

Environmental Justice and Climate Policy: Is California's Cap and Trade Failing Disadvantaged Communities?

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Undergraduate Honours Thesis
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Under the direction of
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June 5, 2017

Abstract

Pollution pricing policies offer advantages over traditional environmental regulation in compliance flexibility and cost effectiveness, but introduce more uncertainty over where emissions will occur. Consequently, environmental justice organisations have raised equity concerns about California's flagship cap-and-trade program; greenhouse gas emissions trading could generate increased local concentrations of criteria air pollutants in socioeconomically disadvantaged neighbourhoods. Using U.S. Environmental Protection Agency (EPA) air quality monitoring station data, I use spatial interpolation to construct a census tract-level ten-year panel of concentration for six pollutants. I estimate a difference-in-differences model with fixed effects, and find that cap and trade generally improved relative equity for CO, NO₂, PM2.5, PM10 and SO₂ but worsened it for O₃.

Keywords: environmental justice, cap and trade, equity, criteria pollutants

JEL: Q53, Q54, Q58

*Email address: zcyou@stanford.edu. I thank Thomas Ginn, Liran Einav, and Caroline Hoxby for their suggestions and advice throughout this process. I also thank David Medeiros for his patient guidance with ArcGIS, Jef Caers for geostatistical assistance, Lynn Hildemann for her input on air pollution transport, and Marcelo Clerici-Arias for his tireless direction of the honours program. I am indebted to my friends for their help and encouragement, reminding me that justice is worth working for. Above all, I am deeply grateful for Lawrence Goulder's patience in his combined role as my research advisor, major advisor and thesis advisor; his time, comments and support have been foundational to my growth as an economist.

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1 Introduction

The only reason for thinking that sustainability is a problem is that you think that some people are likely to be shortchanged, namely, in the future. Then I think you really are obligated to ask, "Well, is anybody being shortchanged right now?" (Solow, 1991)

Climate change mitigation policy is often motivated on the grounds of intergenerational equity. We deplete fossil fuel reserves too fast and emit greenhouse gases (GHG) too much since the costs fall most heavily on future generations; a policy intervention can correct for these externalities. Yet the sentiment that Robert Solow expresses above highlights the logical necessity of considering intragenerational as well as intergenerational equity. Imposing a climate policy is not costless, and the present-day distribution of these costs must therefore be accounted for as a trade-off by policy-makers. In a bid at minimising these costs (for a given reduction in greenhouse gas emissions), policy-makers have turned to markets for pollution allowances as a remedy; they are commonly hailed as a more cost-effective means of reducing pollution than prior command-and-control alternatives (Lawrence H. Goulder, 2013). However, achieving this *overall* cost-effectiveness necessitates leaving unspecified where emissions abatement will take place, raising the broad question: How does emissions trading impact the *distribution* of policy costs and benefits?

In this paper, I investigate this question in the context of air pollution costs under California's cap-and-trade program. Though climate policy may impact equity through a number of channels, such as the choice of mitigation technology (Casillas and Kammen, 2012) or tax incidence (Parry et al., 2005; Shammin and Bullard, 2009), one potential channel is via ambient air pollution health impacts. Air pollution has detrimental effects on health with both acute and cumulative exposures, and these translate to reductions in welfare along many economic measures. A large literature has documented that air pollution negatively influences worker productivity (Graff Zivin and Neidell, 2012), lifetime income (Isen, Rossin-

Slater, and Walker, 2017), fetal, infant, and adult mortality (Sanders and Stoecker, 2015; Chay and Greenstone, 2003; World Health Organization, 2016), and education (Currie et al., 2009). Correspondingly, co-benefits due to reductions in air pollution constitute a large proportion of the overall benefits of climate mitigation policies (Burtraw et al., 2003; Bollen et al., 2009). The net economic impact of California’s cap and trade is therefore dependent on the size of ancillary benefits of air pollution reductions.

From an environmental justice standpoint, there are two distinct but related concerns about how cap and trade might affect the distribution of the costs of air pollution exposure and benefits of reductions. There is already significant inequity in air pollution; lower income and racial/ethnic minority populations face higher ambient air pollution concentrations than their higher income and white counterparts (Payne-Sturges and Gee, 2006; Clark, Millet, and Marshall, 2014). Cap and trade might narrow or widen these gaps, so a first question is about *relative equity*: whether neighbourhoods with lower socioeconomic status received more or less pollution thanks to cap and trade compared to higher socioeconomic status communities. In other words, did disadvantaged communities receive more pollution or fewer benefits compared to other communities, meaning that cap and trade reinforced existing inequities? However, since air pollution is already concentrated in disadvantaged communities, a second valid question is about *absolute equity*: whether cap and trade delivered greater reductions in air pollution for these communities compared to some comparison policy, such as a technology mandate. I focus on the first of these questions in this paper.

I choose to study the cap-and trade system in California for two main reasons. Firstly, it is the most comprehensive and ambitious of the established carbon trading systems, covering sectors representing over 85% of California’s greenhouse gas emissions, compared to around half for similar systems in Europe and New England (Schmalensee and R. Stavins, 2015). California’s intended emissions cuts are also deeper and faster than any other similar jurisdiction; cap and trade will bring the state’s GHG emissions down to 1990 levels by 2020, and 40% below 1990 levels by 2030. With California now the world’s sixth-largest economy,

lessons from California’s system are likely to be relevant to systems of similar scale in the future. As one of the founders of the Under2 Coalition, California has expressly taken a lead on developing subnational climate policy; the success of the program is therefore likely to influence considerations for other subnational governments.¹

Secondly, and perhaps more relevantly for this paper, California has had some of the most sustained environmental justice objections to cap and trade. Sze et al. (2009) note that environmental justice groups are uniquely well-organised at the state level in California, contributing to the passage of 20 state laws with environmental justice components by 2009. Environmental justice advocates successfully avoided a legislatively mandated cap-and-trade system (the current program is administratively implemented) and have declared that they will “fight at every turn all efforts to extend the California Cap and Trade system in California beyond 2020” (California Environmental Justice Movement, 2017). These two factors mean that California is a crucial case study for the resolution of tension between effective climate change mitigation and equity concerns.

Existing literature on pollution equity in cap and trade systems has primarily used emissions data, combined with proximity measures or more detailed pollutant transport models, to evaluate equity impacts (examples include Chan et al., 2015; Fowlie, Holland, and Mansur, 2012; Cushing et al., 2016). For a greenhouse gas emissions trading system, this approach is insufficient; many covered entities are not direct emissions sources but have indirect impacts on air pollution. Instead, I construct a new census-tract level dataset on measured ambient pollutant concentrations. Concentration data is a much stronger proxy for pollution exposure than proximity to emissions sources or output of dispersion models in this context, because we are concerned less with how pollution was emitted or transported to a particular location and more with the outcome after the policy. I then employ a difference-in-differences specification to identify the relative equity impact of cap and trade. I find that the program

¹The Under2 Coalition is the group of state, regional and city governments that have signed the Subnational Global Climate Leadership Memorandum of Understanding. This group has made commitments to heavy emissions reductions, either 80% below 1990 levels or 2 tons of CO₂ equivalent per capita, and aims to share ideas for, experiences with, and best practices on implementing policies to achieve this goal.

generally narrowed the pollution disparity between advantaged and disadvantaged neighbourhoods for five of my six study pollutants: carbon monoxide, nitrogen dioxide and PM2.5, PM10, and sulphur dioxide. However, I found that relative equity worsened for ozone. On balance, this is a positive effect, indicating that the "cap effect" of reducing pollution across the board dominates any "trade effect" that could have concentrated pollution in specific locations. These results suggest that relative equity concerns are not in conflict with cap and trade in California, though absolute inequity still persists.

The paper is organised as follows. Section 2 examines more closely the relationship between cap-and-trade and air pollution, presents an overview of the environmental justice debate to date, and summarises related research. Section 3 outlines my data sources and interpolation methods, while Section 4 discusses my empirical methodology. Section 5 presents and discusses my results, and Section 6 concludes.

2 Background and Literature Review

In this section, I first provide background on cap and trade and its suitability for regulating different types of pollutants. Next, I outline the basics of California's cap-and-trade program and the grounds of concerns raised by environmental justice advocates. Finally, I discuss the relevant existing evidence on pollution equity in cap-and-trade systems.

2.1 Pollution and Emissions Markets

Cap and trade is a market-based method of pollution control with three key components (Lawrence H Goulder, 2010). First, a *cap* on emissions is imposed. This cap is the total quantity of emissions allowed in a certain period, and is divided into allowances each representing a unit of pollutant (CO₂-equivalent, in the case of climate policy). Second, the regulator allocates these allowances to polluters; either freely allocated, at auction, or with some combination of both. Finally, a market for the allowances is created, allowing polluters

to *trade* allowances with each other. This last trade component is key to the theoretical cost-effectiveness of cap and trade. Polluters will always have an incentive to reduce emissions if their abatement costs are lower than the allowance price, since they could profit by reducing emissions cheaply and selling the allowances they no longer needed. Similarly, polluters with high abatement costs will purchase allowances rather than reduce emissions expensively. The consequence is that the firms which can cut emissions most cheaply across the entire market are the ones that will end up doing so, minimising the total cost of the policy. However, regulators lose the ability to guarantee emissions reductions at any particular firm or facility.

Moving from theory to practice, evaluations of previous cap-and-trade programs have generally found that they do indeed achieve significant cost reductions compared to counterfactual policies, though the extent to which this occurs depends on aspects of program design. The EPA enacted a trading system for lead in the 1980s, which was not a full cap and trade system but nevertheless featured banking and trading of allowances; Nichols (1997) found that this produced annual savings of over \$200 million. Under the 1990 Clean Air Act Amendments, a trading system for sulphur dioxide (SO_2) at electric utilities was created to deal with acid rain. Carlson et al. (2000) found that in the long run, the program would save more than \$700 million, or around 50% annually compared to command-and-control regulation. The South Coast Air Quality Management District in California created the REgional CLean Air Incentives Market (RECLAIM) in 1994, covering NO_x and SO_2 . Johnson and Pikelney (1996) modeled an average annual cost savings of \$58 million for the 6 years after the policy came into effect. From this and other evidence, Schmalensee and R. Stavins (2015) discuss how a cap-and-trade system that covers all emissions sources, includes linkages with other jurisdictions, allows intertemporal trading (banking allowances for the future or borrowing them for the present), and takes steps to reduce emissions leakage and limit allowance price volatility is likely to be successful. The fact that California's allowance market has all of these features (and many of the above markets did not) is indicative that it will also achieve significant cost savings relative to a suitable command and control coun-

terfactual. This places equity impacts into perspective; if remedying them requires forgoing cap and trade, it also means forgoing these cost savings.

