NRDC California Cap-and-Trade 2021 Senior Practicum Report

Natural Resources Defense Council and UCLA Institute of the Environment and Sustainability

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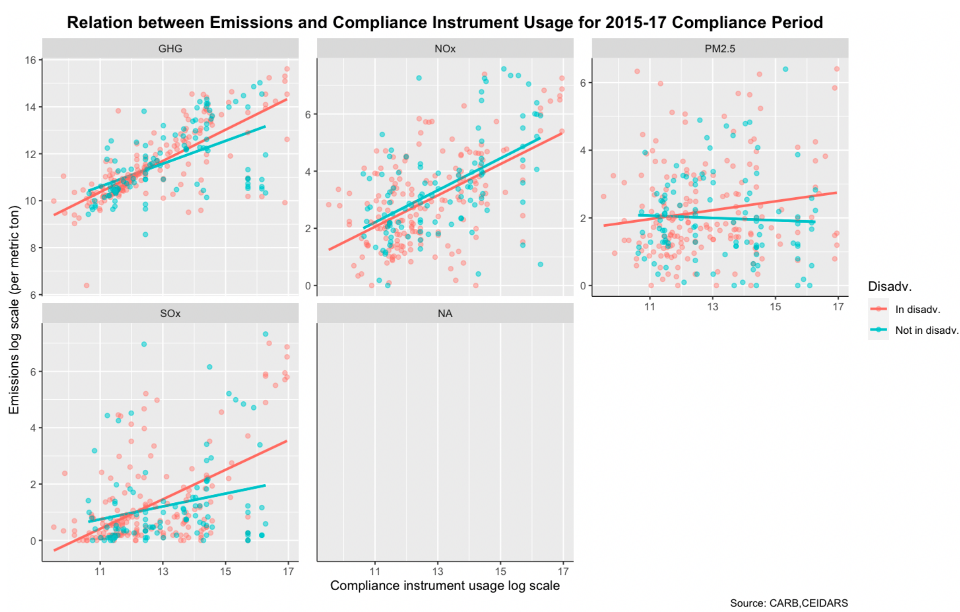
Executive Summary

We aim to understand to what extent and in what ways, if any, disadvantaged communities have been impacted by California's cap-and-trade system. In order to inform environmental, climate, and public health policy.

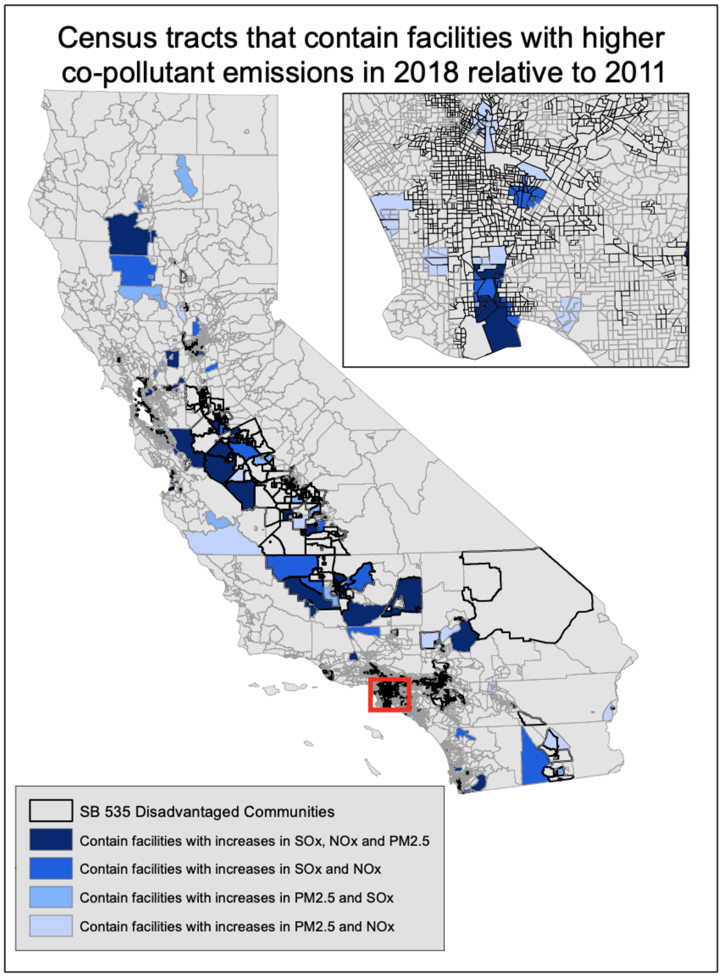
Our report's objective was to see the impact of California's cap-and-trade system on disadvantaged communities through the following research questions:

1. How are cap-and-trade revenues being utilized to mitigate impacts in disadvantaged communities, and how are these tracked and prioritized?
2. How does the use of compliance instruments by facilities relate temporally and by industry to co-pollutant emissions trends (2013-17)?
3. How is the location and nature of these facilities, as well as the amount of allocations used, related geospatially to demographic data or other EJ considerations?

Our analysis of program compliance instruments and their relationship to individual facility emissions utilized available public data from CARB and CEIDARS. Our analyses are based on linear and nonlinear regression models fit using R. Overall, we found that except for GHG, there was little to no interaction between emissions and instrument usage for the first compliance period (2013-2014). Nevertheless, there was a significant relationship between instrument usage and emissions for GHGs and SOx for the second compliance period (2015-2017).

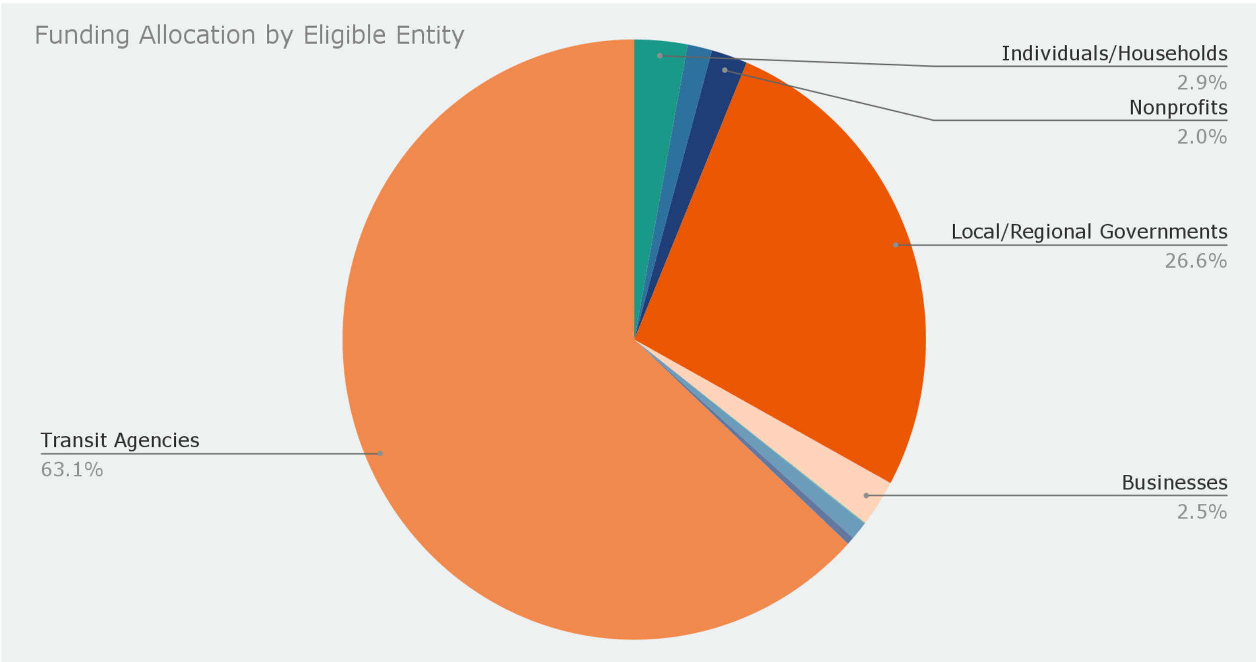


Next, we investigated further into relationships between instrument usage and emissions by sector for 2015-17. We found the most significant relationship between them for the Electricity and Oil & Gas sectors. Disadvantaged communities saw much higher emissions in the pollutant categories with strong fits for the relationship (see Table 2.1).We consider this relationship may indicate higher compliance instrument usage could lead to higher emissions that may disproportionately impact disadvantaged communities. However, given the gaps in the publicly available data among other confounding factors (e.g. the relatively short time frame of study) this is not conclusive.



Geospatial analysis used ArcGis to visually display and compare the locations of facilities under the cap-and-trade program, their Greenhouse Gas and co-pollutant emissions, and California's top disadvantaged communities as defined by SB 535. We also focused on four hotspots of emissions within disadvantaged communities of California: Los Angeles, Riverside area, North Central Valley, and South Central Valley. We found that people who live in census tracts within 1 mile of a facility that saw an increase of co-pollutant emissions are more likely to live below the poverty line, have less than a college education, and less likely to be white.

Program funding analysis led to our discovery of inequitable distribution of funding from Climate Change Investments (CCI), which is the mechanism through which funding raised from cap-and-trade auctions are reinvested into California communities. We analyzed CCI programs by eligible entities, such as nonprofits, local governments, businesses, etc, and compared eligibility to actual funding received. Our analysis found that while local/regional governments and transit agencies are only eligible for a combined 31% of programs, they receive about 90% of funding. On the other hand, tribal governments, eligible for 11.7% of programs, and farmers, eligible for 4.5%, only receive a combined 0.00076% of funding. We also looked into the geospatial funding distribution by census tract and found that tribal governments and prison populations are overrepresented in the areas which have received little to no CCI funding. 7.8% of tribal lands are unfunded, and 19.62% are low-funded; for prison populations, 31.96% of areas which hold prisons are unfunded, and 14.31% are low-funded. Secondary research analysis on other academic sources, reports, and case studies revealed program implementation in disadvantaged communities and effectiveness. Through synthesis of other reports and policy analysis, suggestions for the cap-and-trade program were also given and stated within the report.The secondary analysis shows that there is a lack of public health influence, lack of support for the grant application process, and also accessibility to the grant application for disadvantaged communities. Given these findings, cap-and-trade funding would be improved by explicitly addressing short and long-term environmental health issues and having grant distribution include strengthened community engagement, aid for the application process, guidance after grant distribution, and more outreach overall.



Introduction

As the global climate crisis worsens, we must implement new measures to secure a livable future for ourselves and the generations that follow. California has long been a leader in innovative climate policy that has the potential to serve as a model for what can be implemented elsewhere, with legislative successes like Assembly Bill 32 (2006) and Senate Bill 535 (2012) that advocate, not simply for the mitigation of climate change, but also for climate equity and the protection of our most vulnerable communities that are predominantly of color. However, whether this legislation has actually succeeded in achieving its stated goals is unclear.

As part of its suite of climate legislation, California has implemented a cap-and-trade program – a market-based mechanism central to the statewide goals of greenhouse gas (GHG) reductions. The program includes reductions to 1990 levels by 2020, which was met in 2016; 40% below 1990 levels by 2030; and 80% below 1990 levels by 2050 (CARB, 2018a; CARB, 2018b; Garcia, 2017). The cap-and-trade program establishes a decreasing limit on statewide emissions for regulated facilities, such as large electric power plants, large industrial plants, and fuel distributors, covering around 80% of California's total emissions and about 450 entities (Center for Climate and Energy Solutions, n.d.). The California Air Resources Board (CARB) translates the limit on total emissions, or the 'cap', into a set of allowances, each equivalent to one metric ton of carbon dioxide equivalent (CO2e) emissions. As this cap declines each year, so does the number of allowances. These allowances are either freely allocated or auctioned off to regulated facilities, and the annual auction reserve, or 'floor', price, increases each year. This increasing floor and decreasing cap creates a steady carbon pricing signal which is meant to prompt carbon reductions in regulated facilities, encapsulating the market-based mechanism behind the program (CARB, n.d.b).

As stated in Lara Cushing and Manuel Pastor's paper on carbon trading, environmental justice advocates are concerned that this "pay to pollute" system disproportionately affects disadvantaged communities (Cushing 2018). Part of the problem is that facilities that emit high levels of GHGs regulated under the cap-and-trade program also often emit other pollutants such as particulate matter (PM2.5), nitrogen oxides (NOx) and sulfur oxides (SOx), which are significant health threats at the local level. The claim by environmental justice groups then follows this line of argument: a polluting facility which buys GHG credits from another facility would then be allowed to surpass their emission 'cap' set by California's emission standards, leading to communities surrounding the facility with the elevated emissions being exposed to the increased impact of the excess GHG and dangerous co-pollutant emissions.

This study focuses on co-pollutants like PM2.5, SOx, and NOx due to their known health impacts. Fine particulate matter with a diameter of 2.5 microns or less has very adverse health effects due to it's extremely small size that allows it to travel and deposit deep in lung tissue. Particles which deposit onto the lung surface can cause tissue damage and inflammation (California Air Resources Board [CARB], n.d.-a). Sulfur Oxides (or SOxs) is highly reactive and can therefore interact with other pollutants like PM2.5 to indirectly cause adverse health effects and inflammation. Nitrogen Oxides (or NOxs) react in the atmosphere to create acid rain, smog, and respiratory irritation. These pollutant impacts are felt most adversely by children, asthmatics, and the elderly, and are causes of many premature deaths and disease in these demographic groups.

Research surrounding the possible disproportionate effects of the cap-and-trade system on such disadvantaged communities is inconclusive. Prior research done by Manuel Pastor and his colleagues at USC studied the relationship between disadvantaged communities and cap-and-trade in California, finding preliminary co-pollutant emissions and social equity patterns (Blaustein, 2018). This landmark research was critically important, but needs to be revisited as it explored data from 2011-2015, while the cap-and-trade program was not introduced until 2013 – which we hope to address by placing the scope of our study from 2011-2018.

Therefore the goal of this project was to analyze qualitative, quantitative, and geospatial data in order to explore the relationship between cap-and-trade emissions and disadvantaged communities in California. Using Pastor et al's work as a foundation, we furthered perspectives through analyzing geospatial, financial, and compliance instrument usage data. We aimed to analytically determine to what extent, if any, there is evidence that the cap-and-trade system has impacted disadvantaged communities, including when co-pollutants such as SO_x, NO_x and $PM_{2.5}$ are factored in.

Financial Analysis

How are cap-and-trade revenues being utilized to mitigate impacts in disadvantaged communities, and how are these tracked and prioritized?

Methodology

Existing research and data were available for us to analyze and synthesize how California cap-and-trade revenues are being spent, primarily through California Climate Investments (CCI), which oversees all use of cap-and-trade revenue for climate and environmental programs. We used data from CCI, CARB, the California Environmental Protection Agency, and other state and regional governmental agencies which facilitate the use of cap-and-trade revenue. We analyzed their recent reports, as well as previous map projects, revenue tracking, and policy evaluations. The secondary research focused on retrieving case studies from hotspot locations that we had established through our own map creations. Once we retrieved these case studies, we compared each of the programs and what benefits were being implemented.

<u>Program Eligibility Analysis</u>

We used data from the aforementioned agencies to analyze which entities, such as nonprofits, local governments, tribal governments, etc, are eligible for funding through the different programs funded by CCI. Most programs have multiple eligible entities. We compared this eligibility to actual CCI funding allocated and received by these entities, to evaluate whether the distribution of funding is equitable across sectors. To analyze this data, we created a large table of all programs funded by CCI and marked which entities were eligible for funding. We then took those same programs and checked to see how much funding was actually allocated to each entity. The percentage breakdown of both program eligibility and actual funding received by entity was visually demonstrated through pie charts. Finding data on funding breakdowns for each program was sometimes inaccessible and did require extra outreach to the administering agencies for programs which did not fully report allocations. After we finished gathering data for both eligibility and funding allocation, we created pie charts that showed the percentage of eligibility based on specified entities (individuals/households, land conservancies, nonprofits, local/ regional governments, tribal governments, businesses, farmers, public schools/school districts, universities/research institutions, and transit agencies) and did the same for funding allocation to compare how many eligible entities actually receive funding.

We included 55 of the 67 CCI programs in this analysis. Programs that were excluded include Climate Adaptation and Resiliency, Low Carbon Economy Workforce, Clean Off Road Equipment Voucher Incentive Project (CORE), Clean Truck and Bus Vouchers (HVIP and Low NOx Engines), Clean Vehicle Rebate Project (CVRP), Community Air Protection Program, Increased Public Fleet Incentives for CVRP Eligible Vehicles, Technical Assistance, Water-Energy Grant Program, Forest Health, and Local Coastal Program, which were excluded due to issues including lack of award-specific funding distribution data and structural incompatibility with providing award-specific funding data (such as programs providing community-wide technical assistance or individual vouchers). We also excluded the Affordable Housing and Sustainable Communities program from this analysis, as funding for this program is allocated to multiple entities as lead applicants, most of which span different sectors, and funding distribution among each lead applicant is unclear.

<u>Census Tract-Level Funding Gaps</u>

We also incorporated geospatial data into this analysis by cross-referencing the spatial distribution of CCI funding from the most recent CCI Program Map with CalEnviroScreen 3.0, to see where there are gaps in funding at the census tract level. We focused on two groups:

unfunded census tracts, which have never received any CCI funding; and low-funded census tracts, which have received less than $10,000 of CCI funding cumulatively. To begin this analysis, we manually checked the census tracts in each group on Google Maps satellite view to see each tract's primary land use to identify if there were patterns or trends within these unfunded and low-funded communities. We identified two demographic groups that seemed to be overrepresented in these tracts, tribal communities and prison populations, so we overlaid our maps with tribal lands, using the data from the California Governor's Office of Emergency Services Data Library on American Indian Reservations (AIR) and Federally Recognized Tribal Entities (FRTE), as well as prison boundaries, using Homeland Infrastructure Foundation-Level Data from the US Department of Homeland Security on secure detention facilities ranging in jurisdiction from federal (excluding military) to local.

To analyze these geospatial patterns for each demographic group (tribal communities and prison populations) and funding group (unfunded and low-funded census tracts), we calculated the total area for each group to serve as a reference point. We then used the Intersect tool in ArcMap's Analysis toolkit to identify the areas where each demographic group overlapped with each funding group – for example, where tribal lands intersect with unfunded census tracts. We then put all of these values into a table and calculated the intersect area (e.g., the total area of all intersecting tribal and unfunded lands) divided by the total demographic area (e.g., the total area of tribal lands) as well as the intersect area divided by the total funding area (e.g., the total area of unfunded census tracts). We calculated these two values (intersect/demographic area and intersect/funded area) for all combinations of our groups of interest to create our results table. For the map, we depicted these groups overlaid with disadvantaged census tracts.

One restriction of this analysis is that there were 23 missing census tracts – census tracts which were present in the Federal Communications Commission's full list of California census tracts but were not present in CalEnviroScreen, or were present as a dot rather than a full tract. When we cross-referenced these tracts with the California Hard-to-Count Index Map from the CA Census, these tracts had populations of 0 and no demographic data. Many of them were still dots, but some were small tracts in uninhabited areas.

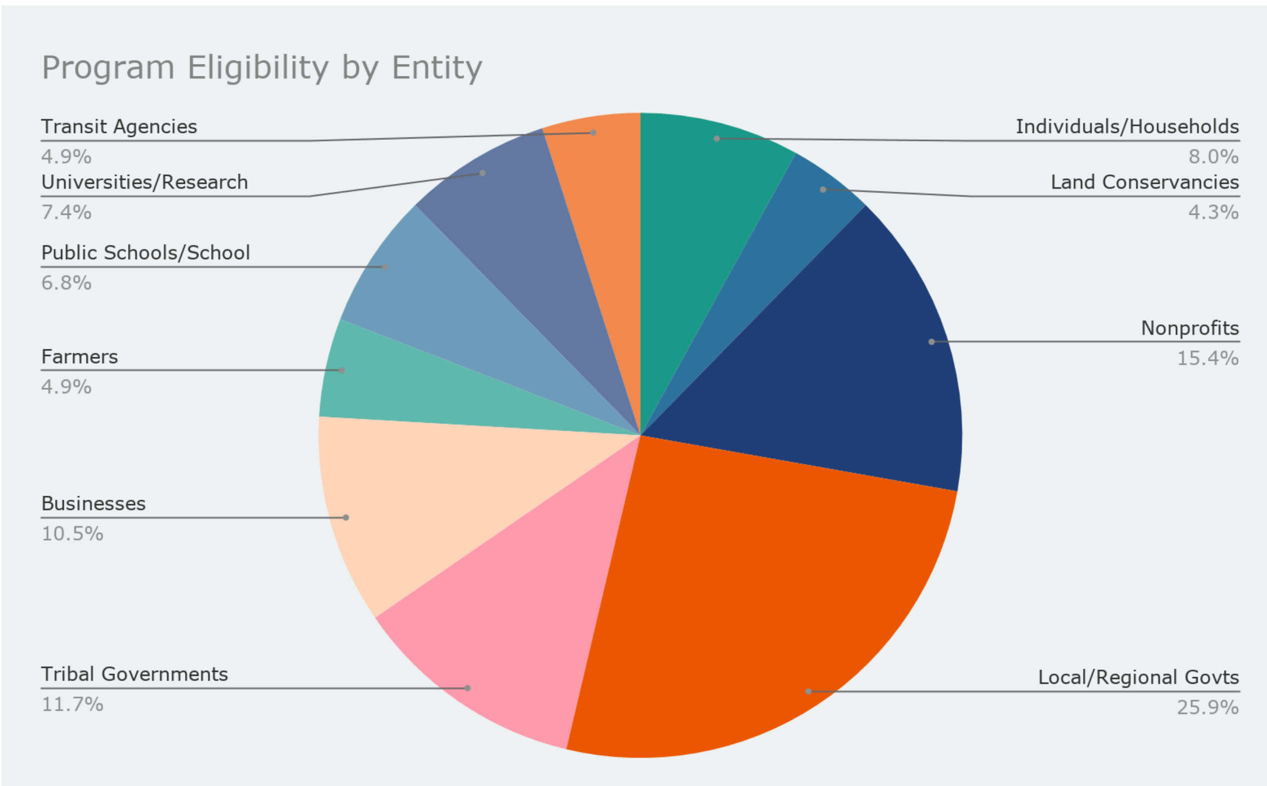
Cap and Trade Comparison and Recommendations

We did analysis and explored how the cap-and-trade program could be improved. Aside from these agencies, we looked over other research done by other academics, professionals, and policymakers which included court cases, policy reports such as policy implications and plans, and research papers. We focused on highlighting and identifying flaws or improvements that could be made on the funding process that have already been identified in previous literature. Through synthesis, we were able to cohesively outline issues with CCI funding distribution and overall the distribution of cap-and-trade allocations.

Results

Program Eligibility Analysis

In analyzing the entities eligible for CCI funding, we created two pie charts, one for the percentage of programs each entity is eligible for (top) and one for the percentage of funding actually allocated to each eligible entity (bottom). Moving clockwise from the top, entities for both charts follow the same coloring scheme and order: individuals/households, land conservancies, nonprofits, local/regional governments, tribal governments, businesses, farmers, public schools/school districts, universities/research institutions, and transit agencies. The top Program Eligibility chart shows that the entities with the highest shares of program eligibility are local/regional governments (25.9%), nonprofits (15.9%), and tribal governments (11.7%). However, the bottom Funding Allocation chart shows that the entities receiving the most allocated funding are transit agencies (63.1%) and local governments (26.6%), with all other entities receiving less than 3% each. For comparison, this means that while local/regional governments and transit agencies are only eligible for a combined 31% of programs, they receive about 90% of funding. On the other hand, tribal governments, eligible for 11.7% of programs, and farmers, eligible for 4.5%, only receive a combined 0.00076% of funding.



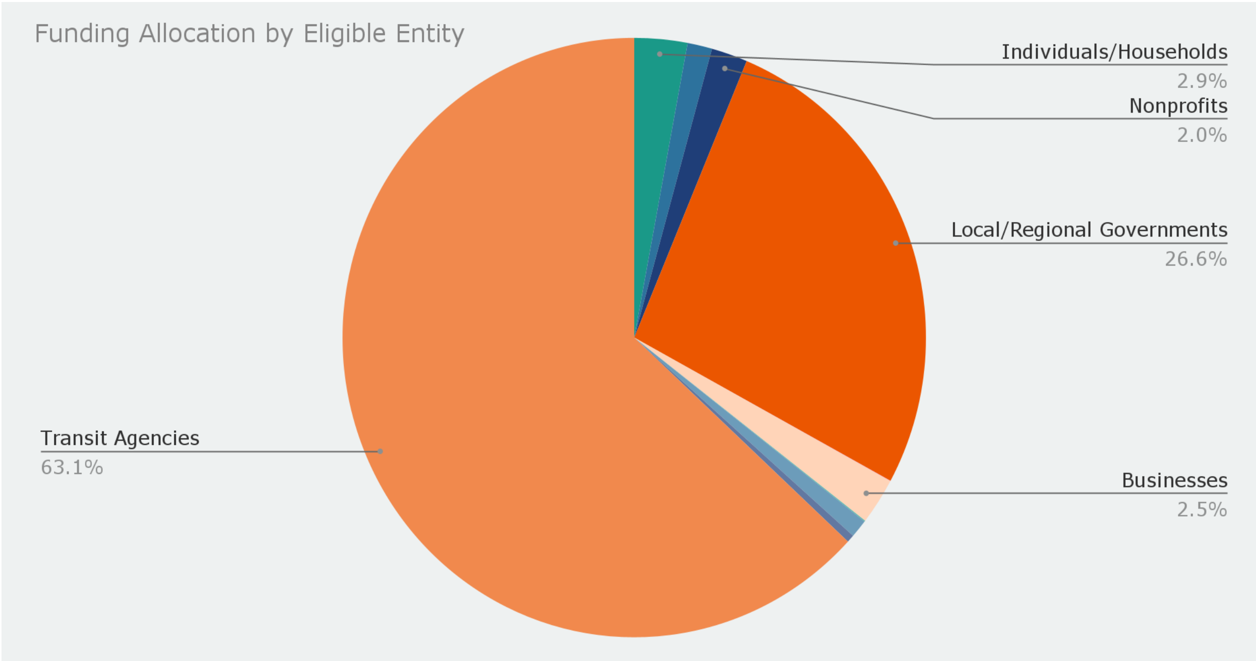


Chart 3.1 and 3.2. Chart 3.1 represents program eligibility by entity. Local governments are represented by the dark orange and transit agencies are in light orange. Tribal governments are represented in pink and farmers in teal. Chart 3.2 displays funding allocation by eligibility entities from the same programs in Chart 3.1. Color representation is replicated from Chart 3.1. See Appendix B for sources and program usage.

