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On the road to recovery: Gasoline content regulations and child health

Michelle Marcus*

Abstract

Gasoline content regulations are designed to curb pollution and improve health, but their impact on health has not been quantified. By exploiting both the timing of the regulation and spatial variation in children's exposure to highways, I estimate the effect of gasoline content regulation on pollution and child health. The introduction of cleaner-burning gasoline in California in 1996 reduced asthma admissions by 8 percent in high exposure areas. Reductions are greatest for areas downwind from highways and heavy traffic areas. Stringent gasoline content regulations can improve child health, and may diminish existing health disparities.

Keywords

asthma; gasoline content regulation; air pollution; traffic; vehicle emissions

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 evidence from epidemiological research shows a strong correlation between traffic pollution and health outcomes for children and infants.¹ In an effort to curb pollution from motor vehicle exhaust and improve health outcomes, state and federal governments have enacted gasoline content regulations. However, gasoline content regulations have significant economic costs. The compliance cost to refineries is over \$1 billion per year in California. Some of these costs are passed to consumers and can increase the price and price volatility of gasoline (Brown et al., 2008; Muehlegger, 2002).² Given these high costs, it is important to identify whether or not gasoline content regulation significantly decreases pollution, improves health, and reduces health expenditures.

Several states, including California, have adopted more stringent gasoline programs than those imposed by the federal government. In 1996, California Air Resources Board (CARB)

*Marcus: Brown University, Department of Economics, Brown University, 64 Waterman Street, Providence, RI 02912, michelle.marcus@brown.edu.

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¹See 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).

²Brown 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.

required the introduction of cleaner-burning gasoline (CBG) throughout the state in order to reduce vehicle emissions of pollutants that cause or contribute to various health problems. Although this paper focuses childhood asthma, cleaner-burning gasoline may improve health along many dimensions, such as reductions in heart disease, lung disease, and cancer. The precisely targeted, inflexible regulations of California's CBG required the removal of particularly harmful compounds from gasoline. CBG 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 based on residential location to estimate the effect of gasoline regulation on both pollution and child health.³ A cross-sectional comparison of people living near and far from highways would 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 Using a differences-in-differences framework I examine the change in both pollution and asthma admissions in areas near and far from highways, before and after the introduction of CBG. This identification strategy requires only that the differences between neighborhoods near and far from highways do not shift discontinuously at the time of the CBG regulation.⁵

Previous literature establishing the link between air pollution and health has exploited natural experiments to avoid the inherent endogeneity problems of cross-sectional comparisons (Chay and Greenstone, 2003*a,b*; Lleras-Muney, 2010; Currie and Walker, 2011; Neidell, 2004; Currie and Neidell, 2005; Schlenker and Walker, 2015). For example, Neidell (2004) and Currie and Neidell (2005) exploit seasonal variations in pollution within zip codes to identify pollution's impact on child asthma hospitalizations and infant mortality. Knittel, Miller and Sanders (2015) go further in trying to understand the role that automobile congestion plays in impacting pollution and infant mortality. In addition, Anderson (2015) exploits variation in wind direction to estimate the impact of highway pollution on adult mortality. One important way that policy makers can try to reduce the negative impact of automobile congestion on health is through gasoline content regulations. However, existing research has yet to document whether these regulations can be successful in protecting health. 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.⁶

³Recent 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 alternative distances, such as within 300m of highways, as shown in Table 9.

⁴In fact, Table B1 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.

⁵Neighborhood characteristics are somewhat stable over time since people are not perfectly mobile and the housing market is not perfectly 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 B1 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.

Auffhammer and Kellogg (2011) find that only the precisely targeted, inflexible CBG regulations improved air quality. However, the health impacts of gasoline content regulations have not yet been quantified.

This paper asks whether or not CBG improved health outcomes, measured by childhood asthma, by reducing pollution. Identifying the pollution reduction and associated health benefits from CBG 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, 2008*b*). I contribute to the literature in several ways.

First, I quantify the impact of CBG on three criteria pollutants: NO_2 , CO , and SO_2 . Whereas Auffhammer and Kellogg (2011) estimate air 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, zip code level variation in exposure to highway pollution to identify the impact of CBG on pollution in California. Estimates show a decline of about 2 percent, 6 percent, and 11 percent in high exposure areas for NO_2 , CO , and SO_2 , respectively.

Second, I quantify the impact of CBG 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 CBG caused an 8 percent decline in childhood asthma hospitalizations in high exposure areas. Using confidential data containing a unique patient identifier, I also link patients over time and estimate the change in an individual's probability of hospital admission for asthma and the length of stay after the policy. The individual level estimates suggest that CBG reduced the probability of asthma hospitalization and length of stay by about 3 and 6 percent, respectively.

Next, I incorporate information on both wind direction and traffic density to test whether reduced highway pollution drives the health improvements. I explore differential effects of CBG on zip codes that are downwind, crosswind, and upwind from the nearest highway, based on the prevailing wind direction. Results suggest that downwind zip codes experience the greatest declines in pollution and asthma. In addition, the incorporation of traffic information suggests that zip codes near high traffic highways exhibit large reductions in pollution and asthma. These results are consistent with the idea that reductions in highway pollution are the driving force behind the asthma decline.

Finally, I present a cohort level analysis to estimate the cumulative effect of exposure to CBG and show that the health benefits of regulation grow over time as pollution effects accumulate. Each of these additional specifications provides further evidence that these results are driven by the gasoline content regulation and not through some other mechanism. It is unlikely that some other mechanism would produce this precise pattern of effects, with

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⁶Pollution abatement policies are often met with unintended consequences that reduce effectiveness (Henderson, 1996). For example, driving restrictions based on the last digit of the vehicle's license plate in Mexico City failed to improve air quality as drivers responded by purchasing more vehicles (Davis, 2008).

larger reductions in pollution and asthma near highways, downwind from highways, in areas with heavy traffic, and for cohorts with longer exposure to the CBG policy.

The paper is organized as follows. Section 1 motivates the paper and provides background on asthma, pollution, and the CBG regulations. Section 2 describes the empirical strategy for estimating the impact of regulation on both pollution and asthma. Section 3 describes the data and defines key variables. Section 4 shows the results, and Section 5 tests the robustness of the main results. Section 6 provides some discussion and a cost-benefit analysis, and Section 7 concludes.

1 Motivation and Background

1.1 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. California's reformulated gasoline (CaRFG) program set stringent standards for gasoline to reduce emissions from gasoline-powered vehicles. The new stringent state-wide gasoline standard affected all cars simultaneously, unlike restrictions made to engines and vehicles, such as low-emission vehicle standards, which are implemented only through vehicle turnover. The program was implemented in three phases.⁷ The most significant changes occurred with the introduction of cleaner-burning gasoline (CBG) in Phase 2, which set specifications for sulfur, aromatics, oxygen, benzene, T50, T90, olefins, and RVP. Specifically, CBG 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

Based on estimates from California's EPA, one would expect to see an overall decline of about 5.8 percent, 8.7 percent, and 5.6 percent for NO_x , CO , and SO_2 , respectively (CARB, 2008a; EPA, 2000).⁹ Estimates from this paper show a 2, 6, and 11 percent decline in high exposure areas for NO_2 , CO , and SO_2 , respectively. It is not surprising that the declines in NO_2 and CO 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 may be understated.

⁷Phase 1 eliminated lead from gasoline and set regulations for deposit control additives and Reid vapor pressure (RVP) in 1992. However, lead limits had already been decreased significantly by this time to a limit of 0.8 g/gal and the lead phase-down efforts had already decreased lead usage in gasoline by 99 percent between 1977 and 1989 (from 16,500 to 194 tons). Several major oil companies had already phased out leaded gasoline and ambient concentrations had already fallen so low that the official elimination of lead from gasoline was unlikely to have a dramatic impact. Phase 3 eliminated methyl-tertiary-butyl-ether (MTBE) from California gasoline in January of 2003, which is after the sample period studied in this analysis.

⁸CBG 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).

⁹California's EPA estimated that CBG would cause a reduction of 11%, 11%, and 80% in the amount of on-road pollution from NO_x , CO , and SO_2 , respectively. On-road pollution accounts for about 53%, 79%, and 7% of total NO_x , CO , and SO_2 emissions. California's EPA also estimated a reduction in smog-forming gases, volatile organic compounds (17%), benzene, and 1,3-butadiene.

1.2 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 have at one time been diagnosed with asthma, 7 million still have asthma, and 4 million 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, Jones and Freeman, 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).

The prevalence of asthma imposes a great financial burden across the U.S. health care system. Direct costs include payments for ambulatory care visits, hospital out-patient services, hospital inpatient stays, emergency department visits, physician and facility payments, and prescribed medications. Indirect costs can also result from days of missed work or restricted work activity for adults, and school absences or diminished academic performance for children and adolescents. 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, Zhong and Wheeler, 2005).

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).