California's cap-and-trade program is distinct from the above pollution markets because it is a climate policy, and so the regulated pollutants are not toxic criteria pollutants but greenhouse gases. Greenhouse gases trap radiation in the atmosphere, warming the Earth and contributing to climate change. These gases have long lifetimes between emission and decay, so they are "well mixed", that is to say they are homogeneously distributed throughout the atmosphere. California's cap and trade program covers the major greenhouse gases and converts them to a carbon dioxide equivalent (CO₂e) for comparison purposes.² In contrast, criteria pollutants are those for which the EPA sets regulatory *criteria* under the 1990 Clean Air Act Amendments. Rather than causing warming, criteria pollutants impose health and economic costs. They are also much shorter lived, so unlike the well-mixed GHGs, criteria pollutant concentration varies spatially and depends heavily on the location of emission.

Given this difference in spatial homogeneity, we might expect cap and trade to be even more suited to greenhouse gases. Uncertainty about the spatial distribution of emissions matters little when GHGs are well mixed. However, a major source of criteria air pollutants is as co-pollutants emitted alongside greenhouse gases. Further, over 100 counties in California did not meet National Ambient Air Quality Standards (NAAQS) in February 2017 (EPA, 2017b), and the California Air Resources Board (CARB) only operates an adaptive management program for pollution equity, responding reactively to concerns raised about air pollutants. This indicates that the other regulations on criteria pollutants are not strong constraints on pollutant concentration, due to loopholes in source standards and ineffective enforcement. Hence if climate policy affects the distribution of GHG emissions, it can also affect the distribution of air pollution reduction co-benefits and exposure costs.

²It includes the six Kyoto Protocol gases, namely carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulphur hexafluoride (SF₆). The program also covers nitrogen trifluoride (NF₃) and other minor fluorinated greenhouse gases. The Kyoto Protocol was a 1997 international treaty on climate change that laid groundwork for climate mitigation in the 21st century.

2.2 Environmental Justice and California Climate Policy

U.S. environmental justice (EJ) movements since the 1980s have worked to highlight and challenge the disproportionate risks from environmental hazards that poor communities of colour face, particularly around the siting of undesirable land uses (Ikeme, 2003). Environmental justice advocates have generally framed their concerns in two dimensions. First are the distributive or outcome-based goals; environmental hazards should have their costs allocated equally across the population. Since existing inequities, as Kaswan (2011) notes, “likely stem from a tangle of past zoning decisions, housing discrimination, and socioeconomic constraints rather than from current intentional discrimination,” specific attention from environmental justice groups is needed to address them. Second, there are participatory or procedural goals, which aim to give communities involvement in key environmental policy decisions that impact them. Participation empowers groups who have not previously had much power in this decision-making. Both concerns have been levied against California cap and trade; this paper’s results concern the former.

California’s cap and trade program has been tied up with environmental justice concerns since its authorisation under the 2006 Global Warming Solutions Act, referred to as AB32. The California Air Resources Board was directed to plan and implement regulation that would reduce the state’s GHG emissions to 1990 levels by 2020, and it adopted cap and trade in 2011 as a key component of its plan to meet this goal. The regulation was gradually phased in, and has recently been extended to meet the state’s new climate mitigation target: reducing emissions 40% below 1990 levels by 2030. Efforts by environmental justice organizations led to the incorporation of participatory environmental justice components into the bill, such as advisory workshops and committees overseeing CARB’s development of regulation (Sze et al., 2009). However, concerns about the distributive effects of cap and trade were not alleviated, and a collection of environmental justice organisations filed suit against CARB in *Association of Irrigated Residents v. California Air Resources Board*. Among other points, the plaintiffs argued that CARB had not adequately considered the public health impacts of

cap and trade, especially on vulnerable communities (Takade, 2013). The court ruled that AB32 granted CARB discretion over the policy choice, but media coverage and political organising from environmental justice groups has remained staunchly opposed to the cap and trade program. The California Environmental Justice Alliance declared that cap and trade “is not delivering public health or air quality benefits, not achieving local emissions reductions, and it is exporting our climate benefits out of state.” Informing ongoing political tension is a primary motivation for this equity-based evaluation of the cap and trade program.

Uncertainty about whether emissions trading worsens or improves equity is the prime reason for concern. As Farber (2012) says, the key factor determining should be the relative abatement cost of facilities in different areas. The scenario in which, say, poor neighbourhoods receive fewer air quality benefits than richer neighbourhoods is one where it costs more for sources of air pollution in poor neighbourhoods to reduce their emissions. They would then be purchasers of emissions allowances, and could continue to pollute. Why might poor neighbourhoods have higher-abatement-cost emission sources? As a brief sketch, abatement costs are driven by the emissions intensity per unit output and the level of output of emissions sources. Since there is a high existing pollution burden for poor communities, we expect their associated sources to have some combination of low production costs and high emissions intensities per unit output. The former would tend to increase abatement costs, while the latter would tend to decrease it, creating uncertainty about outcomes. This is heavily complicated by the inexact relationship between production costs and profit margin when products are not the same, the potential for sources to be at production capacity, the effects of large one-time investments in reducing emissions intensity, the imperfect correlation between GHG and criteria pollutant emissions, perverse incentives in regulated industries such as utilities, and a myriad of other factors. In light of this complexity, Pastor et al. (2013) describe the need for studies of industrial organization under emissions pricing for facilities, firms and industries to better identify which firms might have higher abatement

costs. Without clear answers, it is understandable that environmental justice organisers distrust potential cap-and-trade outcomes.

2.3 Equity Under Cap and Trade

Compared to analyses of cost-effectiveness, there has been limited research on the distributional effects of cap-and-trade programs. Chan et al. (2015) took a health damages approach in evaluating the SO₂ allowance market as part of the US Acid Rain Program (ARP). This approach focuses on the potential differences in marginal damages from region to region, especially since pollution shifts from the sparsely populated areas west of the Mississippi River towards the Eastern Seaboard. They use an integrated assessment model to link emissions data to ambient concentrations and then to pollution damages. They found that relative to a no-trade scenario, the trade component of the program increased aggregate damages by 1.8%, as pollution was shifted towards higher population areas. However, the regional approach means that they did not look at how these shifts differentially impacted income groups. Ringquist (2011) does look at equity effects specifically, using definitions of communities by ZIP code and by facility proximity to control for different sources of bias. He finds that communities with higher proportions of black and Hispanic residents are less likely to have facilities that import SO₂ allowances, though communities with high proportions of adults without high-school diplomas do tend to import SO₂. This analysis addresses neighbourhood-level pollution concerns more directly than Chan et al. (2015), but does not attempt to deal with concentration data.

Fowlie, Holland, and Mansur (2012) carried out a similar analysis on the RECLAIM program for NO_x in Southern California. They use facilities in nonattainment areas to estimate counterfactual emissions trends for facilities covered by the market. The authors again use emissions data and weight block group demographics around facilities to estimate heterogeneous demographic effects. They do find that high-income white households experienced the largest reductions in nitrogen oxide concentrations, while low-income black households

experienced the smallest. However, this disparity is not attributable to the RECLAIM program, since the same would have occurred under a command-and-control alternative. These examples are the most extensive for their respective emissions trading programs, and they indicate that negative equity effects are not inherent to emissions trading. Instead, as noted earlier, effects will depend on the unique setting for each allowance market, specifically which emissions sources have the lowest abatement costs.

Fewer studies have been done on pollution equity in carbon trading. A preliminary study by Cushing et al. (2016) uses a comparable methodology to Ringquist (2011) and Fowlie, Holland, and Mansur (2012) for California, combining facility GHG emissions data with demographic data at the census tract level to estimate exposure changes with a pre-post comparison. The authors note that the largest emitters are located near neighbourhoods with 16% more residents of colour and 11% more residents living below the poverty line, and that several industry sectors increased their emissions over the 2011-2014 study period, in part due to use of out-of-state offsets. More recently, an initial report by California's Office of Environmental Health Hazard Assessment (OEHHA) also uses emissions data from stationary sources and reiterates that the cap-and-trade program is likely to impact criteria pollutant levels for disadvantaged communities, because of their proximity to GHG sources and the correlation between GHG and criteria pollutant emissions (OEHHA, 2017).

OEHHA (2017) acknowledge that emissions data is an imperfect proxy for exposures to air pollutants. Even when only considering stationary industrial sources, factors such as the stack height, the local meteorological conditions, and nearby terrain can lead to different fate and transport of pollutants around the emissions source. Schatzki and R. N. Stavins (2009) also note that roughly half the state's criteria pollutant emissions do not come from stationary sources, and that in regions such as the South Coast mobile sources are far greater contributors to air pollution health risks than stationary sources. In this paper, I construct a pollutant concentration dataset to bypass these two issues of transport and mobile sources. Concentration data should be a stronger proxy for exposures as it accounts for differences

in transport of pollutants, and it also addresses the lack of geolocated emissions data for mobile sources. In the next section, I outline my approach in creating this dataset.

3 Data

In this section, I describe the sources and nature of my data on air pollutant concentrations and on census tract demographics. I then outline my spatial interpolation methodology, and then present descriptive statistics with discussion about the limitations of the data.

3.1 Sources

To obtain the base data on ambient criteria pollutant concentrations, I look to EPA’s AirData website (EPA, 2017a). California’s 35 Air Quality Management Districts and analogous groups in other states are required to maintain an ambient air monitoring network and submit the gathered data to EPA’s Air Quality System (AQS) for aggregation. I use the pre-generated daily data from the AirData portal, containing the daily measured pollution concentrations for each of six criteria pollutants from every monitor at every site.³ The six pollutants I choose for this analysis are carbon monoxide (CO), nitrogen dioxide (NO₂), ozone (O₃), particulate matter smaller than 2.5 micrometres and 10 micrometres (PM_{2.5} and PM₁₀), and sulphur dioxide (SO₂). This database also contains information on the location of every monitoring site, as well as various other useful variables, including geographic identifiers, the averaging period for the measurement, and the pollutant standard used.

I restrict the data to those measurement standards as outlined in Table 8, so that the results are comparable to the National Ambient Air Quality Standards, and aggregate by quarter, to capture seasonal effects. There are approximately 100 monitoring stations for each pollutant in any given period; the Air Quality Management Districts activate and deactivate stations over time so different pollutants have different station densities. I report

³A monitor, in the AQS, refers to a instance of a pollutant being measured at a site, rather than a physical piece of equipment. Not all pollutants have monitors at all sites.

these station counts in Table 10, and Figure 2 shows station locations in the first quarter of 2016 for each pollutant, as an illustration. In general, station density is higher in urban areas, such that station density is high where population and census tract density is high.

For demographic data, I turn to the 2011-2015 five-year American Community Survey (U. S. Census Bureau, 2017). This repeated sample carried out by the Census Bureau provides data on income and race at the census tract level. Census tracts are statistical geographic groups with population between 1,200 and 8,000, ideally around 4,000. California has about 8,000 such tracts, with their area varying significantly (cite table). Each tract is a fairly good approximation of a "neighbourhood" or "community" for the purposes of identifying pollution inequity effects. This is not the smallest geographical unit available, but the sole smaller unit (the block group) does not have sufficiently comprehensive coverage of the demographic variables of interest. I use the 2015 vintage TIGER/Line shapefiles as the geographic definitions for each tract's extent.⁴ I choose to use demographic indicators of income, race and ethnicity, education, and property value as measures of socioeconomic status, and additionally include estimates on age and sex. I source Gross State Product data from the Department of Commerce's Bureau for Economic Analysis.⁵ for the last few years of regional GDP estimates.

