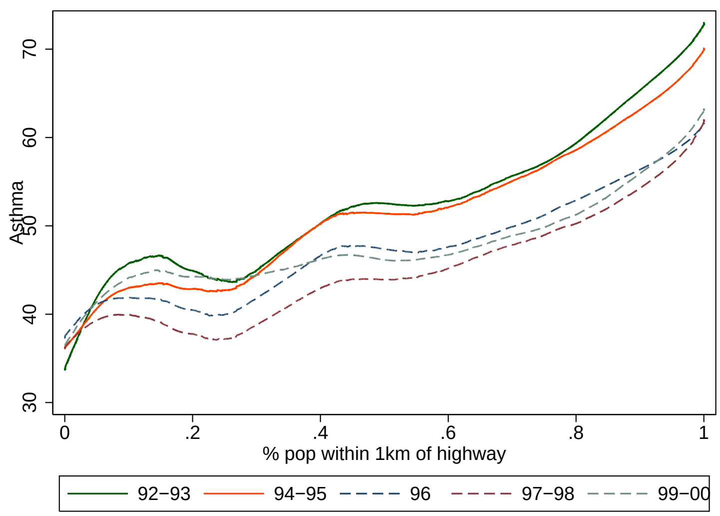
	NO2 (1)	CO (2)	SO2 (3)
Panel A.			
DD (T1)	-0.870***	-0.104***	-0.597***
	(0.160)	(0.0101)	(0.0835)
%Δ from pre-treat	-1.9	-5.5	-10.7
%Δ in gap	-20.4	-35.9	-72.9
%Δ of std dev	-4.8	-9.9	-16.2
Panel B.			
DD continuous	-1.510***	-0.214***	-1.215***
	(0.247)	(0.0157)	(0.126)
Observations	112,055	114,387	73,625
R-squared	0.797	0.733	0.521
Zipcode FE	yes	yes	yes
Year dummies	yes	yes	yes
Quarter dummies	yes	yes	yes
Time trend	yes	yes	yes

Notes: Panel A shows regression results based on the binary treatment status indicator. Panel B shows regression results based on the continuous measure of treatment status. Estimates are based on a consistently observed set of monitors, as defined in section 3. Standard errors clustered at the zip code level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.2 Reduced Form Results: Asthma

Graphical evidence of the reduction in asthma near highways after CARB can be seen in Figure 4. One can see the smoothed relationship between asthma hospitalizations and the percentage of the zip code population living within 1km of a highway, τ, over time. After the implementation of CARB in 1996, the gradient shifts downward for zip codes with the largest τ values. For lower values of τ, the gradient remains fairly consistent over time. As expected, the reduction in asthma after CARB is concentrated in zip codes with a large percentage of the population living near the highway.

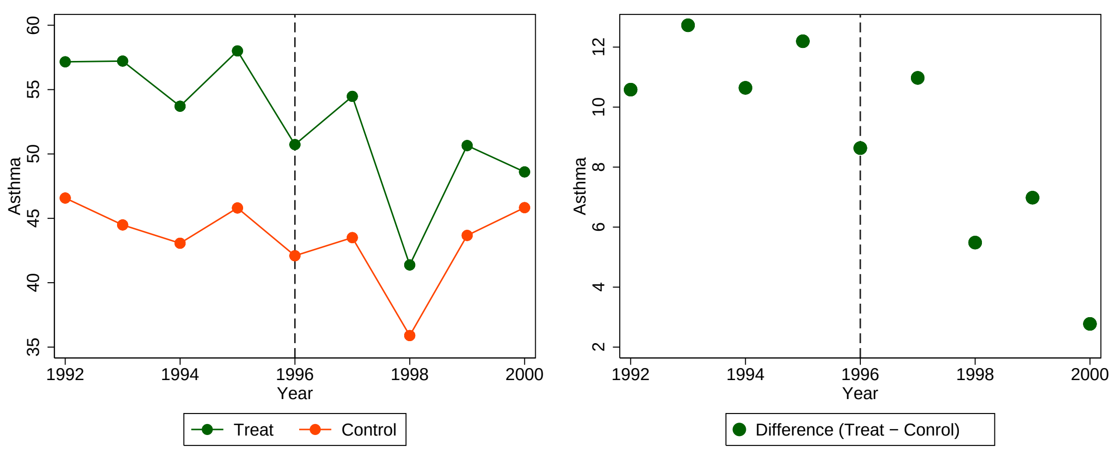
Figure 4: Asthma hospitalizations by exposure to pollution



Notes: Figure shows the smoothed relationship between asthma hospitalizations and the percentage of the population living within 1km of a highway, τ, in different years. Dashed and solid lines indicate years after and before the policy, respectively. Lines are smoothed using "lowess" and a 0.4 bandwidth. Asthma hospitalizations dropped by a larger amount for zip codes with larger percentages of the population living within 1km of a highway.

Further graphical evidence of the decrease in childhood asthma can be seen in Figure 5. The left panel shows the raw means by year for treatment and control zip code groups. As expected, there is a level difference between the two groups, with asthma hospitalizations higher in the treatment group. Prior to the policy, these two lines follow similar yearly patterns with shocks affecting both treatment and control groups in the same way. After the policy, the gap between the treatment and control groups decreases as the level of asthma in the treatment group becomes more similar to that of the control group, as expected. The right panel plots the difference between treatment and control groups by year. The difference is fairly constant at around 12 hospitalizations per 10,000 children prior to the policy. This difference between treatment and control group drops in 1996 and continues in a downward trend.

Figure 5: Mean asthma hospitalizations over time



Notes: The first figure shows raw mean childhood asthma hospitalizations by year for the treatment and control groups, separately. The second figure plots the difference in the average yearly asthma hospitalization level between treatment and control groups.

Regression results showing estimates of equation 5 support the graphical evidence. Table 3 shows the difference-in-difference estimates of the effect of CARB on asthma. Panel A shows estimates based on the binary treatment status indicator and Panel B shows estimates based on the continuous measure of treatment status, τ. The first five columns present the zip code level estimates. Column (2) includes year dummies to account for widespread yearly shocks to asthma. Column (3) weights the regression results by zip code child population to give greater weight to the more precisely estimated zip codes. Column (4) uses an age-adjusted outcome measure for the asthma rate to account for different prevalence rates among age groups. The results remain consistent across these specifications, suggesting a reduction of about 4.5 asthma hospitalizations per 10,000 children following CARB gasoline implementation. This is a reduction of about 8 percent from the pre-policy treatment zip code level, or a reduction in the treatment-control asthma gap of 40 percent. This effect is both statistically and economically significant. Column (5) presents estimates of the impact on infant deaths, indicating that CARB gasoline reduced infant deaths by about 24 per 10,000 children under age 1. This is a reduction of about 10 percent from the pre-policy treatment zip code level. However, it is important to remember that the outcome variable also contains neonatal transfers, so although it appears that infant deaths are decreasing by 10 percent, some of this may be due to decreases in transfers. Column (6) presents the individual level estimate of equation 4. After including individual level fixed effects and year dummies, the results suggest CARB gasoline reduced the probability of asthma hospitalization by about 6 percent from pre-policy treatment levels. Not only did CARB gasoline reduce the probability of an asthma hospitalization, but it decreased the severity of hospitalizations, as proxied by length of stay. The final column shows that the length of stay declined by about 10 percent from pre-policy treatment levels, or about 0.07 days, after controlling for individual fixed effects and year dummies.[19]

[19]Given that length of stay is measured in discrete units, days, estimates from a Poisson regression are similar in magnitude and significance.