Growing evidence suggests that air pollution can cause exacerbation of pre-existing asthma, as well as new-onset asthma (Guarnieri and Balmes, 2014; Brunst et al., 2015). Air pollution can induce oxidative stress and damage, airway remodeling, inflammatory pathways and immunological responses, and enhancement of respiratory sensitization to aeroallergens (Guarnieri and Balmes, 2014). Outdoor air pollution almost always occurs as a mixture, which makes it difficult to disentangle the causal impact of individual pollutants in epidemiological studies (Barnes, 1995; Esposito et al., 2014). Likewise, California's CBG introduced restrictions on multiple pollutants that have been linked with asthma, such as NO_x , VOCs, CO , SO_2 , Benzene and 1,3-Butadiene. Unfortunately, data limitations prevent a first stage analysis of CBG regulation on all of the restricted pollutants. This analysis will focus on NO_2 , CO , and SO_2 , because they are both well measured and have been linked with asthma (Sheppard et al., 1980; Huang, Wang and Hsieh, 1991; Orehek et al., 1976; Kleinman et al., 1983; Bauer et al., 1986; Koenig, Pierson and Horike, 1983; Leikauf, 2002). Nevertheless, the policy likely led to reductions in additional pollutants not measured here. The reduced-form estimates of the impact of CBG on asthma admissions capture the overall health effects from the entire pollution bundle reduction.

In addition to childhood asthma, reductions in air pollution from CBG may also lead to other health improvements. For example, exposure to air pollution has been linked with stroke, heart disease, lung cancer, both chronic and acute respiratory diseases, adverse pregnancy outcomes, and even death.

2 Empirical strategy

Among other things, the intensity of exposure to highway pollution depends on an individual's distance to a highway, the wind direction, and the density of highway traffic. A reduction in highway pollution from cleaner-burning gasoline should have the largest effects on asthma for children living very close to highways, downwind from highways, and near high traffic highways. The main results exploit spatial variation in the intensity of exposure to highway pollution based on residential location, and subsequent analysis investigates the additional effects of living downwind and near heavy traffic highways.¹⁰ These additional sources of variation provide further evidence that reductions in highway pollution drive the improvements found in child health.

Research has shown that traffic pollution can travel up to 1km from highways in California (Hu et al., 2009). Ideally, patient addresses would identify precise proximity to highways, but patient confidentiality constraints restrict residential information to the zip code level. 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 in a zip code that lives within 1km of a highway, τ .

I start by showing the first-stage impact of cleaner-burning gasoline on air pollution. CBG is likely to reduce many air pollutants, but this study focuses on NO_2 , CO , and SO_2 , because of data availability. Using a differences-in-differences frame-work, I estimate the change in pollution in areas near to highways relative to far from highways, before and after the introduction of CBG. *Near* is defined as either the continuous measure of τ , or a binary indicator equal to one for zip codes over the median value of τ . Figure 1 shows the location of the binary treatment and control zip codes in California. Treated zip codes are dispersed across the entire state and do not represent any specific region. Although the choice of a cut-point is somewhat arbitrary, the binary indicator can be easier to interpret and the results are robust to alternative cut-point choices (see Appendix C). *After* is equal to one after CBG takes effect in 1996. The results are estimated with zip code fixed effects, Z , year dummies, Θ , and quarter dummies, Q .

$$\text{Pollution}_{zt} = B_0 + B_1 \text{Near}_z \times \text{After}_t + Z + \Theta + Q + \varepsilon_{1zt} \quad (1)$$

¹⁰I 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.

where z indexes zip codes and t indexes time, in months. Standard errors are clustered at the zip code level. The parameter of interest, B_1 , estimates the change in pollution concentration in the treatment group following the implementation of CBG, net of trends in the control group.

Ideally, we would like to estimate the direct effect of air pollution changes on asthma admissions. However, like many air pollution policies, CBG reduced multiple pollutants simultaneously. In this instance, the CBG policy implementation provides one instrument, but there are many endogenous pollutants. Using the policy as an instrument for a single pollutant would necessarily violate the exclusion restriction, because the policy impacts many other pollutants that would likely also influence health. Therefore, I present only the first-stage impacts on pollution and the reduced-form impact of CBG on asthma admissions, which can be thought of as an intent-to-treat estimate. Defining *Asthma* as the number of asthma admissions per 10,000 children, I estimate the following specification:

$$\text{Asthma}_{zt} = \delta_0 + \delta_1 \text{Near}_z \times \text{After}_t + Z + \Theta + \varepsilon_{2zt} \quad (2)$$

where z indexes zip code and t indexes time, in years. Standard errors are clustered at the zip code level. The parameter of interest is δ_1 , which estimates the change in asthma admissions in treatment group following the implementation of CBG, net of trends in the control group.

To address any concern that changing demographics at the zip code level might be driving these results, I present additional results at the individual level. I estimate the impact of CBG on an individual's probability of asthma admission and length of stay, using confidential data to link patient-level admissions over time. The probability of admission represents the extensive margin, while the length of stay takes the intensive margin into account. The impact on the probability of asthma admission is estimated in a linear probability model, while the impact on length of stay is estimated using a Poisson model, since length of stay is measured in days:

$$\text{Outcome}_{it} = \omega_0 + \omega_1 \text{Near}_i \times \text{After}_t + I + \Theta + \varepsilon_{3it} \quad (3)$$

where i indexes individuals and t indexes time, in years. Individual fixed effects, I are included, and the sample is limited to non-movers. Ages are restricted to be between 0 and 18 years old, and regressions are weighted by the number of available observations per person during the study period. Standard errors are clustered at the individual level.

Next, I introduce additional sources of variation, wind direction and traffic, to test whether the results are consistent with the claim that these health improvements are driven by the reduction in highway pollution from CBG. First, I investigate whether prevailing wind direction is important in determining which locations experience the largest reductions in pollution and asthma admissions. I estimate the impact of CBG in downwind, crosswind, and upwind zip codes. Residents living downwind from a highway experience higher levels of highway pollution and are likely to have benefited the most from cleaner-burning gasoline. Zip codes are classified as downwind, crosswind, and upwind, as described in

section 3. Since these zip code level classifications may not accurately describe each individual's relationship to the highway, we would expect to find the largest reductions in asthma among downwind zip codes, but it would not be surprising to find more modest effects in crosswind zip codes since parts of these zip codes may actually be downwind. There should be little to no effect for upwind zip codes. I estimate:

$$\text{Pollution}_{zt} = \lambda_0 + \lambda_1 \text{Near}_z \times \text{After}_t \times \text{Down}_z + \lambda_2 \text{Near}_z \times \text{After}_t \times \text{Cross}_z + \lambda_3 \text{Near}_z \times \text{After}_t \times \text{Up}_z + Z + \Theta + Q + \text{Down}_z \times \Theta \kappa + \text{Cross}_z \times \Theta \chi + \varepsilon_{4zt} \quad (4)$$

$$\text{Asthma}_{zt} = \varphi_0 + \varphi_1 \text{Near}_z \times \text{After}_t \times \text{Down}_z + \varphi_2 \text{Near}_z \times \text{After}_t \times \text{Cross}_z + \varphi_3 \text{Near}_z \times \text{After}_t \times \text{Up}_z + Z + \Theta + \text{Down}_z \times \Theta \eta + \text{Cross}_z \times \Theta \psi + \varepsilon_{5zt} \quad (5)$$

where *Down*, *Up*, and *Cross* are indicators equal to one if the zip code is downwind, upwind, or crosswind from a highway, respectively. The remaining variables include zip code, year, and quarter dummies, as well as downwind-year and upwind-year dummies which control flexibly for differential shocks or trends among upwind and downwind zip codes. Standard errors are clustered at the zip code level.

Second, I look at the role of traffic density. Highways with high traffic should produce more pollution than low traffic highways and might experience a greater reduction in pollution from the implementation of CBG.¹¹ However, human exposure depends on both distance to a highway and the traffic intensity on that highway. Areas with high highway traffic levels may have high traffic density on non-highway roads as well. For this reason, the percent of the population living near highways in high traffic zip codes may matter less. Therefore, I look separately at three potentially treated groups: "Near & High Traffic," "Far & High Traffic," and "Near & Low Traffic." The reference group includes zip codes where people live far from highways with low traffic levels.

$$\text{Pollution}_{zt} = \gamma_0 + \gamma_1 \text{Near}_z \times \text{After}_t \times \text{High}_z + \gamma_2 \text{Near}_z \times \text{After}_t \times \text{Low}_z + \gamma_3 \text{Far}_z \times \text{After}_t \times \text{High}_z + Z + \Theta + Q + \varepsilon_{6zt} \quad (6)$$

$$\text{Asthma}_{zt} = \rho_0 + \rho_1 \text{Near}_z \times \text{After}_t \times \text{High}_z \times \text{After}_t + \rho_2 \text{Near}_z \times \text{After}_t \times \text{Low}_z + \rho_3 \text{Far}_z \times \text{After}_t \times \text{High}_z + Z + \Theta + \varepsilon_{7zt} \quad (7)$$

¹¹Previous research has shown that traffic jams and highway idling have a large impact on pollution levels as well (Currie and Walker, 2011; Friedman et al., 2001). I focus only on the average number of vehicles using a highway each day (AADT) due to data availability constraints.