3.2 Interpolation

I carry out the interpolation of data using global ordinary kriging on a 0.1km grid. Kriging is a geostatistical procedure that accounts for spatial correlation in the data; it weights station contribution to any one grid cell by estimating a relationship between separation distance and value similarity. This is appropriate for air pollution interpolation, since we expect that air pollution concentrations are spatially correlated (they are emitted from common sources and face decay conditions that are spatial in nature such as temperature and sunlight). I choose ordinary kriging as it enables me to make no assumptions about the mean pollution

⁴Available at the Census Bureau website

⁵I use the BEA's most recent May 2017 revisions

across the state. Normally I would not choose global kriging since I expect anisotropy of the pollution concentration across the state; geographic features such as the Central Valley and the Sierra Nevada lend directionality to the pollution field. However, because the relatively low overall station density creates artifacts in rural areas of the state, I instead use a minimum station count of 12 in a global kriging model to estimate a spherical semivariogram. This method is similar to that used by Wong, Yuan, and Perlin (2004), who find that ordinary kriging is comparable to other interpolation methods for air pollution in California.

Using ArcGIS, I convert the monitoring station data from a geographic datum (measuring in degrees) to a projected datum (measuring in metres). I run the above kriging model to interpolate a pollution concentration raster for each quarter and pollutant. Finally, I zonally average the raster to obtain census tract-level estimates of pollution concentration. Figure 3 provide examples of the end result of this process, showing the change in geographic distribution of each pollutant between the first quarter of 2007 and the first quarter of 2016.

3.3 Descriptive Statistics

My final dataset is a 38-year long panel dataset of demographic and pollutant variables for every census tract in California. The panel is slightly unbalanced, because of limitations with the monitoring station data; I could not interpolate far outside the geographic extent of the stations causing a few tracts on the edge of the state to be omitted occasionally for each pollutant. These omissions are visible as tracts not drawn in the maps in Figure 3, and the tract counts are reported in Table 11. Table 1 shows basic summary statistics for the time-varying factors in the panel. All the pollutants except ozone show downward trends in concentration. The first allowance auctions took place in 2012, so 2013 marks the start of compliance. The 2016 results are a little anomalous due to comparatively patchy data for the fourth quarter; I excluded the last period for later analysis.

Table 2 shows basic summary statistics on the cross-sectional factors: the characteristics of census tracts which I treat as time-invariant. We can see that California is about 40%

Year ^a	GSP ^b millions 2009 \$	CO ^c ppm	NO ₂ ^c ppb	O ₃ ^c ppb	PM 2.5 ^c µg m ⁻³	PM 10 ^c µg m ⁻³	SO ₂ ^c ppb
2007	1,999,340	0.460781	16.89486	0.026027	12.61141	32.44531	1.31255
2008	1,993,244	0.429723	16.28679	0.026749	12.30177	28.63244	1.158082
2009	1,912,116	0.379302	15.17766	0.02637	11.51066	25.73725	1.013936
2010	1,936,488	0.368438	13.98292	0.025854	9.749686	21.84469	0.75291
2011	1,962,926	0.376214	13.73298	0.026485	10.57312	23.67064	0.739014
2012	2,013,611	0.420997	13.01333	0.02748	9.790318	23.16476	0.604526
2013 ^d	2,064,534	0.367048	13.00323	0.026961	10.49664	25.35375	0.512688
2014	2,141,893	0.347457	12.56387	0.028285	10.05948	25.26713	0.503295
2015	2,235,433	0.367759	12.59269	0.028538	9.753523	24.1737	0.509864
2016	2,300,623	0.32096	9.706676	0.030639	9.106256	23.68724	0.558785

^a All data aggregated from quarterly to annual values for this summary.

^b GSP data sourced from the Bureau of Economic Analysis.

^c Concentration data sourced from the Environmental Protection Agency and spatially interpolated.

^d Cap and trade is implemented from 2013 onwards

Table 1: Summary statistics on census tract time-varying characteristics

non-Hispanic white, and that the census tracts have a population of about 4,500 each. The proportion of male residents is transformed from gender ratio data, which reduces the distortionary effect of outliers on the mean. I also include proportions of residents in a census tract working in each industry. Table 9 shows the correlation matrix for the key demographic variables; indicating, as we expect, that the mean income of a census tract is positively correlated with the proportion of non-Hispanic white residents, the proportion of residents with a high-school degree and the median property value.

I provide some graphs and tables to highlight the differential outcomes of tracts at different income levels, as the key driver of socioeconomic disadvantage in this analysis. Similar graphs can be drawn for the other measures of socioeconomic status, because of their high correlation. Table 12 shows summary statistics for the data before and after cap and trade began its compliance period by income quartile. We can see that the general trend for decreasing concentrations is also visible here for all of the pollutants, again with the exception of ozone. It is also the case that for every pollutant except carbon monoxide after cap and

Tract characteristic	N	Mean	SD	Min	Max
Population	8,057	4,795	2,096	5	39,454
Area (1000 sq m) ^a	8,057	49,263	410,695	10	18,111,580
Proportion non-Hispanic, white only	8,012	40%	27%	0%	100%
Proportion high school graduate or higher	8,009	81.0%	16.0%	0.0%	100.0%
Proportion bachelor's degree or higher	8,009	30.7%	20.7%	0.0%	100.0%
Proportion male	8,002	49.7%	4.6%	20.0%	99.9%
Median age	8,008	37.32	7.82	15	78
Mean household income (2015 dollars)	7,973	85,492	43,967	9,040	537,130
Median household income (2015 dollars)	7,956	67,265	32,787	4,541	248,750
Median house value (2015 dollars)	7,774	431,213	275,915	15,800	1,976,200
Agriculture, forestry, fishing, mining ^b	7989	2.6%	6.9%	0.0%	64.8%
Construction	7989	6.1%	3.9%	0.0%	87.5%
Manufacturing	7989	9.6%	5.6%	0.0%	41.9%
Wholesale trade	7989	3.1%	2.3%	0.0%	35.0%
Retail trade	7989	11.1%	4.2%	0.0%	52.0%
Transportation and utilities	7989	4.7%	3.1%	0.0%	25.6%
Information	7989	2.8%	3.0%	0.0%	29.7%
Finance, insurance, and real estate	7989	6.1%	3.8%	0.0%	31.7%
Scientific, management, admin	7989	12.6%	6.1%	0.0%	62.1%
Educational, health, social	7989	21.0%	7.1%	0.0%	100.0%
Arts, entertainment, accommodation, food	7989	10.4%	5.5%	0.0%	100.0%
Other services	7989	5.5%	3.2%	0.0%	57.9%
Public administration	7989	4.6%	4.2%	0.0%	60.2%

^a Area data calculated from Census Bureau geographic shapefiles. All other data sourced from the American Community Survey 2015 5-year estimates.

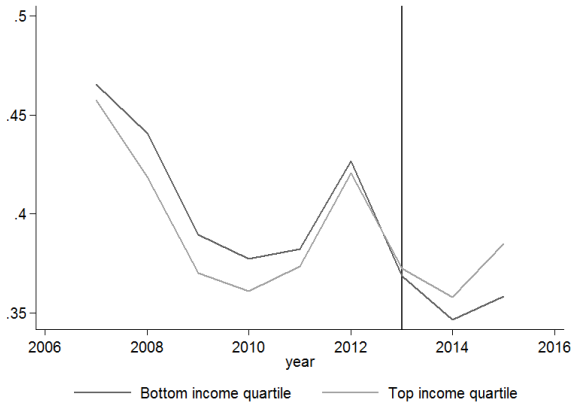
^b Ensuing data on industries expressed as proportion of employed residents 16 and over in the respective industry.

Table 2: Summary statistics on tract demographic characteristics

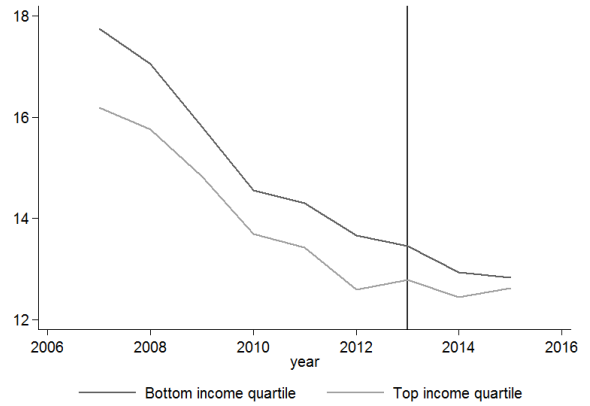
trade, census tracts higher income up the income distribution face lower pollution burdens. This table's contents are illustrated graphically in Figure 1. Each graph shows the group annual average pollutant concentration for the top and bottom income quartiles, with a marker for the onset of cap and trade. The shift in relative equity is particularly noticeable in Figure 1a, where poorer tracts actually end up doing better than rich tracts on an absolute level. However, the gap also narrows for nitrogen dioxide and PM 2.5, preempting the results to come.

This dataset is limited in two important respects. Because the American Community Survey 5-year estimate is required to obtain census tract-level data on income, I must treat all demographic variables as time-invariant.⁶ This is a reasonable approximation, since time variation in demographic variables is unlikely to outweigh cross-sectional variation. Further, the interpolation on a relatively sparse set of data points likely smooths the geographic concentration distribution; we expect that cap and trade has some effects that are more local than the broader regional shifts we see in Figure 3.

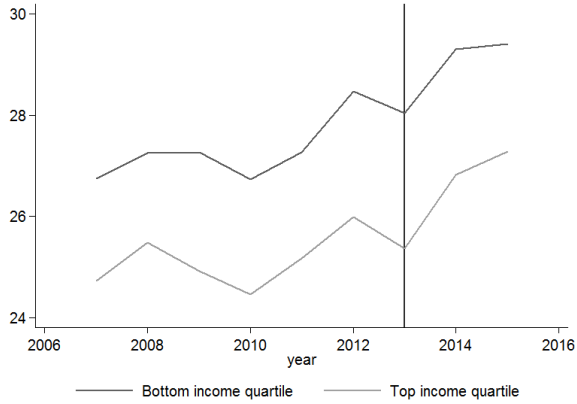
⁶Other datasets with income data, such as the Current Population Survey (CPS) or the Small Area Income and Poverty Estimates (SAIPE) do not have sufficient spatial resolution.