Table 3: Reduced-form impact on asthma

	Zip code level analysis					Individual level analysis	
	Asthma	Asthma	Asthma	Asthma	Infant Death	Asthma (binary)	Length of Stay
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A.							
DD (T1)	-4.074***	-4.063***	-4.505***	-4.313***	-24.84***	-0.00771***	-0.0679***
	(1.312)	(1.312)	(1.157)	(1.468)	(8.166)	(0.00157)	(0.0247)
%Δ from pre-treat	-7.2	-7.2	-8.0	-6.3	-10.2	-6.1	-9.6
%Δ in gap	-35.3	-35.2	-39.0	-48.3	-442.8	-107.7	-281.3
%Δ of std dev	-9.8	-9.8	-10.8	-8.7	-11.9	-2.3	-1.4
Panel B.							
DD continuous	-7.603***	-7.580***	-7.865***	-7.520***	-42.08***	-0.0131***	-0.0995**
	(2.351)	(2.350)	(2.071)	(2.267)	(15.53)	(0.00303)	(0.0493)
Observations	11,568	11,568	11,568	10,449	11,425	1,038,159	1,038,132
R-squared	0.615	0.620	0.823	0.811	0.514	0.029	0.126
Zip Code FE	yes	yes	yes	yes	yes	-	-
Individual FE	-	-	-	-	-	yes	yes
Year dummies	no	yes	yes	yes	yes	yes	yes
Pop Weights	no	no	yes	yes	yes	-	-
Age-adjusted	no	no	no	yes	-	-	-

Notes: Panel A shows regression results based on the binary treatment status indicator. Panel B shows regression results based on the continuous measure of treatment status. The outcome variable for columns 1-4 is the number of childhood asthma admissions per 10,000 children, as defined in section 3. The outcome variable for column 5 is the number of "neonates, died or transferred" (DRG code 385) per 10,000 infants, as defined in section 3. The outcome variable for column 6 is a binary variable equal to one if an individual was admitted to the hospital for asthma in each year. Standard errors are clustered at the zip code level for columns 1-5 and at the individual level for column 6. *** p<0.01, ** p<0.05, * p<0.1

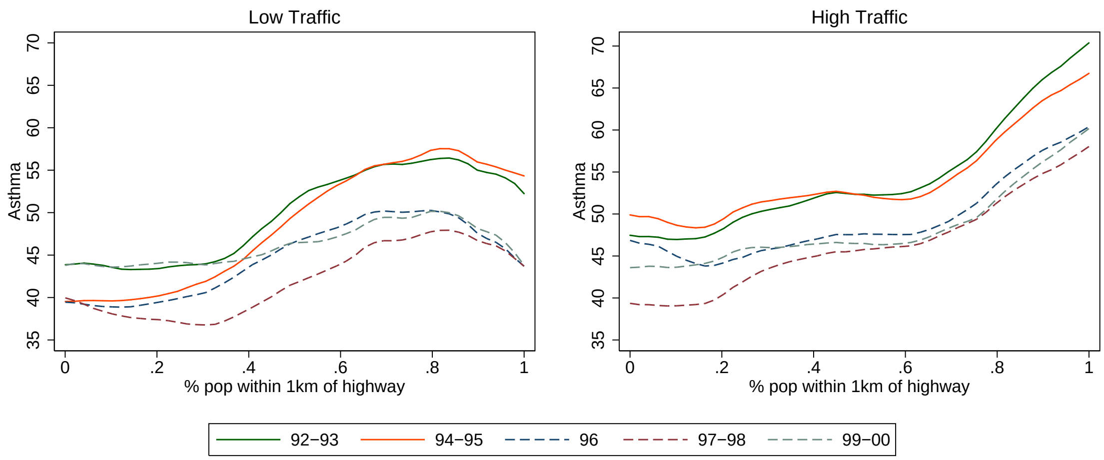
5.3 Heterogeneous & Cumulative Effects

The results presented above show that CARB gasoline did indeed reduce childhood asthma in zip codes with high exposure to highway pollution. Previously, I have only considered the impact of living near the highway, but the type of traffic conditions on the highway might also cause a differential impact on asthma rates. It is not clear a priori whether living near high traffic or low traffic highways will yield a greater reduction in asthma. It is likely that the decrease in pollution will be largest for high traffic locations. However, it may not be the case that high traffic areas experience the largest reduction in asthma.

Consider, for example, the possibility that there is some linear (or perhaps concave) relationship between pollution and asthma up to a certain pollution threshold level, at which point, increases in pollution have little to no effect on asthma. If the pollution exposure level for children living near high traffic roads is already much higher than the threshold, then a small reduction in pollution may have little to no effect on asthma rates. On the other hand, the pollution exposure level for children living near lower traffic roads may be much closer to the threshold for inducing asthma. In this case, a small reduction in pollution from gasoline could reduce pollution enough to bring the level below the threshold. Therefore, conditional on children living near the highway, a gasoline content regulation could cause a greater reduction in asthma near low traffic highways than high traffic highways. In fact, the results suggest that this is the case. Figure 6 is analogous to Figure 4 and shows the smoothed relationship between the percent of the population living near the highway, τ, and asthma by year for zip codes with high traffic and low traffic separately. The downward rotation of the gradient for large τ values after 1996 is even more distinct for the low traffic zip codes, whereas the high traffic zip codes show a general downward trend, but very little rotation after 1996 for large τ values.

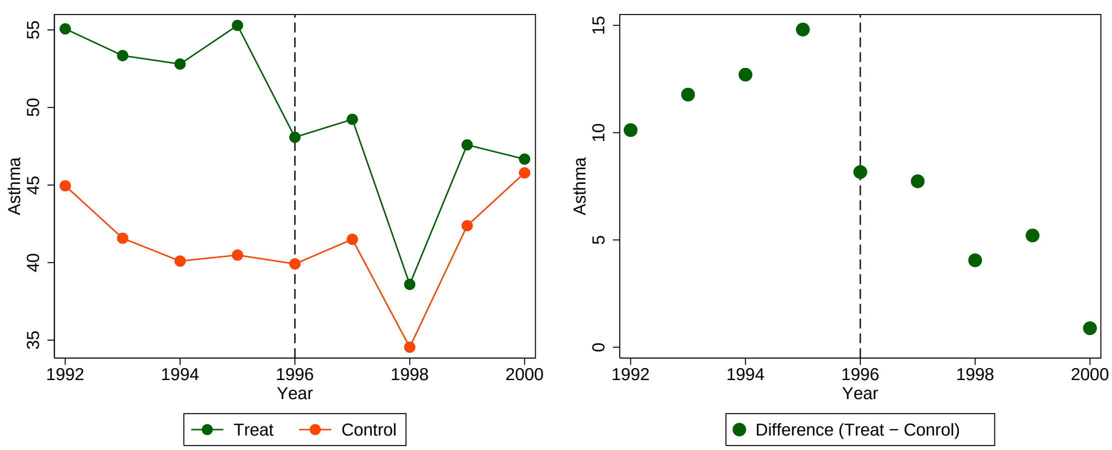
Moreover, Figure 7 shows clear graphical evidence that the gap between treatment and control rates of asthma was rising prior to 1996 for low traffic zip codes. With the implementation of CARB in 1996, there was a sharp drop in relative asthma rates and the relative rate continued on a new downward path after CARB. This suggests that the results will be stronger for zip codes with lower traffic rates.

Figure 6: Asthma hospitalizations by exposure and traffic density



Notes: Figures show the smoothed relationship between asthma hospitalizations and the percentage of the population living within 1km of a highway, τ, in different years. Dashed and solid lines indicate years after and before the policy, respectively. Lines are smoothed using "lpoly," with degree zero and a 0.1 bandwidth. High (low) traffic zip codes are defined as zip codes with an average AADT of at least (less than) 60,000 vehicles per day.

Figure 7: Difference in mean asthma hospitalizations over time: low traffic



Notes: The first figure shows raw mean childhood asthma hospitalizations by year for the treatment and control zip codes with low traffic levels. The second figure plots the difference in the average yearly asthma hospitalization level between treatment and control zip codes with low traffic levels. Low traffic is defined as average AADT less than 60,000 vehicles per day.