Finally, I incorporate all three sources of exposure intensity into one measure. The index is an equally weighted sum of the three binary treatment groups, *Near*, *Downwind*, and *HighTraffic*, and is scaled to be between 1 and 0. I estimate the following specifications for both pollution and asthma admissions:

$$\text{Pollution}_{zt} = \mu_0 + \mu_1 \text{Index} \times \text{After}_{zt} + Z + \Theta + Q + \varepsilon_{8zt} \quad (8)$$

$$\text{Asthma}_{zt} = \nu_0 + \nu_1 \text{Index} \times \text{After}_{zt} + Z + \Theta + \varepsilon_{9zt} \quad (9)$$

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 and zip code of residence. 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. According to the CDC, asthma hospitalizations occur at the rate of about 2 per 100 persons with asthma. Although these hospitalization estimates may not be representative of the general asthmatic population, children admitted to a hospital are an important and expensive patient group. Furthermore, this dataset provides a large number of observations at a fine geographic scale across the entire state, whereas many surveys are only representative of select MSAs and large counties.

I define asthma admissions using the International Classification of Diseases, Ninth Revision, (ICD-9) codes to identify patients admitted to the hospital for asthma related conditions (code 493). The results are very similar when I use the diagnosis-related group code for bronchitis and asthma (code 98).¹² The population of interest is children under 10 years old, since they are especially vulnerable. Therefore, the measure of asthma is defined as the number of childhood discharges for asthma, per 10,000 children under age 10, for each zip code.¹³ The preferred specification also includes all respiratory related discharges for children less than one year old, since diagnosis of asthma among infants is especially difficult (Martinez et al., 1995).¹⁴ Table 1 shows the overall level of asthma admissions is

¹²The 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. 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.

¹³The 1990 and 2000 U.S. Census data will provide population counts by age, race, and gender for each zip code. I use linear interpolations of population to calculate the number of children in each zip code for each year between 1990 and 2000.

¹⁴The 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.

48.3 per 10,000 children, with higher levels of asthma admissions in near relative to far zip codes.

Individual-level outcome variables include an indicator for asthma admission and length of stay in days. *BinaryAsthma* is equal to one if a child was admitted for asthma at least once during that year, and zero if the child was not admitted or admitted for another reason. *StayLength* is the number of days spent in the hospital, where stays less than 24 hours are counted as 1 day.

Air Pollution Data

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 at the monitor level. 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, I limit the main sample to consistently observed monitors, which are observed for at least 3 months in every year of the sample period. Results are similar for the full sample of monitors. Figure 2 shows consistently observed air quality monitors, which are generally located in areas with higher population density. There are 90 monitors consistently recording NO_2 , 74 recording CO , and 30 recording SO_2 .

To link Californian air quality monitors with zip codes, I follow the methodology used in Neidell (2004) and Currie and Neidell (2005). I create a weighted average of pollution from all monitors within 20 miles of the zip code centroid, using the inverse of distance to the centroid as the weight.¹⁵ The sparsity of monitors for SO_2 will cause more measurement error in estimates for this pollutant.

Another option is to use Kriging, which estimates parameters that describe the spatial correlation between observed data points, and then uses these estimates to find predictions that minimize the sum of squared errors (Cressie, 1993). Some research has suggested that Kriging methods provide superior predictions over deterministic interpolation (Lleras-Muney, 2010; Anselin and Le Gallo, 2006; Zimmerman et al., 1999). One additional benefit is that the Kriging methodology provides a measure of the accuracy of the predictions. The appendix shows the main pollution results using the Kriging methodology and also weighting the results by the inverse of the prediction error.¹⁶

In addition to average pollution levels, respiratory conditions may respond more to days with extreme pollution levels. To capture these effects, I create measures of both the monthly average pollution levels and the percent of pollution days within a month that exceed 75 percent of the EPA's threshold. Pollution levels are measured as the daily maximum 1-hour

¹⁵The results were estimated using a weighted average of all monitors within alternative distances from the centroid with similar results. Neidell (2004) and 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).

¹⁶See Appendix Table C4. Details of the models that were used to generate Kriging predictions are available from the author on request.

concentration for NO_2 and SO_2 , and the daily maximum 8-hour concentration for CO , following EPA standards. The EPA's NAAQS primary standards for NO_2 , CO , and SO_2 are 100 ppb, 9 ppm, and 75 ppb, respectively. Summary statistics for the average level and percent of bad pollution days pollutants are shown in Table 1. Pollution is higher in the treatment zip codes relative to the control, which is to be expected.

Highways and Traffic Data

Highway locations come 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 geocoded traffic volume data is not available for the study period, 1992–2000, traffic volumes from 2011 are strongly correlated with past volumes.¹⁷ Annual average daily traffic (AADT) is recorded for 6,926 count locations on Californian highways. I calculate the average AADT level for each zip code. Table 1 shows that the average AADT is about 75,870 across all zip codes, but that traffic is higher in the near zip codes relative to the far zip codes. 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.

Wind Data

Wind direction comes from the GHCN (Global Historical Climatology Network)-Daily database obtained from NOAA's National Climatic Data Center. GHCN-Daily is an integrated database of daily climate summaries from land surface stations across the globe. Average wind directions are calculated for the 79 stations in California recording wind direction during the study period. Using ArcMap 10.1, the prevailing wind direction is interpolated across California using inverse distance weighting (see Figure A1 in the appendix for a map of prevailing wind direction and station locations).

I designate zip codes into one of three groups: downwind, crosswind, or upwind from the highway. Groups are based on the difference between the angle from which the prevailing wind originates and the angle from the zip code centroid to the nearest highway. If these two angles are very similar, the zip code is classified as downwind from the highway.

Downwind, crosswind, and upwind zip codes are those with an absolute value angle difference less than 45, 45 to 135, and over 135 degrees, respectively (see Figure A2 in the

¹⁷Whereas the 2011 data have been geocoded and can be mapped in ArcGIS relative to each zip code location, earlier data cannot be geocoded. Instead, to see how well recordings in 2011 correlate to past traffic volumes in 2001 (the earliest year for which traffic volume excel tables are available), I link data across years using the district, route, county, and postmile information. I successfully link 1,901 postmile locations that have traffic volumes recorded in both 2011 and 2001. The correlation across years is 98.5%, which is very high and provides some confidence that areas with heavy traffic in 2001 also have heavy traffic in 2011. In addition, a Kolmogorov-Smirnov test fails to reject the null hypothesis that the distributions of traffic volumes in 2001 and 2011 are equal (p-value 0.937).

appendix for a map of zip code classifications). While we may expect to find the largest effects on zip codes classified as downwind, cross-wind zip codes may also experience effects from the policy. It is possible that not all areas within the zip code fall into the same classification, so crosswind zip codes may have some individuals who actually live downwind. Although I use the angle to the nearest highway segment, highway segments at other angles may matter also. Since the precise location of each person within the zip code is unknown, using the zip code centroid location also introduces some error. Finally, daily fluctuations in wind direction may change the realized wind angle.

As seen in Table 1, the percent of zip codes classified in each group is fairly balanced across near and far zip codes, with about 23 percent classified as upwind, 51 percent classified as crosswind, and 26 percent classified as downwind. The prevailing wind direction is fairly consistent over time in this region. When considering yearly variation in wind direction, zip codes I classify as downwind are downwind 76 percent of the time.

4 Results

4.1 First Stage Results: Pollution

Graphical evidence of the reduction in pollution following CBG is shown in Figures 3 and 4, which plot the percent of bad pollution days and the average pollution levels over time for each pollutant. The left panel shows the unadjusted means by year for treatment and control zip code groups. As expected, there is a level difference between the two groups for both NO_2 and CO , with a larger percent of bad pollution days 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 percent of bad pollution days 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. Prior to the policy, the percent of bad NO_2 days is about 3 percentage points higher in the near relative to far zip codes, and about 0.3 percentage points higher for bad CO days. These near-far group gaps fall to about 1.5 and almost 0 percentage points after the policy for NO_2 and CO , respectively. The drop in the percent of bad pollution days coincides with the timing of the policy. There is some evidence of a decline in the average SO_2 level after the policy, but little evidence of a drop in the percent of bad SO_2 days. Throughout the analysis the results are weaker for SO_2 , but this is not surprising since on-road pollution accounts for only 7 percent of overall SO_2 levels and there are only about 30 monitors that can be used to measure SO_2 levels in California. The increased measurement error from using so few monitors to interpolate SO_2 pollution may make the results for SO_2 unreliable.