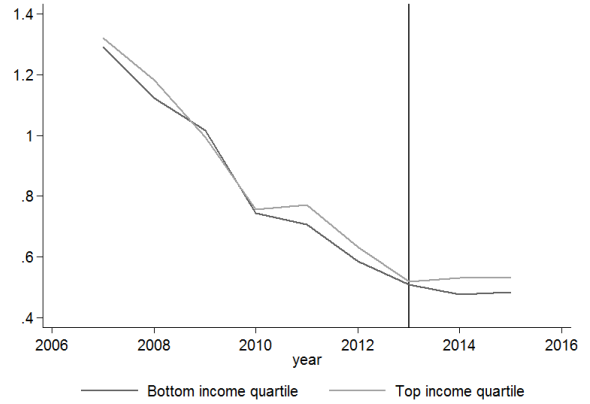
(a) CO concentration over time



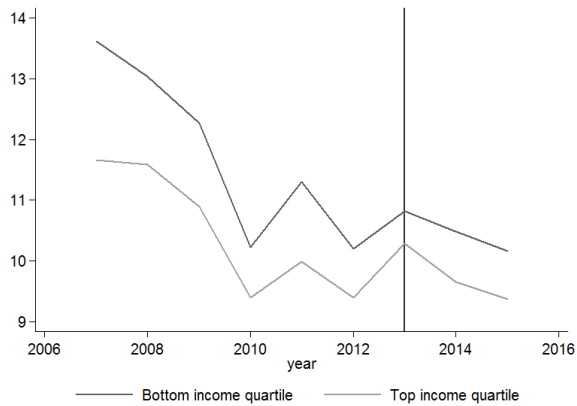
(b) NO₂ concentration over time



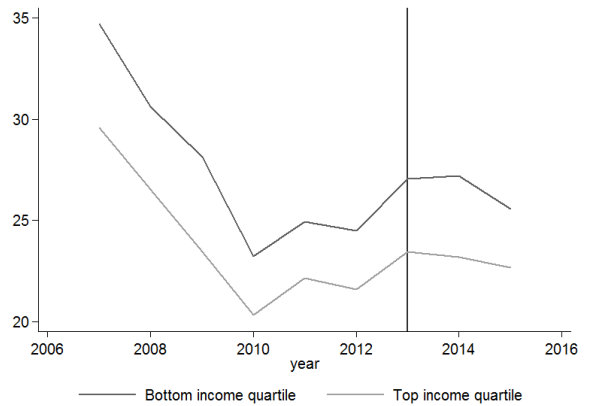
(c) O₃ concentration over time



(d) SO₂ concentration over time



(e) PM 2.5 concentration over time



(f) PM 10 concentration over time

Figure 1: Time series of pollutant concentrations by income

4 Empirical Approach

In this section, I will first present my choice of econometric model. I continue to discuss its advantages and shortcomings, and my methods for testing robustness.

4.1 Model Specification

The conceptual setting is that California cap and trade affects relative pollution equity by improving pollutant concentration levels more or less in disadvantaged census tracts as compared to advantaged census tracts. Thus, to estimate the effect of cap and trade on relative pollution equity in the state, I make a strong identifying assumption: that more advantaged census tracts and less advantaged census tracts would not have converged or diverged in their pollution level absent cap and trade. I then specify a difference-in-differences model using the equation below:

$$c_{it} = \gamma_i + \lambda_t + \beta(p_t \times d_i) + \delta y_t + \epsilon_{it} \quad (1)$$

Here I model the pollution level in census tract i at period t as dependent on a tract-specific factor, a time factor, as well as a measure of the intensity of treatment, which is 0 before treatment and depends on a demographic variable after treatment. c_{it} represents the result of interpolation and zonal averaging; it is the average concentration for one of the six criteria pollutants in tract i at time t . γ_i represents tract fixed effects; these terms control for *ex ante* differences in tract characteristics. λ_t represents time fixed effects; these terms control for the general downward time trend in pollution levels across the state. I cluster standard errors at the tract level, to account for correlation of errors for a given tract i in different time periods t .

p_t is a dummy variable for whether or not cap and trade is in effect; it takes value 0 for periods 1-24 and value 1 for periods 25-40, i.e. 2013-2016. d_i is one of the six demographic variables that I analyse as potential dimensions of socioeconomic disadvantage. β

is the coefficient of interest for this regression; if my assumptions hold then it represents the incremental effect of living in a more advantaged tract on your pollution level thanks to cap and trade. y_t is the GSP in that quarter. I estimate this equation for each pollutant concentration c and each demographic variable d .

4.2 Advantages and Limitations

This difference-in-differences model is well suited to this setting because of the significant heterogeneity in census tract characteristics, which might conceal unobserved factors that affect pollution levels in advantaged tracts differently than in disadvantaged tracts. Including tract fixed effects enables us to account for all of these time-invariant effects. As a consequence, I look at each demographic variable at a time; the others would be collinear with the fixed effects term which captures their effects as well as the effects of unobserved variables.

Similarly, time fixed effects allow us to eliminate bulk time trend effects. I include GSP as an additional time-variant control; since emissions are not evenly distributed, changes to aggregate production will unevenly impact emissions and consequently pollution concentrations. Combined with the difference-in-differences interaction term, which accounts for the preexisting pollution equity, this model isolates the treatment effect of the cap-and-trade program. A naive regression without controls or fixed effects would conflate preexisting trends with this effect.

The primary limitation of the model is that identification rests on the common trend assumption; that trends were parallel for tracts at different levels of advantage. The assumption enables us to infer that a departure from parallel trends is due to cap and trade. I test this assumption by including interactions of the demographic treatment variable with time period indicators, similarly to Autor (2003). This allows me to see whether pollution levels are convergent or divergent in the pre-treatment period, which would bias my results; I would overestimate and underestimate the treatment effect on reducing equity, respectively.

I conduct additional robustness tests by excluding various combinations of controls and fixed effects, as well as alternative treatment of standard errors and different specifications of the relationship between demographic variables and treatment intensity.

5 Results

In this section, I describe the results of my analysis. I then provide discussion on the interpretation and robustness of these results.

5.1 Estimates

I outline my results sequentially for four measures of a tract's socioeconomic status, and additionally for two other demographic variables. For each of the socioeconomic variables (income, race, education and property value) positive values of β , the coefficients in the top row of each table, are associated with improvements to relative equity. I illustrate with income first.

Table 3 shows that cap and trade narrowed the pollution gap between tracts with higher and lower incomes for four pollutants. The first column shows that a census tract that had a 1% higher mean income faced a CO concentration that was 0.02 ppm higher thanks to cap and trade. Because of the higher starting concentrations for lower-income census tracts, this is an improvement to relative equity. In other words, lower-income tracts saw better CO concentration outcomes from cap and trade than higher-income tracts, reducing the pollution gap. Similarly, for each 1% increase in mean income, column 2 shows a 0.52 ppb higher NO₂ concentration, column 4 shows a 0.45 $\mu\text{g m}^{-3}$ higher PM 2.5 concentration, and column 5 shows a 0.13 $\mu\text{g m}^{-3}$ higher PM 10 concentration. In contrast, column 3 shows a 0.19 ppb *lower* O₃ concentration for a 1% higher income, indicating that relative equity decreased for ozone. Column 6 shows no significant effect for SO₃. On balance, increased equity for four of six pollutants represents a relative equity improvement for income from

cap and trade.

Table 4 shows that cap and trade also narrowed the pollution gap between tracts with higher and lower proportions of non-Hispanic white residents. Column 1 shows that tracts with a 1 percentage-point higher share of non-Hispanic white residents saw 0.01 ppm higher CO concentrations because of cap and trade. Column 2 shows that these tracts saw 0.82 ppb higher NO₂ concentrations, column 4 shows that they saw 1.22 $\mu\text{g m}^{-3}$ higher PM 2.5 concentrations, column 5 shows that they saw 0.42 $\mu\text{g m}^{-3}$ higher PM 10 concentrations, and column 6 shows that they saw 0.09 ppb higher SO₂ concentrations. Again, only O₃ shows a reduction in pollution equity; tracts that had 1% higher proportions of non-Hispanic white residents saw 1.53 ppb lower concentrations of ozone. This is consistent with the results for income; ozone is the sole pollutant to see reductions in equity and overall, cap and trade improved relative equity for race.

Similarly, Table 5 shows that cap and trade also narrowed the pollution gap between tracts with higher and lower proportions of residents over 18 with a high-school degree, but to a much smaller extent. Column 1 shows that tracts with a 1 percentage-point higher share of non-Hispanic white residents saw 0.0004 ppm higher CO concentrations because of cap and trade. Column 2 shows that these tracts saw 0.01 ppb higher NO₂ concentrations, column 4 shows that they saw 0.02 $\mu\text{g m}^{-3}$ higher PM 2.5 concentrations, and column 6 shows that they saw 0.0007 ppb higher SO₂ concentrations. Here, both O₃ and PM 10 show a reduction in pollution equity; tracts that had 1% higher proportions of non-Hispanic white residents saw 0.02 ppb lower ozone concentrations and 0.002 $\mu\text{g m}^{-3}$ insignificantly lower PM 10 concentrations.

Table 6 shows more mixed results for tracts with higher and lower median house values. Column 1 shows that tracts with 1% higher median house values saw 0.01 ppm higher CO concentrations because of cap and trade, column 2 shows that they saw 0.05 ppb higher NO₂ concentrations, column 3 shows that they saw 0.38 ppb higher O₃ concentrations, and column 4 shows that they saw 0.08 $\mu\text{g m}^{-3}$ higher PM 2.5 concentrations. However, columns

Pollutant ^a	(1)	(2)	(3)	(4)	(5)	(6)
Unit	CO	NO ₂	O ₃	PM 2.5	PM 10	SO ₂
	ppm	ppb	ppb	µg m ⁻³	µg m ⁻³	ppb
INC * POST ^b	0.0223*** -0.00124	0.524*** -0.03	-0.187*** -0.0261	0.454*** -0.0236	0.128** -0.0541	-0.00736 -0.00496
GSP	-1.41e-06*** (4.83e-08)	-3.52e-05*** (1.17e-06)	1.45e-05*** (1.04e-06)	-3.48e-05*** (9.51e-07)	-1.56e-05*** (2.14e-06)	-3.22e-06*** (1.96e-07)
Tract FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Constant	3.383*** (0.0951)	89.59*** (2.308)	-7.412*** (2.053)	82.10*** (1.883)	56.40*** (4.231)	7.938*** (0.388)
Observations	282,987	285,240	286,598	284,742	286,302	282,636
R-squared	0.850	0.890	0.857	0.504	0.499	0.584
No. tracts	7,927	7,927	7,963	7,914	7,960	7,925

^a Pollutant concentration data spatially interpolated from EPA monitoring station data.

^b Income data sourced from the 2015 American Community Survey 5-year estimates. Estimate represents the effect of cap and trade on pollution for a 1% increase in mean income.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Income-dependent effects on census tract pollution concentration

Pollutant ^a	(1)	(2)	(3)	(4)	(5)	(6)
Unit	CO	NO ₂	O ₃	PM 2.5	PM 10	SO ₂
	ppm	ppb	ppb	µg m ⁻³	µg m ⁻³	ppb
RACE * POST ^b	0.0130*** (0.00205)	0.823*** (0.0463)	-1.526*** (0.0428)	1.223*** (0.0396)	0.423*** (0.0860)	0.0928*** (0.00953)
GSP	-8.15e-08*** (2.88e-09)	9.23e-07*** (7.24e-08)	3.40e-06*** (6.02e-08)	-9.67e-06*** (4.05e-08)	7.75e-06*** (1.02e-07)	3.85e-07*** (1.57e-08)
Tract FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Constant	0.760*** (0.00585)	18.30*** (0.134)	14.52*** (0.125)	32.60*** (0.0840)	10.35*** (0.196)	0.827*** (0.0325)
Observations	284,332	286,608	288,002	286,110	287,670	283,950
R-squared	0.849	0.890	0.858	0.506	0.499	0.584
No. tracts	7,965	7,965	8,002	7,952	7,998	7,963

^a Pollutant concentration data spatially interpolated from EPA monitoring station data.