<u>Census Tract-Level Funding Gaps</u>

Our geospatial analysis of demographic groups which had received little to no funding is represented in the table below and in the map in Appendix A. The table shows the areas of each group of interest – our demographic groups of tribal lands and prison populations, and our funded groups of unfunded and low-funded census tracts – as well as the areas of where they intersect, and the percentages of the intersecting area over demographic group and funded group for each combination. This shows that 7.8% of tribal lands are unfunded, and 19.62% are low-funded. In regard to prison populations, 31.96% of areas which hold prisons are unfunded, and 14.31% are low-funded.

Area (square kilometers)	**Tribal/Unfunded**	**Tribal/Low-Funded**	**Prison/Unfunded**	**Prison/Low-Funded**
Intersect	307,334	772,825	12,378	5,543
Demographic Group	3,938,118	3,938,118	38,726	38,726
Funded Group	46,607,027	46,593,166	46,607,027	46,593,166
% of Demographic Group	7.80%	19.62%	31.96%	14.31%
% of Funded Group	0.66%	1.66%	0.03%	0.01%

Table 3.1 shows the area, in square kilometers, of each demographic group (tribal and prison) and funding group (unfunded and low-funded), as well as the area of regions where they overlap (intersect) and these overlapping areas as a percentage of total area. For example, in the Tribal/Unfunded column, it shows that tribal and unfunded areas have 307k square kilometers of overlap; the demographic group (tribal) has 3,938k square kilometers of total area in CA and the funded group (unfunded) has 46.6m square kilometers. The overlapping area makes up 7.80% of the total tribal area and 0.66% of the total unfunded area.
Sources: https://www.fcc.gov/general/census-blocks-state; https://webmaps.arb.ca.gov/ccimap/; https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30; https://gis-calema.opendata.arcgis.com/datasets/23348a6fb3e44322a0c0a862aba62a24_0?geometry=-114.258%2C20.353%2C114.258%2C88.913; https://hifld-geoplatform.opendata.arcgis.com/datasets/2d6109d4127d458eaf0958e4c5296b67_0?geometry=-66.981%2C-3.068%2C47.276%2C75.954

Case Study Analysis

Although there are several locations where spending is allocated, there are specific areas that are deemed as hotspots. Some hotspots that we included in our secondary analysis consisted of the LA area, the Central Valley, Fresno, and San Bernardino County. Within these areas, CCI was able to take information regarding the programs that were implemented and how they have progressed. Each program primarily focused on partnering with the Greenhouse Gas Reduction Fund (GGRF) to improve different aspects of each area.

Los Angeles

For the LA area, it was broken down into Boyle Heights and also into South LA. The GGRF provides funding for ELACC for Boyle heights to renovate low-income apartment housing and to make more housing that is TOD (Transit Oriented Development). As for the South Los Angeles Region, KYCC is planning to create more tree canopy within South LA and Pico-Union which are places that have the most pollution but also more of the Los Angeles disadvantaged community. Within South Los Angeles, the program's focus is to reduce the heat island effect and also involve its community members. Aside from reducing greenhouse gas emissions, *Green Street Through Community Engagement* is trying to make soil in the area more permeable and trying to reduce the heat in South Los Angeles which would ultimately help the residents lower the electricity bills and their overall wellbeing.

Central Valley

Calvans is a program that is a self run program where agriculture workers are able to carpool with one another. The program also creates a job opportunity for some of the workers to be the drivers for this program. Workers use this public transportation to and from work to omit emissions, save the workers money from not using their own private vehicles, increase safety, and also prompt workers to arrive on time to work. This system makes the lives of farmworkers easier by having an easier access to transportation to their job and is economical for them as well.

Fresno

Fresno has a high amount of rotting food within the city which releases lots of methane gas. *Food to Share* is working on changing this methane gas into biomethane which is less harmful. *Food to Share* is trying to displace 65 tons of organic material and 46.73 tons CO2e annually as their goal. The program is trying to receive more funding because most of their funding goes to administration and machinery leaving not as much money for the actual process of changing menthane to biomethane. Another program within the Fresno area is *Fresno EOC Rooftop Solar Electric Solar Power for Central Valley Residents* which promotes solar power roof installation. The program also reaches out to community members to switch to solar power because of the impacts of climate change and how it is disproportionately affecting people of color. In Fresno specifically, residents must pay more to live comfortably since during the summer sometimes it reaches triple digits while in the winter the weather can be below freezing. The program is also promoting to move away from the agriculture industry because of its pollution creation, but also because climate change is affecting the agriculture industry. EOC Conservation Corps is trying to get people equipped through energy and weatherization careers so they no longer have to rely on agricultural jobs and are able to find a career in renewable energy.

San Bernardino County

A specific area in San Bernardino County that Climate Change Investments studied was the city of Montclair. Cal Fire GGRF awarded and provided support for a tree park that was mostly created by the community. The program started off as an idea by a high school student and then gained interest by community members. The community members did all of the work including contracting local tree businesses, learning how to plant and maintain the trees, and continuously keeping the park maintained. It is one of the few of its kind and addressed lack of green space, lack of healthy foods, and also cleaning of air (pollution)

LOS ANGELES

Green Street Through
Community Engagement

Funding: $329,725 FY 2014-2015
Benefits:
- 1,986 tons GHG Reduction
- 1,120 Trees planted
- Reduction of heat island effect
- Improved air quality

FRESNO, TULANE COUNTIES

Fresno EOC - Rooftop Solar Electric
Solar Power For Central Valley
Residents

Funding: $4.05 Million FY 2014-2015

Benefits:
1,212 solar systems
- 900,000 watts of solar power
- 28,031 metric tons of carbon dioxide

SALINAS VALLEY CENTRAL VALLEY IMPERIAL COUNTY

Agricultural Workers
Vanpool Expansion

Funding: $3 million FY 2014-2015

Benefits
-reduction in vehicle use
-transportation benefits

FRESNO

Food to Share

Funding::$2,925,920 Colony Energy
Partners, LLC
$225,920 Food to Share

Benefits:
-651,500 tons estimated GHG reduction
- Recovery of 65 tons of food annually
-improved air quality

MONTCLAIR (SAN BERNARDINO COUNTY)

Montclair Community Fruit Park

Funding: $11,000 for Montclair
Community Fruit
Park, $700,000 from CalFire in FY14-15
Benefits:
- Enhanced public space
- 30 accessible fruit trees
- Healthy food options

LOS ANGELES BOYLE HEIGHTS

1st and Soto Transit Oriented
Development (TOD) Apartments
(Phase II)

Funding: $4.072 million requested
Benefits
- 31 units of affordable housing
- 38 bike parking spaces
:

SAN JOAQUIN VALLEY
Enhanced Fleet Modernization Program Plus-up (EFMP Plus-up) Funding: $4.8 million FY 2013-2015 Benefits: -13,000 repaired cars -reduction in hydrocarbons and NOx

Figure 3.2 Based on the our hotspot findings, we cross referenced case studies that have been done to highlight programs that have been implemented through Climate Change Investment Funding. Each chart focuses on a hotspot, the program that has been implemented, the funding that was provided, and the benefits that each program has had on the community.

Sanchez, S. Alvaro. (2015 October). California Climate Change Investments: 10 Case Studies Reducing Poverty and Pollution. The Greenling Institute. https://greenlining.org/wp-content/uploads/2015/11/CCI-Case-Studies-RPP-to-post-spreads.pdf

Cap-and-Trade Recommendations

The process of using cap-and-trade funding is suggested to be formulated into four components: goals, process, implementation and analysis. The *Greenlining Institute Handbook* provides suggestions for policymakers and stakeholders on how to use CCI funding to promote authenticity and enhance community engagement for grants.

COMMUNITY ENGAGEMENT ACTIVITIES FOR GRANT PROGRAMS[lxxiii]	
CATEGORY	**ACTIVITIES**
Activities to Inform Community Stakeholders and to Solicit Stakeholder Input	• Public workshops/meetings • Door-to-door canvassing • House meetings • Develop website and/or social media • Distributed flyers or other printed materials • Outreach to existing community groups • Surveys • Focus groups • Involve local health departments, which can help reach community-based organizations and frontline community members

Activities to Engage Community Stakeholders in Development of Proposal	• Design charrettes • Community-based participatory research • Participatory budgetinglxxiv • Convene advisory body or shared decision-making body • Develop website and/or social media • Community benefits agreements • Additional activities to ensure community stakeholders have an opportunity to influence the project proposal development
Activities to Ensure Community Engagement During Implementation of Proposal	• Public workshops/meetings • Door-to-door canvassing • House meetings • Established website and/or social media • Surveys • Focus groups • Sub-contract with existing community-based organizations that organize frontline communities to conduct outreach • Allocate staff positions focused on community engagement • Advisory body or shared decision-making body • Maintain community engagement throughout the implementation or proposal

Figure 3.3 Mohnot S., Bishop J., & Sanchez A. (2019 August). Environmental Equity: Making Equity Real In Climate Adaption and Community Resilience Policies and Programs: A Guidebook. https://greenlining.org/wp-content/uploads/2019/08/Making-Equity-Real-in-Climate-Adaption-and-Community-Resilience-Policies-and-Programs-A-Guidebook-1.pdf

There must be emphasis on community empowerment and finding ways to be able to combat community barriers that include cultural barriers,literacy barriers, socioeconomic status, local history, competing interests, language barriers, etc. Aside from focusing on these factors, there must be inclusion of technical assistance that communities can use when applying for grants. Some communities don't know how to fill out these grants or need aid with the after procedures once receiving the graphs. With inclusion of technical assistance, more community organizations would be willing to apply for grants and also feel more supported throughout the entire grant process.

California Climate Investments implement programs within three priority areas: transportation and sustainable communities, clean energy & energy efficiency, and natural resources and waste diversion (California Air Resources Board, 2018). While climate change mitigation and adaptation strategies are linked to public health impacts and benefits, there has been limited engagement by local health departments (LHDs) inactivities funded through the CCI at the local level (Tamanna 105). LHDs role may be currently limited due to lack of clarity on whether LHDs are eligible to apply for funding, limited requirements for eligible applicants to partners with their LHDs, and lack of consideration of health benefits in the grant proposal evaluation process (105)There is a lack of connection between programming by CCI and also the LHDs that are already working with disadvantaged communities. A recommendation is to interconnect the two and have more involvement since

LHDs know the public health impacts and how programming should be done for certain communities which can show CCI programs how much a community actually needs for funding based on the impacts of climate change externalities (137).

Discussion

Program Eligibility Analysis

The eligibility charts suggest that although billions of dollars flow through CCI to fund climate action projects in California communities, much of these funds are being awarded to governmental entities. Although it makes sense that there would be a disproportionate amount of funding allocated for entities like transit agencies – since a nonprofit doesn't have the capacity or role to overhaul a huge transit system – the disproportionality of funding is far beyond this understandable amount. If CCI is meant to facilitate equitable funding from cap-and-trade, a state-level governmental program, it must strive to ensure that funds are not collected by the state-level government and then distributed almost entirely to local- and regional-level governments. Nonprofits, tribal governments, and farmers hold especially nuanced perspectives in the face of climate change that often differ in priorities from governmental entities, and they don't have equal or proportionate funding, let alone equitable funding. Procedural justice is extremely important in this sphere, and if governmental entities have the main say over where and how funding is allocated, there are likely to be issues in procedural justice - who is getting a seat at the table?

Census Tract-Level Funding Gaps

The funding gaps identified in tribal lands and in areas that hold prisons is a clear equity issue. Both of these groupings represent populations which are especially burdened from and vulnerable to climate and environmental impacts which are hard to measure, but with a quantifiable indicator like funding, it should be easier to prioritize ensuring that these groups get the funding they deserve. Prison populations are especially vulnerable to this increased air pollution, and many of the tracts which have received little to no funding and hold prison populations are marked as 'High Pollution/Low Population' on CalEnviroScreen, which seems to mean they lack a CalEnviroScreen score and percentile, and as such, they are excluded from CalEnviroScreen's methodology in determining which census tracts are disadvantaged – if they don't have a percentile, they cannot be in the top 25%. While it may be defensible to have High Pollution/Low Population designations for areas which are uninhabited or lack residential dwellings, such as desert or park areas, prison populations should not fall under this category. Prison populations rarely leave the tract in which they live, which means that although they may have a 'low population', they are being subjected to extremely high levels of pollution every day with likely little to no preventative measures such as masks designed for air pollutant exposure. In terms of why these groups lack funding, it is likely unclear where in the funding process the equity issues lie, and each step of the process requires different remedies to ensure equity. If there are less applications from these groups for CCI program funding, then administering agencies could begin targeting them with marketing and outreach and increasing the accessibility of both the outreach materials and the application materials. If there are similar numbers of applications, but less advance to be awarded, then increasing technical assistance efforts for these groups and increasing the application accessibility – such as through decreasing jargon and the amount of technical supplemental materials which would require high levels of capacity – might help. Additionally, revising scoring guidelines for applications and reviewing the demographic statistics of applicants compared to awardees could ensure that even groups with low technical capacity and those who are new to grant applications have a fair chance at receiving funds might help bridge this gap.

Case Study Analysis

The programs that have been implemented at the hotspots have all been very successful within their respective communities. The case studies give anecdotal reference on how funding is spent Grants were applied for by the state, some by organizations, and some by community members. Grant application is very versatile but still there aren't as many programs with high rates of success compared to how much funding is supposed to be given out. Aside from programming, there isn't as much support or correlation with public health efforts which would prioritize communities that should have the designated funding. Although there is program implementation for greenhouse gas reduction, there isn't enough reference to public health concerns which would include other externalities that disadvantaged communities may face.. The lack of public health input is a flaw with CCI's plan to make grants more geared towards these communities. The grant distribution also lacks more community engagement, aid for the application process, guidance after grant distribution for eligibility groups, and outreach to disadvantaged communities.

Compliance Instrument Analysis

Goal

The goal of this work was to investigate how the use of compliance instruments by facilities may relate temporally and by industry to co-pollutant emissions trends within disadvantaged communities. The study of facility GHG and co-pollutant emissions can be related by industry sector and by disadvantaged community status. This information is required to assess if there is evidence as to whether cap-and-trade affects disadvantaged communities positively or negatively.

Background

In order to meet established caps under the Cap-and-Trade system, individual facilities have allocations and offsets by compliance period which represent the amount of allowable emissions for that facility. This requires a regulatory structure of annual reporting of emissions from all facilities, which is publicly available data. The California cap-and-trade program is reliant on a string of GHG and co-pollutant emissions reporting programs that establish baseline facility-level emissions across the state. These emissions from industrial sources, fuel suppliers, and electricity importers are reported to the California Air Resources Board (CARB) under California's Regulation for the Mandatory Reporting of Greenhouse Gas Emissions (MRR). This rule extends to facilities exceeding 10,000 metric tons of CO2e and process emissions per year. Data from stationary facilities emitting more than 25,000 metric tons of CO2e are verified by CARB-accredited third parties and have been the primary datasets used for a multitude of studies on the program itself. (CARB, 2020b)

In a California Office of Environmental Health Hazard Assessment (OEHHA) study[1] on the cap-and-trade program, facility locations were similarly extracted from the CARB 2014 emissions inventory and covered 281 GHG facilities (OEHHA, 2017b). However, this particular OEHHA study omitted emissions data from 2008-2010, as it was not comparable to later years that brought fuel distributors under the cap-and-trade program.

The compilation of criteria pollutant data for facility specific emissions was most commonly extracted from CEIDARS program data (Cushing, 2017; OEHHA, 2017b), which is also present on the CARB Integrated Emissions Visualization Tool (CARB, 2016). Major fluctuations of such criteria pollutant emissions data that could be attributed to normal year-to-year-variation, economic conditions and market fluctuations, expanded reporting requirements, enhanced capture of emission sources at facilities, methodology changes, and facility mergers. Many of these reasons may make it a challenge to attribute cap-and-trade program impacts directly to facility emissions trends.

Delving into how cap-and-trade program credit allowances have been allocated to facilities specifically presents a difficult challenge, as this data is not publicly available. Though the compliance instrument auctions by parent companies are on the public CARB auction data, this is not differentiated by facility and has therefore not been compared in previous studies at that scale.

Sources of Data

CARB Mapping Tool

This online resource includes a large set of important facility data needed for our analysis, including: ARBIDs, facility location, industry sector, and our primary pollutants of study by year between 2011-18. This was composed of 307 facilities total, which is not the entirety of the cap-and-trade system (about 450 entities[2]) and does not include Quebec facilities. However, most importantly it included co-pollutant data for every facility. All datasets from 2011-18 were downloaded and linked by facility over time for all co-pollutants of study.

MRR

At the beginning of this project, we first analyzed the Regulation for the Mandatory Reporting of Greenhouse Gas Emissions (MRR) provided by CARB. The dataset is extremely detailed, it includes emissions of carbon dioxide, methane and nitrous oxides from different sources. It also indicates whether these emissions are covered by the Cap-and-Trade regulation i.e., not exempted from regulation or not covered by the regulation. However, this dataset did not include data of co-pollutant emissions.

CEIDARS

We also used the California Emission Inventory Development and Reporting System (CEIDARS). CEIDARS is a publicly available data source which provides basic inventory information from all point and area sources along with auxiliary data which helps categorize the information.

CARB Compliance Instrument Auction Data

This data source provided the only known Compliance Instrument data known for the California cap-and-trade system. This includes total allocations of credits and offsets by parent company

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1

2 https://ww2.arb.ca.gov/sites/default/files/classic//cc/capandtrade/guidance/cap_trade_overview.pdf

under the system by compliance period. The first full compliance period began in 2013 and ended 2014, which provides the first comparable block of data. The next full compliance period is 2015-17. The full compliance period summary of 2018-20 has not been made public at the time of this report.

Cleaning up CARB Mapping tool data

As our primary source of data for analyzing co-pollutant trends we used the CARB mapping tool aggregated data for co-pollutants. We decided to concentrate on NOx, SOx and PM2.5 co-pollutants along with GHG emissions for our final analyses. However, from our initial analysis to meet our goals we were met with gaps and inconsistencies in the data. We decided to tackle the problem by manually sorting the data and cross referencing it with another publicly available dataset (CEIDARS). During our manual sorting we found the following inconsistencies:

1. We were able to fill in most gaps in the datasets by cross referencing with CEIDARS. While cross referencing with CEIDARS for the gaps in the dataset we found some of the missing values. We observed different patterns that may have led to the gaps in the dataset. We found emissions from the same address but different facility ID (FACID), different addresses but same facility name and even different address but same FACID. Example: PG&E Topock Compressor Station
    - Facility ID (until 2017): 1500039
    - Gap: 2018 data
    - New Facility ID (found in CEIDARS): 39

One drawback of utilizing the CARB data even after cross reference was the number of missing values. Most facilities had reported GHG values and such emissions would have corresponding co-pollutant emissions. This could be attributed to the different standards of reporting that varied from Air Quality Management Districts (AQMDs).

Compliance instruments in this study are an aggregation of both a facility's offsets and allowances due to its interchangeability in the cap-and-trade program. Compliance Instrument (CI) usage by facility was estimated from CARB auction data from the 2013-14 and 2015-17 compliance periods of the cap-and-trade program. CI usage was auctioned off by the facility parent company with each parent company having ARBIDs. With this relation, facility characteristics from the CARB aggregated mapping tool dataset were matched with CARB auction ARBIDs to disperse CIs. However, parent companies with multiple facilities have no indication of a weighing factor for compliance instrument distribution. In order to complete analysis, the total compliance instruments of a parent company with multiple facilities were distributed equally. Though this is by no means an exact method, the team hopes this will at least give relative orders of magnitude for CI usage for concerned facilities.

Methodology

<u>Statistical methods</u>

Our statistics methodology goal is to study the relationship between facilities that use credit under the cap-and-trade program and their increases in co-pollutants such as PM 2.5 and

NOx emissions. Our next goal is to study the increases in co-pollutants as averages per year and increases by sector. The data we have at our disposal for the first credit allocation analysis is from CARB auction data. Our group separated the analysis into two compliance instrument periods, 2013-2014 and 2015-2017, to study the difference in credit allocation and emissions between these two periods. To conduct our analysis, we used R, a programming software, to study the statistical relationships. Our group had the help of statistics experts Dr. Hannah Carrol, Dr. Cristian Roman Palacios, and Ph.D student Alexandra Arnold to make our graphs. Our analysis was by compliance instrument periods, by pollutant, and then by sector.

Outside of Scope

Regressions measure relationships between variables; the best fit model generally reduces the amount of error between observations and a given line. The closer the R^2, a measure of model fit, is to the number one, the stronger the relationship between variables. Among the many types of regressions, we primarily focus on two types: linear and multiple-linear regression. Linear regression is for two variables (one predictor and one response variable). Multiple linear regression is for more than two predictors. We initially planned to use multiple linear regression to help us distinguish between how much pollution is caused by the mobile sources as compared to what is caused by the facilities. This analysis would have been to see if we can prove the extent to which the increase of pollutants in disadvantaged communities is caused by facilities as compared to external variables such as mobile sources, fires, weather patterns, and the direction and speed of the wind. However, after speaking to experts about this subject, we concluded that multiple-linear regression for this purpose was out of the scope of our project.

Initial directions our research group wanted to pursue were addressed and reshaped throughout several meetings with advisory experts. Input on statistical analysis, data clean up, and sources of error formed a concrete framework for further study.

Compliance Instrument Analysis

Initially our primary goal was to investigate causal impacts (if any) of increases in emissions by facilities due to the cap-and-trade program and the trading of compliance instruments (CIs). However, advice made isolating causal impacts seem impossible to complete within the scope of this project. This may be due to a number of reasons, including a general oversupply conditions in the trade market[1] and the complexity of the cap-and-trade market scheme overall. Therefore, our analysis focuses on the correlation between emissions and CIs and comes to take a three-fold approach:

1. Analyze compliance instrument usage with overall emissions trends by facilities by compliance period
2. Analyze compliance instrument usage by facilities categorized into industry sector by compliance period
3. Analyze compliance instrument usage by individual facilities by compliance period

Each analysis needs to be broken down by compliance period, specifically 2013-14 and 2015-17 which relate to the final surrender and compliance of each parent company. Though we have emissions data from 2011-12 and 2018, these periods only had partial submissions and were therefore non-comparable. However, emissions data from before and after are still used to contextualize CI trading impacts.

Compliance instrument usage and emissions data by facility was then brought into R, a programming software. We transformed all of the data through the dplyr package into individual points that are sorted by pollutant (PM2.5, NOx, SOx, GHGs) and by compliance periods (2013-14, 2015-17) for each facility. This aggregated the pollutants for each facility over the compliance period to enable a comparison with compliance instrument usage. However, since the period of our full data-set spans from 2011-2018, we further broke down the analysis by sector and by pollutant. We also defined facilities within disadvantaged communities based on geospatial analysis. which included all facilities within 1 mile of the border of every disadvantaged community census tract.

As supplementary analysis, one of our initial methods consisted of isolating the contribution of stationary facilities to census tract ambient air emissions. However, due to the variety of sources of pollution (including mobile, natural, etc.) and the difficulty in accountancy this was deemed beyond the scope of the research project. This transitioned into utilizing a regression model to display overall pollution trends related to compliance instruments using the data we did have at our disposal in R.

When pointed out, we were also made aware of several inconsistencies in the CARB aggregated facility datasets, the primary dataset of our analysis. For oil/gas facilities, geocodes are created from which emissions data is reported rather than the site of emissions. Co-pollutant emissions data comes from CEIDARS, which is an online database that only requires self-reported data every 3-5 years and may therefore include several inaccuracies and be influenced by stationarity. Given the large amount of missing data, cross-checking CARB with CEIDARS became a priority. We wanted to supplement our analysis with an estimation normalized to equivalent GHG/co-pollutant ratios, given that facilities cannot have GHG emissions without correlating co-pollutant emissions. However, the amount of missing co-pollutant data and variance among facilities makes this un-viable.

Carson City in Los Angeles County is an example of one of our hotspots. This spot was chosen since it was in the top 5 highest pollution for PM 2.5, NOx, and SOx pollution.

Results and Discussion

<u>Overall</u>

Compliance instruments for each respective compliance period were input into predictive linear models for each pollutant to see if there was a relation. Statistical summaries of the related data act as the main basis of conclusions, while the graphs visualize overall trends. We also further differentiated the analysis between disadvantaged communities and non-disadvantaged communities. Residuals were utilized to determine the relative quality of the dataset and model fit. A log was applied to graphs in order to succinctly visualize data. GAM models were used for data that required non-linear predictive models, which was passed through a GAM check to see if there was a need for a fit.

<u>Table 2.1 Information</u>

E= Electricity, O&G= Oil and Gas

We used a "mgcv::gam" for PM2.5 and SOx and NOx of CP 2 for both sector analysis and overall analysis, which allows for a non-linear regression fit

Green (S) p-values indicate significant values, red (NS) indicate non-significant values

"Not yet by sector" = only take DACs as a factor in the statistical analysis

The last four rows take into consideration both the DACs and Primary Sectors as factors

"Estimate diff" describes the difference in pollution burden wherein positive numbers show a higher rate in non-disadvantaged communities and negative numbers show a higher rate in disadvantaged communities.