Table 2 shows the results from the estimation of equation (1) for the average and percent bad pollution days, for each of the criteria pollutants. Panel A shows estimates based on the binary near indicator and Panel B shows estimates based on the continuous measure, τ . The regression results support the graphical evidence that pollution decreased after the implementation of the CBG regulation in high exposure zip codes. 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

11 percent. CBG also reduced the percent of bad days by 1.7 percentage points for NO_2 , 0.39 percentage points for CO , and 0.03 percentage points for SO_2 . From the baseline pre-policy, treated zip code level, these effects equate to reductions of 14.3 percent, 50.6 percent, and 30.7 percent for NO_2 , CO , and SO_2 , respectively.

4.2 Reduced Form Results: Asthma Admissions

Figure 5 shows the smoothed relationship between asthma hospitalizations and the percentage of the zip code population living within 1km of a highway, τ , over time. Solid and dashed lines indicate years before and after gasoline content regulation, respectively. After the implementation of CBG in 1996, the gradient shifts downward. As expected, the reduction in asthma after CBG is concentrated in zip codes with a large percentage of the population living near the highway.

Further graphical evidence of the decrease in childhood asthma can be seen in Figure 6. The left panel shows the raw means by year for near and far zip codes. As expected, asthma hospitalizations are higher in the near group. Prior to the policy, these two lines follow similar yearly patterns with shocks affecting both groups in the same way. After the policy, the gap between the groups decreases as the level of asthma in the near group becomes more similar to that of the far group, as expected. The right panel plots the difference between near and far groups by year. The difference is fairly constant prior to the policy and seems to decline after the policy.

Regression results showing estimates of equation 2 support the graphical evidence. Table 3 shows the difference-in-difference estimates of the effect of CBG on asthma. Panel A shows estimates based on the binary near indicator and Panel B shows estimates based on the continuous measure, τ .¹⁸ Columns (1)–(7) present the zip code level estimates. Column (1) includes zip code fixed effects and a dummy indicating the post-policy period. Columns (2)–(7) weight the regression results by zip code child population to give greater weight to the more precisely estimated zip codes. Column (3) includes year dummies to account for any widespread yearly shocks to asthma affecting all zip codes.

One might be concerned that near zip codes are more likely urban and that differential changes in urban centers throughout this period may differentially impact health. To address this concern, column (4) includes Core Based Statistical Area (CBSA)-year specific dummies to control flexibly for differential trends or shocks in each CBSA. In addition, column (5) includes zip code specific linear time trends to account for any differential long-run changes that occur over time for each zip code. Finally, column (6) 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 statistically significant reduction of about 4 – 4.5 asthma hospitalizations per 10,000 children following CBG implementation, which is about 8 percent from the pre-policy near level.

The last two columns show individual level estimates based on the equation 3. The linear probability model estimate in Column (7) suggests CBG reduced the probability of asthma

¹⁸The appendix shows a non-parametric specification based on binned values of τ .

hospitalization by about 0.8 percentage points, or 3 percent from pre-policy treatment levels. Not only did CBG reduce the probability of an asthma hospitalization, but it decreased the severity of hospitalizations, as proxied by length of stay. The final column estimates a Poisson model where the outcome variable is length of stay per hospital visit, measured in days. The coefficient implies that hospital stay duration declined significantly, by about 6 percent.¹⁹

4.3 Wind Direction

In this analysis I incorporate information on wind direction to estimate the impact of CBG in downwind, crosswind, and upwind zip codes. Figure 7 shows the smoothed relationship between asthma and the percent of the population living near the highway, τ , by year for downwind and upwind zip codes, separately. Clearly, for downwind zip codes, there is a strong positive relationship between asthma and the percent of the population living near a highway. Asthma rates are especially high for downwind zip codes where over 80 percent of the population lives near a highway. For upwind zip codes, there is an almost flat relationship between asthma rates and percent of the population near the highway. As one might expect, this suggests that living near the highway in a downwind zip code is much more detrimental to health than upwind.

Figure 8 focuses on downwind zip codes. The left panel shows the yearly means for near and far zip codes. As before, there is a level difference between the two groups, with asthma hospitalizations higher in the near group. After the policy, the level of asthma in the near group becomes more similar to that of the far group. The right panel plots the difference between treatment and control groups by year for downwind zip codes. Compared to the full sample in Figure 6, the downwind sample in Figure 8 shows an even more distinct drop in asthma at the time of the policy and continues in a downward trend.

Regression results support this graphical evidence. Table 4 estimates equations 4 and 5 for pollution and asthma, respectively. Column (1) presents the reduced form results for asthma admissions. Both downwind and crosswind zip codes show a statistically significant decline after the policy, while the decrease in asthma in upwind zip codes is not different from zero. However, measurement error in the construction of wind measures prevents any statistical distinction between these three coefficients, as can be seen in the coefficient equality tests.²⁰ However, a test of the joint significance of the downwind and crosswind coefficients shows they are statistically larger than the upwind coefficient. In addition, point estimates and graphical evidence indicate large asthma declines in downwind and crosswind zip codes.

Columns (2)–(4) show the first stage results on pollution. For each pollutant, there is a significant decline for downwind, crosswind, and upwind zip codes. As before, these coefficients are generally not statistically different from one another due to measurement error in both the interpolation of pollution and wind. However, a test of the joint significance of the downwind and crosswind coefficients shows they are statistically larger than the

¹⁹ $100 \times [\exp(-0.0638) - 1] \approx -6.18\%$

²⁰Measurement error arises from the fact that wind is measured with error, from the interpolation of wind direction across space, and from using wind and highway direction angles with reference to the zip code centroid rather than at all points within the zip code and with reference to the nearest highway point rather than all points along nearby highways.

upwind coefficient, and point estimates for CO and NO_2 are largest for the downwind and crosswind zip codes, as expected.

4.4 Traffic

In addition to distance from a highways, highway traffic density might also cause a differential impact on asthma rates. Figure 9 shows the smoothed relationship between the percent of the population living near the highway and asthma by year for zip codes with high and low traffic, separately. The positive relationship between the percent of the population living near the highway and asthma is stronger for high traffic zip codes. Especially for values of τ above 80 percent, the level of asthma is much higher in high traffic zip codes. For high traffic zip codes, there is a drop in asthma after the policy across almost all levels of τ . Whereas, low traffic zip codes exhibit a decline in the gradient that leads to lower asthma for only zip codes with a large percent of the population living near highways. As one might expect, it seems that CBG caused a reduction in asthma for almost all high traffic zip codes, regardless of the percent of the population living close to the highway. On the other hand, for low traffic zip codes, CBG was only effective in reducing asthma in high τ zip codes.

Figure 10 plots the difference in asthma rates for each of the three treated groups relative to the control group, “Far & Low Traffic” zip codes. Across all three treatment groups, there was a sharp initial drop in relative asthma rates which continued on a new downward path after CBG.

Table 5 shows regression results from the estimating equations 6 and 7. Reduced form results on asthma show large significant reductions across all three treatment groups relative to the “Far & Low Traffic” group. The point estimate is highest for the “Close & High Traffic” group, followed by the “Close & Low Traffic” group, but a test of equality shows that these point estimates are not statistically different. Only the point estimate for the “Close & High Traffic” group is significantly larger at the 10 percent level from the “Far & High Traffic” group. Unlike asthma that depends both on residential location and traffic, the pollution results reveal that pollution depends most strongly on traffic. Focusing on CO and NO_2 , the decrease in pollution is much larger for both high traffic groups. While pollution declined most in high traffic zip codes, significant asthma declines occurred for high traffic zip codes, as well as low traffic zip codes where many residents live very near to a highway.

4.5 Exposure Intensity Index

Finally, I combine all three measures of exposure intensity into an index. The index is an equally weighted sum of the three binary treatment groups, *Near*, *Downwind*, and *HighTraffic*, and is scaled to be between 1 and 0. Panel A of Table 6 shows the results using this index. The coefficients on both asthma admissions and pollution are negative and statistically significant, indicating that effects of CBG are largest for zip codes with high exposure intensity to highway pollution. Panel B estimates the effect of being in one, two, or all three treatment groups, relative to the control group of zip codes. As expected, there is a monotonic relationship between the intensity of exposure and the reduction in asthma admissions after CBG. Although all three treatment groups are statistically significant relative to the control group, it is not possible to statistically distinguish between these three

intensity levels for asthma. For pollution, the two highest exposure levels are statistically significantly larger than the first level of exposure intensity, but it is generally difficult to distinguish between these two highest levels of exposure intensity.

Figure 11 shows the difference in asthma rates for each of the three groups of exposure intensity relative to the control group. All three intensity groups are fairly stable prior to the policy and show both an immediate drop and a break in trend at the time of the policy.