Regression results support this graphical evidence. Table 4 shows estimation of the following equations for pollution and asthma:

$$\begin{aligned} Pollution_{zt} = \gamma_0 + \gamma_1 DD^{*}LowTraffic_{zt} + \gamma_2 DD^{*}HighTraffic_{zt} \\ + HighTraffic_z{}^{*}\Theta_y\lambda + Z_z + \Theta_y + Q_q + \mu_{zt} \end{aligned} \tag{6}$$

$$\begin{aligned} Asthma_{zy} = \rho_0 + \rho_1 DD^{*}LowTraffic_{zy} + \rho_2 DD^{*}HighTraffic_{zy} \\ + HighTraffic_z{}^{*}\Theta_y\phi + Z_z + \Theta_y + \omega_{zy} \end{aligned} \tag{7}$$

where DD is the difference-in-difference estimator, such that $DD = Treat^{*}After$, $LowTraffic$ is an indicator for low traffic zip codes, $HighTraffic$ is an indicator for high traffic zip codes, and the remaining variables are analogous to those defined previously. Table 4 shows the regression estimates for both the first stage and reduced form. The first stage results of CARB on pollution, show that there was a significant decrease in pollution for both low and high traffic areas. As one would expect, the decrease in pollution was larger for high traffic areas. A test of equality between the coefficients on $DD^{*}HighTraffic$ and $DD^{*}LowTraffic$ shows that the difference in the reduction in pollution is only statistically significant for CO. Nevertheless, the point estimates indicate a larger reduction for high traffic areas. While pollution may have fallen by a larger amount in high traffic areas, the largest reductions in asthma hospitalizations were found in low traffic areas. While both coefficients for high and low traffic are negative, the coefficient on low traffic is significantly larger in magnitude and strongly statistically different from zero. These regression results support the graphical evidence that the reduction in asthma was greatest for lower levels of traffic. This seems to support the hypothesis that the pollution exposure level for children living near lower traffic highways is closer to the threshold for the induction of asthma. It is possible that CARB gasoline was able to reduce pollution exposure in lower traffic areas below the asthma threshold, causing a drop in asthma, whereas the reduction in pollution was not sufficient to bring high traffic areas near enough to this threshold.

Table 4: Impact of CARB by level of traffic

		Pollution		
	Asthma	CO	NO2	SO2
	(1)	(2)	(3)	(4)
DD*HighTraffic	-2.398	-0.105***	-0.748***	-0.512***
	(1.666)	(0.0131)	(0.213)	(0.0859)
DD*LowTraffic	-8.884***	-0.0574***	-0.469*	-0.263*
	(2.240)	(0.0178)	(0.261)	(0.147)
Equality test	0.0203	0.0327	0.405	0.142
Observations	10,493	110,946	112,143	77,123
R-squared	0.825	0.732	0.793	0.515
Zip Code FE	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Traffic-year dummies	yes	yes	yes	yes
Quarter dummies	-	yes	yes	yes

Notes: Table presents estimates based on equations 6 and 7. Equality test shows the p-value from testing whether the two interaction coefficients are equal. Asthma regression weighted by zip code population. Standard errors clustered at the zip code level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Furthermore, I can explore heterogeneous effects of the policy by exploiting demographic information in the hospital data. Table 5 shows the difference-in-difference estimates for different subsamples of the population by age, gender, and race. While results appear similar for males and females, it does appear that the results are stronger for black children and younger children. From the summary statistics presented in Table 9, one can see that blacks are more likely to live in census tracts with close proximity to highways, while whites are far less likely to live very near highways. Given this stylized fact, but only having zip code level residential information, one might expect to find a stronger effect for black patients since they are more likely to be impacted by CARB. As expected, the effect of CARB on asthma is only statistically significant for black children. In fact, the coefficient for white children is positive. Within a zip code, black children are more likely to live very close to highways, and therefore more likely to benefit from a reduction in traffic pollution. This suggests that gasoline content regulation could reduce health disparities for children of low socio-economic status who are more likely to live near highways.

Table 5: Heterogeneous effects by age, gender, and race

	Age			Gender		Race	
	<1 yr	1-4 yrs	5-9 yrs	Male	Female	White	Black
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A.							
DD (T1)	-29.53**	-2.069**	-1.108*	-4.469**	-4.062***	5.368	-9.043*
	(11.99)	(0.997)	(0.625)	(1.775)	(1.279)	(3.534)	(4.681)
%Δ from pre-treat	-6.4	-5.3	-6.2	-5.5	-7.7	11.1	-7.5
%Δ in gap	-109.5	-20.5	-21.5	-35.3	-50.0	181.6	-49.9
%Δ of std dev	-7.6	-5.4	-5.7	-5.8	-6.7	9.7	-5.5
Panel B.							
DD continuous	-45.63**	-3.653**	-1.662	-8.257**	-5.231**	17.14**	-4.822
	(20.20)	(1.834)	(1.161)	(3.231)	(2.410)	(7.202)	(7.967)
Observations	10,637	10,846	10,696	12,006	11,968	11,028	8,275
R-squared	0.781	0.647	0.616	0.754	0.682	0.630	0.472
Zip Code FE	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes

Notes: Panel A shows regression results based on the binary treatment status indicator. Panel B shows regression results based on the continuous measure of treatment status. Each column shows the difference-in-difference estimate based on a subset of the population. The outcome variables are asthma hospitalization rates based on group-specific population levels. Regressions are weighted by zip code population. Standard errors clustered at the zip code level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 also shows that CARB gasoline has the largest impact for children under one year old and that the effect diminishes with age. This may be due to the fact that younger children are more sensitive to pollution. Additionally, pollution may have a cumulative impact on health, such that exposure to pollution at a young age may impact health in later years.

The following cohort analysis explores the possible cumulative impact of pollution. First, I define *Exp* as the number of years each cohort has been exposed to CARB gasoline.[20][21]

[20] Exp is defined using age and year data such that $Exp = min(max(year - 1996, 0), age)$.

[21] Note that there is some inherent measurement error associated with this definition. I cannot determine exact duration of exposure since I cannot identify how long each child has lived in the zip code of current residence.

Table 6 shows results from the estimation of the following equations.

$$Asthma_{zy} = \alpha_0 + \alpha_1 \tau^* Exp_{zy} + Z_z + \Theta_y + \upsilon_{zy} \tag{8}$$

$$Asthma_{zy} = \pi_0 + \sum_{i=1}^{4} [\pi_i \tau^* \mathbb{1}\{Exp = i\}_{zy}] + Z_z + \Theta_y + \kappa_{zy} \tag{9}$$

where τ is the percent of the zip code's population that lives within 1km of a highway, and both equations include zip code fixed effects, Z_z, and year dummies, Θ_y. If there is a cumulative impact of CARB gasoline, one would expect to see that years of exposure to CARB is negatively related to asthma for zip codes with high τ values. Column (1) of Table 6 shows that this is the case. Column (2) shows that as the years of exposure increase, the negative coefficient becomes larger in magnitude and more significant. These results can be visualized in Figure 8 which graphs the coefficients by years of exposure and the associated 90% confidence intervals. As expected, the figure shows a monotonic decrease in asthma with years of exposure to the policy. These results suggest that there is indeed a cumulative impact of the policy.[22]

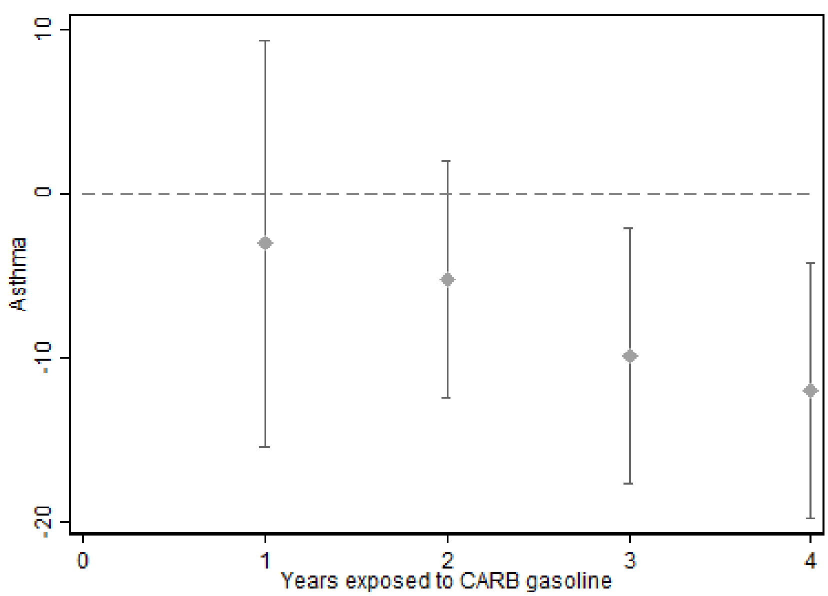
[22]Data on population estimates by zip code for the 1990 census are limited to age groups, rather than individual years. This prevents the analysis from being conducted at the individual age-year level.