Pollutant	**Compliance period**	**Variance ex. (AdjustedR^2)**	**p-value**	**Estimate diff (disadv. Vs. non.)**
GHG (not yet by sector)	2013-14	61.23%	NS 0.117	1.624
NOx (not yet by sector)	2013-14	22.91%	NS 0.284	1.854
PM2.5(not yet by sector)	2013-14	0.34%	NS 0.520	0.992
SOx (not yet by sector)	2013-14	19.49%	NS 0.906	-0.205
GHG (not yet by sector)	2015-17	46.30%	S 0.034	2.196
NOx (not yet by sector)	2015-17	30.56%	NS 0.979	0.036
PM2.5(not yet by sector)	2015-17	2.30%	NS 0.132	1.936
SOx (not yet by sector)	2015-17	20.70%	S 0.010	3.576
GHG (E)	2015-17	60.44%	S 0.077	-10.407
NOx (E and	2015-17	50.90%	S 0.045 and	-9.763 and

O&G)			0.024	-10.106
PM2.5 (E)	2015-17	21.30%	S 0.099	-8.163
SOx (E and O&G)	2015-17	58.90%	S 0.005 and 0.001	-13.556 and -12.290

2013-2014 Compliance Period Analysis

For the 2013-2014 analysis, use of the predictive linear model showed almost no interaction between emissions, compliance instrument usage, and whether or not the concerned facility was in a disadvantaged community with the exception of GHGs. The factors of PM2.5, NOx, and SOx being deemed unrelated is based on a high p-value and minimal difference in 'estimates' between disadvantaged communities and non-disadvantaged. This may be evident due to the nascency of the cap-and-trade program trading system and subsequently minimal impact on emissions within the first compliance period. However, for GHGs there is a clear relation showing with higher compliance instrument usage there are higher emissions. This may be related to the higher accuracy of the GHG reporting in the dataset in general. The linear model for NOx and SOx also explained about 20% of the variance in data, which is quite high relative to real world data.

2015-2017 Compliance Period Analysis

Analysis of the 2015-2017 compliance period also first utilized a predictive linear model. For both GHGs and SOx, the model found high interactions between emissions and disadvantaged communities. For GHGs, there was a strong relation that higher compliance instrument usage is related to more emissions in disadvantaged communities than non-disadvantaged communities. This was based on a low p-value and largely negative p|t| value (for emissions in disadvantaged communities as opposed to non-disadvantaged communities. For SOx, the linear model was a significant predictor for emissions in disadvantaged communities explaining about 20% of variation (high for real world data).

However, for PM2.5 and NOx there is a marginal to zero relationship between disadvantaged communities, CIs, and emissions. The linear model for PM2.5 shows a small interaction between disadvantaged communities CI usage and emissions ($p=0.0679$), but is not a well fit model without this predictive community factor ($p=0.2928$). This means that the relation alone is not a solid predictive model between CI usage and emissions. For NOx there was a very high p-value, insinuating no relation between such factors.

In the SOx and PM2.5 data, we saw data residuals had a non-linear shape and therefore may be more suited to a non-linear fit utilizing a GAM model. The utilization of the model reaffirmed the relation between higher CI usage being a predictor for higher SOx emissions in disadvantaged communities due to a significant p-value. The non-relation between PM2.5 emissions and CI usage was also reaffirmed (2% variance, large p-value).

However, in general there seem to be minimal differences between aggregate emissions from facilities in disadvantaged communities and facilities in non-disadvantaged communities for this compliance period. In fact, there are slightly more emissions in non-disadvantaged communities according to estimate differences in the data.

<u>2015-2017 Industry Sector Analysis</u>

Seeing possible relations within the 2015-2017 compliance period, predictive linear models by industry delved further into relationships. In general, high values showed near negligible relations between industries overall and compliance instrument usage. However, when broken down by pollutant and sector there may be relationships indicated by low p-values and high variance explained.

For GHGs, the low p-value indicated compliance instruments could be predictors for electricity generation in disadvantaged communities. Emissions were seen to be much higher in disadvantaged communities. However, the relationship on the plotted data shows facilities in non-disadvantaged communities have more rapidly increasing emissions with increasing CI usage. This held true for both NOx and SOx plotted data for the electricity generation sector. This is opposing the relation that higher compliance instrument usage in disadvantaged communities lead to more emissions over non-disadvantaged communities.

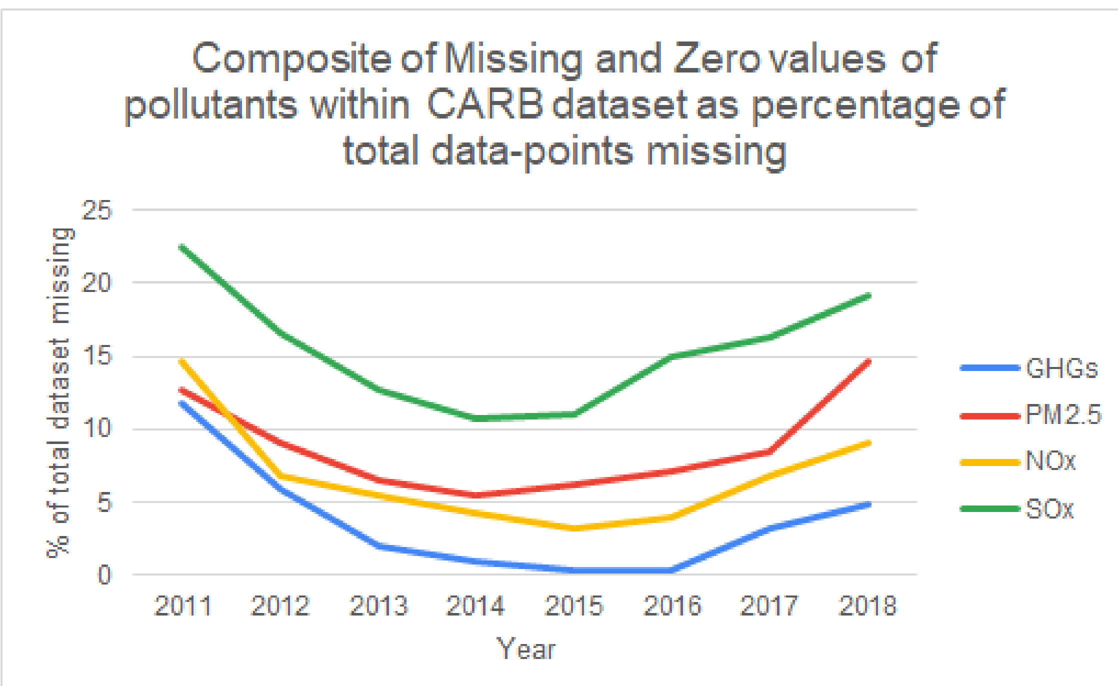


Figure A: Distribution of percentage of missing or zero values by pollutant over time. This shows GHGs as the most complete dataset, and SOx as the most incomplete. The curvature of all pollutants is noticeably parallel, which may hint that the same facilities had un-reported data by year. This is consistent with qualitative observations of certain facilities consistently missing data.

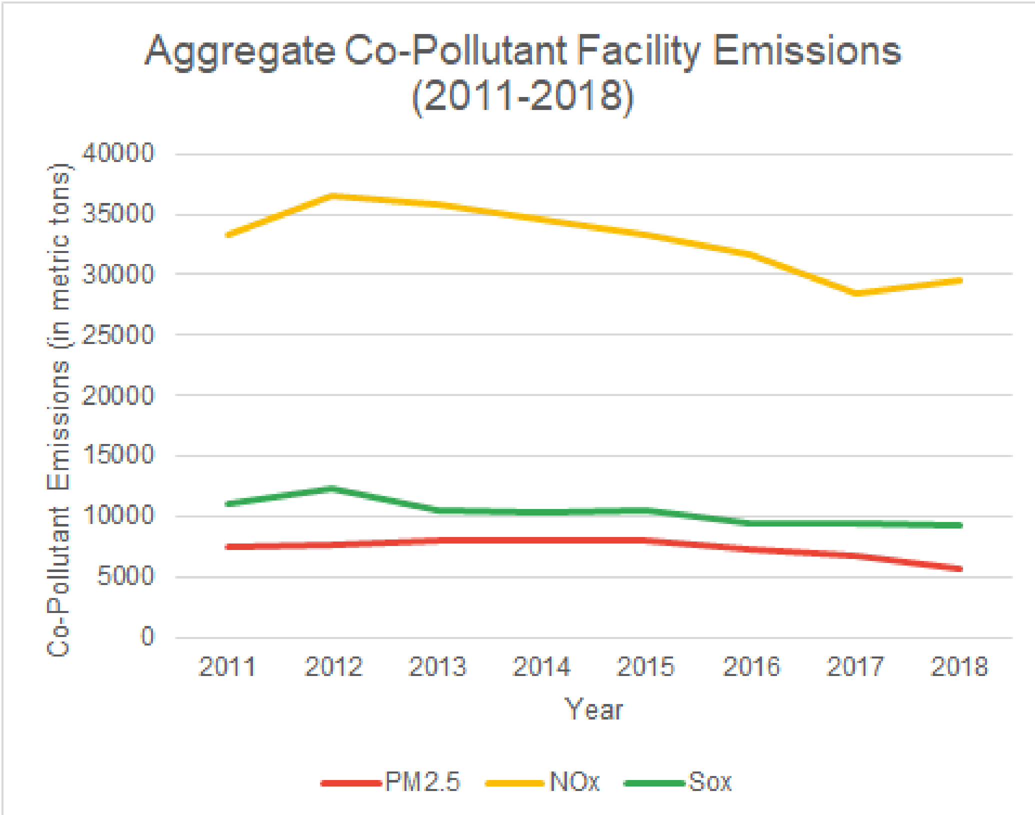


Figure B: Aggregation of primary co-pollutants from facilities of study dataset over concerned years (2011-2018). This figure shows evidently minor changes over time. However, PM2.5 aggregate emissions decreased by almost 25%, while NOx and SOx also decreased overall by 11.3% and 15.6% respectively.

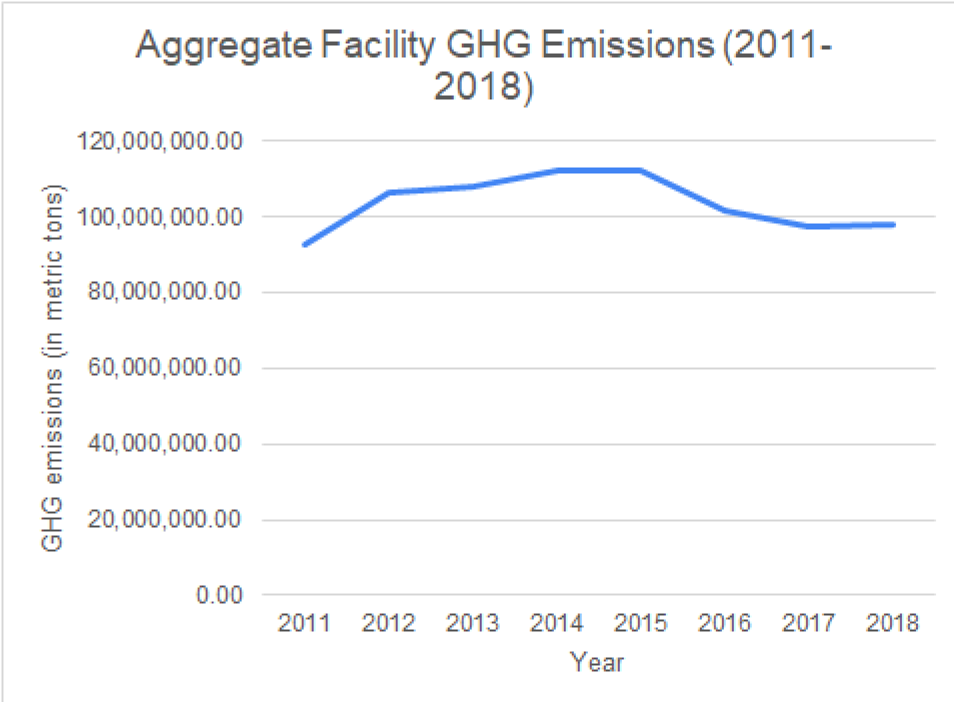


Figure C: Graph of aggregate GHG emissions over the study period (2011-2018). This shows a general increasing trend of overall emissions until 2015, whereby the trend begins to decrease.

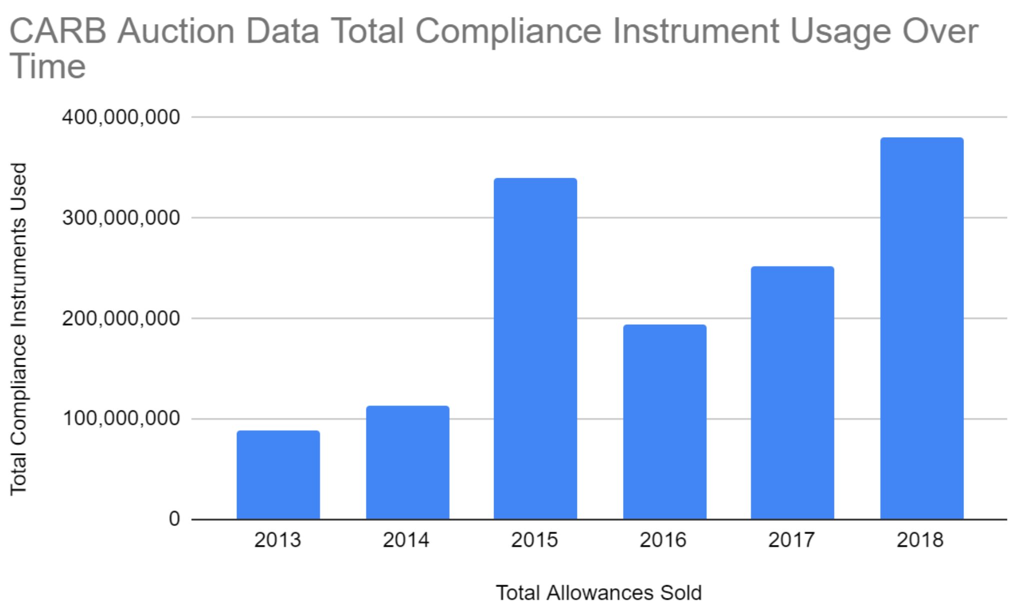


Figure D: Total allowances sold based on CARB auction data. This dataset utilized the CARB Auction dataset to give a broader overview of the market that may influence emissions, as opposed to utilizing only facilities within our dataset.

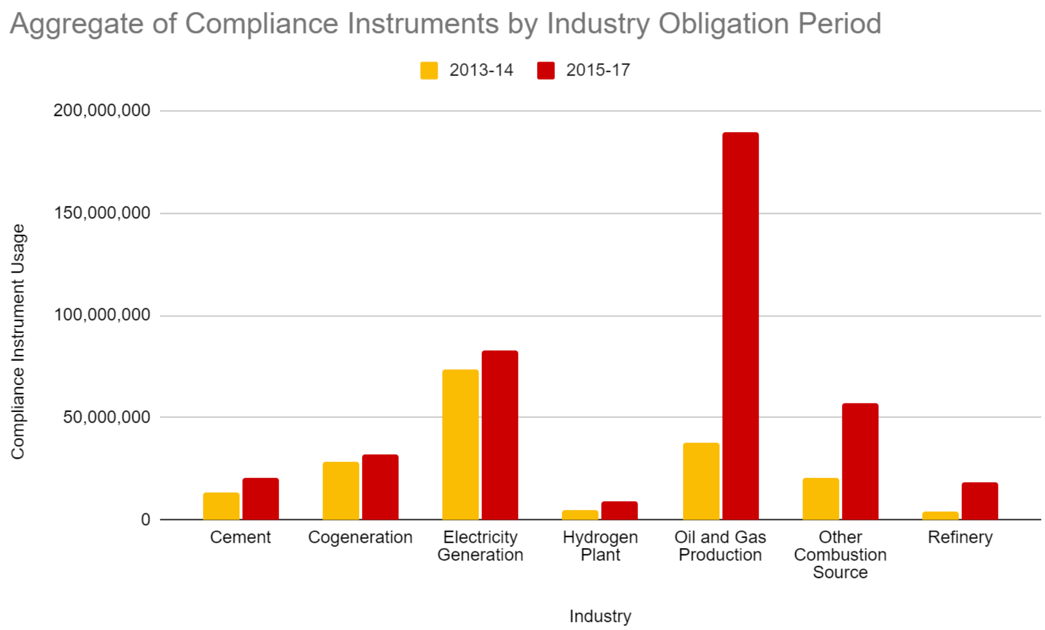


Figure E: Total aggregate compliance instrument usage by industry sector comparing the 2013-14 and 2015-17 compliance period for facilities within our dataset. The most noticeable change is the jump in CIs from the 2013-14 to 2015-17 period for the oil and gas production sector above all other sectors. When compared to the overall pollutant emissions by sector however, qualitatively there is little overlap between compliance instrument usage and average emissions from facilities by sector.

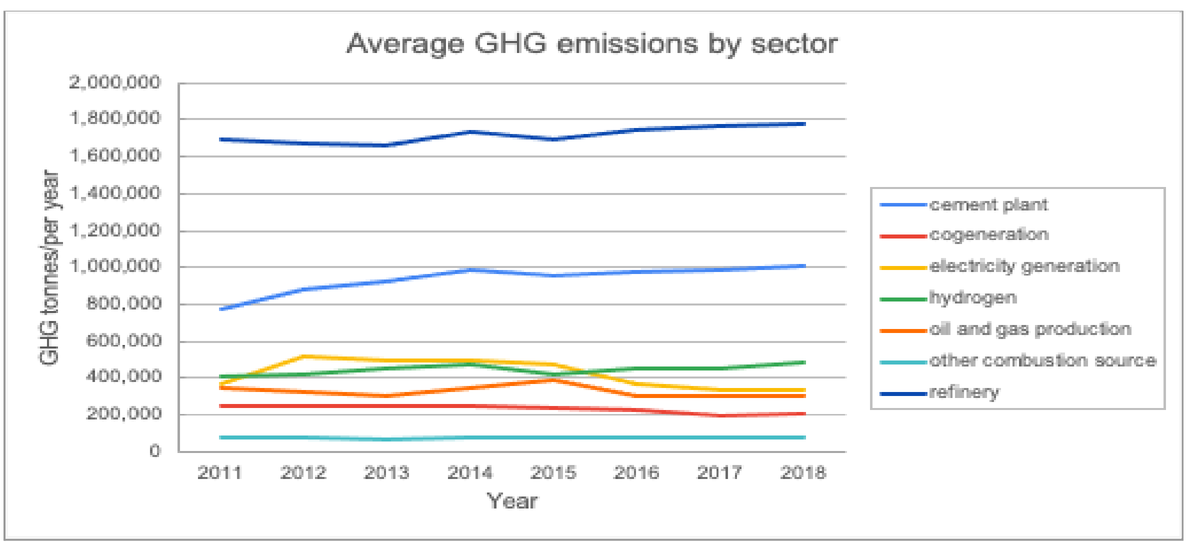


Figure G: Aggregation of total GHG emissions of facilities by industry sector over period of study (2011-2018). This shows refineries and cement plants as the largest GHG emitters.

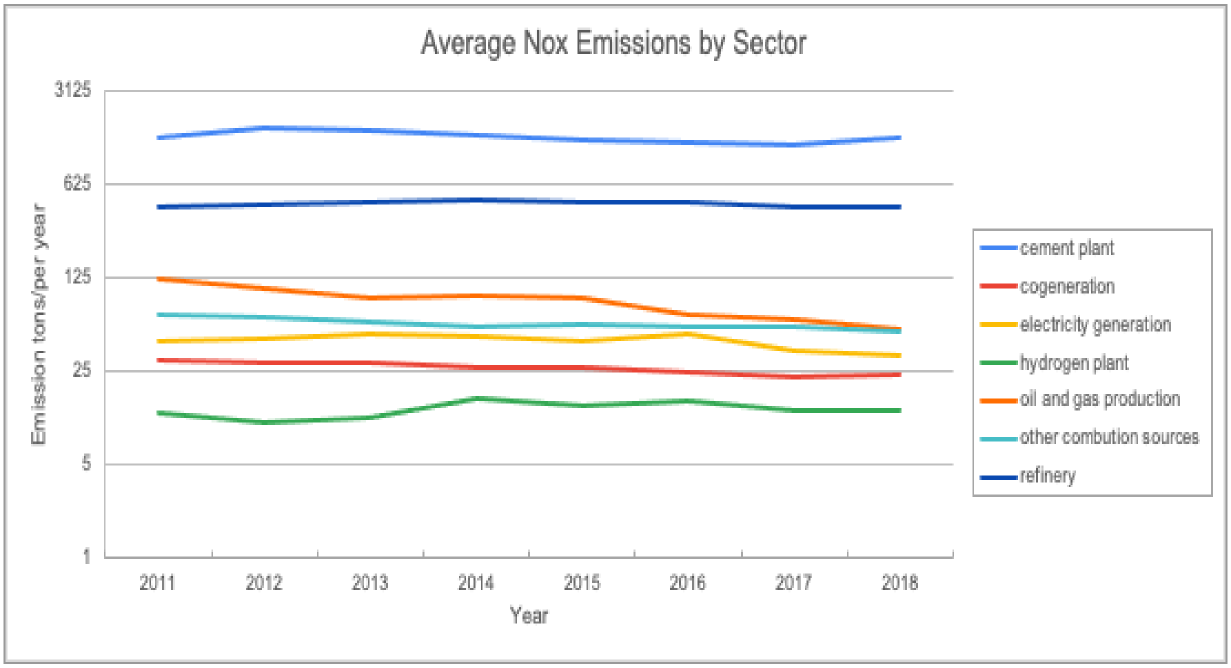


Figure F: Aggregation of total NOx emissions of facilities by industry sector over period of study (2011-2018). Similar to GHGs, cement plants and refineries are the largest emitters.

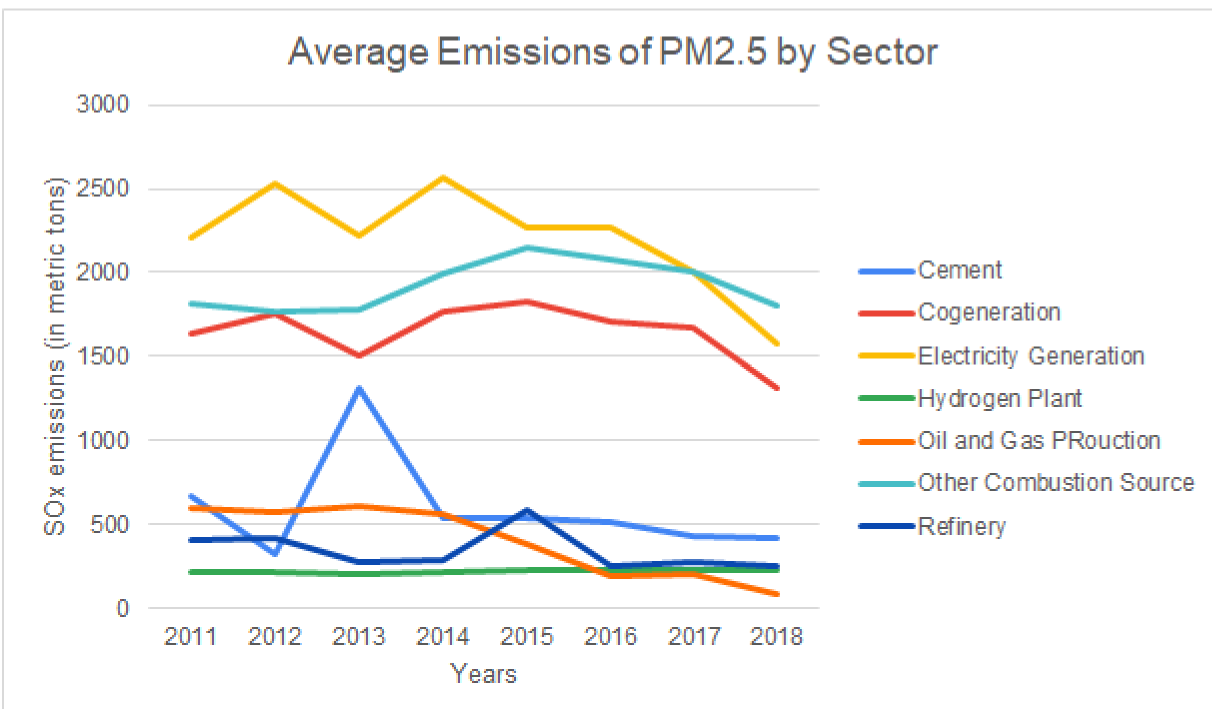


Figure H: Aggregation of total PM2.5 emissions of facilities by industry sector over period of study (2011-2018). This differs greatly from other pollutants, wherein electricity generation, cogeneration and other combustion sources are the largest emitting sectors.