4.6 Cumulative Effects

The following cohort analysis explores the possible cumulative impact of the pollution reduction from the CBG policy. First, Exp is defined as the number of years each cohort has been exposed to CBG.²¹ Table 7 shows results from the estimation of the following equations.

$$Asthma_{zat} = \alpha_0 + \alpha_1 \tau^* Exp_{zat} + E + A + Z + \Theta + \varepsilon_{10zat} \quad (10)$$

$$Asthma_{zat} = \pi_0 + \sum_{i=1}^4 [\pi_i \tau^* 1\{Exp=i\}_{zat}] + E + A + Z + \Theta + \varepsilon_{11zat} \quad (11)$$

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, age group dummies, A , cohort exposure dummies, E , and year dummies, Θ . If there is a cumulative impact of CBG, one would expect to see that years of exposure to CBG is negatively related to asthma for zip codes with high τ values. Column (1) of Table 7 shows that this is the case. Column (2) shows that as the years of exposure increase, the negative coefficient becomes monotonically larger in magnitude and more significant. These results suggest that there is indeed a cumulative impact of the policy.²²

5 Confounders, Robustness & Measurement Error

5.1 Potential confounding policies

It is important to consider the impact of several other policies which occurred during our sample period. First, one might be concerned that trading markets for SO_2 and NO_x were responsible for the decrease in pollution shown previously. Title IV of the 1990 Clean Air Act (CAA) Amendments established the SO_2 emissions allowance trading program for electric generating units. The first phase began in 1995, but virtually all of the affected electricity-generating facilities were located east of the Mississippi River, suggesting that

²¹ $Exp = \min(\max(year - 1996, 0), age)$. Data on population estimates by zip code for the 1990 census are limited to age groups, rather than individual years. I conduct the analysis at the age group-year-zip code level, using the following groups: under 1, 1–2, 3–4, 5, 6, and 7–9 years old. There is some inherent measurement error in 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.

²² The cumulative effect is qualitatively similar when estimated at the individual level using data linked across time by the confidential patient record linkage number.

facilities in California were likely unaffected (Burtraw and Szambelan, 2009). The CAA Amendments also addressed the problem of acid rain by regulating NO_x emissions from coal-fired electric generators. In California, the South Coast Air Quality Management District was the first to start a large urban cap-and-trade program for NO_x in 1994, known as Regional Clean Air Incentives Market (RECLAIM). One might be concerned that this cap-and-trade program caused a general downward trend in pollution in areas near highways that was unrelated to CBG if coal-fired electric generator plants were more likely to locate near highways as well. However, there were few real emissions reductions, low allowance prices, and little trading in the early years of the program (Klier, Mattoon and Prager, 1997). Meaningful trades in the NO_x market did not begin to take place until the beginning of 2000, after my sample period (Burtraw and Szambelan, 2009).

Second, federal reformulated gasoline (RFG) was required in certain parts of California in 1995, one year prior to the implementation of CBG. However, existing evidence in Auffhammer and Kellogg (2011) suggests that RFG had little impact on pollution, as opposed to the stricter CBG regulations. Results in Appendix D confirm that RFG also had little impact on asthma and that the results presented above are driven by the introduction of CBG.

Third, there were some changes to Medicaid plans and eligibility during this period. County-level mandates required most Medicaid recipients to enroll in a managed care plan. The staggered rollout of these mandates led to a steady increase in the share of managed care enrollment throughout the sample period in California. Importantly, Duggan (2004) finds no impact on infant health from the shift to managed care. Given the lack of significant changes in health and the staggered implementation of mandates, it is unlikely that the increase in managed care enrollment is driving the health effects found here. In addition, as a result of changes to welfare and Medicaid eligibility rules from the passage of the Personal Responsibility and Work Opportunity Reconciliation Act in 1996 (PRWORA), monthly Medicaid enrollment declined 12 percent in California from 1995 to 1998 (Ellwood et al., 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 than hospital admissions. A reduction in access to asthma control medications would likely increase the number of hospitalizations for asthma. Therefore, if anything, the results here will be understated.

5.2 Pollution Robustness

Table 8 tests the robustness of the 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 and negative for NO_2 and CO , but the estimate for the percent of bad SO_2 days becomes positive and significant. This is not surprising given the graphical results shown previously for SO_2

and the fact that there are only half as many monitors recording SO_2 as the other criteria pollutants.

Due to the method of inverse distance weighted interpolation of pollution measures for each zip code, measurement error is an inherent problem for these results. In order to address this concern, I present specifications where measurement error should be diminished. First, measurement error should be smaller when there are more nearby pollution monitors from which to interpolate the zip code level of pollution. Column (3) weights the results by the number of air quality monitors used in the calculation of pollution for each zip code. Second, measurement error should be smaller if the pollution monitor is located very close to the zip code centroid. Column (4) weights the results by the inverse of the average air quality monitor distance to the centroid. Finally, measurement error should be smaller when more pollution monitors are used in the pollution interpolation. Column (5) limits the sample to zip codes with pollution levels calculated from at least 3 nearby monitors. The results remain significant and of similar magnitude to the baseline results.

5.3 Asthma Robustness

The reduced-form asthma results are robust to alternate specifications, as seen in columns (2)–(6) of Table 9. 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 distances smaller than 1km may be more relevant, such as 300m. Results based on the percent of residents living within 300m of a highway, shown in column (2), are significant and similar in magnitude to the baseline. This gives confidence that the results are not driven by the cutoff choice for pollution dispersion from a highway.

Another concern is that the inclusion of rural zip codes with large areas and few residents may bias the results and introduce unnecessary measurement error. Column (3) 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. Therefore, it seems that the results are not driven by the inclusion of these large zip codes. Though it is not necessary for the control group to look identical to the treated group, using control zip codes that are more similar to treated zip codes may help reduce any concern that the results are driven by differential changes over time between these groups. Column (4) uses only control zip codes that share a border with a treated zip code, and the results remain significant.

Both asthma and traffic pollution levels are influenced by weather conditions. In order to control for any differential changes in weather that may be driving the results, Column (5) shows the coefficient remains of similar magnitude even after adding zip code-year specific weather variables, including minimum and maximum temperatures, wind speed, absolute humidity, and precipitation.²³

²³Weather data are obtained from the National Climatic Data Center's (NCDC) Global Summary of the Day files. Daily absolute humidity was calculated from daily dew point and temperature, following standard meteorologic formulas (Parish and Putnam, 1977). Zip code specific weather measures were calculated using the same inverse distance weighting methodology as the pollution measures.

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 (6) 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 asthma.

In the final column, I perform a placebo test. 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 CBG on hospital admissions for “injuries, poisonings and toxic effects of drugs” and “burns” (Major Diagnosis Categories 21 & 22). One would not expect to find a significant effect of CBG legislation on the admissions 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 estimate is insignificant and the confidence interval does not overlap with the baseline results, which provides greater confidence that the decrease in asthma hospitalizations is a result of CBG rather than an overall trend across all hospitalizations.

Finally, 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 spatial autocorrelation, 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 (see Appendix C). This suggests that a spatial model would not be appropriate for this process.

6 Economic Impact

Gasoline content regulations are associated with numerous costs, including compliance costs, enforcement costs and increased prices for consumers. On the other hand, the main findings in this paper indicate that gasoline content regulation can also improve health outcomes, leading to a reduction in costly medical expenditures. Given the health benefit estimates shown previously, one can make a back-of-the-envelope calculation of the costs and benefits from the CBG legislation.

Auffhammer and Kellogg (2011) suggest a compliance cost of about 8–11 cents per gallon for refineries.²⁴ Data from the U.S. Department of Transportation estimates that gasoline consumption in California in 2006 was 15.8 billion gallons, which implies a yearly cost of about \$1.2–\$1.7 billion.

²⁴Interestingly, 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.

I estimate that CBG reduced asthma hospitalizations by about 4 per 10,000 children in areas near highways. According to these estimates, CBG reduced childhood asthma hospitalizations by about 1,449 in California in 2006 alone. Hospital expenditures accounted for over half of all expenditures for asthma. In fact, Stranges, Merrill and Steiner (2008) estimates that asthma hospitalizations cost about \$9,100 per child in 2006, which means that CBG reduced medical expenditures from asthma hospitalizations by about \$13.2 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, Currie and Neidell (2005) estimate that a 1 ppm decline in CO leads to about 18 fewer deaths per 100,000 births. Given that the EPA's official value of a statistical life is \$6.45 million, the estimated 0.1 ppm reduction in CO from CBG saved \$68.3 million in 2006.

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 data on the total number and average cost of CVD admissions in 2006, along with my estimate that CBG decreased CO by about 0.1 ppm, the savings amount to about \$630 million.²⁵

Accounting for the reduced childhood asthma, infant mortality, and CVD, the benefits from CBG are about \$711.6 million per year, which is somewhat smaller than 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 CBG. Other potentially important direct benefits include benefits to the environment, improvements in birth outcomes (low birth weight, prematurity, etc.), reductions in respiratory conditions among adults and the elderly, improvements in quality of life, and reductions in cancer. Indirect benefits would include improvements in school and work attendance, school performance, and labor market productivity (Currie et al., 2009; Ebenstein, Lavy and Roth, 2016; Chang et al., 2016).