Table 6: Cumulative effects by exposure to CARB

	Asthma	
	(1)	(2)
$\tau * Exp$	-3.030**	
$\tau * \mathbb{1}\{Exp = 1\}$		-3.077
$\tau * \mathbb{1}\{Exp = 2\}$		-5.249
$\tau * \mathbb{1}\{Exp = 3\}$		-9.924**
$\tau * \mathbb{1}\{Exp = 4\}$		-12.05**
Observations	60,025	60,025
R-squared	0.685	0.685
Zip Code FE	yes	yes
Year dummies	yes	yes
Age dummies	yes	yes
PolicyYear dummies	yes	yes

Notes: *Exp* as the number of years each cohort has been exposed to CARB gasoline, and τ is the percent of the zip code's population that lives within 1km of a highway. Results weighted by zip code-cohort population. Standard errors clustered at the zip code level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 8: Cumulative effects by exposure to CARB



Notes: Graph shows the coefficients from the cohort analysis by years of exposure to the policy and the 90 percent confidence intervals.

6 Robustness & Measurement Error

6.1 Pollution Robustness

Table 7 tests the robustness of the first stage pollution estimates and addresses some measurement concerns. First, one may be concerned that treated zip codes may have different long-run trends from control zip codes. Column (2) includes zip code specific linear time trends to account for any zip code specific long-run trends. The results remain significant for both NO_2 and CO, but become insignificant for SO_2. This is not surprising given that only half as many monitors record SO_2 as the other criteria pollutants.

Secondly, due to the method of construction of pollution measures for each zip code, measurement error is an inherent problem for these results. In order to address this concern, Columns (3)-(5) present estimates designed to reduce measurement error. Column (3) weights the results by the number of air quality monitors within 20 miles of the zip code's centroid that were used to calculate the zip code level of pollution. Column (4) weights the results by the inverse of the average air quality monitor distance from the centroid. Column (5) limits the analysis to only zip codes with at least 3 monitors within the 20 mile radius of the zip code centroid. The results remain significant and of similar magnitude to the baseline results.

Table 7: Pollution robustness

	Baseline (1)	Zip time trends (2)	Weight: # Mon. (3)	Weight: Mon. dist. (4)	≥ 3 Mon. (5)
NO2	-0.870***	-1.516***	-0.979***	-0.638***	-0.658***
	(0.160)	(0.140)	(0.198)	(0.175)	(0.205)
CO	-0.104***	-0.166***	-0.107***	-0.0992***	-0.0777***
	(0.0101)	(0.00741)	(0.0122)	(0.0146)	(0.0102)
SO2	-0.597***	-0.247***	-0.510***	-0.561***	-0.315***
	(0.0835)	(0.0768)	(0.0804)	(0.0956)	(0.0818)
Zip FE	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes
Time trend	yes	yes	yes	yes	yes

Notes: Each coefficient represents a separate regression. Column 1 reproduces the main results from Table 2. Column 2 includes zip code specific linear time trends. Column 3 weights the estimates by the number of air quality monitors within 20 miles that were used to calculate the inverse distance weighted pollution level for each zip code. Column 4 weights the estimates by the inverse of the average air quality monitor distance from the zip code centroid. Column 5 limits the analysis to only zip codes with at least 3 monitors within the 20 mile radius of the zip code centroid. Standard errors clustered at the zip code level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6.2 Asthma Robustness

The reduced-form asthma results are robust to alternate specifications, as seen in columns (2)-(5) of Table 8. First, column (2) tests the robustness of the results to an alternate choice of the relevant distance that pollution may travel from the highway. It is likely that this distance depends on many factors including the direction of the wind, temperature, and surrounding geographies. Some epidemiological literature has suggested that a distance smaller than 1km may be more relevant, such as 300m. The results in column (2) are significant and similar in magnitude to the baseline. This gives confidence that the results are not driven by the choice of cutoff for how far pollution may travel from a highway source.

Next, I address the concern that the results are driven by differential long run trends in certain zip codes. Column (3) includes zip code specific linear time trends to account for any long-run changes that occur over time for each zip code. Differential trends or shocks for urban areas may also be driving the results. Column (4) includes dummies for each Core Based Statistical Area (CBSA) and year. These dummies control flexibly for any differential trends or shocks in each CBSA. The estimates in columns (3)-(4) remain significant and of similar magnitude to the baseline results.

Another concern is that the inclusion of rural zip codes with large area and few residents may bias the results and introduce unnecessary measurement error. Column (4) presents results based on a sample of zip codes that excludes the 10 percent of the zip codes with the largest areas. The results remain significant and increase slightly in magnitude from the baseline. Therefore, it seems that the results are not driven by the inclusion of these large zip codes.

It is also important to note that the asthma outcome variable exhibits a probability mass at zero. It is not possible for any zip code to attain an asthma rate that is below zero, but there are certainly zip codes that are much closer to crossing the margin to attain a positive value than others. Therefore, I estimate the results using a corner solution model. Column (5) presents the average partial effects from a Tobit model. The effects maintain significance and are of similar magnitude to the baseline. This suggests that the main results are not biased by the probability mass at zero for the asthma outcome variable.

In the final two columns, I use data on hospital admissions for other primary diagnoses to perform placebo tests. The choice of a placebo hospital admission must meet two criteria. First, there should be no pathway through which traffic pollution might impact the prevalence of the condition. Second, the condition should occur with sufficient frequency among children under 10 years old. Given these criteria, I estimate the impact of CARB on hospital admissions for "diseases and disorders of the nervous system" (Major Diagnosis Category 1) and "injuries, poisonings and toxic effects of drugs" and "burns" (Major Diagnosis Categories 21 & 22). One would not expect to find a significant effect of CARB legislation on the amount of discharges for these conditions. If one were to see an impact, it would call into question the validity of the results presented above. As expected, the estimates shown in columns (6) and (7) are insignificant, which provides greater confidence that the decrease in asthma hospitalizations is a result of CARB rather than an overall trend across all types of hospitalizations.

Table 8: Asthma robustness

	Robustness Tests						Placebo Tests	
	Baseline	300m cutoff	Zip code linear trends	CBSA-Year Dummies	Drop large Zip codes	Tobit	Injuries & Burns	Nervous system
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A.								
DD (T1)	-4.248***	-3.771***	-3.911***	-4.015***	-4.858***	-3.722***	-0.295	-1.429
	(1.365)	(1.392)	(1.195)	(1.380)	(1.502)	(1.334)	(0.436)	(1.110)
Panel B.								
DD continuous	-7.652***	-12.04**	-6.170***	-7.995***	-8.933***	-6.894***	-0.555	-1.828
	(2.461)	(4.808)	(1.600)	(2.547)	(2.654)	(2.440)	(0.826)	(2.012)
Observations	11,787	11,374	11,787	11,568	9,703	11,787	11,850	11,850
R-squared	0.594	0.595	0.666	0.644	0.665	-	0.201	0.219
Zip Code FE	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
Clustered SE	yes	yes	yes	yes	yes	-	yes	yes

Notes: Panel A shows regression results based on the binary treatment status indicator. Panel B shows regression results based on the continuous measure of treatment status. Column 1 reproduces the main results from Table 3. Column 2 alters the treatment status to be defined based on a 300m distance from the highway, rather than 1km. Column 3 includes zip code specific linear time trends. Column 4 excludes the 10 percent of zip codes with the largest areas. Column 5 presents average partial effects from a Tobit model, censored at zero. Columns 6 and 7 present placebo tests based on hospital admissions for diagnoses unaffected by the policy (see text for criteria). The outcome variable for column 6 is the number of children admitted for "diseases and disorders of the nervous system" (Major Diagnosis Category 1) per 10,000 children. The outcome variable for column 7 is the number of children admitted for "injuries, poisonings and toxic effects of drugs" and "burns" (Major Diagnosis Categories 21 & 22) per 10,000 children. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