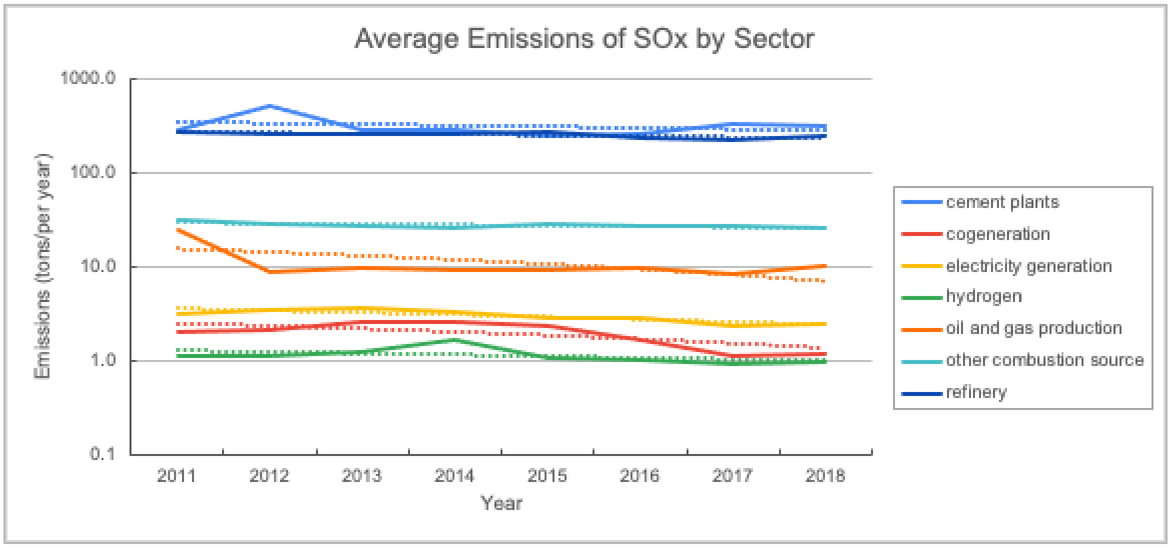
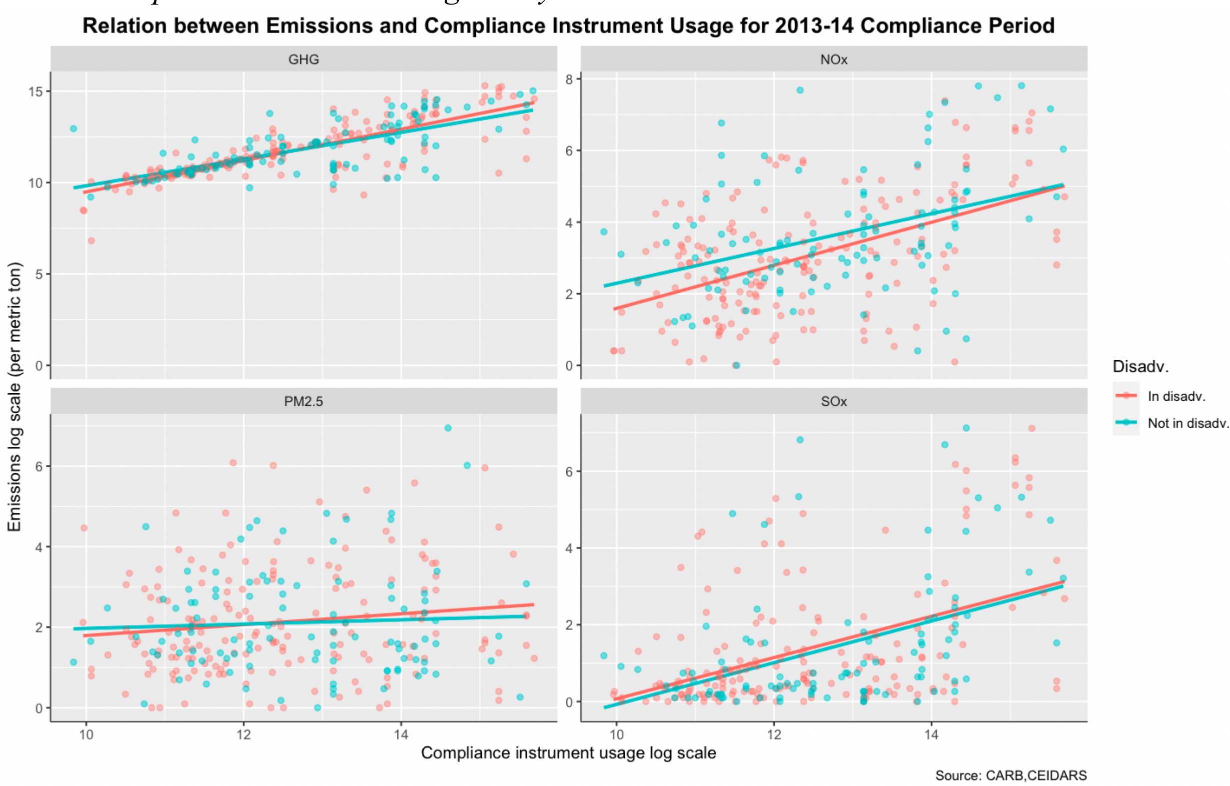


Figure I: Aggregation of total SOx emissions of facilities by industry sector over period of study. (2011-2018). This is consistent with GHG and NOx emissions wherein cement plants and refineries are the largest sector emitters.

Overall compliance instrument usage analysis



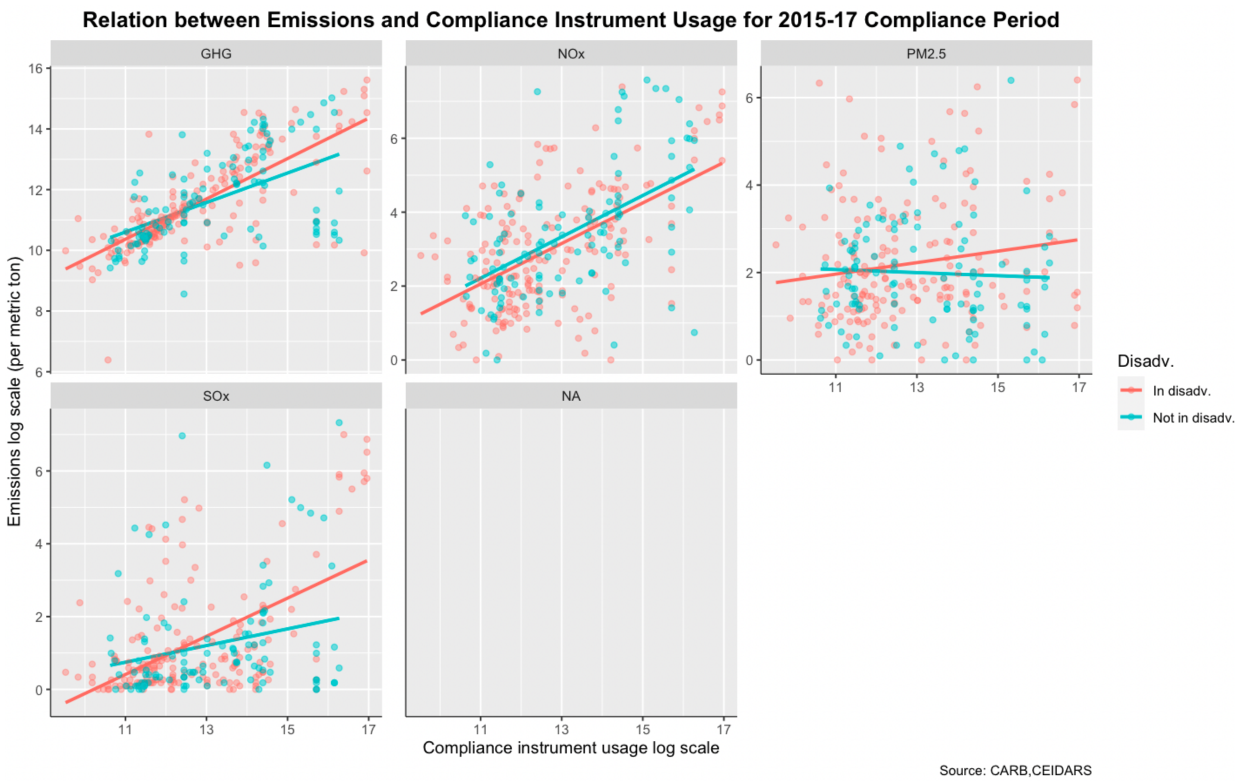


Figure J and K: these compare compliance instrument usage with emissions by pollutant and indicate whether the facility data is within a disadvantaged community or not. Based on statistical summaries in R, there was little to no relation between CIs and emissions within the first compliance period (2013-14). However, for every pollutant apart from PM2.5 in the compliance period of 2015-17 there was a significant relationship determined from our model. This may be attributed to the nascency of the program in the first compliance period and subsequent delay in relationality. There could also be un-accounted for differences between compliance periods at larger scales (i.e. the market itself) as opposed to individual facilities.

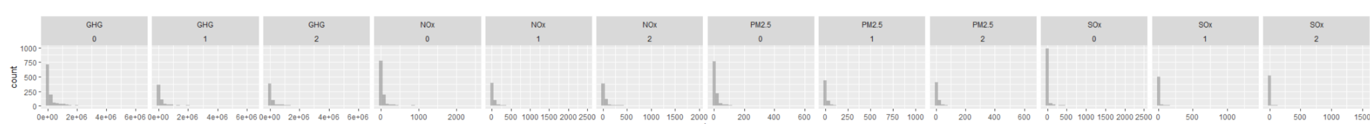


Figure L: Multiple Histograms of pollutant emissions by compliance period. CP 0 is for data 2011-12 and 2018, CP 1 is for data 2013-14, and CP 2 is for data 2015-17. This was ancillary analysis to see the numerical spread of data. Noticeably, values consistently for all pollutants are heavily skewed to the right, meaning many data points are low.

(Title and axes need edits): Interaction between Compliance Instrument Usage (x axis) and facility emissions by sector compared between disadvantaged and non-disadvantaged communities for CP 2015-17

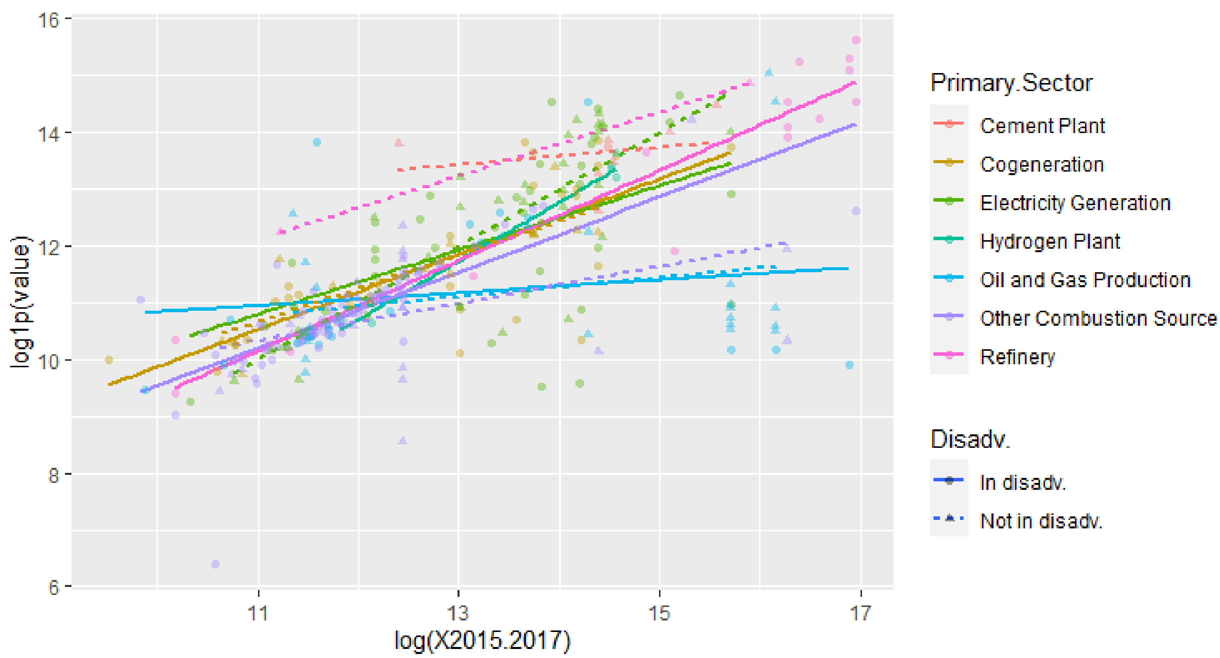


Figure M: Graph of the interaction between Compliance Instrument Usage (x axis) and facility emissions by sector compared between disadvantaged and non-disadvantaged communities for CP 2015-17. There is not a large noticeable difference between facilities in disadvantaged and non-disadvantaged communities. However, cement and refineries in non-disadvantaged communities has somewhat higher emissions with similar use of compliance instruments while oil&gas facilities in both types of communities seem to have lower emissions with similar compliance instrument usage.

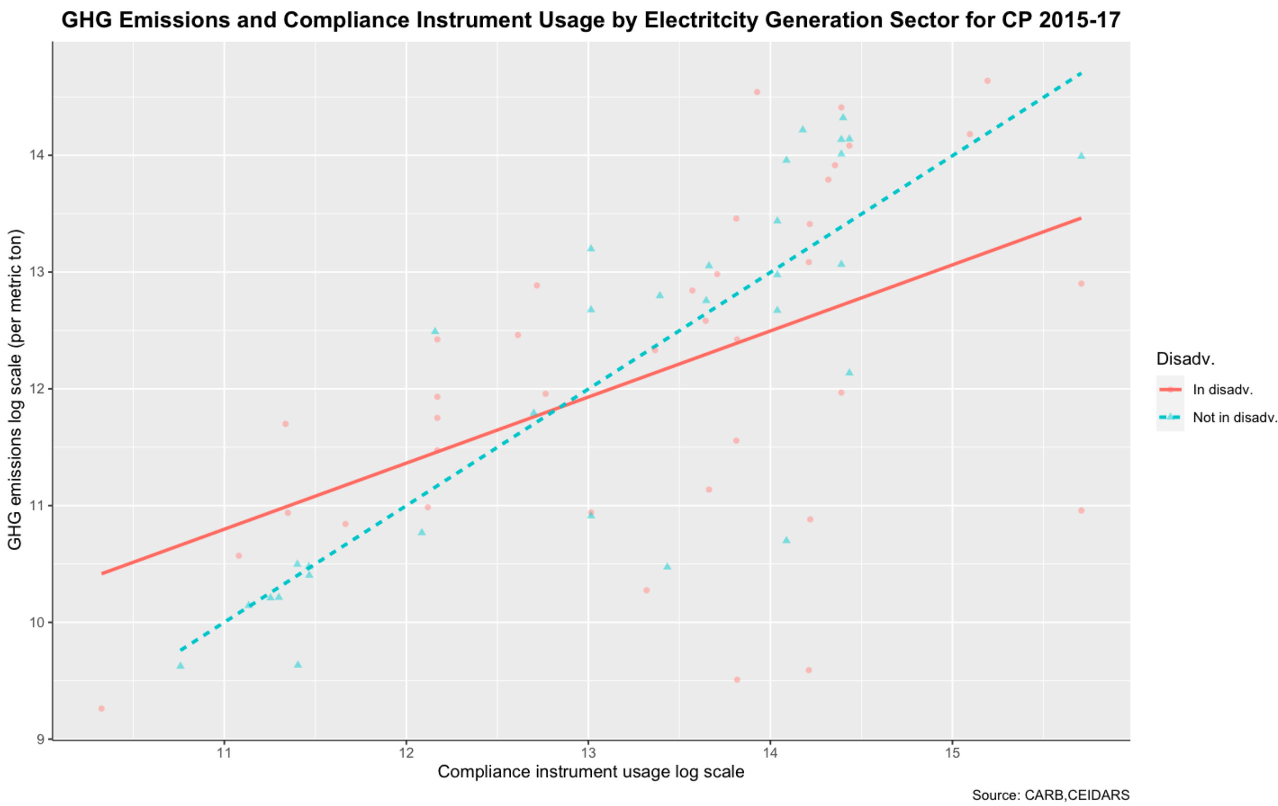


Figure N: Graph of GHG emissions and compliance instrument usage for the Electricity generation sector for CP 2015-17 on a log scale. While compliance instrument usage may relate to higher emissions at low values for communities within disadvantaged communities, the trend seems to invert as compliance instrument usage increases. In other words, there seem to be higher emissions in non-disadvantaged communities at higher CI usage.

Policy Suggestion/Future Work

Though a cap-and-trade system may lead to a decrease in overall pollution, more stringent command-and-control instruments may need to be implemented to protect disadvantaged communities. This could include a stringent ruling for facilities within the top 10% AB-685 disadvantaged communities stating there can be no trading involved or have more command-and-control methods like a carbon tax implemented.

We believe our analysis could be expanded upon in future work with the further access to compliance instrument usage and a more complete dataset. With time, we had hoped to follow up with facility AQMD to fill in missing facility values within our dataset, as well as confirm the exact geo-location of facility emissions wherein reporting locations may give a false emissions location. Analysis also could have related cap-and-trade program impacts to alternatives, such as command-and-control methods like a carbon tax. However, given time constraints this remains outside the scope of the project. We also wanted to explore specifically by sector the relation greater compliance instrument usage may lead to more rapidly increasing emissions as seen in our sector analysis.

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[1]

Geospatial Analysis

Methodology

Base Map

The base map contains all of the necessary data used to build the other maps. We started with the CalEnviroScreen 3.0 Results Shapefile[3] from their website and the CARB Aggregated Facilities data from the compliance instrument analysis. We decided to categorize the CalEnviroScreen data for PM2.5 to create a color ramp of 0-19.6 μg/m^3. This was visualized through CA census tracts with the most concentrated areas being the darkest blue. Next, we duplicated the same CalEnviroScreen layer but categorized for the SB 535 Disadvantaged Community attribute. We filtered the data so that census tracts that equaled "yes" (were disadvantaged) were outlined in yellow.

The CARB Aggregated data file gave us longitude and latitude coordinates for each of the facilities under the cap and trade program but we had a difficult time getting them to show up. We knew this could be done through the 'add x and y data' function but when we tried this the longitude and latitude columns were not an option. After days of troubleshooting and googling questions we were able to get some progress. We export the CARB attribute table as a dBase file and added the new layer to the map. We then added two new fields for longitude and latitude and using the field calculator made them equal to the old longitude and latitude fields. We made sure to specify the coordinate system as GCS_WGS_1984. When we tried to add the x and y data again, the process would work but all of the facilities were showing up inside a single census tract. We knew this was wrong and suspected there was something wrong with the coordinate system, although we double checked that all the layers were under GCS_WGS_1984. From here, we met with Noam Rosenthal, our fall quarter TA and GIS specialist. He suggested that we use the convert coordinate notation tool under data management tools. We did this and converted to GCS_WGS_1984 and the facilities finally showed up in their correct locations. At this point, the map had all the facility locations overlaid on the PM2.5 census tract concentrations.

Maps of Emissions for 2011 and 2018

For these maps, we wanted to show the facilities as different size points to correlate with their amount of PM2.5 emissions. We made identical maps for 2011 and 2018. Under the symbology tab of the facility layer, we changed the size to 'specify attribute' and chose the 2011 and 2018 PM2.5 emissions attributes respectively. The dots were extremely large so we used the field calculator to divide all values by 100. From here, we made the dots a light grey with black outline and slightly transparent to see where they overlap with the underlying layers. We added a title, legend, north arrow and scale to the final maps.

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[3] CalEnviroScreen. Ces3results.xlxs. June 2018. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30

Map of Increases in Emissions

For this map we wanted to show which census tracts were in a 1 mile radius of facilities that saw an increase of PM2.5, NOx and/or SOx emissions from 2011 to 2018. First in excel, we created a few new columns in the CARB aggregated data sheet to calculate the differences in emissions from 2011 to 2018 for PM2.5, NOx and SOx. Values that were positive meant an increase in emissions while negative meant decrease. We uploaded this new attribute table to GIS and used the definition query tab to filter the data so that only positive values would be displayed by their facility locations. We did this for each pollutant and made three separate layers. Next, we used the buffer tool to make a 1 mile buffer around each of these facilities. We chose 1 mile because that is what Cushing et al. used in their study[4] "Carbon trading, co-pollutants, and environmental equity: Evidence from California's cap-and-trade program". Then we used the 'select by location tool' to choose those census tracts that intersect with these buffers and created 3 new census tract layers for each of the 3 pollutants. From here, we used the statistics tool to summarize demographic statistics for all census tracts and added the data into an excel chart. We switched the selection of all 3 as well to find statistics for those census tracts not within 1 mile of a polluting facility. We summarized the percent white, percent with less than a high school diploma and percent under the poverty line for each group of census tracts. Next, we used the intersect tool to find the census tracts where NOx and SOx intersected, NOx and PM2.5, SOx and PM2.5 and where all three intersected. We created 4 new layers for these intersections and distinguished them by different colors for the legend. Then we created an inset map for Los Angeles because it was difficult to see.

Hotspot Maps

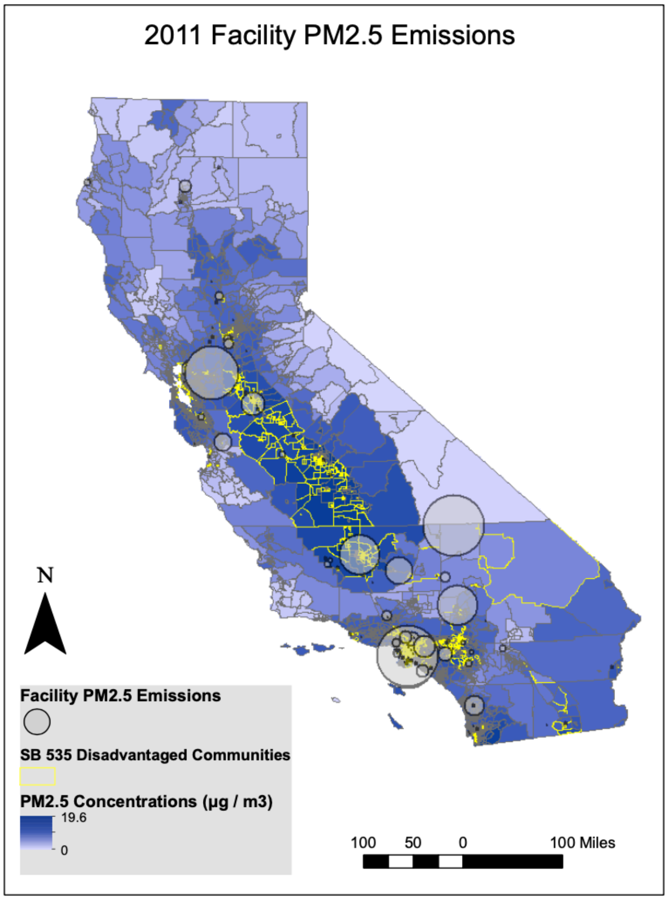
The methodology used for the primary was repeated for the hotspot maps, once again relying on the CalEnviroScreen 3.0 Results Shapefile and the CARB Aggregated Facilities data from the compliance analysis for PM2.5 to create a color ramp of 0-19.6 $\mu g/m^3$. Our goal with the hotspot maps was to give a close up visualization of our areas of interest: Los Angeles, Riverside, Northern Valley, and Southern Valley. These regions were identified as hotspots since they were areas which portrayed disadvantaged communities with high levels of PM2.5 emissions. After representing these regions geospatially, we then focused our efforts on geospatial analysis of each hotspot, finding the percentage of population that is white, under the poverty line, and who have less than a highschool education. Comparing these statistics to that of our primary map, we are able to discuss the increase in these categories and the possibility of these vulnerable regions being at a higher risk of PM2.5 exposure. Each of the four hotspot maps repeat this methodology, only varying in location.

[4] Carbon trading, co-pollutants, and environmental equity: Evidence from California's cap-and-trade program (2011–2015). Cushing L, Blaustein-Rejto D, Wander M, Pastor M, Sadd J, et al. (2018) Carbon trading, co-pollutants, and environmental equity: Evidence from California's cap-and-trade program (2011–2015). PLOS Medicine 15(7): e1002604. https://doi.org/10.1371/journal.pmed.1002604

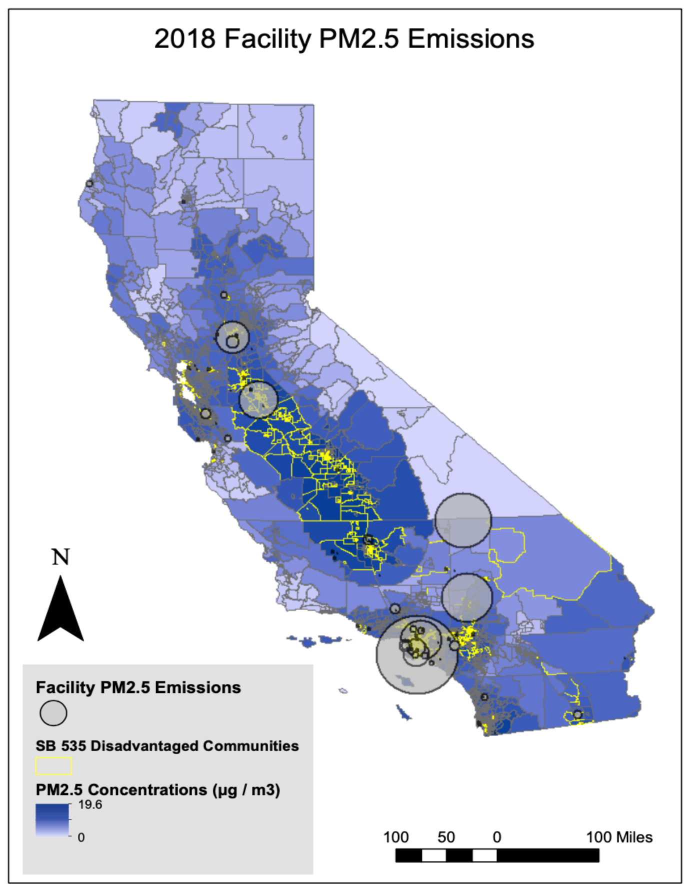
Discussion

Maps of Increases in Emissions for 2011 and 2018

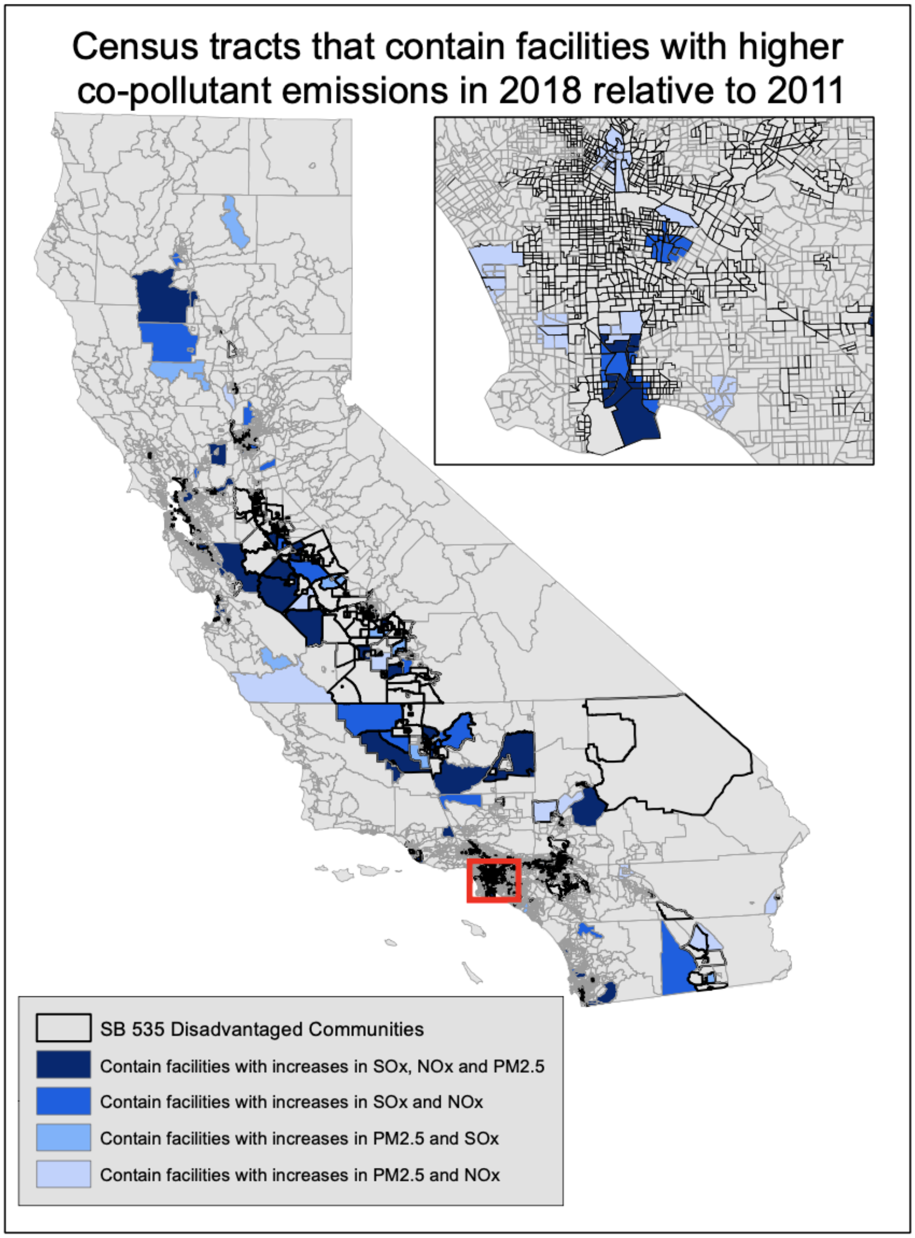
Maps of facility PM2.5 emissions in 2011 and 2018 in California. Data sourced from CIEDARS and CalEnviroScreen.