^b Race data sourced from the 2015 American Community Survey 5-year estimates. Estimate represents the effect of cap and trade on pollution for a 1 percentage-point increase in the proportion of non-Hispanic white residents.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Race-dependent effects on census tract pollution concentrations

Pollutant ^a	(1)	(2)	(3)	(4)	(5)	(6)
Unit	CO ppm	NO ₂ ppb	O ₃ ppb	PM 2.5 μg m ⁻³	PM 10 μg m ⁻³	SO ₂ ppb
EDUC * POST ^b	0.000417*** (3.18e-05)	0.0140*** (0.000779)	-0.0166*** (0.000808)	0.0167*** (0.000646)	-0.00203 (0.00167)	0.000723*** (0.000134)
GSP	-6.50e-07*** (9.02e-09)	-1.86e-05*** (2.23e-07)	1.19e-05*** (2.55e-07)	-2.16e-05*** (2.19e-07)	-9.95e-06*** (4.97e-07)	-3.72e-06*** (3.86e-08)
Tract FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Constant	1.881*** (0.0179)	56.75*** (0.443)	-2.193*** (0.511)	56.15*** (0.451)	45.26*** (0.983)	8.914*** (0.0784)
Observations	284,224	286,500	287,894	286,002	287,562	283,842
R-squared	0.849	0.890	0.858	0.505	0.499	0.584
No. tracts	7,962	7,962	7,999	7,949	7,995	7,960

^a Pollutant concentration data spatially interpolated from EPA monitoring station data.

^b Education data sourced from the 2015 American Community Survey 5-year estimates. Estimate represents the effect of cap and trade on pollution for a 1 percentage-point increase in the proportion of residents over 18 with a high-school degree.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Education-dependent effects on census tract pollution concentration

Pollutant ^a	(1)	(2)	(3)	(4)	(5)	(6)
Unit	CO ppm	NO ₂ ppb	O ₃ ppb	PM 2.5 μg m ⁻³	PM 10 μg m ⁻³	SO ₂ ppb
PROP * POST ^b	0.0107*** (0.000956)	0.0579*** (0.0212)	0.379*** (0.0170)	0.0802*** (0.0178)	-0.441*** (0.0466)	-0.0494*** (0.00383)
GSP	-1.01e-06*** (4.21e-08)	-1.72e-05*** (9.33e-07)	-9.82e-06*** (7.49e-07)	-2.05e-05*** (8.26e-07)	9.19e-06*** (2.11e-06)	-1.30e-06*** (1.77e-07)
Tract FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Constant	2.588*** (0.0829)	53.99*** (1.836)	40.61*** (1.472)	53.95*** (1.639)	7.537* (4.158)	4.154*** (0.350)
Observations	275,859	278,112	279,470	277,614	279,174	275,544
R-squared	0.849	0.889	0.858	0.502	0.499	0.584
No. tracts	7,729	7,729	7,765	7,716	7,762	7,727

^a Pollutant concentration data spatially interpolated from EPA monitoring station data.

^b Property value data sourced from the 2015 American Community Survey 5-year estimates. Estimate represents the effect of cap and trade on pollution for a 1% increase in median house value.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Property value-dependent effects on tract pollution concentrations

5 and 6 shows that they saw $0.44 \mu\text{g m}^{-3}$ lower PM 10 concentrations, and 0.05 ppb lower SO_2 concentrations. Since 4 pollutants display a widening and 2 display a narrowing of the pollution gap with respect to property value, it is less clear what the overall effect of cap and trade on relative equity was along this dimension.

Tables 13 and 14 are more illustrative, since we do not expect the same associations with socioeconomic disadvantage for these two variables that we would for the first four variables. Though disparities in pollution concentration do exist for age and sex, we do not treat the unequal distribution of pollution costs as reinforcements of existing inequities. Nevertheless it is interesting to see that cap and trade had significant effects along these two demographic dimensions. In Table 13, columns 2, 4, and 5 indicate that cap and trade brought higher concentrations of NO_2 , PM 2.5 and PM 10 for tracts with more male residents, while column 3 indicates that it brought lower O_3 concentrations for those tracts. In Table 14, columns 1, 2, 4, and 6 indicate that cap and trade brought higher concentrations of CO, NO_2 , PM 2.5, and SO_2 for tracts with higher median ages, while column 3 indicates that it brought lower O_3 concentrations for those tracts.

Overall, these estimates suggest that cap and trade in California has succeeded in improving relative pollution equity on balance. Of thirty-six estimated effects, only 7 suggested that the pollution gap had widened, while 22 showed significant narrowing of the pollution disparity. Ozone is the main outlier, moving in the opposite direction to the other pollutants for 5 of 6 demographic variables. I hypothesize that ozone behaves differently because it is predominately generated in atmospheric reactions around other criteria pollutants rather than directly emitted. This weakens the mechanisms connecting cap and trade to ozone concentrations, and also makes it more likely that unobserved meteorological effects have significant effects (such as the 2012-2017 California drought). More research is needed to confirm this.

5.2 Evaluation

The estimates indicate that cap and trade’s effect on relative pollution equity can be substantial. For context, I present the effects in Table 7 as fractions of the average pollution disparity prior to treatment (reported in Table 15). For example, from 2007-2012, census tracts with 1 percentage-point higher shares of non-Hispanic white residents faced 5.89 ppb lower NO₂ concentrations. Cap and trade lowered this gap by 0.82 ppb for each percentage-point difference in racial share, so the program ameliorated 14% of the preexisting disparity (Row 2, Column 2). The few cells with values over 100% are those where the more disadvantaged census tracts end up with greater It is apparent that the shifts in pollution caused by cap and trade are very consequential, accounting for large portions of the existing inequity.

	CO	NO ₂	O ₃	PM 2.5	PM 10	SO ₂
Income	219%	63%	10%	43%	4%	29%
Race	20%	14%	42%	43%	6%	
Education	70%	24%		40%	2%	98%
Property	52%	6%	12%	17%	22%	184%
Sex	33%	10%	15%			
Age	108%	23%		48%	2%	

Significant estimates of cap and trade relative equity effect magnitudes expressed as percentages of the pollution disparity prior to cap and trade. Insignificant estimates are left as blank cells.

Table 7: Cap and trade relative equity effects as fractions of preexisting disparities

While this analysis uses concentration data as a better proxy for pollution costs than emissions data, it is hard to directly compare changes in concentration for different gases. In reality, the interactions between different pollutants can have very nonlinear health effects, and are not well understood. This makes it hard to draw clear conclusions about whether one demographic variable is associated with stronger relative equity effects from cap and trade. In this paper, I rely on one-to-one comparison of criteria pollutants to each other. However, particularly severe health effects of ozone might lead its costs to dominate benefits from improvements in equity of the other five pollutants, changing conclusions drawn from

these results. Further work should directly model pollution exposures to better translate effects on pollution changes to health and economic costs.

The temporal and spatial smoothing in this analysis is likely to bias my estimates downwards. Aggregation of data to a quarterly level was necessary to prevent unreasonable runtimes for spatial interpolation. This aggregation necessarily smooths out acute air pollution incidents that can have important health consequences. Similarly, the sparse station data hides a good deal of spatial heterogeneity in interpolation. It is likely that certain locations have more extreme pollution concentrations than shows up in this data; kriging underestimates true exposure variability. Interpolation from fewer points also reduces accuracy, since there is much less variation in the calculated data. This is particularly relevant for CO and SO₂ estimates, since they have many fewer monitoring stations than the other pollutants as shown in Table 10. My results should consequently be seen as reflecting only cap-and-trade effects on cumulative pollution exposure at a regional level. Complete equity effects, accounting for both acute exposures and more local variation, may be larger than estimated here.

These results are robust against a variety of methodological changes. I model the treatment of cap and trade as increasing over time, to account for the increasingly stringent caps; estimates retain the same sign and significance. Using robust rather than clustered standard errors also does not affect significance of the estimates. I include control variables directly instead of using fixed effects, and obtain similar estimates; this suggests that the demographic variables I analyse encompass much of the variation in tract-level characteristics. Finally, I interact the treatment variable with time dummies; few coefficients prior to treatment are significant, suggesting that the common trend assumption holds broadly.

This result seems to contradict the conclusion of Cushing et al. (2016): that cap and trade leads to worsened pollution equity. However, the authors primarily make conclusions about absolute equity, which I do not directly address. Further, they do not control for confounding factors, and focus only on stationary sources. I include for time trends and use

concentration data to include all sources in my analysis, which could change the observed sign of the estimate to be closer to the true value. I therefore believe that incorporating mobile sources and eliminating the effect of confounding factors accounts for this discrepancy in the apparent equity effect of cap and trade.

6 Conclusion

In this paper, I construct a census tract-level dataset of criteria pollutant concentration. I exploit the common trend of advantaged and disadvantaged census tracts prior to cap and trade to estimate the program's effect on relative equity. I find that cap and trade generally caused more advantaged census tracts to face higher pollution concentrations than less advantaged census tracts, redressing neighbourhood relative pollution equity. The effects are large fractions of preexisting pollution disparities, and are strongest for carbon monoxide, nitrogen dioxide and PM 2.5. However, ozone displays opposite trends and sees increasing pollution disparities after cap and trade.

My results suggest that there has not been a trade-off between relative pollution equity and cost-effectiveness in California climate policy. Low abatement costs proved not to be sufficiently concentrated in advantaged neighbourhoods to reduce pollutant concentrations there at the expense of less advantaged neighbourhoods. Despite this, it is important to note that absolute inequity still exists for criteria pollutants along many demographic dimensions. Cap and trade has not fully closed the disparity, and environmental justice advocates are certainly justified in demanding better enforcement of other regulations that control criteria pollutants. In the meantime, rather than choosing to "fight at every turn", they would do better to push for cap and trade's renewal past 2020. Resolving this political gridlock will be key to reaching an equitable pollution outcome into the future.

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8 Appendix

This appendix contains tables and figures that provide additional context for the results described in this paper. Data is all publicly available and the author can be contacted for analysis code.