It is also important to consider the potential for spatial autocorrelation. Given the spatial nature of the zip code level data, it is possible for neighboring zip codes to have correlated error terms. There are three types of spatial models that might not be captured by clustered standard errors: spatial lag of the dependent variable, spatial lag in the error term, or a combination of both a spatial lag in the dependent variable and error term (SARMA model). In order to test for this spatial relationship, I create a queen weights matrix to define the relationship of each zip code to its neighboring zip codes.[23] With this information, I perform Lagrange Multiplier tests for spatial lag, spatial error, and SARMA models. For each model, I fail to reject the null hypothesis of no spatial dependence among zip codes. This suggests that a spatial model would not be appropriate for this process.[24]

Finally, Appendix D addresses two potential confounders to the policy. First, federal reformulated gasoline (RFG) was required in certain parts of California in 1995, one year prior to the implementation of CARB gasoline. However, existing evidence in Auffhammer and Kellogg (2011) suggests that RFG had little impact on pollution, as opposed to the stricter CARB regulations. Results in the appendix confirm that RFG also had little impact on asthma and that the results presented above are driven by the introduction of CARB gasoline. Second is the passage of the Personal Responsibility and Work Opportunity Reconciliation Act in 1996 (PRWORA). As a result of changes to welfare and Medicaid eligibility rules, monthly Medicaid enrollment declined 12 percent in California from 1995 to 1998 (Ellwood 1999). This would be problematic if patients eligible for Medicaid were more likely to live in the treatment zip codes, and they were less likely to show up in the hospital data due to enrollment issues rather than an asthma decline. Evidence presented in Appendix D suggest that this is not driving the results. Barriers to Medicaid enrollment are more likely to impact access to and use of asthma prescription drugs. State utilization data from the Medicaid Drug Rebate Program show that the total amount reimbursed for asthma prescription drugs declined sharply during this period in both California and the nation. The reduction in access to asthma control medications would likely increase the number of hospitalizations for asthma. Therefore, if anything, the results here will be

[23] A queen weights matrix defines a zip code's neighbors as those with either a shared border or vertex (in contrast to a rook weights matrix, which only includes shared borders).

[24] The test statistics and associated P-values are shown in Appendix C.

understated.

7 Economic Impact

As shown previously, gasoline content regulation can improve health outcomes of the population, leading to a reduction in costly medical expenditures. However, gasoline content regulations are associated with numerous costs, including enforcement costs and production costs to refiners. Given the estimates presented previously, one can make a "back of the envelope" calculation of the costs and benefits from the CARB gasoline legislation.

Auffhammer and Kellogg (2011) suggest a compliance cost of about 8-11 cents per gallon for refineries.[25] Data from the U.S. Department of Transportation estimates gasoline consumption in 2006 at 15.8 billion gallons in California, which implies a yearly cost of about $1.2-$1.7 billion.

I estimate that cleaner-burning CARB gasoline reduced asthma hospitalizations by about 4 per 10,000 children in areas near highways relative to far from highways. According to these estimates, CARB gasoline reduced childhood asthma hospitalizations by about 2,130 in California in 2006 alone. Hospital expenditures accounted for over half of all expenditures for asthma. In fact, Stranges et al. (2008) estimates that hospitalizations cost about $9,100 per child in 2006, which means that CARB gasoline reduced medical expenditures from asthma hospitalizations by about $19 million per year in California.

Without considering any other benefits, the compliance cost to refineries greatly outweighs the cost savings from reduced childhood asthma hospitalizations. However, this calculation does not take into account other benefits from cleaner-burning gasoline, such as a reduction in infant mortality and a reduction in cardiovascular disease (CVD).

In terms of infant mortality, previous estimates suggest that CARB gasoline may have reduced infant deaths by up to 24 per 10,000 infants each year, which equates to about 1,284 saved lives in 2006.[26] Given that the EPA's official value of a statistical life is $6.45

[25] Interestingly, Brown et al. (2008) estimate that the price to consumers increased by an average of 3 cents/gal in metropolitan areas with gasoline content regulations, relative to a control group. This price effect, however, varied by 8 cents/gal across different regulated markets depending on geographic isolation.

[26] Again, this estimate is likely overstated due to the fact that infant deaths cannot be separated from infant transfers in the data. Nevertheless, it is likely that infant deaths dropped significantly after the policy and this measure can be used as a proxy.

million, this implies a savings of over $8 billion.

In terms of cardiovascular disease, previous research has established a link between air pollution and hospital admissions for cardiovascular disease. Estimates from Schwartz (1997) translate into a 1.68 percent decrease in CVD admissions per 1 ppm decrease in CO. Using California's OSHPD data on the total number and average cost of CVD admissions in 2006, along with my estimate that CARB decreased CO by about 0.1 ppm, I calculate a savings of about $630 million.[27]

Accounting for the reduced childhood asthma, infant mortality, and CVD, the benefits from CARB gasoline amount to about $8.9 billion per year, which is well above the estimated compliance costs of $1.2-$1.7 billion. A comprehensive accounting for all health and environmental benefits would likely increase the cost savings of CARB gasoline even further. Other potentially important benefits include benefits to the environment, a reduction in poor birth outcomes (low birthweight, prematurity, etc.), a reduction in respiratory conditions among adults and the elderly, a reduction in cancer, and a decrease in health inequality among low socio-economic families living near highways.

8 Conclusion

This paper provides an estimate of the effect of the 1996 CARB gasoline content regulation on asthma hospitalizations among children in California. This paper exploits variation in residential exposure to highways in order to, first, support existing evidence that CARB reduced air pollution, and second, to show that the reduction in pollution was associated with a decline in asthma hospitalizations for children. As hypothesized, the strict gasoline content regulations caused a greater reduction in childhood asthma in areas close to major highways, as compared to areas further away, after the regulations were introduced in March 1996. The results from this difference-in-difference estimation strategy suggest that the CARB regulations caused a significant and large reduction in childhood asthma admissions of about 8 percent in California, or 4 per 10,000 children. These results are robust to

[27] CVD admissions include all admissions for ICD-9 codes 390-429. OSHPD Patient Discharge Data reports 3,508,221 discharges for CVD in 2006. The average cost of heart attack hospitalizations was $106,845, which was calculated across all payer categories for 2006 (OSHPD, 2011).

numerous alternative specifications.

Exploration of heterogeneous effects indicate that there is likely a threshold level at which traffic pollution induces asthma. Once pollution levels rise far enough above this threshold, the reduction in pollution from gasoline content regulation has little impact. Moreover, a cohort-level analysis reveals that the reduction in asthma is larger for cohorts which have been exposed to the cleaner-burning gasoline for longer periods of time, suggesting a cumulative impact. Finally, we know that families living near major highways are of lower SES and the results confirm that the largest health improvements occurred among low SES patients. It seems that this policy and potentially future gasoline emission restrictions may reduce disparities in asthma-related health outcomes. These results suggest that more stringent regulation of gasoline content could have significant impacts on child health and quality of life, as well as reduce medical expenditures for the treatment of asthma.