These maps show the amount of PM2.5 emissions from facilities under the cap and trade program in 2011 and 2018. The size of the grey circle correlates to how many emissions were released. Further, the blue represents PM2.5 concentrations by census tract, with dark blue being the highest. Yellow outlined census tracts are SB535 Disadvantaged Communities as defined by CalEnviroScreen. Los Angeles saw the most significant increase in emissions between the years while the Northern Central Valley and Victorville area also increased. The bay area and Southern Central Valley saw decreases. Most of the emissions circles fall in disadvantaged communities, especially Los Angeles and the Central Valley.



Map of Increases in Emissions



This map shows which census tracts fall in a 1 mile radius of a facility under the cap and trade program that has increased its emissions of PM2.5, NOx and/or SOx from 2011 to 2018. The black outline represents SB 535 Disadvantaged Communities. The three lightest shades of blue census tracts contain facilities that have seen an increase in 2 emissions, while the darkest blue shows those that have seen an increase in all 3. Many of these census tracts overlap with disadvantaged communities. Dark blue is especially present in the Central Valley.

Map of California census tracts that contain facilities with higher co-pollutant emissions in 2018 relative to 2011. Data sourced from CIEDARS and CalEnviroScreen.

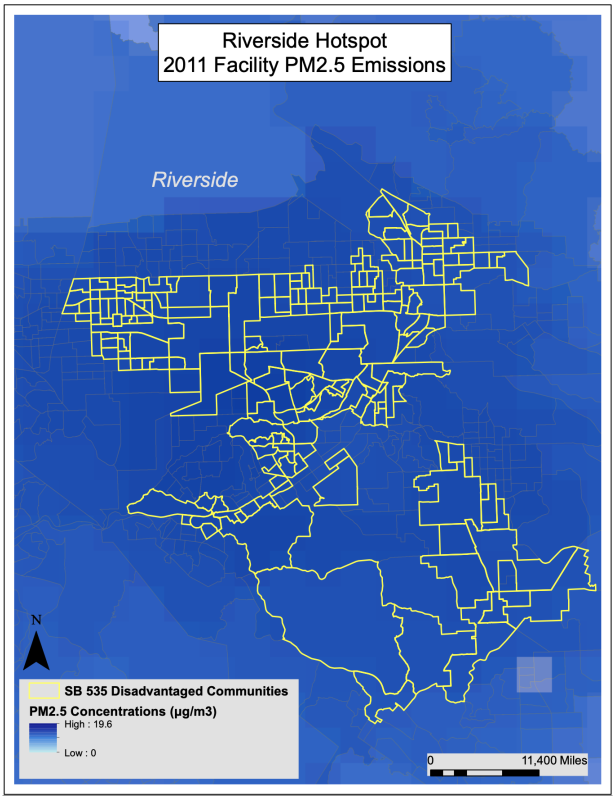
Charts of CA Demographic Statistics

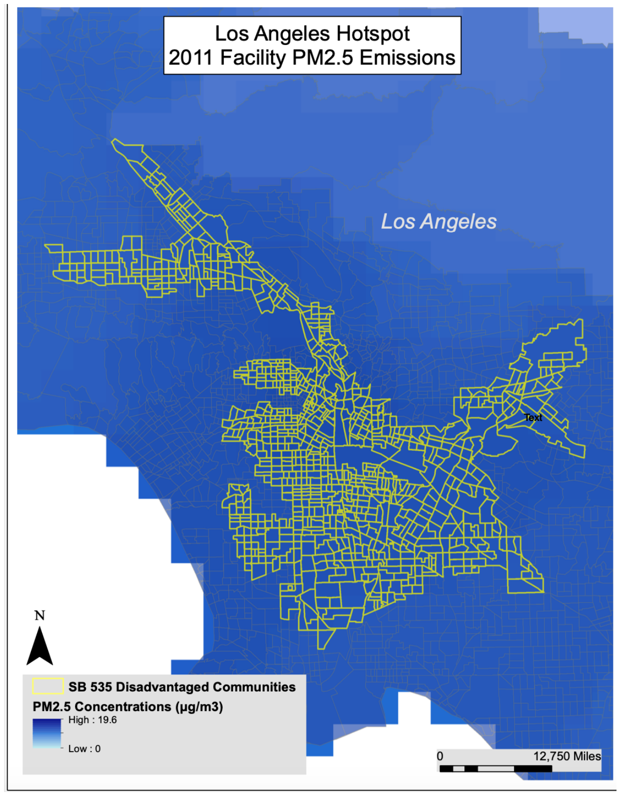
Census Tracts that are within 1 mile of a facility with increased emissions				
	PM2.5	NOx	SOx	Average
White	35.6%	33.9%	39.7%	36.4%
Under poverty line	42.1%	41.5%	40.7%	41.5%
Less than high school education	23.7%	24.7%	21.6%	23.3%
Census Tracts that are not within 1 mile of a facility with increased emissions				
	PM2.5	NOx	SOx	Average
White	41.9%	42.0%	41.8%	41.9%
Under poverty line	35.6%	35.7%	35.7%	35.7%
Less than high school education	18.6%	18.6%	18.7%	18.6%

Charts that show demographic statistics of census tracts within 1 mile of a facility with increased emissions and census tracts that are not within 1 mile of a facility with increased emissions

These charts show demographic statistics for census tracts located within 1 mile of a facility under the cap-and-trade program with increased emissions from 2011 to 2018 as compared to those not located within 1 mile. For those located within 1 mile, the percentage of people that are white is significantly higher (average of 5.49%) than those that are not. On average 4.77% more people live under the poverty line and 4.7% more have less than a high school diploma if they live within 1 mile of a polluting facility than if they do not.

Hotspot Maps



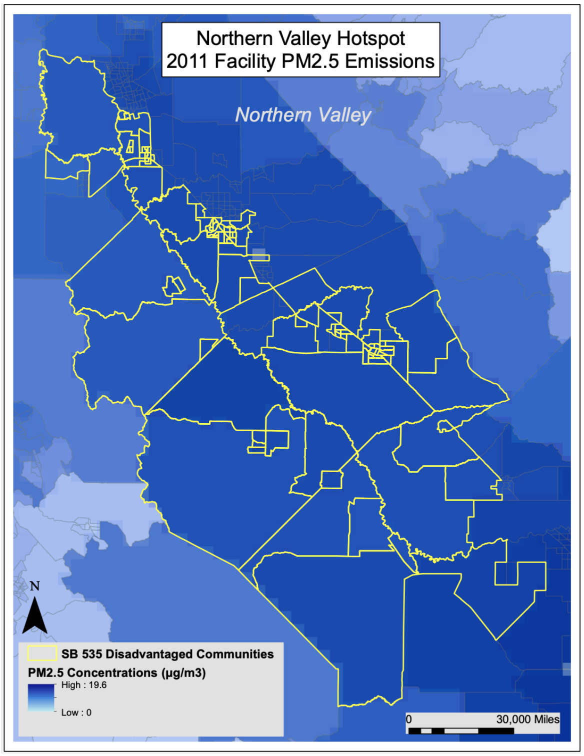


Riverside Hotspot *Los Angeles Hotspot*

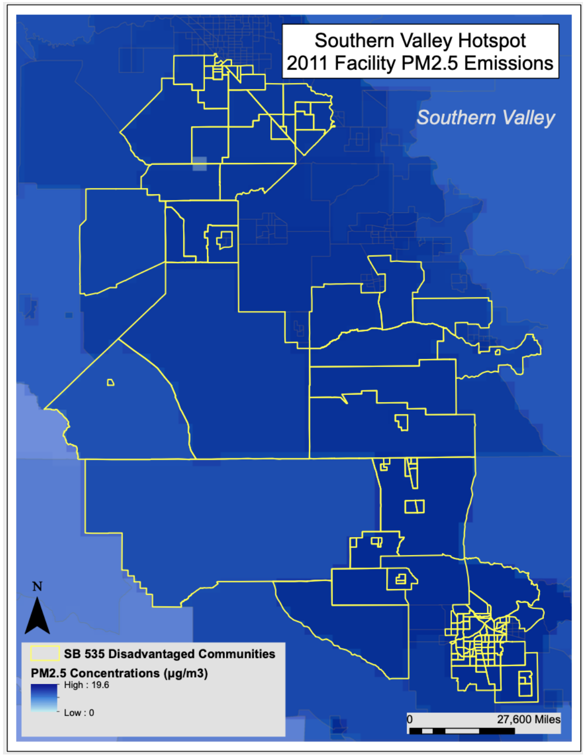
These maps show the SB 535 Disadvantaged Communities outlined with a yellow border, representing the regions Riverside and Los Angeles. These two hotspots display regions with excess PM2.5 emissions.

The blue gradient is the indicator for levels of PM2.5 emissions, with most of our hotspot census tracts falling within the darker shades of blue. This tells us that regions like Riverside and Los Angeles experience high concentrations of PM2.5 emission from nearby facilities.

The two maps below are in line with the maps above, just for the Northern Valley Region as well as the Southern Valley region. These hotspots were especially interesting, as seen in their maps the PM2.5 concentrations within the census tracts were dramatically higher than the surrounding regions. The blue color gradient shows a very dark hue within the affected regions then quickly lightens as we move away from the census tracts, showing an uneven distribution of PM2.5 concentrations.



North Central Valley Hotspot



South Central Valley Hotspot

Charts of Hotspot Statistics

Census Tracts Demographs by Hotspot Region				
	Northern Valley	Southern Valley	Los Angeles	Riverside
Percent White	32.17	29.88	12.07	18.42
Percent under poverty line	53.75	54.34	53.81	53.85
Percent with less than high school education	32.66	34.08	36.71	33.64

Chart that shows demographic statistics of census tracts within specified regions. These statistics represent the mean percentages for each of the above listed categories.

This chart's purpose is to give insight as to the differences in the same categorical statistics as the entire state of California, but focused on these specified hotspots. As seen, we experience an decrease in percent white as compared to the entire state, while percent under the poverty line and percent with less than a high school education experience dramatic increases.

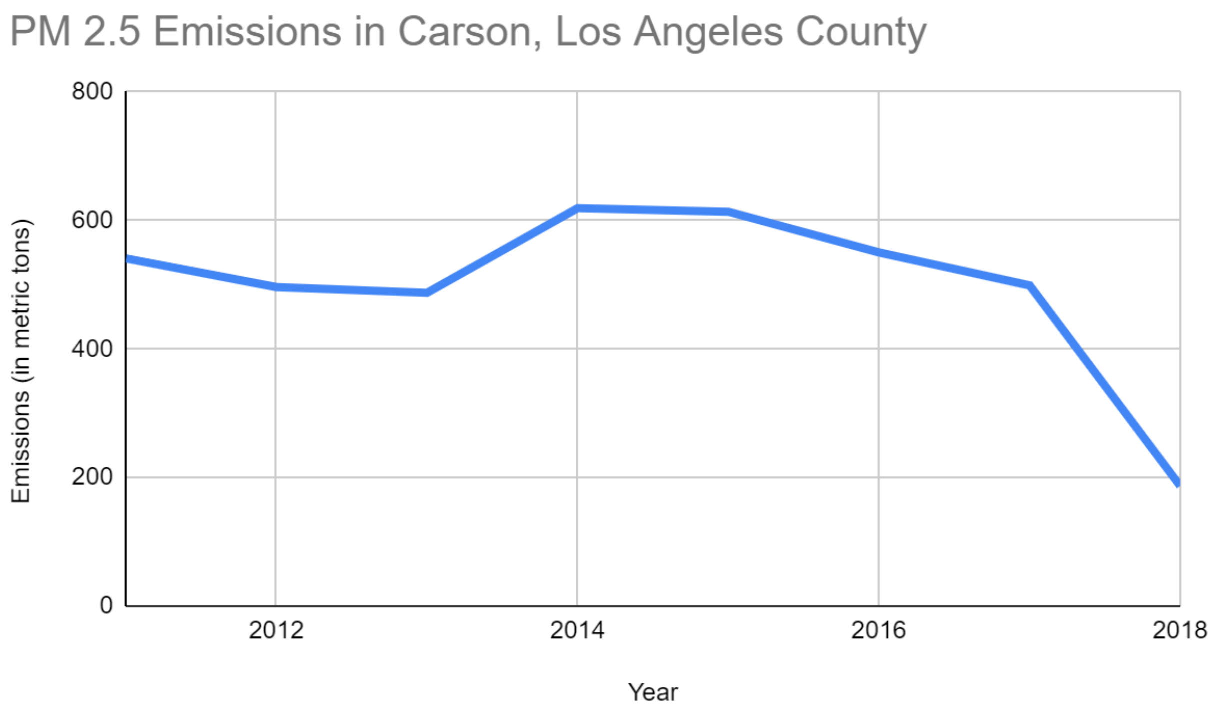
For the census tracts located within 1 mile of a facility, the percentage of people that are white is 5.5% higher, 4.8% more people live under the poverty line and 4.7% more have less than a high school diploma.

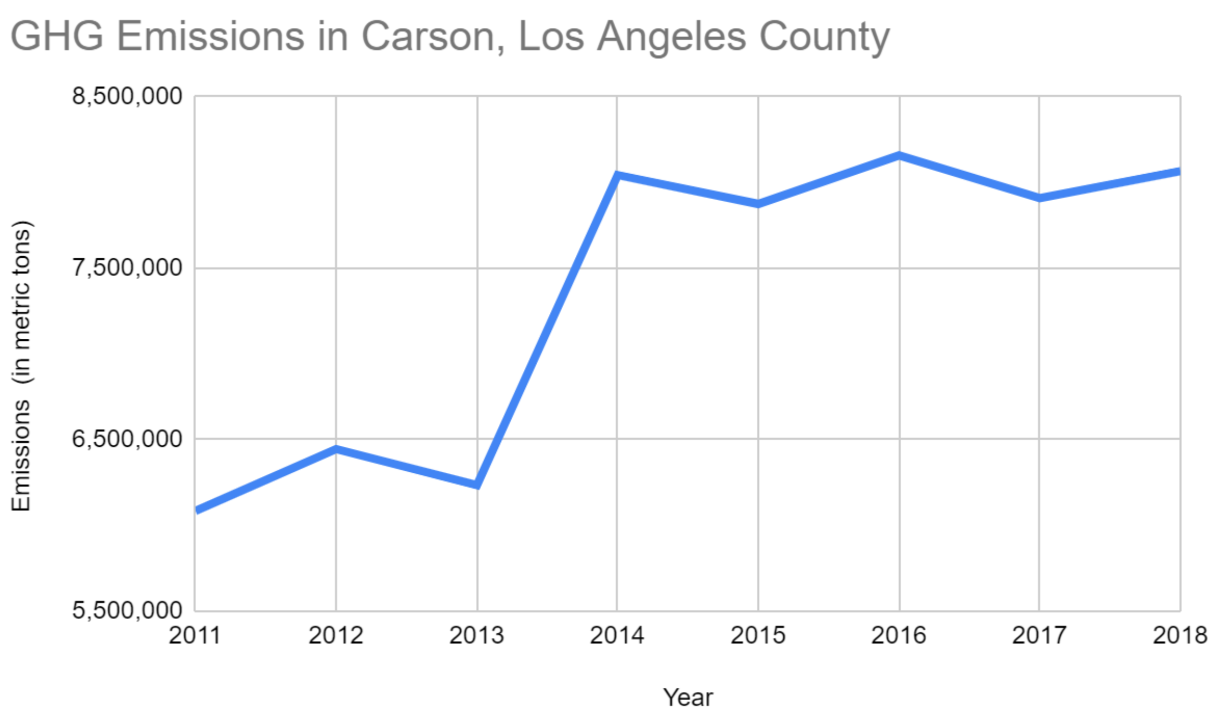
Further Geospatial Analysis

Our investigation into the potential relationship between the Cap and Trade program and disadvantaged communities, we have focused primarily on the emissions from facilities as they relate to the communities they directly affect. It is important to recognize the fate and transport of co-pollutants such as PM2.5 and NO_x, as California's topological features and atmospheric conditions may affect the dispersion patterns of emitting-facilities listed under Cap and Trade.

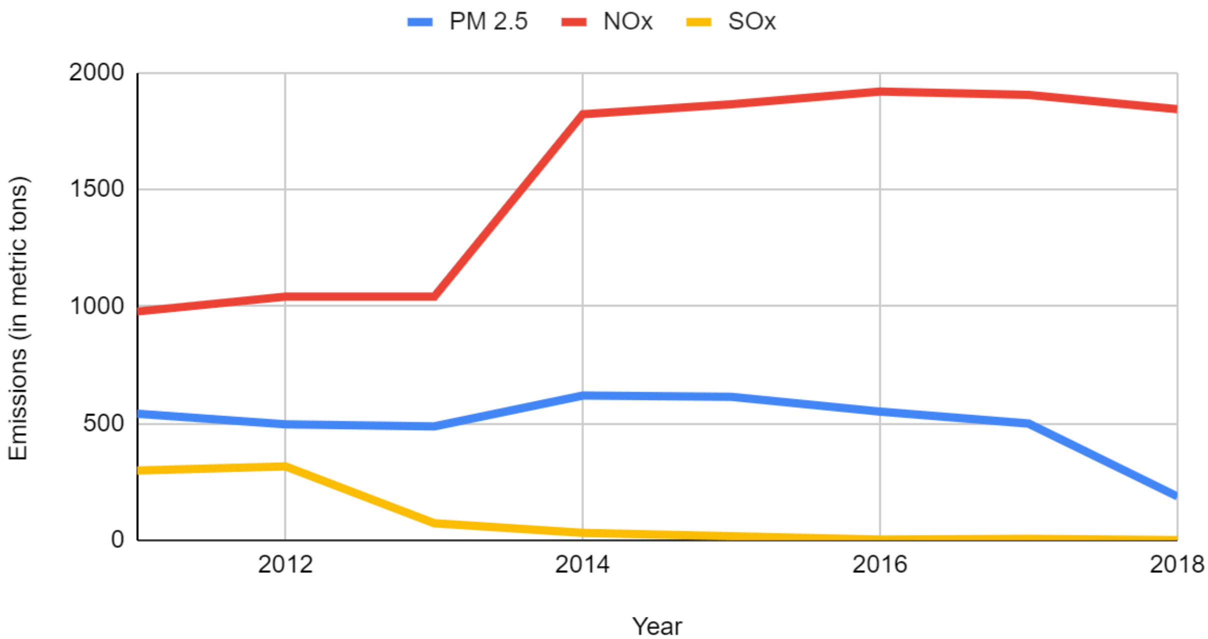
Dispersion modeling software such as the Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT), developed by the U.S. National Oceanographic and Atmospheric Administration (NOAA), use variables such as facility location and stack height with meteorology conditions in order to display pollutant dispersion behavior. Although incorporating dispersion modeling did not fall into the scope of our research, recognition of the far reaching effects of co-pollutants highlights the possibility for communities which do not lie near Cap and Trade facilities to still be affected by emissions.

Hotspot Graphs

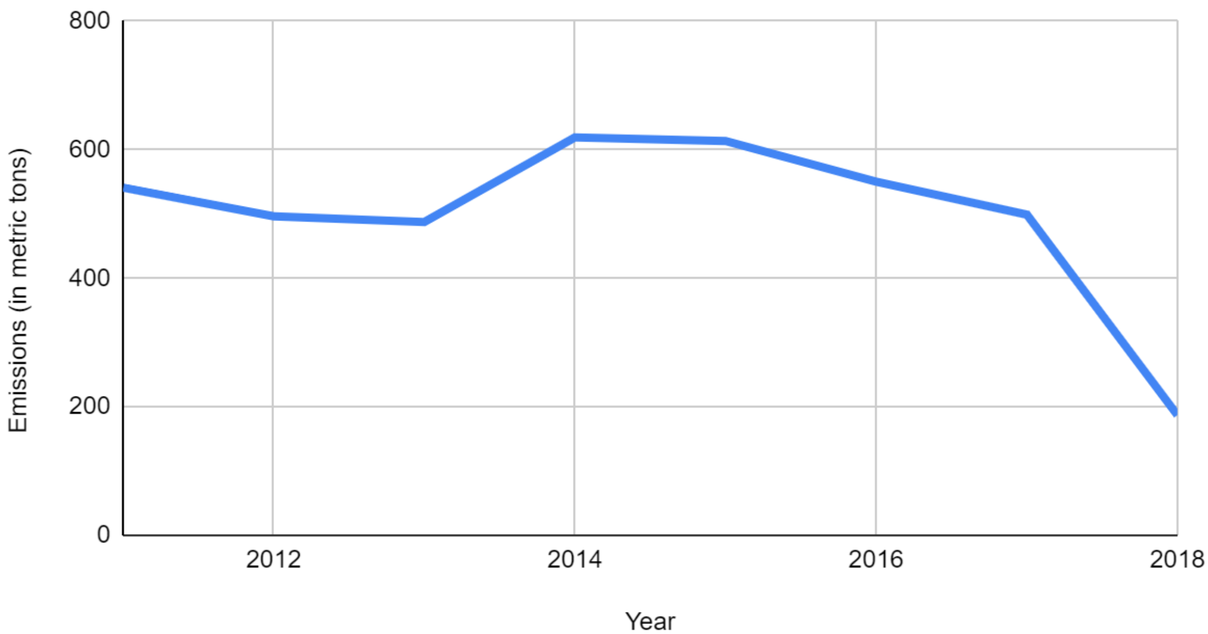


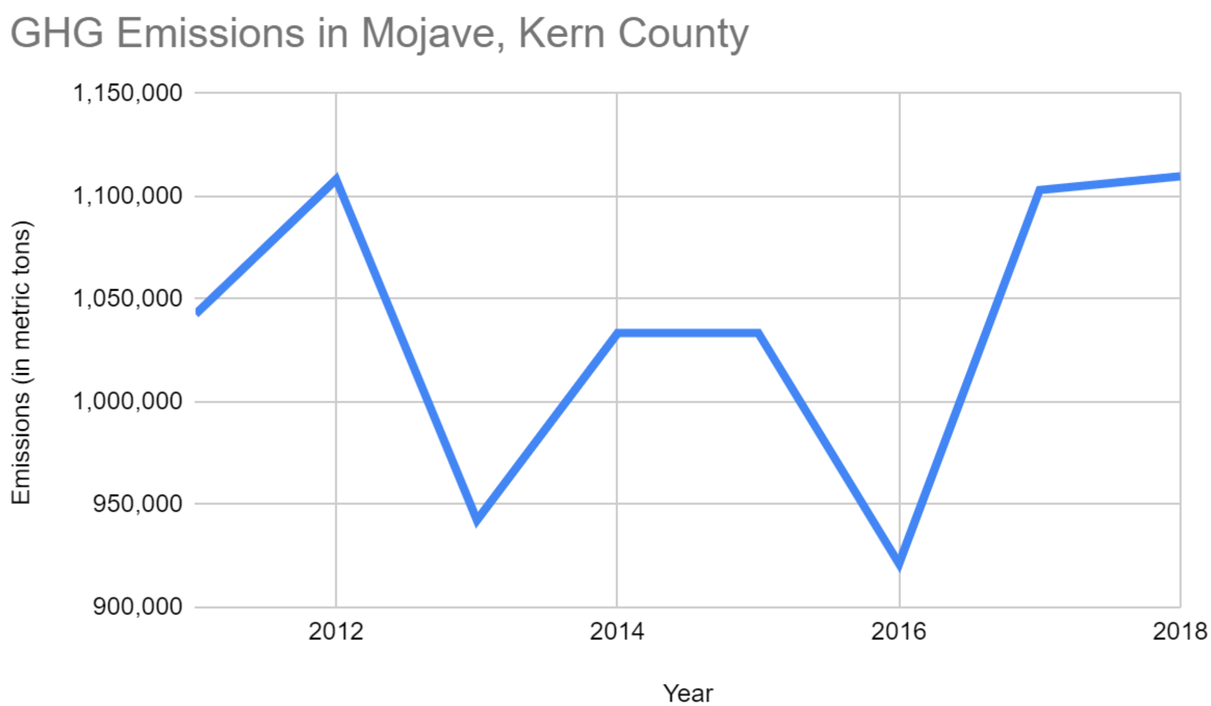


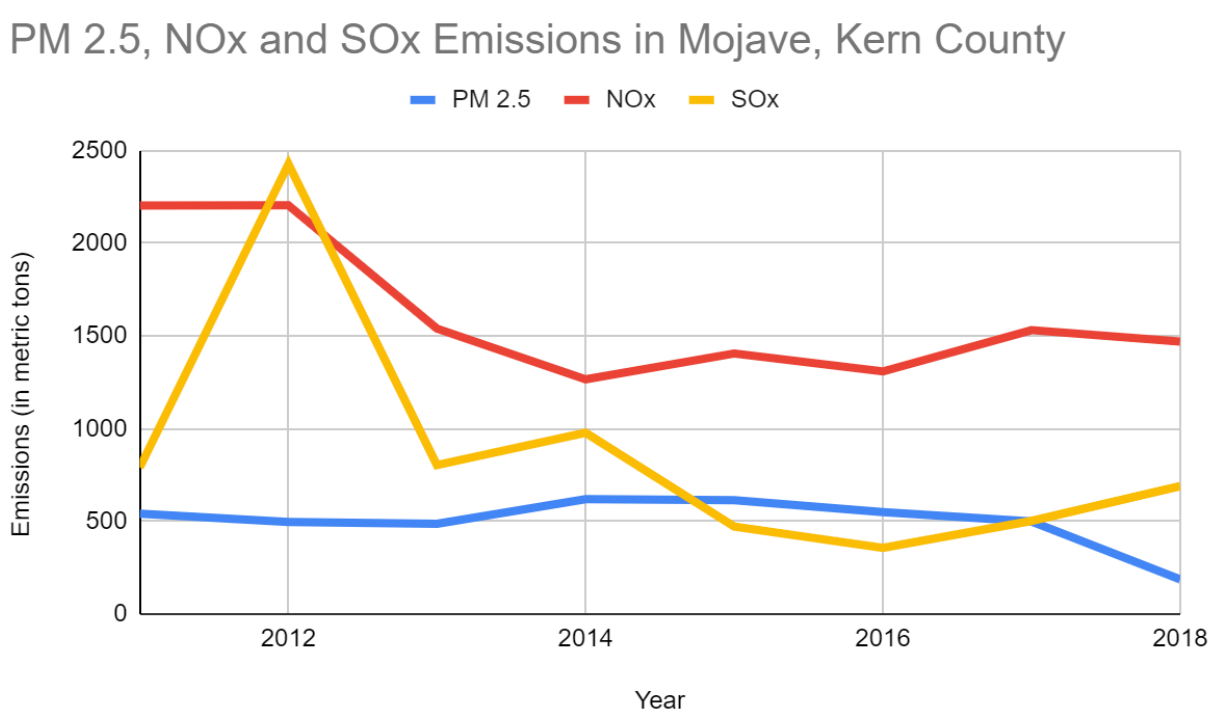
PM 2.5, NOx and SOx Emissions in Carson, Los Angeles County