7 Conclusion

This paper provides an estimate of the effect of the 1996 cleaner-burning gasoline content regulation on pollution and childhood asthma hospitalizations in California. I exploit variation in residential exposure to highways in order to, first, support existing evidence that CBG reduced air pollution, and second, to show the decline in childhood asthma hospitalizations. As hypothesized, the strict gasoline content regulations caused a greater

²⁵CVD 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).

reduction in childhood asthma hospitalizations in areas close to major highways after the regulations were introduced than in areas further away. CBG regulations reduced childhood asthma admissions by about 8 percent in high exposure areas in California, or by about 4.5 per 10,000 children. These results are robust to numerous alternative specifications.

Exploration of additional sources of exposure intensity indicate that downwind and high traffic zip codes experience the greatest declines in pollution and asthma. Finally, a cohort-level analysis reveals that asthma reductions are larger the longer cohorts have been exposed to cleaner-burning gasoline, suggesting a cumulative impact. Given that low income and non-white children are more likely to live near high traffic highways (Gunier et al., 2003), gasoline content restricts may reduce disparities in asthma-related health outcomes among these groups. 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 Wind

Figure A1. Prevailing Wind Direction

Notes: Average wind directions are calculated for the 79 stations in California recording wind direction during the study period. Using ArcMap 10.1, the prevailing wind direction is interpolated across California using inverse distance weighting.

Figure A2. Prevailing Wind Direction Classifications

Notes: Groups are based on the difference between the angle from which the prevailing wind originates and the angle from the zip code centroid to the nearest highway. Downwind, crosswind, and upwind zip codes are those with an angle difference less than 45, 45 to 135, and over 135 degrees, respectively.

A.2 Highways

Figure A3. U.S. and state highways in California

Notes: 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.

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 A4. Distribution of τ across zip codes

B Neighborhood Characteristics

CBG 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 B1 shows summary statistics from the 1990 and 2000 Censuses for census tracts based on proximity to highway traffic.²⁶ Looking at the average characteristics of tracts far and near highways in 1990 (columns 2 and 3), tracts near the highway are generally more disadvantaged. They 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.

Table B1 also 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.

Table B1

Census tract demographic characteristics (%)

	1990				2000				2000–1990 Difference			Diff-in-diff
	Total (1)	Far (2)	Near (3)	Diff (4)	Total (5)	Far (6)	Near (7)	Diff (8)	Total (9)	Far (10)	Near (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

²⁶The “near” group contains all census tracts with over 99.9 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).

	1990				2000				2000–1990 Difference			Diff-in-diff (12)
	Total (1)	Far (2)	Near (3)	Diff (4)	Total (5)	Far (6)	Near (7)	Diff (8)	Total (9)	Far (10)	Near (11)	
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 11).

***
p<0.01,
**
p<0.05,
*
p<0.1

C Robustness

Table C2

Robustness to variation in treatment definition

	Asthma admissions				
	Median (1)	50% (2)	Tercile (3)	Quartile (4)	%Near (5)
Treat × After	−4.248 *** (1.365)	−3.602 *** (1.289)	−4.468 *** (1.723)	−5.445 *** (2.110)	−7.652 *** (2.461)
% from pre-treat	−8.3	−7.0	−8.7	−10.6	−14.9
Observations	11,787	11,787	7,707	5,740	11,787

	Asthma admissions				
	Median (1)	50% (2)	Tercile (3)	Quartile (4)	%Near (5)
R-squared	0.594	0.593	0.586	0.564	0.594

Notes: The first column is based on treated (control) zip codes with at least (less than) the median percentage (42.5 percent) of τ . Column 2 is based on treated (control) zip codes with at least (less than) 50 percent of τ . Column 3 is based on treated (control) zip codes that are in the highest (lowest) tercile of τ . Column 4 is based on treated (control) zip codes that are in the highest (lowest) quartile of τ . All regressions include zip code fixed effects and year dummies. Standard errors clustered at the zip code level are in parentheses.

***
p<0.01,
**
p<0.05,
*
p<0.1

Table C3

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, which defines a zip code's neighbors as those with either a shared border or vertex.

C.1 Non-parametric results

$$\text{Asthma}_{zy} = B_0 + \sum_{x=2}^{10} [B_x \text{After}^* \tau_x] + Z_z + \Theta_y + \varepsilon_{11zy} \quad (12)$$

where τ_x is a set of indicators for each 10 percentage point range of τ .

Figure C5. Non-parametric results

Notes: Coefficients and 90% confidence intervals are shown for each of the $After^* \tau_x$ variables from equation 12. The largest and most significant declines in asthma occur in zip codes with the largest portion of the population living within 1km from a highway, as expected.

C.2 Pollution Interpolation: Kriging

Table C4

First stage: interpolation by Kriging

	Average					
				Weight: inverse prediction error		
	NO2 (1)	CO (2)	SO2 (3)	NO2 (4)	CO (5)	SO2 (6)
<i>Panel A.</i>						
Near $\times$ After	-0.750 *** (0.141)	-0.098 *** (0.0101)	-0.228 *** (0.0431)	-0.546 *** (0.150)	-0.094 *** (0.0109)	-0.204 *** (0.0374)
<i>Panel B.</i>						
%Near $\times$ After	-1.381 *** (0.244)	-0.195 *** (0.0182)	-0.532 *** (0.0801)	-0.977 *** (0.258)	-0.188 *** (0.0195)	-0.450 *** (0.0677)

	Average					
				Weight: inverse prediction error		
	NO2 (1)	CO (2)	SO2 (3)	NO2 (4)	CO (5)	SO2 (6)
Observations	13,434	13,471	10,610	13,434	13,471	10,610
R-squared	0.980	0.971	0.716	0.979	0.969	0.740

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. All regressions include zip code fixed effects and year dummies. Standard errors clustered at the zip code level are in parentheses.

***
p<0.01,
**
p<0.05,
*
p<0.1

D Potential Confounders

D.1 RFG

As part of the Clean Air Act Amendment of 1990, the federal government 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 CBG 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 CBG 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 California's CBG. Table D5 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 CBG in 1996. Even though the sample size is smaller, the results remain significant, which provides some confidence that CBG 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 CBG difference-in-difference estimator in column (5), the CBG estimator is strongly significant and the RFG estimator is insignificant. This supports the claim that the more stringent CBG regulations had a strong impact on asthma hospitalizations and this impact was not driven by federal RFG gasoline.

D.2 PRWORA

The Personal Responsibility and Work Opportunity Reconciliation Act was passed 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 required 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).

Table D5

Control for Federal RFG gasoline regulation in 1995

	Asthma admissions				
	Baseline (1)	Non-RFG (2)	(3)	(4)	(5)
Near × After96	-4.248 *** (1.365)	-4.419 ** (2.097)			-4.422 *** (1.498)
RFG × After95			-0.0377 (1.520)		
Near_RFG × After95				-2.184 (1.423)	0.376 (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

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 since they are likely to be of lower SES. However, in Table D6 we see a decline in asthma for private insurance patients in treatment zip codes following CBG 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 (column 5), and using the sample of asthma patients whose visit was unscheduled (column 6).

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 D6, 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 D7 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 CBG. 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 D6. 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 stabilizers, methylxanthines, and short-acting inhaled beta-2 agonists.

Table D6

Insurance type, ER, and unscheduled hospitalizations

	Insurance Type					
	Medicare or Medi-Cal (1)	Private (2)	Self-Pay (3)	Other (4)	ER (5)	Unscheduled (6)
<i>Panel A.</i>						
Near × After	−3.748 *** (1.122)	−2.300 *** (0.743)	0.480 * (0.267)	−0.185 (0.204)	−3.163 *** (1.113)	−5.292 *** (1.407)
% from pre-treat	−9.6	−9.5	19.8	−16.4	−8.4	−9.8
% in gap	−52.12	−36.4	−95.8	−70.3	−35.4	−46.4
% of std dev	−9.0	−15.1	11.1	−4.8	−9.8	−12.9

Panel B.

	Insurance Type					
	Medicare or Medi-Cal (1)	Private (2)	Self-Pay (3)	Other (4)	ER (5)	Unscheduled (6)
%Near × After	-8.104 *** (2.043)	-3.496 *** (1.278)	1.113 ** (0.478)	-0.422 (0.370)	-5.641 *** (2.119)	-10.05 *** (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.

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p<0.01,

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p<0.05,

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p<0.1

Figure D7. 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 stabilizers, and methylxanthines.

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Figure 1. Near and far zip codes

Notes: Near (far) 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. There is also a wide distribution of τ values across zip codes (see Appendix A).

Figure 2. Air quality monitors

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.

Figure 3. Percent bad pollution days over time

Notes: The left panels show the average percent of bad pollution days per month for the near and far groups, separately. Bad pollution days have pollution levels greater than 75% of the EPA standard. The right panels plot the difference in the average percent of bad pollution days per month between near and far groups.