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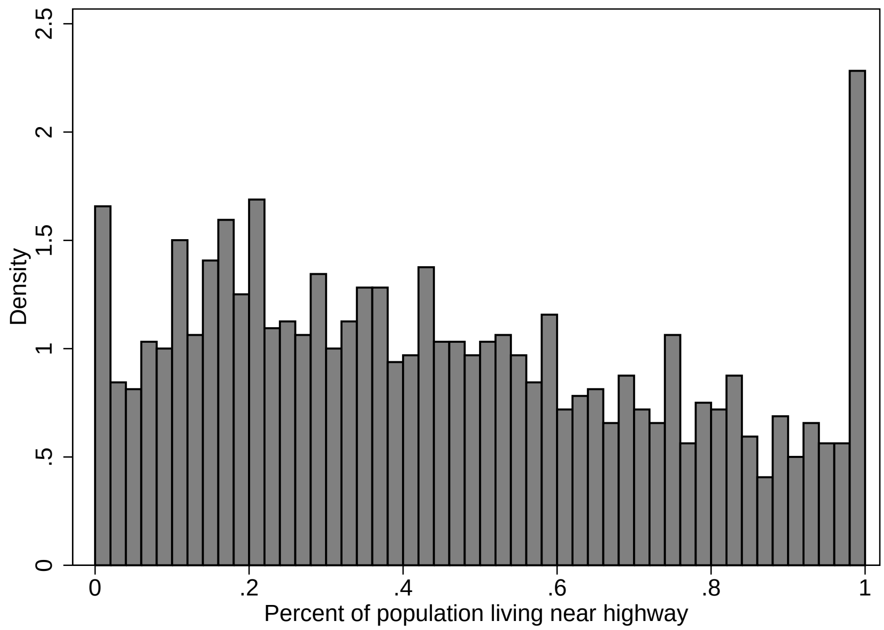
Appendix

A Data Appendix

A.1 Key Variables

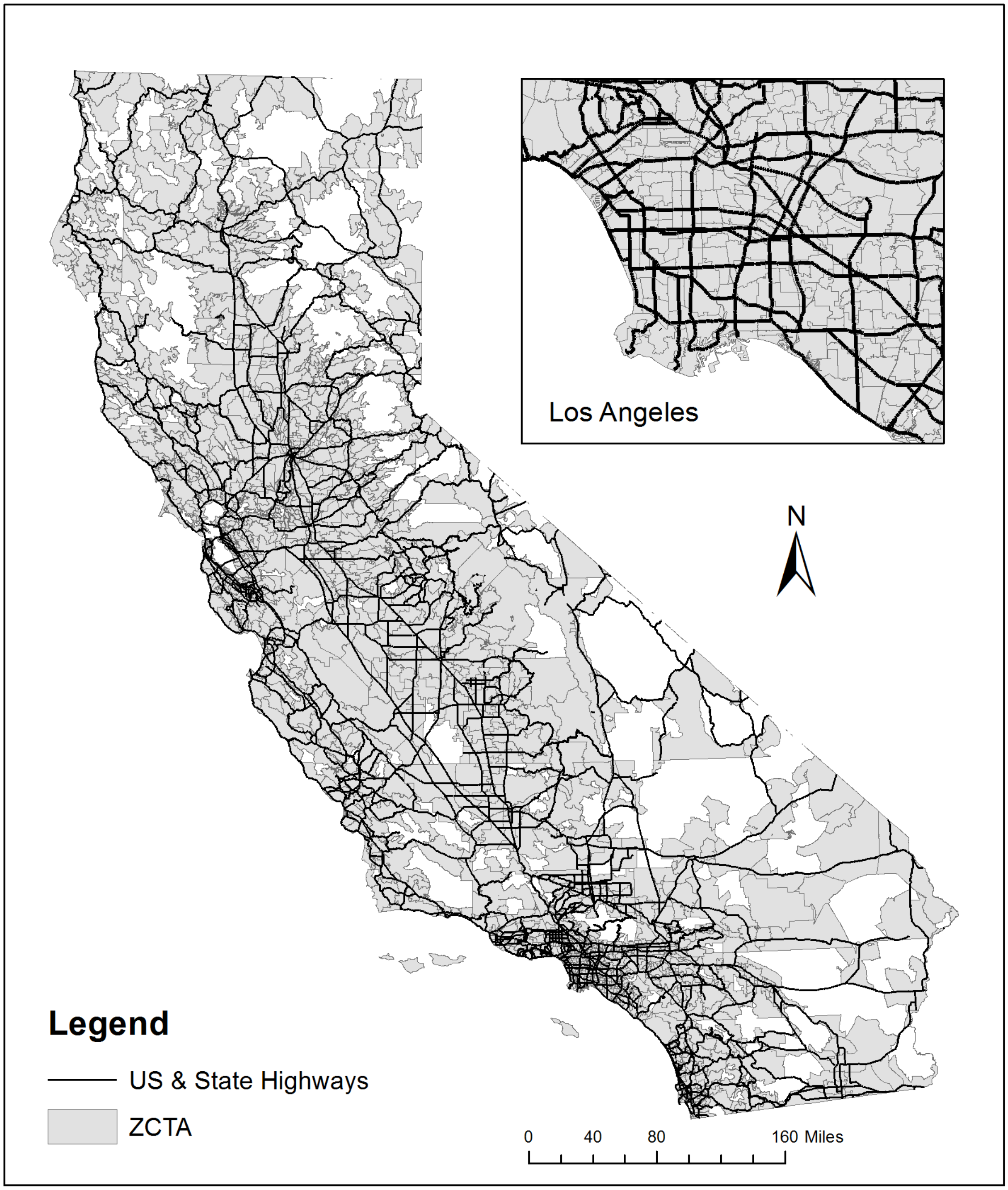
Figure 9: Distribution of τ across zip codes



A.2 Highways

The U.S. Census Bureau classifies U.S. and State highways in the following way. U.S. highways fall under one of two categories: "Primary highway with limited access" (A1) and "primary road without limited access" (A2). Interstate highways and some toll highways are in the A1 category and are distinguished by the presence of interchanges. These highways are accessed by way of ramps and have multiple lanes of traffic. The A2 category includes nationally and regionally important highways that do not have limited access as required by category A1. It consists mainly of U.S. highways, but may include some state and county highways that connect cities and larger towns. State highways are defined by the U.S. Census Bureau as category A3, "secondary and connecting roads", which include mostly state highways and some county highways that connect smaller towns, subdivisions, and neighborhoods. For the purposes of this project I will consider highways to be all roadways that fall into categories A1, A2, or A3.

Figure 10: U.S. and state highways in California



Information on the location of highways comes from combining data on U.S. and State Highways from the U.S. Census Bureau's 2000 TIGER/Line geographical information systems (GIS) shapefiles available through the Californian Spatial Information Library. The highway data is spatially linked to Cartographic Boundary files for census tracts and zip codes using ArcMap 10.1. I define a highway as either a U.S. or State highway, as defined by the U.S. Census Bureau.

B Neighborhood Characteristics

Cleaner-burning CARB gasoline is likely to have the largest impact on people living near highways, given the documented relationship between distance from highways and level of traffic-related air pollution (Gilbert et al., 2003). However, a cross-sectional comparison of people living near and far from highways will be biased by differences in observable and unobservable characteristics which are correlated both with choice of residence and susceptibility to asthma. Table 9 shows summary statistics from the 1990 and 2000 Censuses for census tracts based on proximity to highway traffic.[28] Looking at the average characteristics of tracts far and near highways in 1990 (columns 2 and 3), tracts near the highway are more likely to have a larger percentage of non-white residents, a larger percentage of Hispanics, a larger percentage of single female households with young children, lower levels of educational attainment, a larger percentage of foreign born and non-citizens, higher unemployment, a larger percentage of blue collar workers, and a greater percentage below the poverty level. Clearly, a cross-sectional comparison would be biased by the differences in underlying population characteristics that are known to be related to health outcomes as well.

However, it is not unreasonable to think that the differences between these neighborhoods will remain fairly constant over time. Neighborhood characteristics are somewhat stable over time since people are not perfectly mobile and the housing market is not very fluid. In fact, according to census 2000 estimates, about 80% of residents lived in the same county for the previous 5 years, and 50% remained in the same house. Table 9 shows the change in demographic characteristics from the 1990 to 2000 Censuses for tracts that are both near and far from highways. Columns (10) and (11) show the 2000-1990 difference in characteristics for tracts far and near to highways, respectively. For example, the percentage white decreased by about 10.3 percent and 9.9 percent for far and near tracts, respectively, from 1990 to 2000. The relative change in characteristics from 1990 to 2000 between far and near tracts is shown in the final column. As you can see, there are statistically significant differences in characteristics between near and far tracts in both 1990 and 2000 (columns 4 and 8), but column (12) shows that the relative change in characteristics over time is much less often significant. Although some characteristics remain significant, such as the percentage black, the magnitude of the difference-in-difference is very small, less than 1 percent, and it is unlikely that these demographic characteristics shifted discontinuously at the time of the policy.