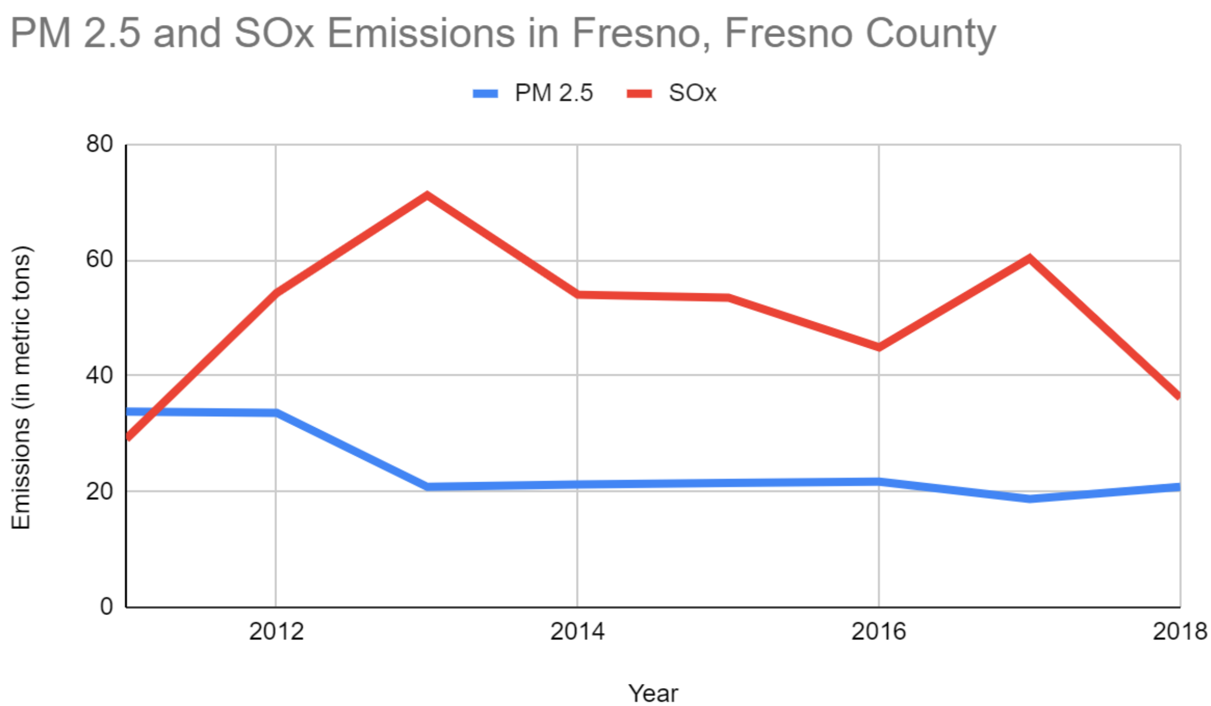


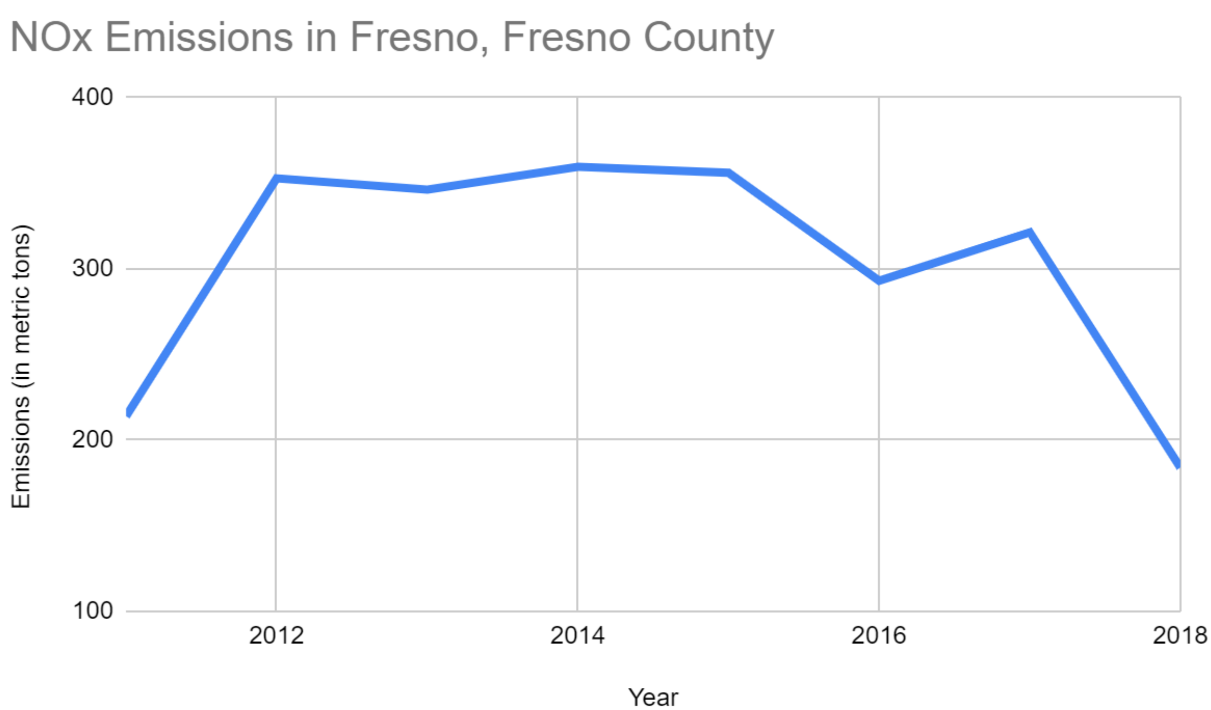
PM 2.5 Emissions in Mojave, Kern County

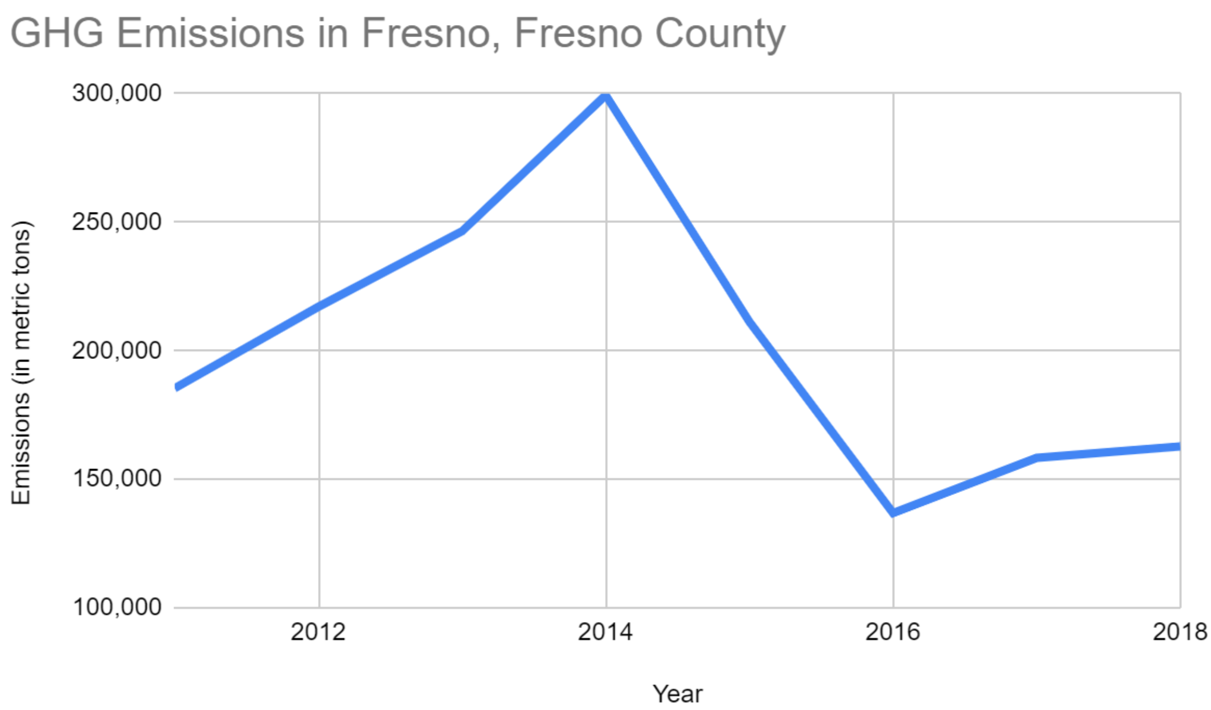


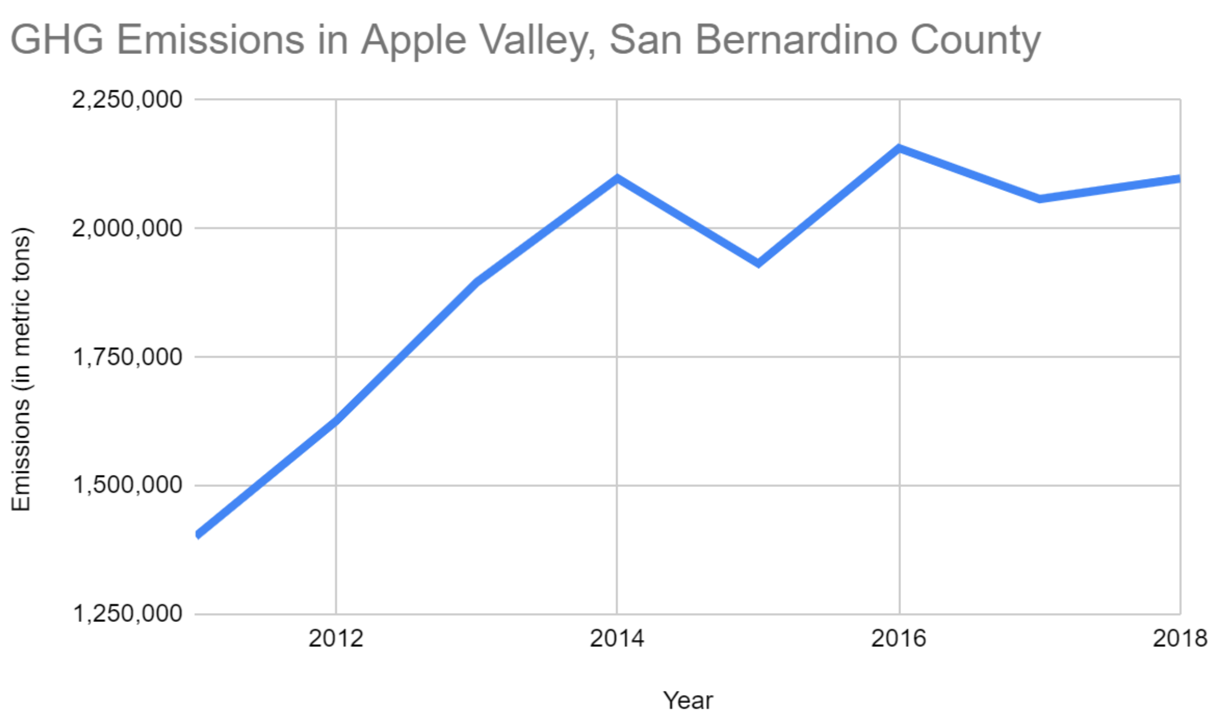

GHG Emissions in Mojave, Kern County
Emissions (in metric tons)
1,150,000
1,100,000
1,050,000
1,000,000
950,000
900,000
2012
2014
2016
2018
Year


PM 2.5, NOx and SOx Emissions in Mojave, Kern County
PM 2.5
NOx
SOx
Emissions (in metric tons)
2500
2000
1500
1000
500
0
2012
2014
2016
2018
Year

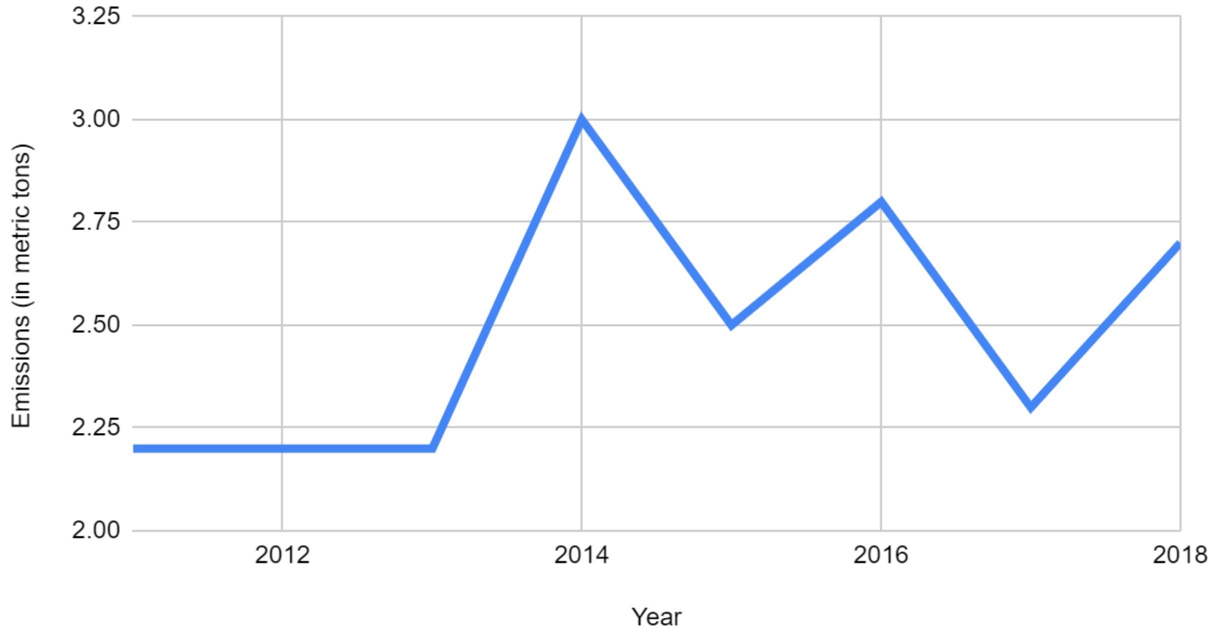

PM 2.5 and SOx Emissions in Fresno, Fresno County
PM 2.5
SOx
Emissions (in metric tons)
80
60
40
20
0
2012
2014
2016
2018
Year


NOx Emissions in Fresno, Fresno County
Emissions (in metric tons)
400
300
200
100
2012
2014
2016
2018
Year

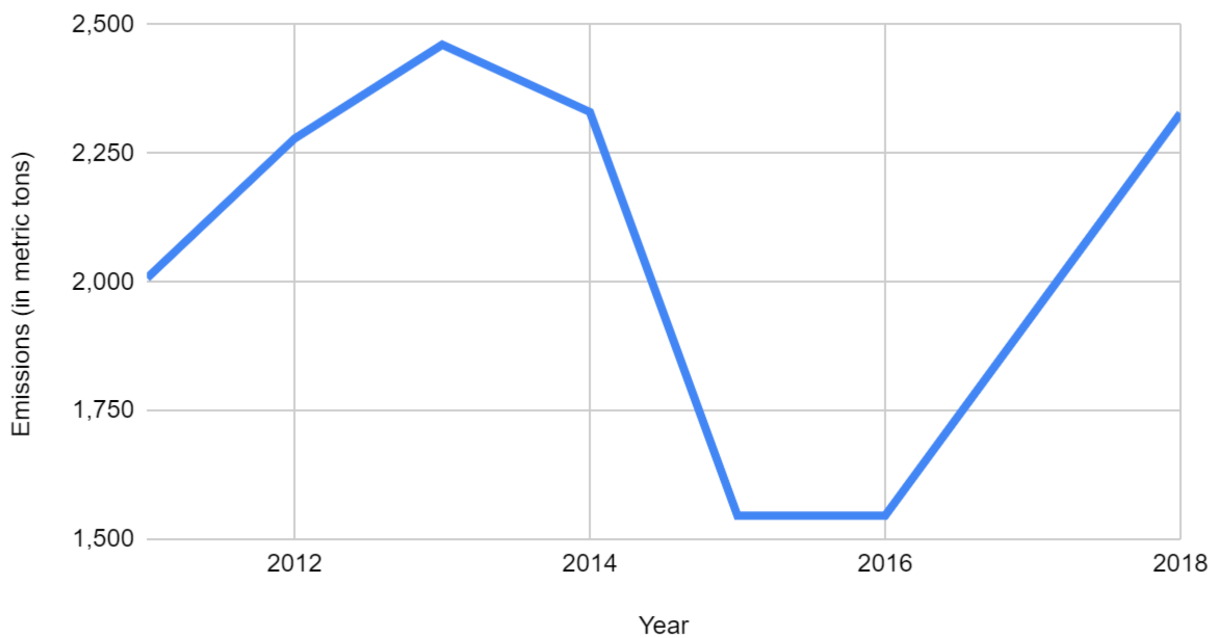

GHG Emissions in Fresno, Fresno County
300,000
250,000
200,000
150,000
100,000
Emissions (in metric tons)
2012
2014
2016
2018
Year


GHG Emissions in Apple Valley, San Bernardino County
2,250,000
2,000,000
1,750,000
1,500,000
1,250,000
Emissions (in metric tons)
2012
2014
2016
2018
Year

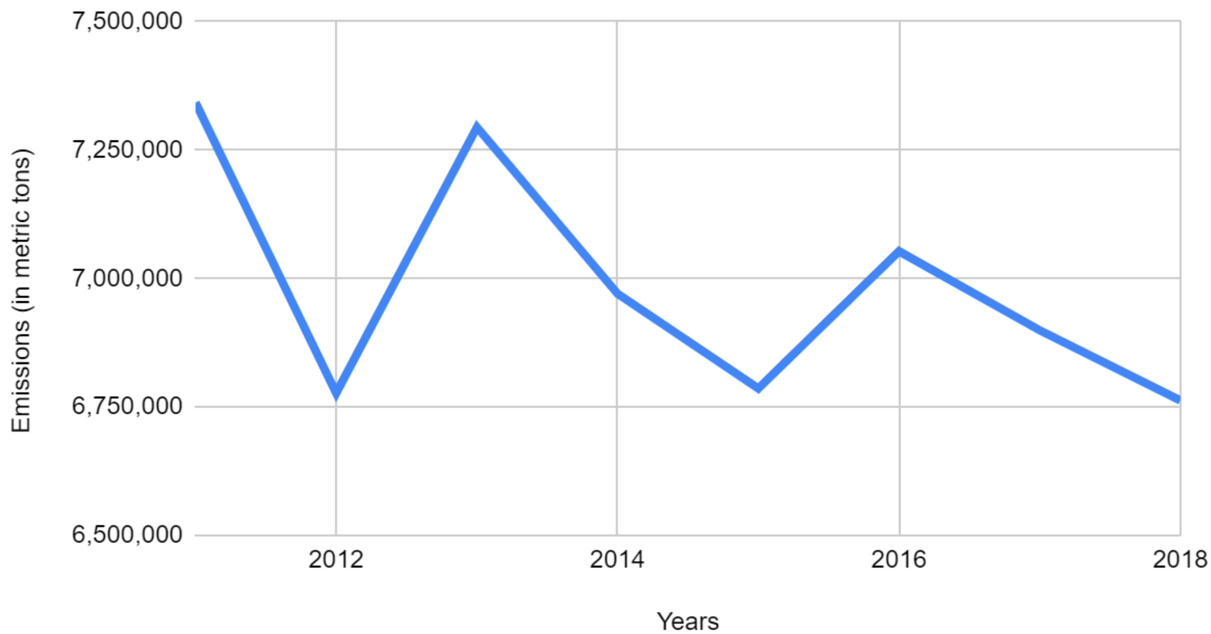
PM 2.5 Emissions in Apple Valley, San Bernardino County



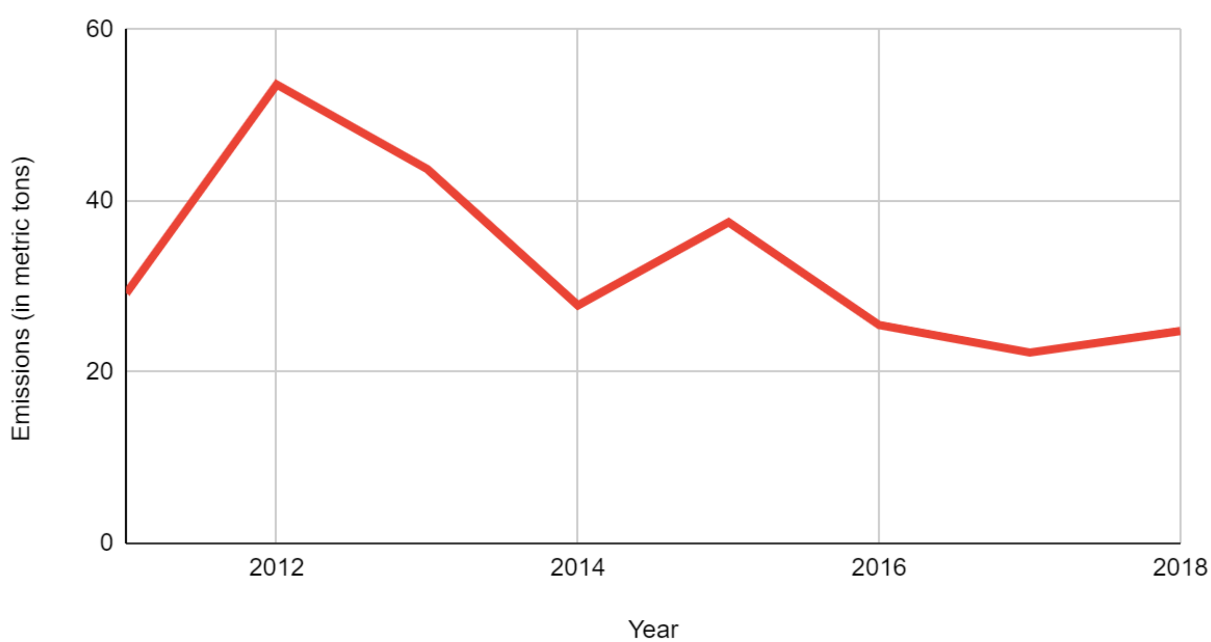
NOx Emissions in Apple Valley, San Bernardino County



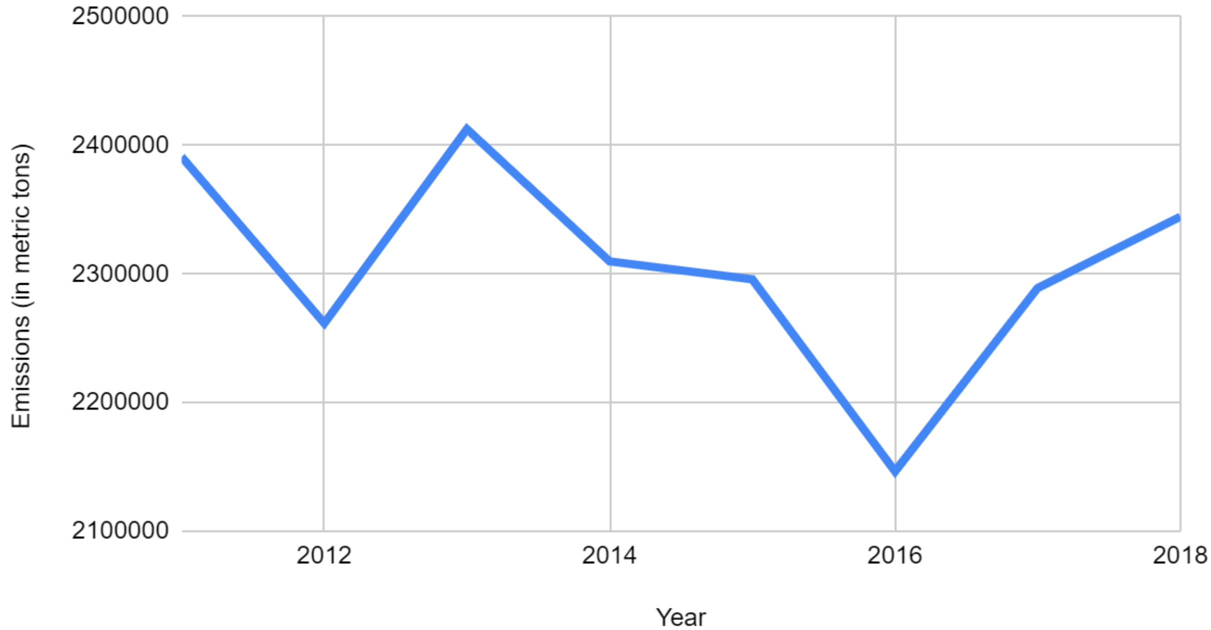
GHG Emissions in Martinez, Contra Costa County