Figure 4. Average pollution over time

Notes: The left panels show the average pollution for the near and far groups, separately. The right panels plot the difference in the average pollution between near and far groups.

Figure 5. Asthma hospitalizations by exposure to pollution

Notes: Figure shows the smoothed relationship between childhood asthma admissions 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 show local mean smoothing using “lpoly,” with degree zero and a 0.07 bandwidth.

Figure 6. Mean asthma hospitalizations over time

Notes: The left panel shows raw mean childhood asthma admissions by year for the groups separately. The right panel plots the difference in the asthma admissions level between near and far groups.

Figure 7. Asthma Admissions Gradient Over Time: Upwind vs. Downwind

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. Downwind (upwind) zip codes are defined as zip codes where the difference between the wind source angle and the angle from the zip code centroid to the nearest highway is less than 45 degrees (greater than 135 degrees).

Figure 8. Mean Asthma Admissions Over Time: Downwind

Notes: Sample is limited to downwind zip codes, where the difference between the wind source angle and the angle from the zip code centroid to the nearest highway is less than 45 degrees. The left panel shows raw mean childhood asthma hospitalizations by year for the near and far groups, separately. The right panel plots the difference in the average yearly asthma hospitalization level between near and far groups.

Figure 9. Asthma hospitalizations by exposure and traffic density

Notes: 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 “lpoly,” with degree zero and a 0.1 bandwidth. High (low) traffic zip codes zip codes with an average AADT of at least (less than) 60,000 vehicles per day.

Figure 10. Relative difference in asthma admissions by distance to highways and traffic
 Notes: Plots the difference in the average yearly asthma hospitalization level between each possible treatment group and control zip codes (“Far-Low”). High (low) traffic zip codes are zip codes with an average AADT of at least (less than) 60,000 vehicles per day. Close (far) zip codes have greater than (less than or equal to) the median value of τ .

Figure 11. Relative difference in asthma by exposure intensity

Notes: Plots the difference in asthma admissions between each possible exposure intensity level and control zip codes, which are neither *Near*, *Downwind*, nor *HighTraffic*. The T1, T2, and T3 groups include zip codes in 1, 2, or all 3 of the exposure intensity groups.

Table 1

Summary statistics

	Far	Near	Total
Asthma Admissions	43.38 (44.06)	52.42 (38.53)	48.26 (41.41)
NO2			
Average (ppb)	39.14 (16.17)	43.06 (16.78)	41.64 (16.67)
% Bad Days	6.424 (12.85)	8.835 (14.57)	7.961 (14.02)
CO			
Average (ppm)	1.362 (0.890)	1.620 (0.965)	1.524 (0.946)
% Bad Days	0.227 (2.034)	0.402 (2.737)	0.337 (2.500)
SO2			
Average (ppb)	4.686 (2.998)	5.232 (3.172)	5.053 (3.126)
% Bad Days	0.0393 (0.443)	0.0594 (0.646)	0.0528 (0.587)
τ	0.210 (0.119)	0.699 (0.179)	0.456 (0.288)
Upwind	0.236 (0.425)	0.222 (0.416)	0.229 (0.420)
Crosswind	0.500 (0.500)	0.518 (0.500)	0.509 (0.500)
Downwind	0.264 (0.441)	0.260 (0.439)	0.262 (0.440)
Average AADT Traffic	49912.3 (68244.6)	101333.8 (74903.8)	75870.9 (76152.4)

Notes: Table presents means and standard deviations for key variables in far zip codes, near zip codes, and the full sample. Near (Far) 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 (τ). Asthma Hospitalizations are per 10,000 children. NO2 and SO2 are measured as the mean daily maximum 1-hour concentration. CO is measured as the mean daily maximum 8-hour concentration, following EPA standards. Downwind, crosswind, and upwind are equal to one for zip codes with an absolute value angle difference between prevailing wind origin and angle to the nearest highway of less than 45, 45 to 135, and over 135 degrees, respectively, as described in section 3.

Table 2

First stage: difference-in-difference estimates

	Average			% Bad Days		
	NO2 (1)	CO (2)	SO2 (3)	NO2 (4)	CO (5)	SO2 (6)
<i>Panel A.</i>						
Near × After	-0.912 *** (0.160)	-0.104 *** (0.0101)	-0.591 *** (0.0834)	-1.677 *** (0.283)	-0.392 *** (0.0636)	-0.0262 *** (0.00777)
% from pre-treat	-2.0	-5.5	-10.6	-14.3	-50.6	-30.7
% in gap	-21.4	-35.8	-72.1	-54.3	-118.2	-74.4
% of std dev	-5.0	-9.9	-16.0	-9.9	-10.1	-3.1
<i>Panel B.</i>						
% Near × After	-1.605 *** (0.247)	-0.214 *** (0.0157)	-1.200 *** (0.126)	-3.245 *** (0.447)	-0.876 *** (0.118)	-0.0623 *** (0.0127)
Observations	112,055	114,387	73,625	112,055	114,387	73,625
R-squared	0.797	0.734	0.522	0.541	0.124	0.047

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. Columns 1–3 estimate the impact on average pollution levels and columns 4–6 estimate the impact on the percent of days that have pollution levels greater than 75% of the EPA threshold levels. Estimates are based on a consistently observed set of monitors, as defined in section 3. All specifications include zip code fixed effects, year dummies, and quarter dummies. Standard errors clustered at the zip code level are in parentheses.

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p<0.01,

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p<0.05,

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p<0.1

Table 3

Reduced-form impact on asthma hospitalizations

	Zip code level analysis					Individual level analysis		
	Asthma (1)	Asthma (2)	Asthma (3)	Asthma (4)	Asthma (5)	Asthma (6)	Asthma (binary) (7)	Length of Stay (8)
<i>Panel A.</i>								
Near × After	−4.074 *** (1.312)	−4.514 *** (1.156)	−4.505 *** (1.157)	−4.113 *** (1.206)	−4.020 *** (0.919)	−4.587 *** (1.438)	−0.00807 *** (0.00252)	−0.0638 *** (0.00740)
% from pre-treat	−7.21	−7.99	−7.97	−7.28	−7.11	−6.70	−3.2	
% in gap	−35.3	−39.1	−39.0	−35.6	−34.8	−51.4	−82.3	
% of std dev	−9.78	−10.8	−10.8	−9.88	−9.65	−9.30	−1.8	
<i>Panel B.</i>								
%Near × After	−7.603 *** (2.351)	−7.889 *** (2.071)	−7.865 *** (2.071)	−6.913 *** (2.267)	−6.192 *** (1.311)	−7.711 *** (2.560)	−0.0133 *** (0.00490)	−0.0923 *** (0.0142)
Observations	11,568	11,568	11,568	11,568	11,568	10,449	600,858	509,888
R-squared	0.615	0.808	0.823	0.843	0.854	0.811	0.227	-
Individual FE	-	-	-	-	-	-	yes	yes
Zip Code FE	yes	yes	yes	yes	yes	yes	-	-
Pop Weights	no	yes	yes	yes	yes	yes	-	-
Year dummies	no	no	yes	no	no	yes	yes	yes
CBSA-year dummies	no	no	no	yes	no	no	-	-
Zip trends	no	no	no	no	yes	no	-	-
Age-adjusted	no	no	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 1–6 is the number of childhood asthma admissions per 10,000 children, as defined in section 3. Column 4 includes CBSA-year dummies and column 5 includes zip code specific linear trends. Column 7 is a Linear Probability Model where the outcome is a binary variable equal to one if an individual was admitted to the hospital for asthma in each year. Column 8 is a Poisson model where the outcome variable is the length of stay per visit in days. Columns 7–8 are restricted to non-movers between 0 and 18 years old and are weighted by the number years observed per person. Standard errors are clustered at the zip code level for columns 1–6 and at the individual level for columns 7–8.

*** p<0.01,

** p<0.05,

* p<0.1

Wind Direction Results

Table 4

	Average				% Bad Days		
	Asthma (1)	NO2 (2)	CO (3)	SO2 (4)	NO2 (5)	CO (6)	SO2 (7)
Near × After × Down	-5.773 ** (2.579)	-0.873 *** (0.303)	-0.113 *** (0.0200)	-0.683 *** (0.165)	-1.773 *** (0.532)	-0.573 *** (0.129)	-0.0396 ** (0.0167)
Near × After × Cross	-4.866 *** (1.437)	-1.094 *** (0.225)	-0.109 *** (0.0145)	-0.667 *** (0.114)	-1.995 *** (0.401)	-0.400 *** (0.0955)	-0.0257 *** (0.00693)
Near × After × Up	-2.401 (2.720)	-0.679 ** (0.312)	-0.0922 *** (0.0189)	-0.350 ** (0.171)	-1.122 *** (0.553)	-0.232 ** (0.109)	-0.0127 (0.0236)
Equality tests:							
Near × After × Down = Near × After × Up	0.369	0.654	0.453	0.160	0.395	0.0457	0.351
Near × After × Down = Near × After × Cross	0.759	0.556	0.860	0.939	0.739	0.287	0.439
Near × After × Up = Near × After × Cross	0.423	0.278	0.493	0.122	0.200	0.249	0.597
Observations	11,568	112,055	114,387	73,625	112,055	114,387	73,625
R-squared	0.823	0.797	0.733	0.522	0.541	0.123	0.048

Notes: The asthma regression includes zip code fixed effects, year dummies, downwind-year dummies and upwind-year dummies and is weighted by zip code population. The pollution regressions include zip code fixed effects, year dummies, downwind-year dummies, upwind-year dummies, and quarter dummies. Standard errors clustered at the zip code level are in parentheses.