[28]The "near" group contains all census tracts with over 90 percent of the area within 1km of a highway and the "far" group contains all other tracts. Recent research has suggested that traffic pollution can travel up to 1km from the highway (Hu et al., 2009).

Table 9: Census tract demographic characteristics (%)

	1990				2000				2000-1990 Difference			Diff-in-diff
	Total	Far	Near	Diff	Total	Far	Near	Diff	Total	Far	Near	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
White	0.588	0.625	0.473	0.151***	0.486	0.521	0.375	0.146***	-0.102***	-0.103	-0.099	-0.005
Black	0.067	0.058	0.094	-0.036***	0.062	0.056	0.083	-0.027***	-0.005*	-0.003	-0.011	0.009***
American Indian	0.007	0.007	0.005	0.003***	0.006	0.007	0.004	0.003***	-0.001**	-0.001	-0.001	0.000
Asian	0.087	0.082	0.104	-0.022***	0.107	0.102	0.124	-0.022***	0.020***	0.020	0.019	0.001
Other	0.002	0.002	0.002	-0.000***	0.029	0.029	0.029	0.000	0.027***	0.027	0.027	0.001
Hispanic	0.249	0.227	0.322	-0.095***	0.310	0.286	0.386	-0.100***	0.060***	0.059	0.064	-0.005*
Female household	0.117	0.110	0.136	-0.025***	0.129	0.124	0.148	-0.024***	0.013***	0.013	0.012	0.002
Single Mother	0.077	0.074	0.09	-0.016***	0.088	0.084	0.101	-0.017***	0.011***	0.011	0.011	-0.001
Less than 9th grade	0.119	0.108	0.156	-0.049***	0.122	0.110	0.161	-0.051***	0.003	0.002	0.005	-0.002
9th to 12th grade	0.131	0.126	0.144	-0.017***	0.121	0.116	0.137	-0.021***	-0.009***	-0.010	-0.006	-0.004**
High school graduate	0.223	0.227	0.21	0.017***	0.202	0.206	0.191	0.015***	-0.021***	-0.021	-0.019	-0.002
Some college	0.301	0.310	0.275	0.035***	0.296	0.306	0.264	0.041***	-0.006***	-0.004	-0.011	0.007***
Bachelors degree	0.148	0.150	0.14	0.009***	0.165	0.167	0.158	0.009**	0.017***	0.017	0.017	0.000
Graduate degree	0.078	0.079	0.074	0.005*	0.094	0.095	0.089	0.007*	0.016***	0.016	0.015	0.002
Native	0.791	0.814	0.719	0.095***	0.747	0.771	0.672	0.099***	-0.044***	-0.044	-0.047	0.003
Born in CA	0.466	0.481	0.418	0.062***	0.502	0.517	0.453	0.064***	0.036***	0.036	0.034	0.001
Born in other state	0.312	0.320	0.287	0.033***	0.234	0.243	0.208	0.035***	-0.078***	-0.077	-0.079	0.002
Foreign Born	0.209	0.186	0.281	-0.095***	0.253	0.229	0.328	-0.099***	0.044***	0.044	0.047	-0.003
Non-citizen	0.142	0.123	0.202	-0.079***	0.152	0.134	0.209	-0.075***	0.010***	0.011	0.007	0.005*
Unemployed	0.044	0.043	0.049	-0.006***	0.044	0.043	0.047	-0.004***	-0.000	0.001	-0.002	0.003***
Blue Collar	0.410	0.404	0.429	-0.026***	0.393	0.386	0.414	-0.028***	-0.017***	-0.018	-0.015	-0.002
Below poverty level	0.098	0.090	0.125	-0.036***	0.112	0.103	0.143	-0.041***	0.014***	0.013	0.018	-0.005**
Female hh below poverty	0.044	0.040	0.058	-0.018***	0.047	0.042	0.061	-0.019***	0.002**	0.002	0.004	-0.002

Notes: Near designates census tracts that are within 1km of a highway (over 99.9% of the tract area). Far designates all other census tracts. Columns (1) and (5) show average census demographic characteristics in 1990 and 2000 for all census tracts, respectively, and column (9) shows the overall difference in characteristics across all tracts from 1990 to 2000. Columns (2) and (3) show the 1990 average characteristics of tracts far and near highways, respectively, and column (4) shows the far-near difference in 1990. Columns (6) and (7) show the 2000 average characteristics of tracts far and near highways, respectively, and column (8) shows the far-near difference in 2000. Columns (10) and (11) show the difference in average characteristics from 1990 to 2000 for tracts far and near highways, respectively. Finally, and of most interest, column (12) estimates the difference-in-difference, which is the 2000-1990 far difference (column 10) minus the 2000-1990 near difference (column 12).
*** p<0.01, ** p<0.05, * p<0.1

C Robustness

Treatment definitions:

(T1): Treated (control) zip codes are those with at least (less than) the median percentage, 42.5 percent, of τ.

(T2): Treated (control) zip codes are those with at least (less than) 50 percent of τ.

(T3): Treated (control) zip codes contain the highest (lowest) tercile of τ.

(T4): Treated (control) zip codes contain the highest (lowest) quartile of τ.

Table 10: Robustness to variation in treatment definition

	Asthma hospitalizations per 10,000 children				
	(T1)	(T2)	(T3)	(T4)	continuous
	(1)	(2)	(3)	(4)	(5)
DD	-4.248***	-3.602***	-4.468***	-5.445**	-7.652***
	(1.365)	(1.289)	(1.723)	(2.110)	(2.461)
%Δ from pre-treat	-8.3	-7.0	-8.7	-10.6	-14.9
Observations	11,787	11,787	7,707	5,740	11,787
R-squared	0.594	0.593	0.586	0.564	0.594
Zip Code FE	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes

Notes: Standard errors clustered at the zip code level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Diagnostics for spatial dependence

Test	Value	Prob
Lagrange Multiplier (lag)	0.039	0.8438
Robust LM (lag)	0.030	0.8626
Lagrange Multiplier (error)	0.014	0.9062
Robust LM (error)	0.005	0.9436
Lagrange Multiplier (SARMA)	0.044	0.9783

Notes: Test statistics and P-values for Lagrange Multiplier tests for spatial lag, spatial error, and SARMA models. The null hypothesis is no spatial dependence. Neighboring zip codes are defined using a queen weights matrix.

D Potential Confounders

D.1 RFG

As part of the Clean Air Act Amendment of 1990, the federal government has mandated specific requirements for gasoline, such as limitation on lead-based antiknock agents, mandated detergent additives, limitations on Reid Vapor Pressure, mandated oxygen content, and reformulated gasoline (RFG). RFG targets both NO_x and CO emissions. Severe ozone non-attainment areas of the U.S., including parts of California, were required to implement Phase I of RFG gasoline in January of 1995. However, in 1996 the entire state of California, both RFG and non-RFG areas, became subject to more stringent CARB gasoline standards. Therefore, there may be some downward trend in pollution that begins in 1995, rather than 1996 for RFG areas in California. However, research by Auffhammer and Kellogg (2011) finds that RFG gasoline has little impact on pollution. In fact, they find that the only significant impacts on pollution come from the more stringent CARB gasoline regulations.