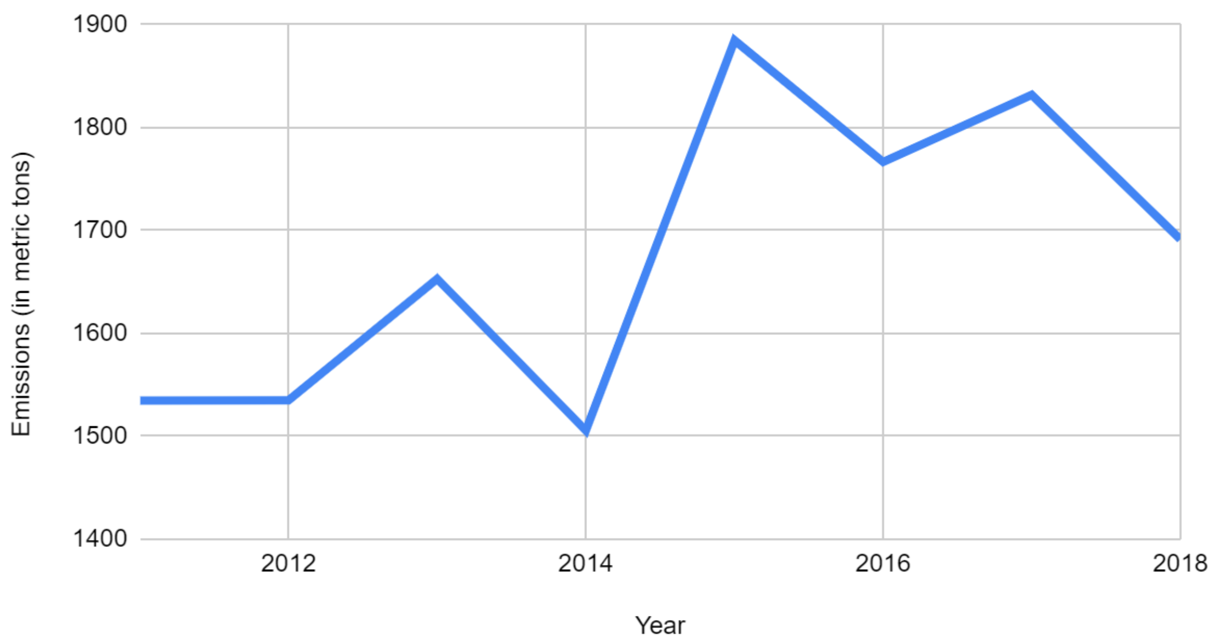
PM 2.5 Emissions in Martinez, Contra Costa County



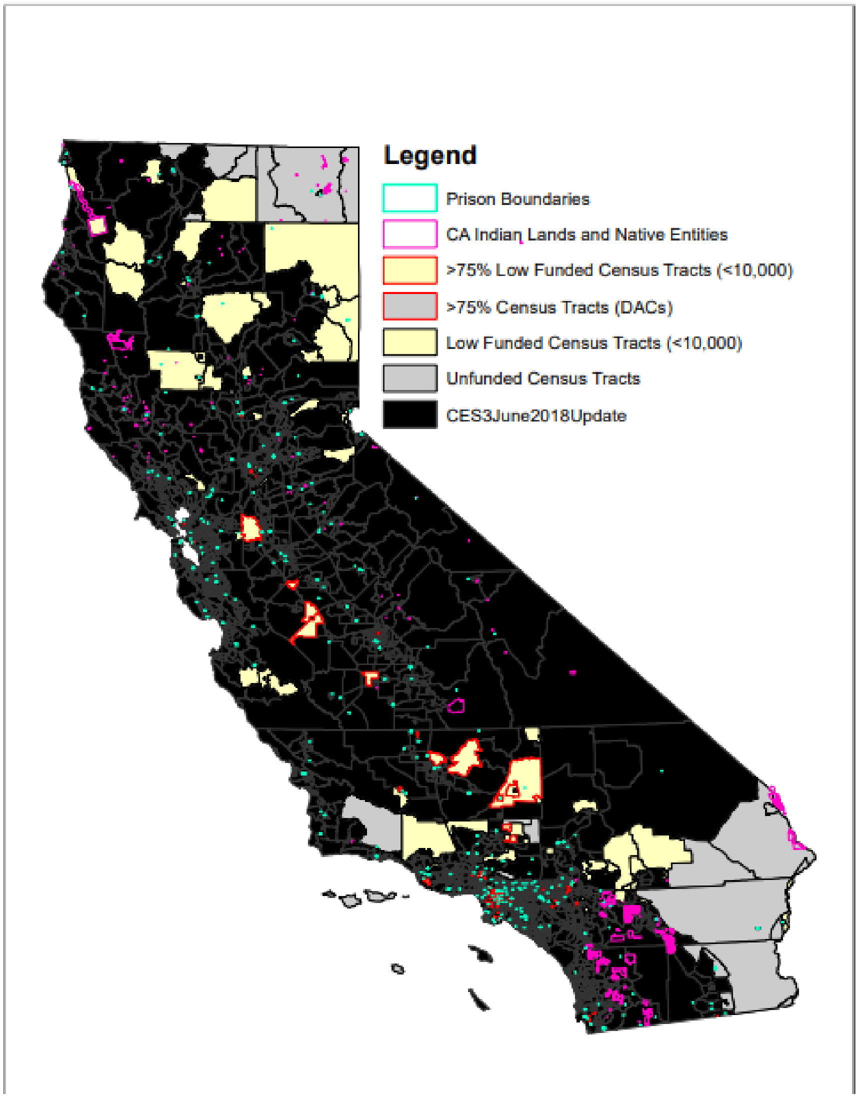
GHG Emissions in Rodeo, Contra Costa County



SOx Emissions in Rodeo, Contra Costa County



Appendix A - Map of Statewide Funding by Census Tract



Appendix A Sources: https://www.fcc.gov/general/census-blocks-state; https://webmaps.arb.ca.gov/ccimap/; https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-30; https://gis-calema.opendata.arcgis.com/datasets/23348a6fb3e44322a0c0a862aba62a24_0?geometry=-114.258%2C20.353%2C114.258%2C88.913; https://hifld-geoplatform.opendata.arcgis.com/datasets/2d6109d4127d458eaf0958e4c5296b67_0?geometry=-66.981%2C-3.068%2C47.276%2C75.954

Appendix B- Chart 3.1 and 3.2 Sources/ Program Information

- California Climate Investments. (n.d.). http://www.caclimateinvestments.ca.gov/.

- *Training and Workforce Development Program*. California Climate Investments. (n.d.). http://www.caclimateinvestments.ca.gov/training-workforce.
- *Prescribed and Fire Smoke Monitoring.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/smoke-monitoring
- *Community Solar.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/community-solar
- *Farmworker Housing Component: Single-Family Energy Efficiency and Solar Photovoltaics.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/farmworker-housing-singlefamily-energy-efficiency-solar-photovoltaics
- *Multi-Family Energy Efficiency and Renewables.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/multifamily-energy-efficiency-renewables
- *Single-Family Energy Efficiency and Solar Photovoltaics.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/single-family-energy-efficiency-solar-photovoltaics
- *Single-Family Solar Photovoltaics.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/single-family-solar-photovoltaics
- *Wetlands and Watershed Restoration.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/single-family-solar-photovoltaics
- *Alternative Manure Management Program (AMMP).* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/alternative-manure
- *Dairy Digester Research and Development.* California Climate Investments. (n.d).
- *Healthy Soils.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/dairy-digester
- *Community Fire Planning and Preparedness.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/healthy-soils
- *Fire Prevention.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/community-fire-planning
- *Fire Prevention Grants Program.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/fire-prevention
- *Forest Health Research.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/forest-health-research
- *Prescribed Fire.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/prescribed-fire
- *Urban and Community Forestry.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/urban-forestry
- *Community Composting for Green Spaces.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/community-composting-green-spaces-grant
- *Food Waste Prevention and Rescue Grants.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/food-waste-prevention-and-rescue-grant-program
- *Organics Grants.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/organics-grant-program
- *Pilot Reuse Grant Program.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/pilot-reuse-grant-program

- *Recycled Fiber, Plastic, and Glass Grant.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/recycled-fiber-plastic-glass-grant
- *Greenhouse Gas Reduction Loan Program.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/greenhouse-gas-reduction-loan-program
- *Active Transportation Program.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/active-transportation
- *Low Carbon Transit Operations Program.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/lctop
- *State Water Project Turbine.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/turbines
- *Food Production Investments.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/fpip
- *Low Carbon Fuel Production.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/fuel
- *Renewable Energy for Agriculture.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/reap
- *Transition to a Carbon-Neutral Economy* . California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/transition-carbonneutral-economy
- *Fire, Engine, and Equipment.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/fire-equipment
- *Wildfire Response and Readiness.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/wildfire-response
- *High-Speed Rail Project.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/hsr
- *Regional Forest and Fire Capacity.* California Climate Investments. (n.d). *http://www.caclimateinvestments.ca.gov/fire-capacity*
- *Urban Greening.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/urban-greening
- *Climate Ready.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/climate-ready
- *Transit and Intercity Rail Capital Program.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/tircp
- *Safe and Affordable Drinking Water Fund.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/safer-drinking-water
- *Climate Change Research.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/research
- *Sustainable Agricultural Lands Conservation Program.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/salc
- *Transformative Climate Communities.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/tcc
- *Advanced Technology Demonstration and Pilot Projects.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/advanced-technology-freight-demonstration-projects
- *Agriculture Worker Vanpools Pilot Project.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/agriculture-worker-vanpools-san-joaquin

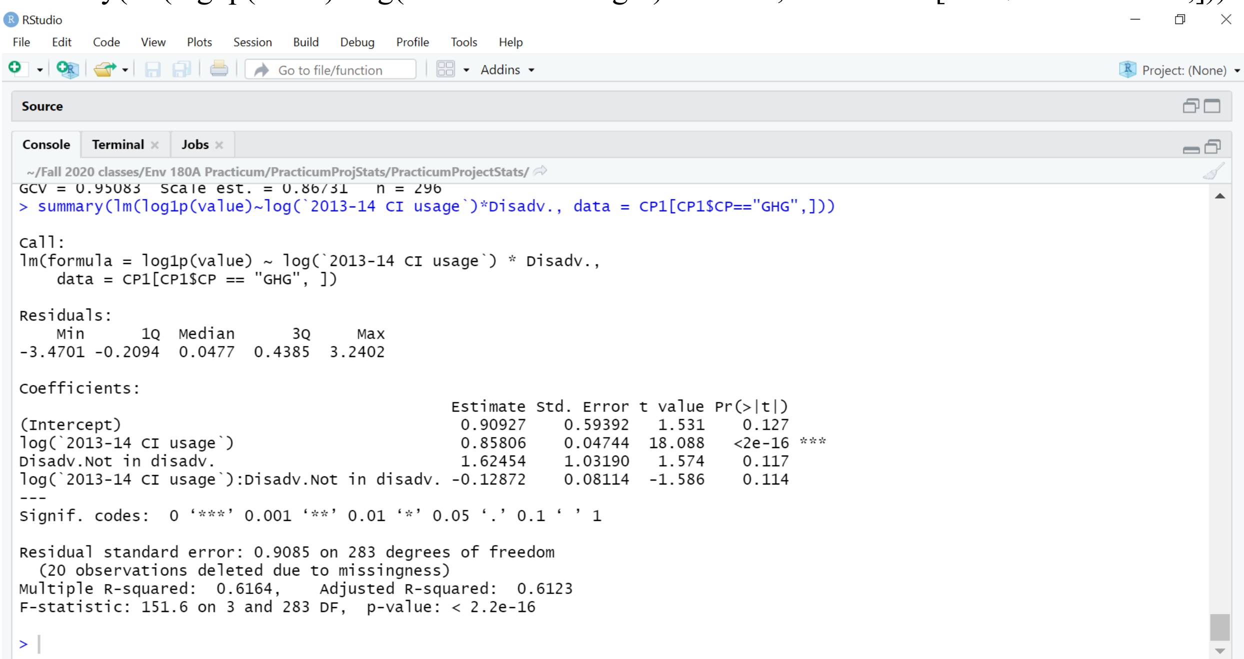
- *Clean Cars for All.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/clean-cars-4-all
- *Clean Mobility Options.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/clean-mobility-options-1
- *Clean Mobility in Schools .* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/clean-mobility-in-schools-pilot-1
- *Community Air Protection Incentive Funds.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/air-protection-funds
- *Financing Assistance for Lower-Income Customers.* California Climate Investments. (n.d).http://www.caclimateinvestments.ca.gov/financing-assistance-for-lowerincome-consumers
- *Fluorinated Cases Emission Reduction Incentives.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/fluorinated-gases-emission-reduction-incentives
- *Funding Agricultural Replacement Measures for Emission Reductions (FARMER).* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/farmer
- *Rural School Bus Pilot Projects.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/rural-school-bus-pilot-project
- *Sustainable Transportation Equity Project (STEP).* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/sustainable-transportation-equity-project
- *Woodsmoke Reduction.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/woodsmoke
- *Zero-and Near Zero-Emission Freight Facilities.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/zero-near-zero-emission-freight-facilities
- *Climate Resilience Planning.* California Climate Investments. (n.d). http://www.caclimateinvestments.ca.gov/climate-resilience-planning

DISCLAIMER: Some Programs were emailed and personally asked about funding because it was not available on the website. Contact information was found on the website from the sources/programs.

Appendix C- R Coding

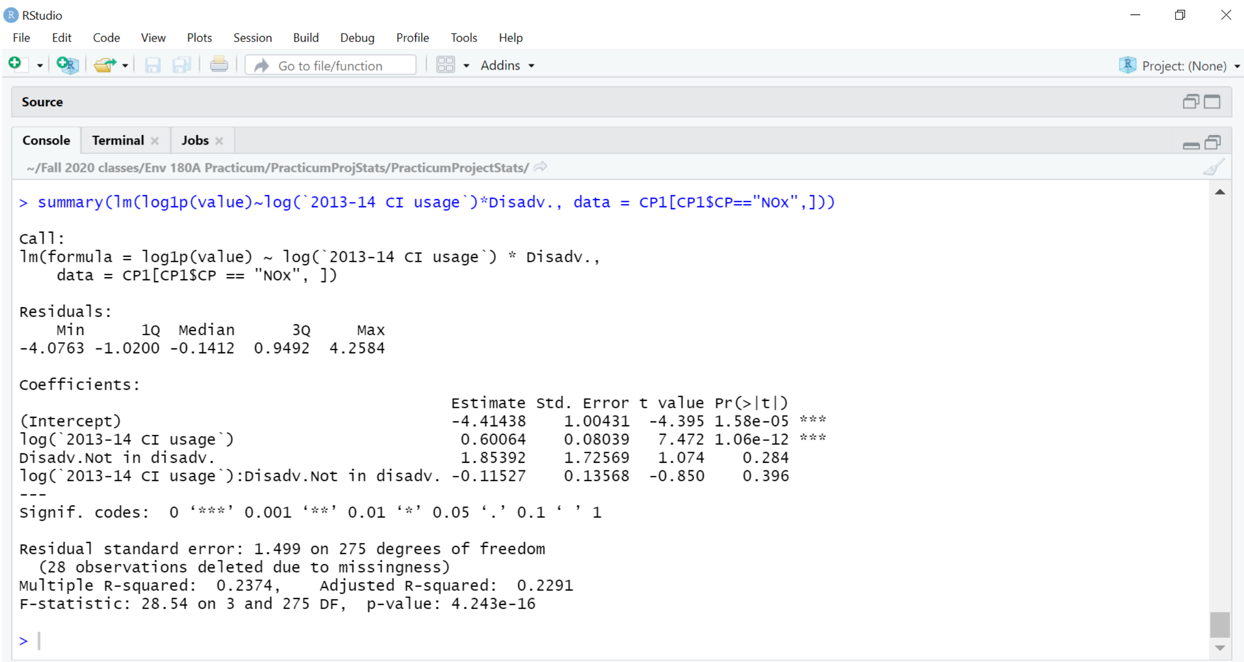
2013-2014 Compliance Period:

summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="GHG",]))



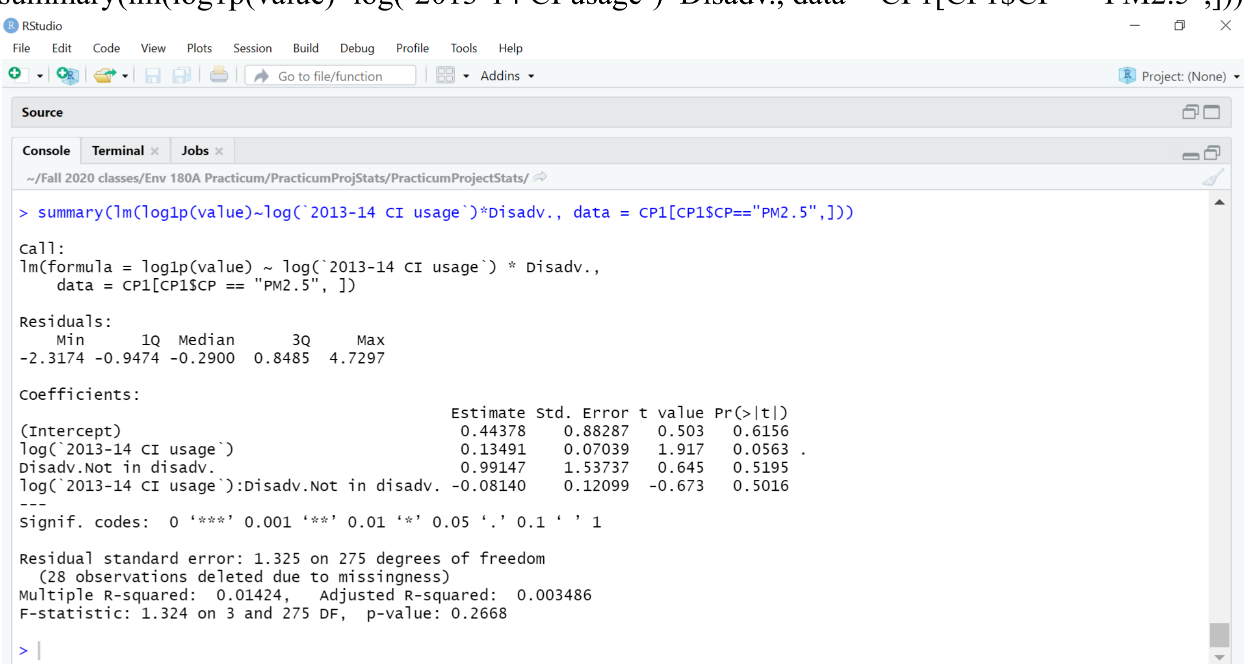

```
GCV = 0.95083  Scale est. = 0.86731   n = 296
> summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="GHG",]))

Call:
lm(formula = log1p(value) ~ log(`2013-14 CI usage`) * Disadv.,
    data = CP1[CP1$CP == "GHG", ])

Residuals:
    Min      1Q  Median      3Q     Max
-3.4701 -0.2094  0.0477  0.4385  3.2402

Coefficients:
                                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                                    0.90927    0.59392   1.531    0.127
log(`2013-14 CI usage`)                        0.85806    0.04744  18.088   <2e-16 ***
Disadv.Not in disadv.                          1.62454    1.03190   1.574    0.117
log(`2013-14 CI usage`):Disadv.Not in disadv. -0.12872    0.08114  -1.586    0.114
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9085 on 283 degrees of freedom
  (20 observations deleted due to missingness)
Multiple R-squared:  0.6164,    Adjusted R-squared:  0.6123
F-statistic: 151.6 on 3 and 283 DF,  p-value: < 2.2e-16

>
```

summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="NOx",]))



```
> summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="NOx",]))

Call:
lm(formula = log1p(value) ~ log(`2013-14 CI usage`) * Disadv.,
    data = CP1[CP1$CP == "NOx", ])

Residuals:
    Min      1Q  Median      3Q     Max 
-4.0763 -1.0200 -0.1412  0.9492  4.2584 

Coefficients:
                                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                -4.41438    1.00431  -4.395 1.58e-05 ***
log(`2013-14 CI usage`)                     0.60064    0.08039   7.472 1.06e-12 ***
Disadv.Not in disadv.                       1.85392    1.72569   1.074    0.284    
log(`2013-14 CI usage`):Disadv.Not in disadv. -0.11527    0.13568  -0.850    0.396    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.499 on 275 degrees of freedom
  (28 observations deleted due to missingness)
Multiple R-squared:  0.2374,    Adjusted R-squared:  0.2291 
F-statistic: 28.54 on 3 and 275 DF,  p-value: 4.243e-16

> 
```

summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="PM2.5",]))



```
> summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="PM2.5",]))

Call:
lm(formula = log1p(value) ~ log(`2013-14 CI usage`) * Disadv.,
    data = CP1[CP1$CP == "PM2.5", ])

Residuals:
    Min      1Q  Median      3Q     Max 
-2.3174 -0.9474 -0.2900  0.8485  4.7297 

Coefficients:
                                           Estimate Std. Error t value Pr(>|t|)  
(Intercept)                                 0.44378    0.88287   0.503   0.6156  
log(`2013-14 CI usage`)                     0.13491    0.07039   1.917   0.0563 .
Disadv.Not in disadv.                       0.99147    1.53737   0.645   0.5195  
log(`2013-14 CI usage`):Disadv.Not in disadv. -0.08140    0.12099  -0.673   0.5016  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.325 on 275 degrees of freedom
  (28 observations deleted due to missingness)
Multiple R-squared:  0.01424,   Adjusted R-squared:  0.003486 
F-statistic: 1.324 on 3 and 275 DF,  p-value: 0.2668

> 
```

summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="SOx",]))

```
> summary(lm(log1p(value)~log(`2013-14 CI usage`)*Disadv., data = CP1[CP1$CP=="SOx",]))

Call:
lm(formula = log1p(value) ~ log(`2013-14 CI usage`) * Disadv.,
    data = CP1[CP1$CP == "SOx", ])

Residuals:
    Min      1Q  Median      3Q     Max
-2.7369 -0.8432 -0.3373  0.3625  5.6257

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                              -5.299057   1.002404  -5.286 2.56e-07 ***
log(`2013-14 CI usage`)                   0.537043   0.080284   6.689 1.27e-10 ***
Disadv.Not in disadv.                    -0.204482   1.724257  -0.119    0.906
log(`2013-14 CI usage`):Disadv.Not in disadv.  0.005907   0.135546   0.044    0.965
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.496 on 272 degrees of freedom
  (31 observations deleted due to missingness)
Multiple R-squared:  0.2037,    Adjusted R-squared:  0.1949
F-statistic:  23.2 on 3 and 272 DF,  p-value: 2.114e-13

>
```

2015-2017 Compliance Period:

NOx model

summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="NOx"& CP2$FACID!=124838,]))

```
> summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="NOx"& CP2$FACID!=124838,]))

Family: gaussian
Link function: identity

Formula:
log1p(value) ~ log(X2015.2017) * Disadv.

Parametric coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
(Intercept)                           -3.97620    0.80229  -4.956 1.23e-06 ***
log(X2015.2017)                        0.54839    0.06286   8.724  < 2e-16 ***
Disadv.Not in disadv.                  0.03612    1.33937   0.027    0.979
log(X2015.2017):Disadv.Not in disadv.  0.01100    0.10246   0.107    0.915
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


R-sq.(adj) =  0.306   Deviance explained = 31.3%
GCV = 1.9605  Scale est. = 1.9337    n = 292
>
```

PM 2.5 model

summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="PM2.5" & CP2$FACID!=124838,]))

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```
> summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="PM2.5" & CP2$FACID!=124838,]))

Family: gaussian 
Link function: identity 

Formula:
log1p(value) ~ log(X2015.2017) * Disadv.