8.1 Tables

Pollutant Code ^a	Pollutant Description	Averaging Period	NAAQS	unit
88101	PM2.5 FRM/FEM Mass	24 hours	35	$\mu\text{g m}^{-3}$
81102	PM10 Mass	24 hours	150	$\mu\text{g m}^{-3}$
44201	Ozone	8 hours	70	ppb
42401	SO2	1 hour	75	ppb
42101	CO	8 hours	9	ppm
42602	NO2	1 hour	100	ppb

^a Air pollution data downloaded from EPA's AirData portal⁷

Table 8: Air pollutant quality standards used in dataset construction

Variable	Correlations					
	(1)	(2)	(3)	(4)	(5)	(6)
1. Mean household income (2015 dollars)	1.0000					
2. Proportion non-Hispanic, white only	0.5384	1.0000				
3. Proportion high school graduate or higher	0.7150	0.7574	1.0000			
4. Median house value (2015 dollars)	0.7655	0.3491	0.5212	1.0000		
5. Proportion male	-0.0059	-0.0295	-0.1076	-0.0167	1.0000	
6. Median age	0.5318	0.6331	0.5868	0.4227	-0.0977	1.0000

Table 9: Correlation matrix for demographic variables

Period	CO	NO2	O3	PM 2.5	PM 10	SO2
0	69	98	169	84	144	35
1	69	98	169	84	144	35
2	70	99	175	84	146	36
3	71	101	173	83	141	36
4	74	102	175	85	144	37
5	77	104	167	84	147	37
6	77	104	179	85	147	37
7	75	104	177	86	140	37
8	76	106	177	89	140	37
9	73	104	163	88	136	36
10	72	103	171	89	132	34
11	71	103	170	92	132	34
12	71	103	170	94	128	33
13	72	104	160	94	128	34
14	70	103	171	94	128	34
15	70	103	174	96	130	36
16	70	104	175	97	130	36
17	68	99	166	96	131	35
18	68	99	175	98	129	35
19	68	100	173	99	126	33
20	67	100	173	101	125	33
21	68	101	170	107	127	33
22	66	100	172	106	124	31
23	68	102	176	106	123	33
24	69	102	176	110	124	33
25	68	101	163	109	125	33
26	68	101	173	110	130	33
27	69	102	174	110	130	33
28	69	101	174	109	127	32
29	70	99	165	114	125	31
30	69	100	172	113	125	30
31	69	103	172	110	125	30
32	72	102	171	111	127	30
33	72	103	169	112	128	31
34	73	105	172	111	126	31
35	70	106	173	110	127	31
36	70	106	172	107	123	31
37	71	103	169	107	121	31
38	71	105	172	110	123	31
39	35	65	105	84	100	23
40	17	29	46	24	9	10

Green cells indicate increases from the previous period, red cells are decreases. There are particularly few stations reporting for the second half of 2016.

Table 10: Station counts for each pollution in the pre-interpolation dataset

Period	CO	NO2	O3	PM 2.5	PM10	SO2
1	7994	7994	8032	7956	8028	7992
2	7994	7994	8032	7956	8028	7992
3	7994	7994	8032	7956	8028	7992
4	7994	7994	8032	7956	8028	7992
5	7994	7994	8032	7956	8028	7992
6	7994	7994	8032	7956	8028	7992
7	7994	7994	8032	7982	8028	7992
8	7994	7994	8032	7982	8028	7992
9	7994	7994	8032	7976	8028	7992
10	7994	7994	8032	7982	8028	7992
11	7994	7994	8032	7982	8028	7992
12	7994	7994	8032	7982	8028	7992
13	7994	7994	8032	7982	8028	7992
14	7892	7994	8032	7982	8028	7992
15	7890	7992	8032	7982	8028	7992
16	7890	7992	8032	7982	8028	7992
17	7890	7992	8032	7982	8028	7992
18	7890	7992	8032	7982	8028	7992
19	7891	7993	8032	7982	8028	7842
20	7891	7993	8032	7982	8028	7842
21	7891	7993	8032	7982	8028	7842
22	7891	7993	8032	7982	8014	7842
23	7891	7993	8032	7982	8014	7842
24	7891	7993	8032	7982	8014	7842
25	7891	7993	8032	7982	8014	7842
26	7891	7993	8032	7982	8014	7842
27	7891	7993	8032	7982	8014	7842
28	7891	7993	8032	7982	8014	7842
29	7891	7993	8032	7982	8008	7842
30	7891	7993	8032	7982	8008	7842
31	7891	7993	8032	7982	8008	7842
32	7891	7979	8018	7982	8008	7842
33	7891	7979	8018	7982	8008	7842
34	7891	7979	8018	7982	8008	7842
35	7891	7979	8018	7982	8008	7842
36	7891	7979	8018	7982	8008	7842
37	7891	7979	8018	7982	7978	7842
38	7891	7979	8018	7982	7978	7842
39	7891	7979	7989	7924	7978	7842
40	6942	7070	7862	6981	2608	6250

Green cells are increases from the previous period, and red cells are decreases. Period 40, the fourth quarter of 2016, has particularly patchy data.

Table 11: Tract counts for each period in the interpolated dataset

Income ^b	Pollutant	Units	Before ^a		After ^a	
			Mean	SD	Mean	SD
Bottom Quartile	CO	ppm	0.41	0.14	0.35	0.11
	NO ₂	ppb	15.52	6.14	12.43	5.67
	O ₃	ppb	27.29	8.88	29.52	7.53
	PM 2.5	µg m ⁻³	11.77	3.78	10.29	2.75
	PM 10	µg m ⁻³	27.69	9.89	26.45	7.54
	SO ₂	ppb	0.91	0.41	0.50	0.24
2 Quartile	CO	ppm	0.41	0.13	0.35	0.11
	NO ₂	ppb	14.90	6.10	12.07	5.65
	O ₃	ppb	27.14	8.32	29.07	7.21
	PM 2.5	µg m ⁻³	11.19	3.50	9.95	2.56
	PM 10	µg m ⁻³	26.53	10.07	25.28	7.43
	SO ₂	ppb	0.93	0.42	0.51	0.25
3 Quartile	CO	ppm	0.40	0.13	0.35	0.11
	NO ₂	ppb	14.56	5.99	11.92	5.54
	O ₃	ppb	26.38	7.75	28.28	6.85
	PM 2.5	µg m ⁻³	10.90	3.30	9.79	2.45
	PM 10	µg m ⁻³	25.46	9.77	24.17	7.14
	SO ₂	ppb	0.94	0.42	0.53	0.26
Top Quartile	CO	ppm	0.40	0.13	0.36	0.11
	NO ₂	ppb	14.42	5.69	12.04	5.27
	O ₃	ppb	25.13	7.06	26.98	6.36
	PM 2.5	µg m ⁻³	10.49	2.91	9.58	2.25
	PM 10	µg m ⁻³	23.95	9.20	22.81	6.57
	SO ₂	ppb	0.94	0.39	0.54	0.23

^a Before is the period 2007-2012, while after is 2013 onwards

^b Income quartiles here refer to the distribution of mean household income among census tracts, not among individual households

Table 12: Pollutant concentration before and after cap and trade by income quartile

	(1)	(2)	(3)	(4)	(5)	(6)
Pollutant ^a	CO	NO ₂	O ₃	PM 2.5	PM 10	SO ₂
Unit	ppm	ppb	ppb	µg m ⁻³	µg m ⁻³	ppb
SEX * POST ^b	-0.0204 (0.0130)	0.529* (0.272)	-0.941*** (0.271)	0.479* (0.254)	2.028*** (0.586)	0.00221 (0.0537)
GSP	-8.14e-08*** (2.89e-09)	9.27e-07*** (7.25e-08)	3.40e-06*** (6.02e-08)	-9.67e-06*** (4.05e-08)	7.75e-06*** (1.02e-07)	3.85e-07*** (1.57e-08)
Tract FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Constant	0.759*** (0.00585)	18.30*** (0.134)	14.52*** (0.125)	32.60*** (0.0846)	10.35*** (0.196)	0.826*** (0.0326)
Observations	284,008	286,284	287,642	285,786	287,346	283,626
R-squared	0.849	0.889	0.857	0.503	0.499	0.584
No. tracts	7,956	7,956	7,992	7,943	7,989	7,954

^a Pollutant concentration data spatially interpolated from EPA monitoring station data.

^b Sex data sourced from the 2015 American Community Survey 5-year estimates. Estimate represents the effect of cap and trade on pollution for a 1 percentage-point increase in the share of male residents.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Sex-dependent effects on census tract pollution concentration

	(1)	(2)	(3)	(4)	(5)	(6)
Pollutant ^a	CO	NO ₂	O ₃	PM 2.5	PM 10	SO ₂
Unit	ppm	ppb	ppb	µg m ⁻³	µg m ⁻³	ppb
AGE * POST ^b	0.000626*** (6.83e-05)	0.0142*** (0.00154)	-0.0172*** (0.00150)	0.0333*** (0.00139)	0.00353 (0.00337)	0.00170*** (0.000339)
GSP	-6.13e-07*** (9.21e-09)	-1.64e-05*** (2.07e-07)	9.41e-06*** (2.20e-07)	-2.12e-05*** (2.18e-07)	-1.10e-05*** (4.65e-07)	-3.73e-06*** (4.92e-08)
Tract FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Constant	1.809*** (0.0183)	52.56*** (0.411)	2.668*** (0.444)	55.43*** (0.449)	47.32*** (0.919)	8.948*** (0.0992)
Observations	284,188	286,464	287,858	285,966	287,526	283,806
R-squared	0.849	0.890	0.857	0.505	0.499	0.584
No. tracts	7,961	7,961	7,998	7,948	7,994	7,959

^a Pollutant concentration data spatially interpolated from EPA monitoring station data.