With data indicating which areas of California were subject to RFG gasoline, I can examine whether the decrease in asthma originates from RFG or CARB gasoline. Table 12 shows the baseline estimates in column (1). Column (2) limits the sample to non-RFG zip codes, showing that there is still a significant decrease in asthma for areas that only experienced CARB gasoline in 1996. Even though the sample size is smaller, the results remain significant, which provides some confidence that CARB gasoline does impact asthma. Column (3) tests whether the RFG zip codes have a significant difference from non-RFG zip codes following RFG implementation in 1995. The estimate is negative but not significant, suggesting that there is not much difference in asthma after 1995 for RFG zip codes. Column (4) exploits zip code level variation in exposure to highways to test whether zip codes close to highways and in RFG areas had fewer asthma hospitalizations following RFG implementation in 1995. Again, the coefficient is negative and slightly larger, but still not significant. When this variable is included along with the primary CARB difference-in-difference estimator in column (5), the CARB estimator is strongly significant and the RFG estimator is insignificant. This supports the claim that the more stringent CARB gasoline regulations had a strong impact on asthma hospitalizations and this impact was not driven by federal RFG gasoline.

Table 12: Control for Federal RFG gasoline regulation in 1995

	Asthma hospitalizations per 10,000 children				
	Baseline	Non-RFG			
	(1)	(2)	(3)	(4)	(5)
DD (T1)	-4.248***	-4.419**			-4.422***
	(1.365)	(2.097)			(1.498)
RFG*after95			-0.0377		
			(1.520)		
Treat_RFG*after95				-2.184	0.376
				(1.423)	(1.545)
Observations	11,787	5,310	11,787	11,787	11,787
R-squared	0.594	0.538	0.593	0.593	0.594
Zip Code FE	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes

Notes: Standard errors clustered at the zip code level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

D.2 PRWORA

The impact of CARB gasoline on asthma is potentially confounded by the passage of the Personal Responsibility and Work Opportunity Reconciliation Act in 1996 (PRWORA). This welfare reform legislation replaced the Aid to Families with Dependent Children (AFDC) with Temporary Assistance for Needy Families (TANF), a new federal block grant to states. Before TANF, eligibility for Medicaid and AFDC were closely linked. In fact, a person who received an AFDC check was automatically entitled to Medicaid. Policymakers unlinked TANF from Medicaid eligibility amidst concerns that tighter welfare eligibility criteria in TANF might unintentionally cause many people to lose health insurance coverage. The new law requires states to use the AFDC eligibility criteria from before the law change in determining Medicaid eligibility for families with children, regardless of TANF eligibility (Ku and Coughlin, 1997).

However, research has suggested that enrollment problems arose following the PRWORA changes. Medicaid policies and eligibility requirements are complex, especially for the poorest families, and welfare staff are not adequately trained in Medicaid policies to assist families who may not qualify for welfare, but could qualify for Medicaid. From 1995 to 1998, monthly Medicaid enrollment declined 12 percent in California (Ellwood et al., 1999).

Although this affects everyone in the state of California, it could be problematic if patients eligible for Medicaid are more likely to live in the treatment zip codes, and they are less likely to show up in the hospital data due to enrollment issues rather than an asthma decline.

However, this is probably not driving the results for the following reasons. First, consider only patients with private insurance. If enrollment issues were driving the main results, then we should not see a decline in asthma among the private insurance patients. Medicaid enrollment issues should only impact the private insurance group if former Medicaid patients switch to private insurance following PRWORA. If anything, these switchers might drive the asthma rate up for the private insurance group. However, we see a decline in asthma for private insurance patients in treatment relative to control zip codes following CARB gasoline implementation. This suggests that Medicaid enrollment issues are not driving the results.

Second, the Emergency Medical Treatment and Active Labor Act (EMTALA) of 1986 required hospitals to provide care to anyone needing emergency health care treatment regardless of citizenship, legal status, or ability to pay. Given that the uninsured are often forced to use the emergency room as their primary source of care, PRWORA should not have an impact on emergency hospitalizations for asthma. We can test this more clearly in two ways: limiting our sample of asthma patients to those whose hospital admission originated in the ER, and using the sample of asthma patients whose visit was unscheduled.

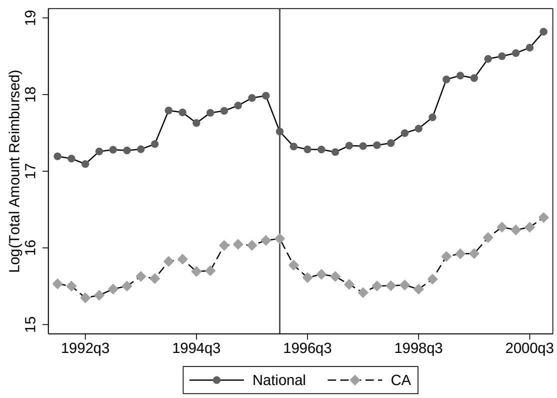
Table 13: Heterogeneous effects: Insurance type, ER, and unscheduled hospitalizations

	Insurance Type					
	Medicare or Medi-Cal	Private	Self-Pay	Other	ER	Unscheduled
	(1)	(2)	(3)	(4)	(5)	(6)
DD (T1)	-3.748***	-2.300***	0.480*	-0.185	-3.163***	-5.292***
	(1.122)	(0.743)	(0.267)	(0.204)	(1.113)	(1.407)
%Δ from pre-treat	-9.6	-9.5	19.8	-16.4	-8.4	-9.8
%Δ in gap	-52.12	-36.4	-95.8	-70.3	-35.4	-46.4
%Δ of std dev	-9.0	-15.1	11.1	-4.8	-9.8	-12.9
DD continuous	-8.104***	-3.496***	1.113**	-0.422	-5.641***	-10.05***
	(2.043)	(1.278)	(0.478)	(0.370)	(2.119)	(2.492)
Observations	10,799	10,799	10,799	10,799	11,850	11,850
R-squared	0.701	0.376	0.197	0.259	0.572	0.583
Zip Code FE	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes

Notes: The insurance variable recorded in the data was modified in 1995 and 1999. The categories presented here were consistently queried over time, but the composition of each may have been affected by changes in the other categories surveyed. The majority of patients fell into either Medicare/Medi-Cal or private insurance. Standard errors clustered at the zip code level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

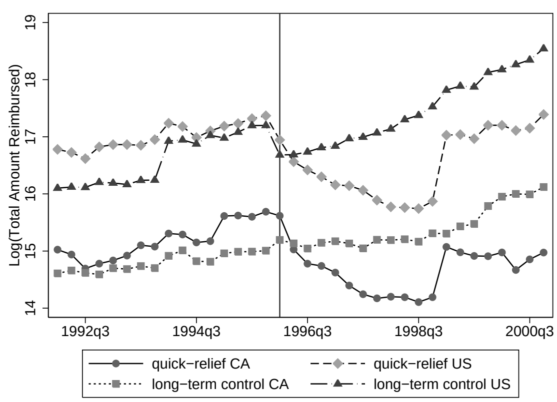
The reduction in asthma admissions remains significant. Furthermore, barriers to Medicaid enrollment from the PRWORA are more likely to impact access to and use of prescription drugs used to treat asthma. In Figure 11, state utilization data from the Medicaid Drug Rebate Program show that the total amount reimbursed for prescription drugs used to treat asthma declined sharply during this period in both California and the entire US. Figure 12 shows that the drop can be attributed almost entirely to quick-relief medicines, or "rescue drugs", used to control asthma symptoms or during an asthma attack. The drop in prescription drug use can be attributed both to Medicaid enrollment issues and a reduction in pollution levels following CARB. It is difficult to distinguish between these two factors since they occurred contemporaneously. However, the reduction in access to asthma control medications from PRWORA would likely increase the number of hospitalizations for asthma. Therefore, if anything, the asthma hospitalization results here will be understated.

Figure 11: Medicaid reimbursement for asthma prescription drugs



Notes: Asthma prescription drugs include antiasthmatic combinations, inhaled corticosteroids, leukotriene modifiers, long-acting inhaled beta-2 agonists, mast cell stablizers, methylxanthines, and short-acting inhaled beta-2 agonists.

Figure 12: Medicaid reimbursement for asthma prescription drugs: quick-relief and long-term control



Notes: Asthma drugs that provide quick-relief from asthma symptoms are the short-acting inhaled beta-2 agonists. Long-term control medications include inhaled corticosteroids, leukotriene modifiers, long-acting inhaled beta-2 agonists, mast cell stablizers, and methylxanthines.