***
p<0.01,

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p<0.05,

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p<0.1

Traffic results

Table 5

	Asthma (1)	Average				% Bad Days			
		NO ₂ (2)	CO (3)	SO ₂ (4)	NO ₂ (5)	CO (6)	SO ₂ (7)		
Near × After × High	-7.399 *** (1.441)	-2.001 *** (0.179)	-0.205 *** (0.0110)	-0.592 *** (0.0982)	-3.785 *** (0.311)	-0.622 *** (0.0757)	-0.0295 *** (0.00921)		
Near × After × Low	-6.401 *** (1.785)	-0.318 (0.226)	-0.0619 *** (0.0161)	-0.636 *** (0.136)	-0.494 (0.346)	-0.187 ** (0.0835)	-0.0268 ** (0.0106)		
Far × After × High	-4.545 *** (1.728)	-1.699 *** (0.228)	-0.180 *** (0.0134)	-0.0726 (0.123)	-3.102 *** (0.407)	-0.347 *** (0.0871)	0.00233 (0.00934)		
<i>Equality tests:</i>									
Near × After × High = Near × After × Low	0.5175	0.000	0.000	0.000	0.000	0.000	0.000		
Near × After × High = Far × After × High	0.0531	0.181	0.037	0.000	0.109	0.004	0.002		
Near × After × Low = Far × After × High	0.3061	0.000	0.000	0.000	0.000	0.119	0.010		
Observations	11,856	116,907	119,632	76,524	116,907	119,632	76,524		
R-squared	0.823	0.798	0.736	0.516	0.544	0.123	0.046		

Notes: Reference group includes zip codes with low traffic and far from highways. The asthma regression includes zip code fixed effects and year dummies, and is weighted by zip code population. The pollution regressions include zip code fixed effects, year dummies, and quarter dummies. Standard errors clustered at the zip code level are in parentheses.

***
p<0.01,

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p<0.05,

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p<0.1

Table 6

Index of exposure intensity

	Average				% Bad Days		
	Asthma (1)	NO2 (2)	CO (3)	SO2 (4)	NO2 (5)	CO (6)	SO2 (7)
Panel A.							
Index $\times$ After	-7.425*** (1.944)	-2.297*** (0.253)	-0.280*** (0.0150)	-0.826*** (0.136)	-4.323*** (0.436)	-0.846*** (0.108)	-0.0329** (0.0149)
Panel B.							
Index1 $\times$ After	-6.557*** (1.930)	-1.208*** (0.213)	-0.151*** (0.0140)	-0.426*** (0.127)	-2.064*** (0.330)	-0.363*** (0.0717)	0.00747 (0.0106)
Index2 $\times$ After	-8.022*** (1.903)	-2.177*** (0.204)	-0.239*** (0.0125)	-0.608*** (0.115)	-3.949*** (0.326)	-0.651*** (0.0764)	-0.00632 (0.0109)
Index3 $\times$ After	-9.099*** (2.267)	-1.901*** (0.291)	-0.251*** (0.0171)	-0.882*** (0.154)	-3.561*** (0.521)	-0.806*** (0.141)	-0.0357* (0.0190)
Equality Tests:							
Index1 = Index2	0.251	0.000	0.000	0.072	0.000	0.000	0.132
Index1 = Index3	0.152	0.015	0.000	0.002	0.005	0.002	0.019
Index2 = Index3	0.537	0.316	0.424	0.039	0.464	0.277	0.118
Observations	11,151	108,189	110,308	71,256	108,189	110,308	71,256
R-squared	0.822	0.798	0.734	0.522	0.544	0.123	0.048

Notes: The asthma regression includes zip code fixed effects, year dummies, and is weighted by zip code population. The pollution regressions include zip code fixed effects, year dummies, and quarter dummies. Standard errors clustered at the zip code level.

***
p<0.01,

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p<0.05,

*
p<0.1

Table 7

Cumulative effects by exposure to CBG

	Asthma Admissions	
	(1)	(2)
$\tau \times Exp$	-2.974 ** (1.389)	
$\tau \times 1\{Exp = 1\}$		-2.327 (7.426)
$\tau \times 1\{Exp = 2\}$		-5.327 (4.229)
$\tau \times 1\{Exp = 3\}$		-9.734 ** (4.545)
$\tau \times 1\{Exp = 4\}$		-11.72 ** (4.609)
Observations	68,517	68,517
R-squared	0.684	0.684

Notes: *Exp* cohort level years of exposure to CBG. τ is the percent of the zip code population within 1km of a highway. Regressions include year, age and exposure dummies, zip code fixed effects, and are weighted by zip code-cohort population. Standard errors are clustered at the zip code level.

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p<0.01,

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p<0.05,

*
p<0.1

Table 8

Pollution robustness

	Baseline (1)	Zip time trends (2)	Weight: # Mon. (3)	Weight: Mon. dist. (4)	3 Mon. (5)
NO2					
Average	-0.912 *** (0.160)	-1.641 *** (0.140)	-1.046 *** (0.199)	-0.680 *** (0.174)	-0.723 *** (0.206)
% Bad Days	-1.677 *** (0.283)	-2.413 *** (0.236)	-1.838 *** (0.360)	-1.388 *** (0.294)	-1.331 *** (0.389)
CO					
Average	-0.104 *** (0.0101)	-0.166 *** (0.00740)	-0.107 *** (0.0121)	-0.0988 *** (0.0145)	-0.0776 *** (0.0102)
% Bad Days	-0.392 *** (0.0636)	-0.590 *** (0.0588)	-0.549 *** (0.115)	-0.342 *** (0.0623)	-0.417 *** (0.0943)
SO2					
Average	-0.591 *** (0.0834)	-0.228 *** (0.0764)	-0.502 *** (0.0802)	-0.554 *** (0.0955)	-0.305 *** (0.0815)
% Bad Days	-0.0262 *** (0.00777)	0.0225 ** (0.00963)	-0.0277 *** (0.00747)	-0.0255 *** (0.00717)	-0.0317 *** (0.0103)

Notes: Coefficients on the *Near* $\times$ *After* variable are shown from separate regressions of equation 1. Regressions include zip code fixed effects, year dummies, and quarter dummies. Column 2 includes zip code specific linear time trends. Column 3 weights the estimates by the number of monitors within 20 miles. Column 4 weights the estimates by the inverse of the average monitor distance. Column 5 limits the analysis to zip codes with at least 3 monitors within 20 miles. Standard errors clustered at the zip code level are in parentheses.

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p<0.01,
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p<0.05,
*
p<0.1

Table 9

Asthma admissions robustness

	Robustness Tests						Placebo Test
	Baseline (1)	300m cutoff (2)	Drop large zip codes (3)	Control borders treat (4)	Weather controls (5)	Tobit (6)	Injuries & burns (7)
<i>Panel A.</i>							
Near × After	−4.505 ^{***} (1.157)	−3.650 ^{***} (1.188)	−3.972 ^{***} (1.217)	−4.238 ^{***} (1.193)	−3.547 ^{***} (1.248)	−4.461 ^{***} (1.098)	−0.0686 (0.627)
<i>Panel B.</i>							
% Near × After	−7.865 ^{***} (2.071)	−11.07 ^{***} (4.156)	−6.786 ^{***} (2.125)	−7.484 ^{***} (2.115)	−6.145 ^{***} (2.152)	−7.843 ^{***} (1.965)	−0.814 (1.161)
Observations	11,568	11,160	10,354	10,535	9,153	11,568	10,865
R-squared	0.823	0.824	0.827	0.827	0.829		0.465
Zip Code FE	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes
Clustered SE	yes	yes	yes	yes	yes	-	yes
Pop weights	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 excludes the 10 percent of zip codes with the largest areas. Column 4 drops control zip codes that do not share a border with a treated zip code. Column 5 includes zip code-year specific controls for minimum and maximum temperature, wind speed, absolute humidity, and precipitation. Column 6 presents average partial effects from a Tobit model, censored at zero. Columns 7 presents a placebo test based on hospital admissions for “injuries, poisonings and toxic effects of drugs” and “burns” (Major Diagnosis Categories 21 & 22) per 10,000 children.

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p<0.01,

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p<0.05,

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p<0.1