^b Age data sourced from the 2015 American Community Survey 5-year estimates. Estimate represents the effect of cap and trade on pollution for a 1-year increase in the median age of residents.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

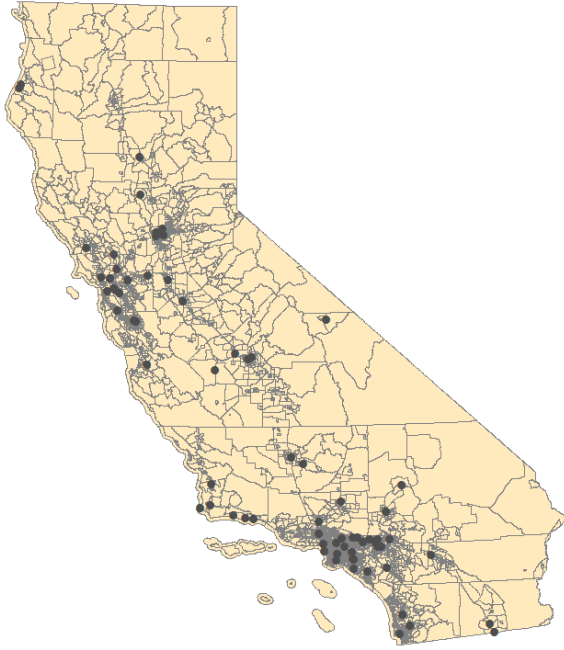
Table 14: Age-dependent effects on census tract pollution concentration

Pollutant Unit	(1) CO ppm	(2) NO ₂ ppb	(3) O ₃ ppb	(4) PM 2.5 µg m ⁻³	(5) PM 10 µg m ⁻³	(6) SO ₂ ppb
Log mean income	-0.0102*** (0.00145)	-0.834*** (0.110)	-1.872*** (0.0983)	-1.053*** (0.0481)	-3.147*** (0.143)	0.0256*** (0.00379)
% non-Hispanic white	-0.0643*** (0.00237)	-5.885*** (0.179)	3.643*** (0.176)	-2.868*** (0.0770)	-7.207*** (0.234)	-0.0135* (0.00757)
% high school degree	-0.000593*** (4.42e-05)	-0.0582*** (0.00325)	0.00165 (0.00286)	-0.0418*** (0.00133)	-0.110*** (0.00376)	0.000737*** (0.000112)
Log median house value	0.0205*** (0.00102)	1.038*** (0.0759)	-3.270*** (0.0716)	-0.471*** (0.0394)	-2.023*** (0.112)	0.0268*** (0.00294)
% male	-0.0619*** (0.0155)	-5.143*** (1.117)	6.238*** (1.028)	-0.985* (0.507)	-0.248 (1.505)	0.00390 (0.0512)
Median age	-0.000577*** (8.14e-05)	-0.0629*** (0.00646)	0.000463 (0.00756)	-0.0693*** (0.00290)	-0.176*** (0.00942)	-0.000420* (0.000247)

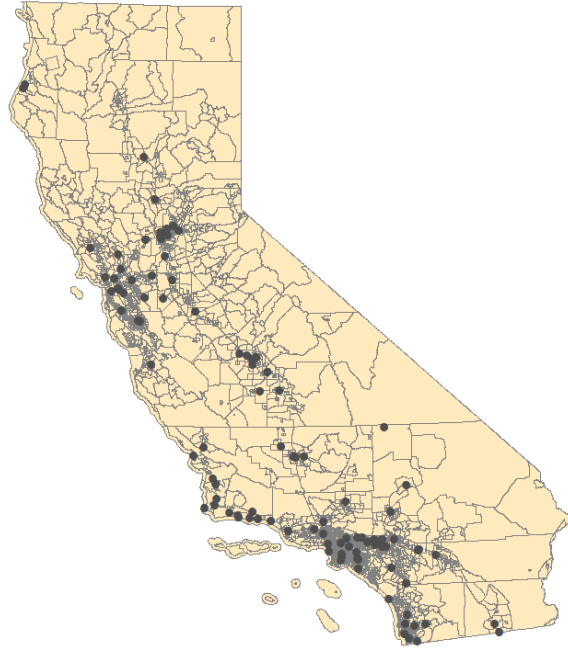
Relationships between pollutant concentration and demographic variables prior to cap and trade
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15: Preexisting pollution concentration disparities

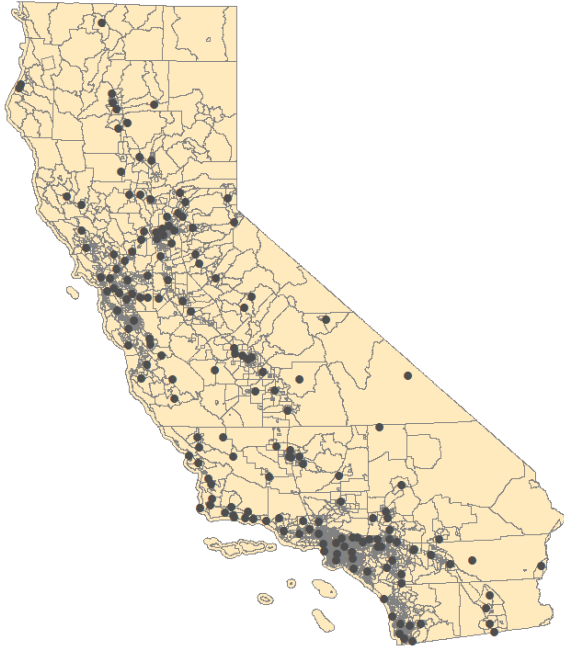
8.2 Figures



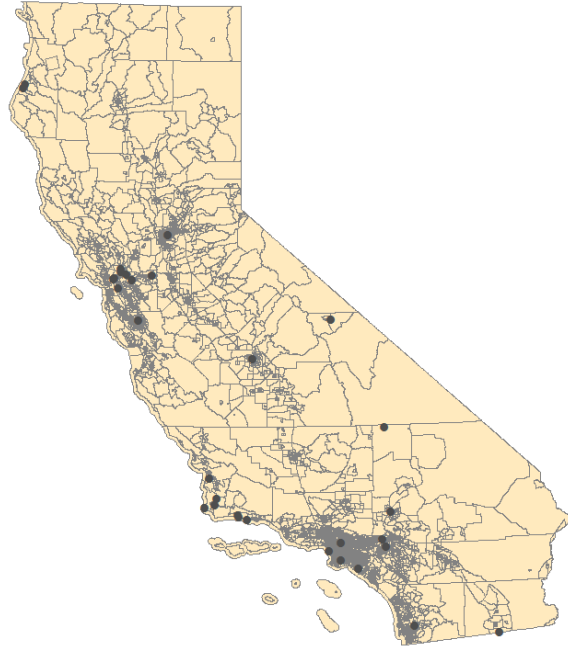
(a) CO station locations Q1 2016



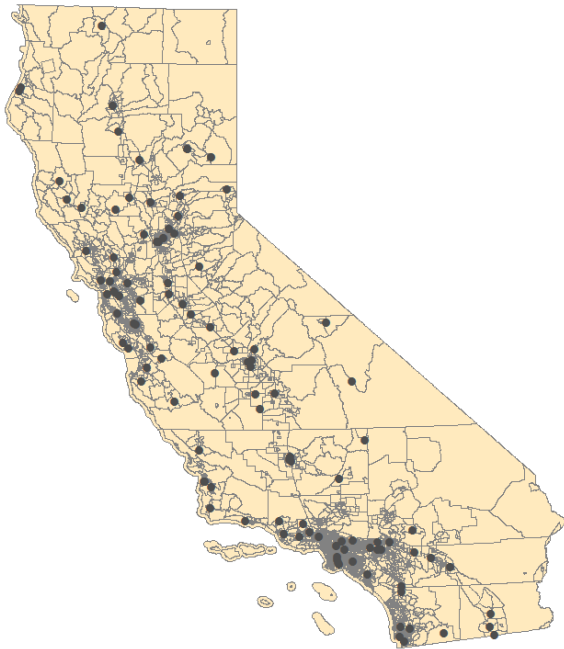
(b) NO₂ station locations Q1 2016



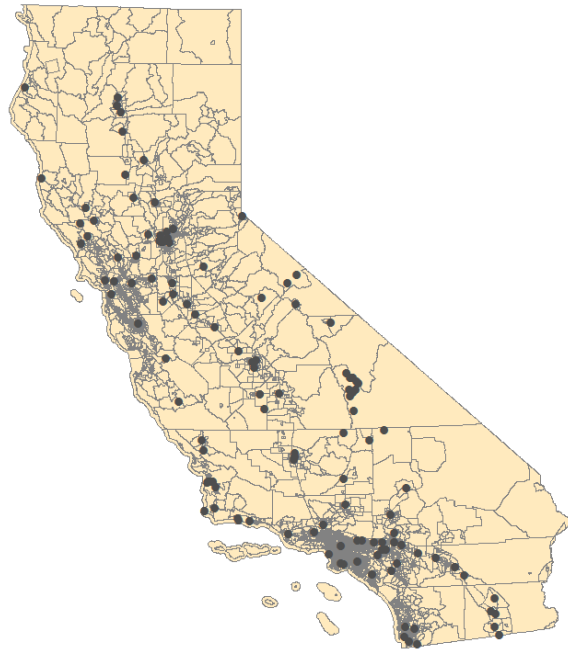
(c) O₃ stations locations Q1 2016



(d) SO₂ station locations Q1 2016

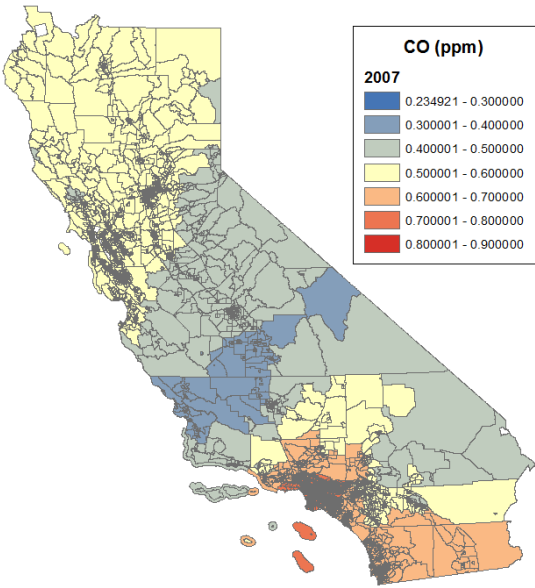


(e) PM 2.5 station locations Q1 2016

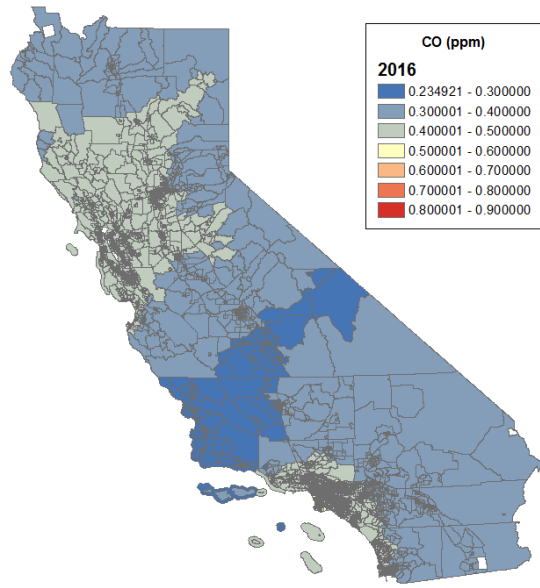


(f) PM 10 station locations Q1 2016

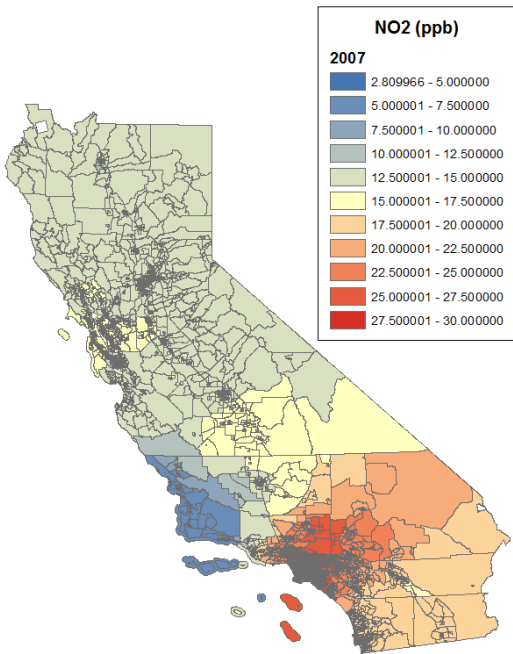
Figure 2: Air pollutant monitoring station locations



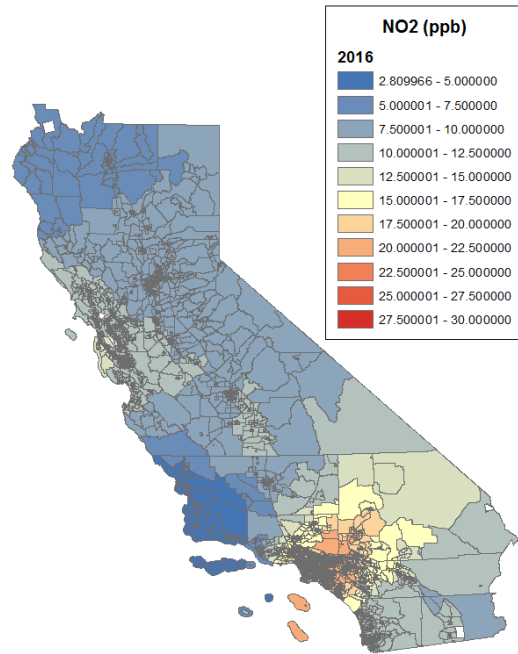
(a) CO distribution Q1 2007



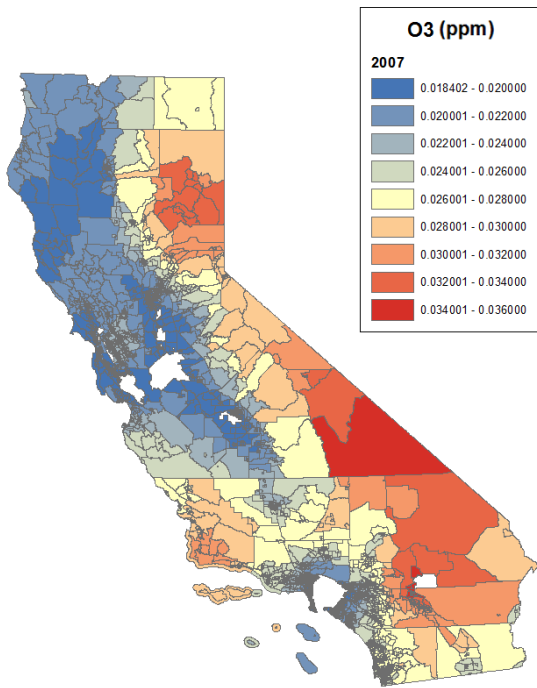
(b) CO distribution Q1 2016



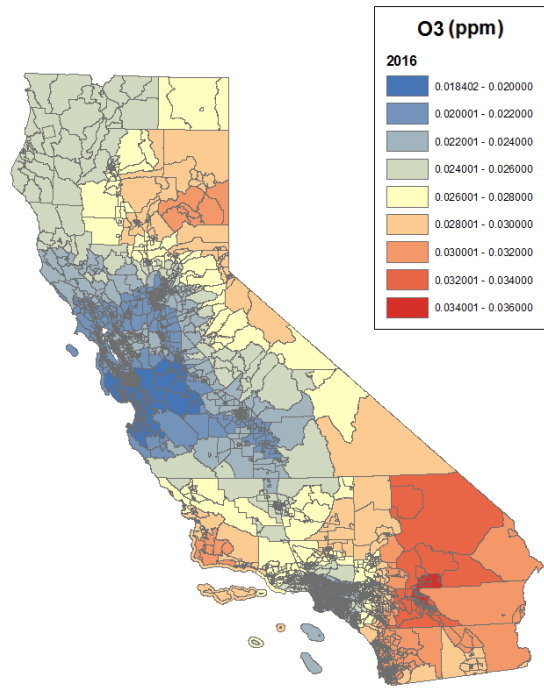
(c) NO₂ distribution Q1 2007



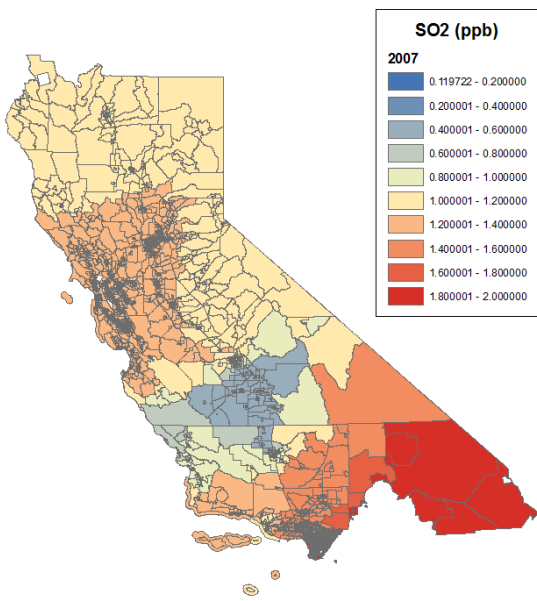
(d) NO₂ distribution Q1 2016



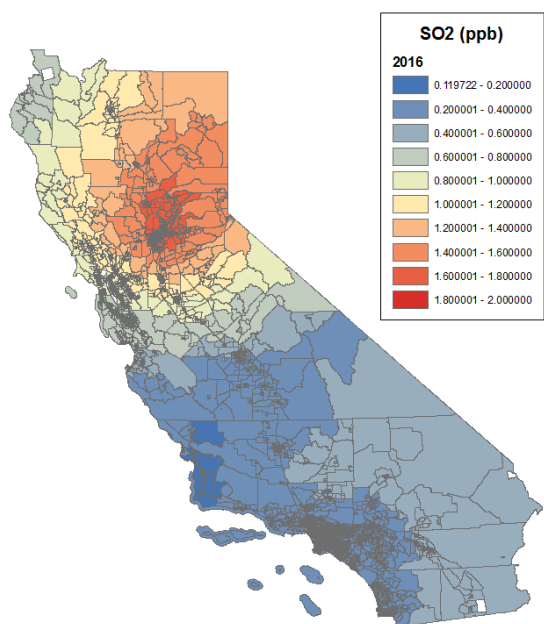
(e) O₃ distribution Q1 2007



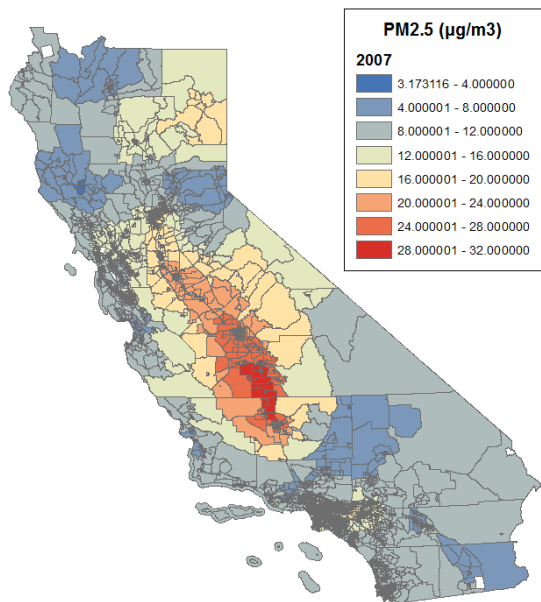
(f) O₃ distribution Q1 2016



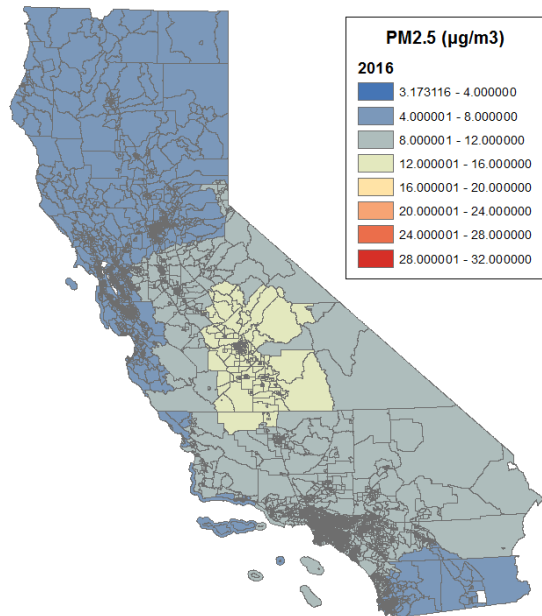
(g) SO₂ distribution Q1 2007



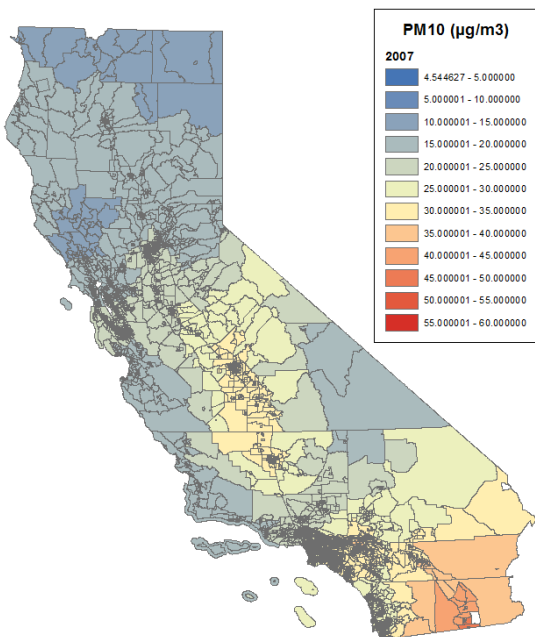
(h) SO₂ distribution Q1 2016



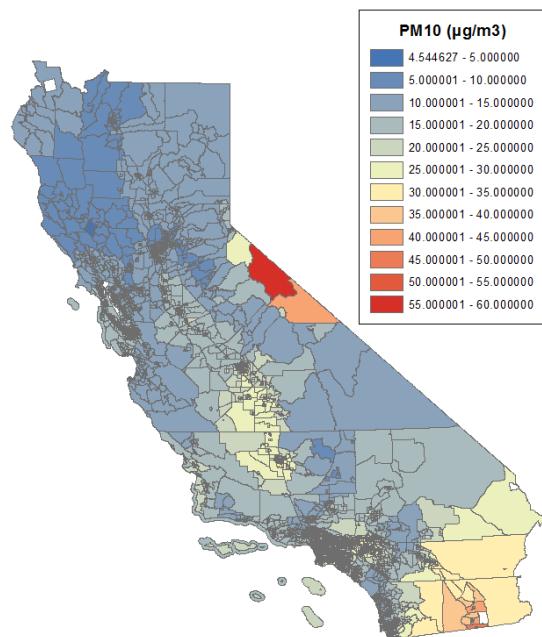
(i) PM 2.5 distribution Q1 2007



(j) PM 2.5 distribution Q1 2016



(k) PM 10 distribution Q1 2007



(l) PM 10 distribution Q1 2016

Figure 3: Shifts in geographic distribution of pollution