Parametric coefficients:
                                       Estimate Std. Error t value Pr(>|t|)  
(Intercept)                             0.51906    0.75475   0.688   0.4922  
log(X2015.2017)                         0.13133    0.05874   2.236   0.0261 *
Disadv.Not in disadv.                   1.93569    1.28098   1.511   0.1319  
log(X2015.2017):Disadv.Not in disadv. -0.16646    0.09760  -1.706   0.0892 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


R-sq.(adj) =  0.0128   Deviance explained =  2.3%
GCV = 1.7957  Scale est. = 1.7709    n = 289
> 
```

SOx model

summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="SOx" & CP2$FACID!=124838,]))

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```
> summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="SOx" & CP2$FACID!=124838,]))

Family: gaussian 
Link function: identity 

Formula:
log1p(value) ~ log(X2015.2017) * Disadv.

Parametric coefficients:
                                      Estimate Std. Error
(Intercept)                           -5.34801    0.82398
log(X2015.2017)                        0.52356    0.06453
Disadv.Not in disadv.                  3.57549    1.38358
log(X2015.2017):Disadv.Not in disadv. -0.29454    0.10560
                                      t value Pr(>|t|)    
(Intercept)                            -6.490 3.86e-10 ***
log(X2015.2017)                         8.114 1.54e-14 ***
Disadv.Not in disadv.                   2.584  0.01026 *  
log(X2015.2017):Disadv.Not in disadv.  -2.789  0.00565 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


R-sq.(adj) =  0.199   Deviance explained = 20.7%
GCV = 2.0474  Scale est. = 2.0187    n = 285
> 
```

GHG model

summary(lm(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="GHG" & CP2$FACID!=124838,]))

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Source

Console Terminal Jobs

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```
> #linear GHG model
> summary(lm(log1p(value)~log(X2015.2017)*Disadv., data = CP2[CP2$CP=="GHG" & CP2$FACID!=124838,]))

Call:
lm(formula = log1p(value) ~ log(X2015.2017) * Disadv., data = CP2[CP2$CP ==
    "GHG" & CP2$FACID != 124838, ])

Residuals:
    Min      1Q  Median      3Q     Max
-4.3601 -0.3974  0.0054  0.5911  3.0761

Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
(Intercept)                            3.05686    0.60883   5.021 8.97e-07 ***
log(X2015.2017)                        0.66445    0.04749  13.990  < 2e-16 ***
Disadv.Not in disadv.                  2.19560    1.02798   2.136   0.0335 *
log(X2015.2017):Disadv.Not in disadv. -0.17806    0.07856  -2.266   0.0242 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.085 on 292 degrees of freedom
  (10 observations deleted due to missingness)
Multiple R-squared:  0.4683,    Adjusted R-squared:  0.4629
F-statistic: 85.74 on 3 and 292 DF,  p-value: < 2.2e-16

>
```

2015-2017 BY SECTOR

#linear GHG model

summary(lm(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="GHG" & CP2$FACID!=124838,]))

```
> #linear GHG model
> summary(lm(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="GHG" & CP2$FACID!=124838,]))

Call:
lm(formula = log1p(value) ~ log(X2015.2017) * Disadv. * as.factor(Primary.Sector),
    data = CP2[CP2$CP == "GHG" & CP2$FACID != 124838, ])

Residuals:
    Min      1Q  Median      3Q     Max
-3.5268 -0.3369 -0.0148  0.3859  3.4007

Coefficients: (2 not defined because of singularities)
                                                                          Estimate Std. Error t value
(Intercept)                                                                 8.1701     7.0993   1.151
log(X2015.2017)                                                             0.3846     0.4857   0.792
Disadv.Not in disadv.                                                       3.2989     4.4261   0.745
as.factor(Primary.Sector)Cogeneration                                      -4.9215     7.2360  -0.680
as.factor(Primary.Sector)Electricity Generation                            -3.5985     7.2779  -0.494
as.factor(Primary.Sector)Hydrogen Plant                                    -9.8724     8.3992  -1.175
as.factor(Primary.Sector)Oil and Gas Production                             1.5380     7.2450   0.212
as.factor(Primary.Sector)Other Combustion Source                           -5.2888     7.2268  -0.732
as.factor(Primary.Sector)Refinery                                          -6.7644     6.9712  -0.970
log(X2015.2017):Disadv.Not in disadv.                                      -0.2340     0.2976  -0.786
log(X2015.2017):as.factor(Primary.Sector)Cogeneration                       0.2772     0.4978   0.557
log(X2015.2017):as.factor(Primary.Sector)Electricity Generation             0.1814     0.5001   0.363
log(X2015.2017):as.factor(Primary.Sector)Hydrogen Plant                     0.6488     0.5879   1.104
log(X2015.2017):as.factor(Primary.Sector)Oil and Gas Production            -0.2722     0.4986  -0.546
log(X2015.2017):as.factor(Primary.Sector)Other Combustion Source            0.2807     0.4988   0.563
log(X2015.2017):as.factor(Primary.Sector)Refinery                           0.4105     0.4765   0.861
Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration                -2.3895     5.3439  -0.447
Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation      -8.8584     5.0018  -1.771
Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant               0.3707     1.4592   0.254
Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production      -4.0884     4.8574  -0.842
Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source      0.5616     4.8517   0.116
Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                     1.2352     1.2447   0.992
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration  0.1634     0.3778   0.433
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation   0.6669     0.3453   1.931
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant          NA         NA      NA
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production   0.2895     0.3328   0.870
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source -0.1049     0.3397  -0.309
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                NA         NA      NA
                                                                          Pr(>|t|)

                                                                                       Pr(>|t|)
(Intercept)                                                                              0.2508
log(X2015.2017)                                                                          0.4291
Disadv.Not in disadv.                                                                    0.4567
as.factor(Primary.Sector)Cogeneration                                                    0.4970
as.factor(Primary.Sector)Electricity Generation                                          0.6214
as.factor(Primary.Sector)Hydrogen Plant                                                  0.2409
as.factor(Primary.Sector)Oil and Gas Production                                          0.8320
as.factor(Primary.Sector)Other Combustion Source                                         0.4649
as.factor(Primary.Sector)Refinery                                                        0.3327
log(X2015.2017):Disadv.Not in disadv.                                                    0.4325
log(X2015.2017):as.factor(Primary.Sector)Cogeneration                                    0.5781
log(X2015.2017):as.factor(Primary.Sector)Electricity Generation                          0.7171
log(X2015.2017):as.factor(Primary.Sector)Hydrogen Plant                                  0.2707
log(X2015.2017):as.factor(Primary.Sector)Oil and Gas Production                          0.5856
log(X2015.2017):as.factor(Primary.Sector)Other Combustion Source                         0.5741
log(X2015.2017):as.factor(Primary.Sector)Refinery                                        0.3897
Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration                              0.6551
Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation                    0.0777 .
Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant                            0.7997
Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production                    0.4007
Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source                   0.9079
Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                                  0.3219
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration              0.6657
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation    0.0545 .
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant                NA
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production    0.3851
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source   0.7578
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                      NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9313 on 270 degrees of freedom
  (10 observations deleted due to missingness)
Multiple R-squared:  0.6379,    Adjusted R-squared:  0.6044
F-statistic: 19.03 on 25 and 270 DF,  p-value: < 2.2e-16

>
```

ggplot(CP2[CP2$CP=="GHG" & CP2$FACID!=124838 & CP2$Primary.Sector=="Electricity Generation",],
      aes(x=log(X2015.2017), y=log1p(value), color=Disadv., shape=Disadv.)) +
  geom_smooth(method = "lm", se=FALSE, width=0.7, aes(lty=Disadv.))+
  geom_point(alpha=0.4)

#PM 2.5 linear model
summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="GHG" & CP2$FACID!=124838,]))

```
> #PM 2.5 linear model
> summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="GHG" & CP2$FACID!=124838,]))

Family: gaussian
Link function: identity

Formula:
log1p(value) ~ log(X2015.2017) * Disadv. * as.factor(Primary.Sector)

Parametric coefficients:
                                                                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                                                                   6.621196   2.661584   2.488  0.01346 *
log(X2015.2017)                                                               0.491514   0.194507   2.527  0.01208 *
Disadv.Not in disadv.                                                         4.847861   3.073709   1.577  0.11592
as.factor(Primary.Sector)Cogeneration                                        -3.372553   2.905256  -1.161  0.24673
as.factor(Primary.Sector)Electricity Generation                              -2.049567   2.976885  -0.688  0.49173
as.factor(Primary.Sector)Hydrogen Plant                                      -8.323490   4.912213  -1.694  0.09133 .
as.factor(Primary.Sector)Oil and Gas Production                               3.086928   2.920732   1.057  0.29150
as.factor(Primary.Sector)Other Combustion Source                             -3.739893   2.889318  -1.294  0.19664
as.factor(Primary.Sector)Refinery                                            -5.215497   2.907514  -1.794  0.07396 .
log(X2015.2017):Disadv.Not in disadv.                                        -0.340855   0.223356  -1.526  0.12816
log(X2015.2017):as.factor(Primary.Sector)Cogeneration                         0.170324   0.215654   0.790  0.43034
log(X2015.2017):as.factor(Primary.Sector)Electricity Generation               0.074491   0.219098   0.340  0.73413
log(X2015.2017):as.factor(Primary.Sector)Hydrogen Plant                       0.541931   0.363004   1.493  0.13663
log(X2015.2017):as.factor(Primary.Sector)Oil and Gas Production              -0.379111   0.217054  -1.747  0.08184 .
log(X2015.2017):as.factor(Primary.Sector)Other Combustion Source              0.173830   0.217955   0.798  0.42583
log(X2015.2017):as.factor(Primary.Sector)Refinery                             0.303615   0.209548   1.449  0.14852
Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration                  -3.938377   4.090596  -0.963  0.33652
Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation       -10.407287   3.693887  -2.817  0.00520 **
Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant                 0.001778   0.006856   0.259  0.79553
Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production        -5.637358   3.537482  -1.594  0.11219
Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source       -0.987318   3.536525  -0.279  0.78032
Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                      -0.313762   4.857239  -0.065  0.94854
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration   0.270291   0.308303   0.877  0.38142
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation   0.773792   0.272396   2.841  0.00484 **
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant   0.025914   0.099904   0.259  0.79553
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production   0.396422   0.259319   1.529  0.12751
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source   0.002032   0.267632   0.008  0.99395
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery       0.106898   0.352441   0.303  0.76189
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Rank: 26/28
R-sq.(adj) =  0.604   Deviance explained = 63.8%
GCV = 0.95083  Scale est. = 0.86731   n = 296
> 
```

```
ggplot(CP2[CP2$CP=="PM2.5" & CP2$FACID!=124838 & CP2$Primary.Sector=="Electricity Generation",],
      aes(x=log(X2015.2017), y=log1p(value), color=Disadv., shape=Disadv.)) +
 geom_smooth(method = "lm", se=FALSE, width=0.7, aes(lty=Disadv.))+
geom_point(alpha=0.4)
```

#NOx model

```
summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="NOx" & CP2$FACID!=124838,]))
```

```
> #NOx model
> summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="NOx" & CP2$FACID!=124838,]))

Family: gaussian
Link function: identity

Formula:
log1p(value) ~ log(X2015.2017) * Disadv. * as.factor(Primary.Sector)

Parametric coefficients:
                                                                                  Estimate Std. Error t value
(Intercept)                                                                      9.032e-01  3.505e+00   0.258
log(X2015.2017)                                                                  4.477e-01  2.561e-01   1.748
Disadv.Not in disadv.                                                            5.420e+00  4.045e+00   1.340
as.factor(Primary.Sector)Cogeneration                                           -5.770e+00  3.834e+00  -1.505
as.factor(Primary.Sector)Electricity Generation                                 -2.186e+00  3.918e+00  -0.558
as.factor(Primary.Sector)Hydrogen Plant                                         -6.889e+00  6.456e+00  -1.067
as.factor(Primary.Sector)Oil and Gas Production                                  6.497e-01  4.094e+00   0.159
as.factor(Primary.Sector)Other Combustion Source                                -5.515e+00  3.804e+00  -1.450
as.factor(Primary.Sector)Refinery                                               -6.366e+00  3.828e+00  -1.663
log(X2015.2017):Disadv.Not in disadv.                                           -3.927e-01  2.939e-01  -1.336
log(X2015.2017):as.factor(Primary.Sector)Cogeneration                            1.505e-01  2.849e-01   0.528
log(X2015.2017):as.factor(Primary.Sector)Electricity Generation                 -1.290e-01  2.883e-01  -0.447
log(X2015.2017):as.factor(Primary.Sector)Hydrogen Plant                          1.654e-01  4.771e-01   0.347
log(X2015.2017):as.factor(Primary.Sector)Oil and Gas Production                 -3.905e-01  3.116e-01  -1.253
log(X2015.2017):as.factor(Primary.Sector)Other Combustion Source                 1.762e-01  2.868e-01   0.614
log(X2015.2017):as.factor(Primary.Sector)Refinery                                2.608e-01  2.758e-01   0.946
Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration                      1.543e-01  5.385e+00   0.029
Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation           -9.763e+00  4.858e+00  -2.010
Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant                   -6.314e-05  9.004e-03  -0.007
Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production           -1.106e+01  4.861e+00  -2.275
Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source          -1.811e+00  4.666e+00  -0.388
Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                          1.080e+00  6.384e+00   0.169
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration     -3.567e-02  4.061e-01  -0.088
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation  7.284e-01  3.582e-01   2.034
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant   -9.200e-04  1.312e-01  -0.007
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production  8.864e-01  3.631e-01   2.441
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source  8.955e-02  3.530e-01   0.254
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery          6.233e-02  4.632e-01   0.135
                                                                                  Pr(>|t|)
(Intercept)                                                                        0.7969
log(X2015.2017)                                                                    0.0816 .
Disadv.Not in disadv.                                                              0.1814
as.factor(Primary.Sector)Cogeneration                                              0.1335
as.factor(Primary.Sector)Electricity Generation                                    0.5774
as.factor(Primary.Sector)Hydrogen Plant                                            0.2869
as.factor(Primary.Sector)Oil and Gas Production                                    0.8740
as.factor(Primary.Sector)Other Combustion Source                                   0.1483
as.factor(Primary.Sector)Refinery                                                  0.0975 .
log(X2015.2017):Disadv.Not in disadv.                                              0.1826
log(X2015.2017):as.factor(Primary.Sector)Cogeneration                              0.5978
log(X2015.2017):as.factor(Primary.Sector)Electricity Generation                    0.6550
log(X2015.2017):as.factor(Primary.Sector)Hydrogen Plant                            0.7291
log(X2015.2017):as.factor(Primary.Sector)Oil and Gas Production                    0.2112
log(X2015.2017):as.factor(Primary.Sector)Other Combustion Source                   0.5395
log(X2015.2017):as.factor(Primary.Sector)Refinery                                  0.3452
Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration                        0.9772
Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation              0.0455 *
Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant                      0.9944
Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production              0.0237 *
Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source             0.6982
Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                            0.8658
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration        0.9301
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation  0.0430 *
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant      0.9944
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production  0.0153 *
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source  0.7999
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery            0.8931
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Rank: 26/28
R-sq.(adj) =  0.463   Deviance explained = 50.9%
GCV = 1.6419  Scale est. = 1.4957    n = 292
>
```

```
ggplot(CP2[CP2$CP=="NOx" & CP2$FACID!=124838 & CP2$Primary.Sector=="Electricity Generation",],
       aes(x=log(X2015.2017), y=log1p(value), color=Disadv., shape=Disadv.)) +
  geom_smooth(method = "lm", se=FALSE, width=0.7, aes(lty=Disadv.))+
  geom_point(alpha=0.4)

ggplot(CP2[CP2$CP=="NOx" & CP2$FACID!=124838 & CP2$Primary.Sector=="Oil and Gas Production",],
       aes(x=log(X2015.2017), y=log1p(value), color=Disadv., shape=Disadv.)) +
```

geom_smooth(method = "lm", se=FALSE, width=0.7, aes(lty=Disadv.))+
geom_point(alpha=0.4)

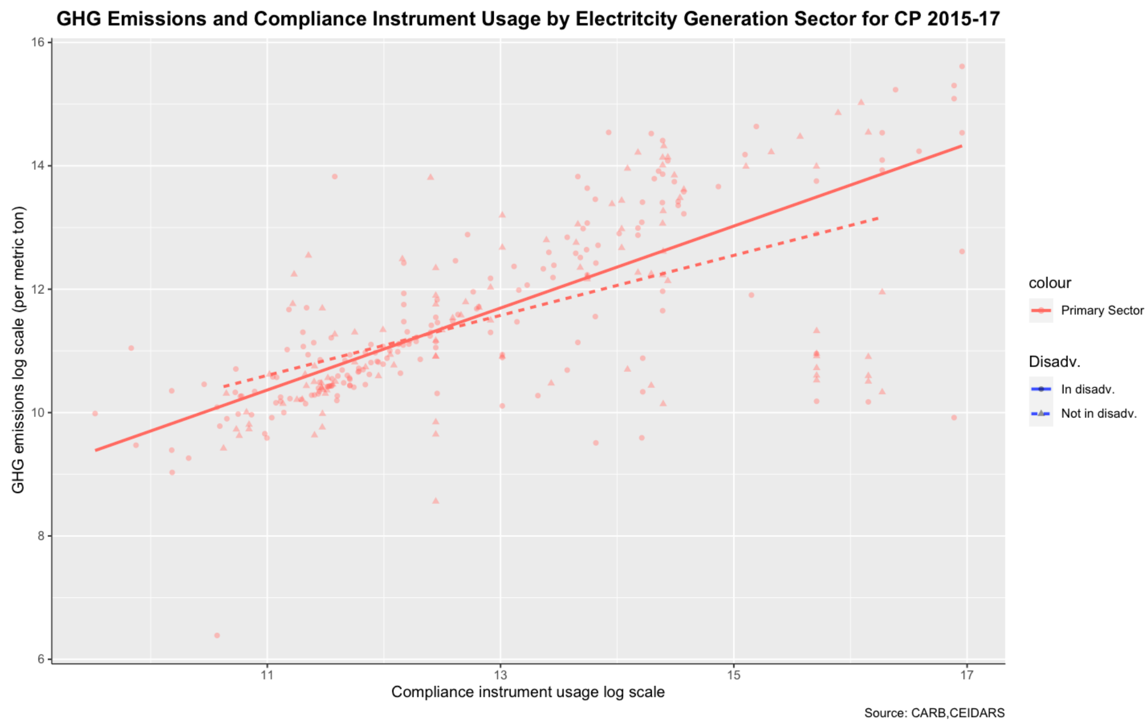
#SOx model

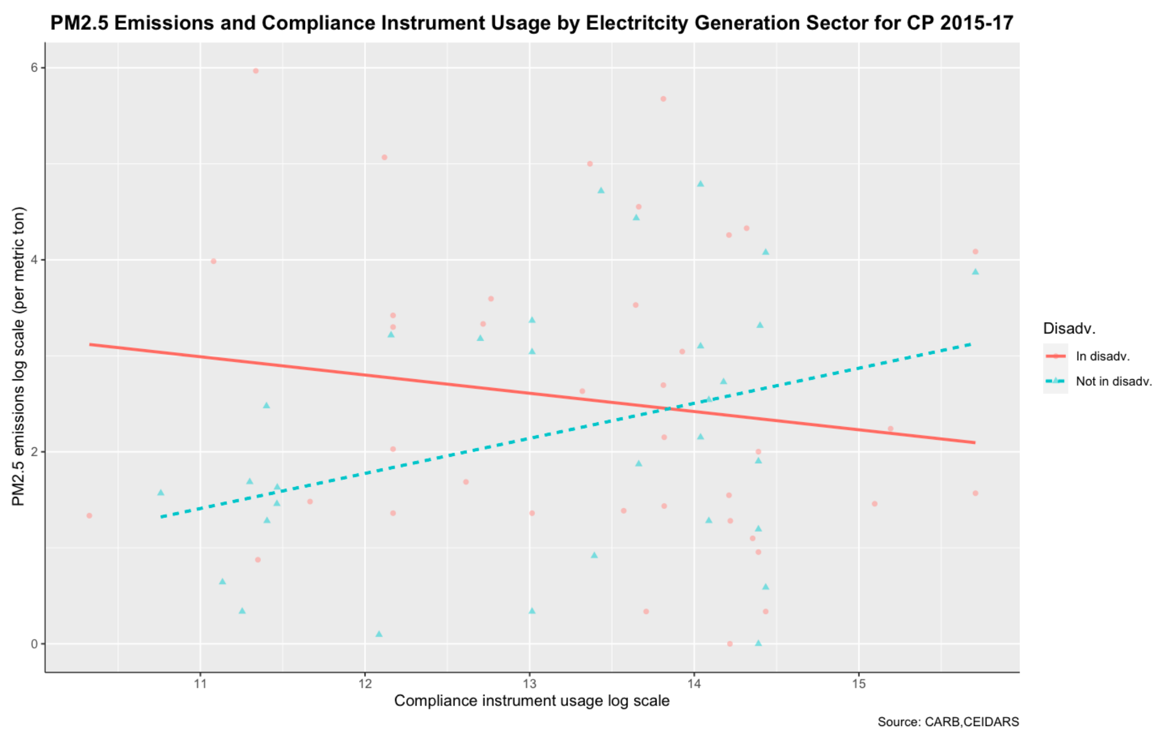
summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="SOx" & CP2$FACID!=124838,]))

```
> #SOx model
> summary(mgcv::gam(log1p(value)~log(X2015.2017)*Disadv.*as.factor(Primary.Sector), data = CP2[CP2$CP=="SOx" & CP2$FACID!=124838,]))

Family: gaussian
Link function: identity

Formula:
log1p(value) ~ log(X2015.2017) * Disadv. * as.factor(Primary.Sector)

Parametric coefficients:
                                                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                                                               4.416571   3.074347   1.437 0.152042
log(X2015.2017)                                                          -0.062049   0.224430  -0.276 0.782405
Disadv.Not in disadv.                                                    10.230715   3.541561   2.889 0.004195 **
as.factor(Primary.Sector)Cogeneration                                    -6.475902   3.358619  -1.928 0.054930 .
as.factor(Primary.Sector)Electricity Generation                          -5.228607   3.434553  -1.522 0.129140
as.factor(Primary.Sector)Hydrogen Plant                                  -6.865228   7.102838  -0.967 0.334672
as.factor(Primary.Sector)Oil and Gas Production                          -0.954446   3.583743  -0.266 0.790200
as.factor(Primary.Sector)Other Combustion Source                        -12.339937   3.333262  -3.702 0.000261 ***
as.factor(Primary.Sector)Refinery                                       -13.402011   3.353013  -3.997 8.37e-05 ***
log(X2015.2017):Disadv.Not in disadv.                                    -0.633605   0.257164  -2.464 0.014397 *
log(X2015.2017):as.factor(Primary.Sector)Cogeneration                     0.292778   0.249363   1.174 0.241431
log(X2015.2017):as.factor(Primary.Sector)Electricity Generation           0.194207   0.252653   0.769 0.442789
log(X2015.2017):as.factor(Primary.Sector)Hydrogen Plant                   0.284509   0.514870   0.553 0.581025
log(X2015.2017):as.factor(Primary.Sector)Oil and Gas Production          -0.150183   0.272518  -0.551 0.582044
log(X2015.2017):as.factor(Primary.Sector)Other Combustion Source          0.824908   0.251121   3.285 0.001161 **
log(X2015.2017):as.factor(Primary.Sector)Refinery                         0.949046   0.241488   3.930 0.000109 ***
Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration              -8.104927   4.703690  -1.723 0.086064 .
Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation   -13.555996   4.248647  -3.191 0.001594 **
Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant            -0.006193   0.007852  -0.789 0.431007
Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production   -12.289528   4.273714  -2.876 0.004368 **
Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source   -7.974058   4.086644  -1.951 0.052106 .
Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                   2.510166   5.571421   0.451 0.652696
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Cogeneration              0.445741   0.354492   1.257 0.209738
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Electricity Generation    0.878623   0.313195   2.805 0.005407 **
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Hydrogen Plant           -0.090241   0.114416  -0.789 0.431007
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Oil and Gas Production    0.795501   0.318511   2.498 0.013126 *
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Other Combustion Source   0.443039   0.308869   1.434 0.152666
log(X2015.2017):Disadv.Not in disadv.:as.factor(Primary.Sector)Refinery                 -0.193252   0.404145  -0.478 0.632930
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Rank: 26/28
R-sq.(adj) =   0.55   Deviance explained = 58.9%
GCV = 1.2481  Scale est. = 1.1342    n = 285
>
```

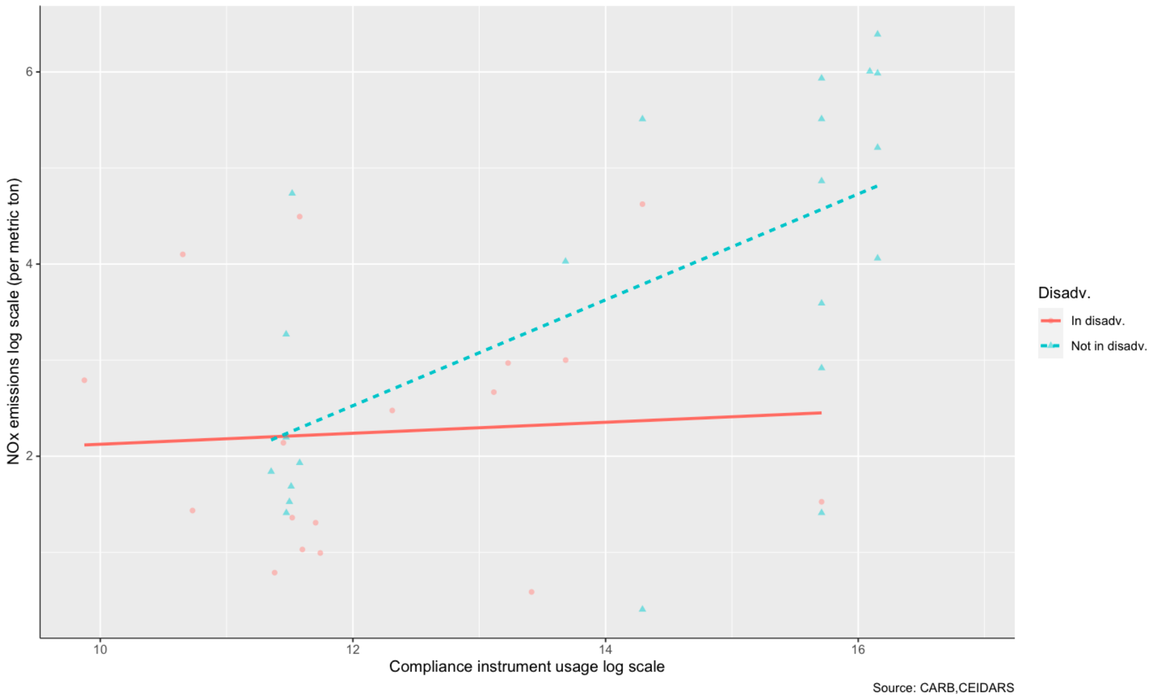
ggplot(CP2[CP2$CP=="SOx" & CP2$FACID!=124838 & CP2$Primary.Sector=="Electricity Generation",],
aes(x=log(X2015.2017), y=log1p(value), color=Disadv., shape=Disadv.)) +
geom_smooth(method = "lm",se=FALSE, width=0.7, aes(lty=Disadv.))+
geom_point(alpha=0.4)

ggplot(CP2[CP2$CP=="SOx" & CP2$FACID!=124838 & CP2$Primary.Sector=="Oil and Gas Production",],
aes(x=log(X2015.2017), y=log1p(value), color=Disadv., shape=Disadv.)) +
geom_smooth(method = "lm", se=FALSE, width=0.7, aes(lty=Disadv.))+
geom_point(alpha=0.4)

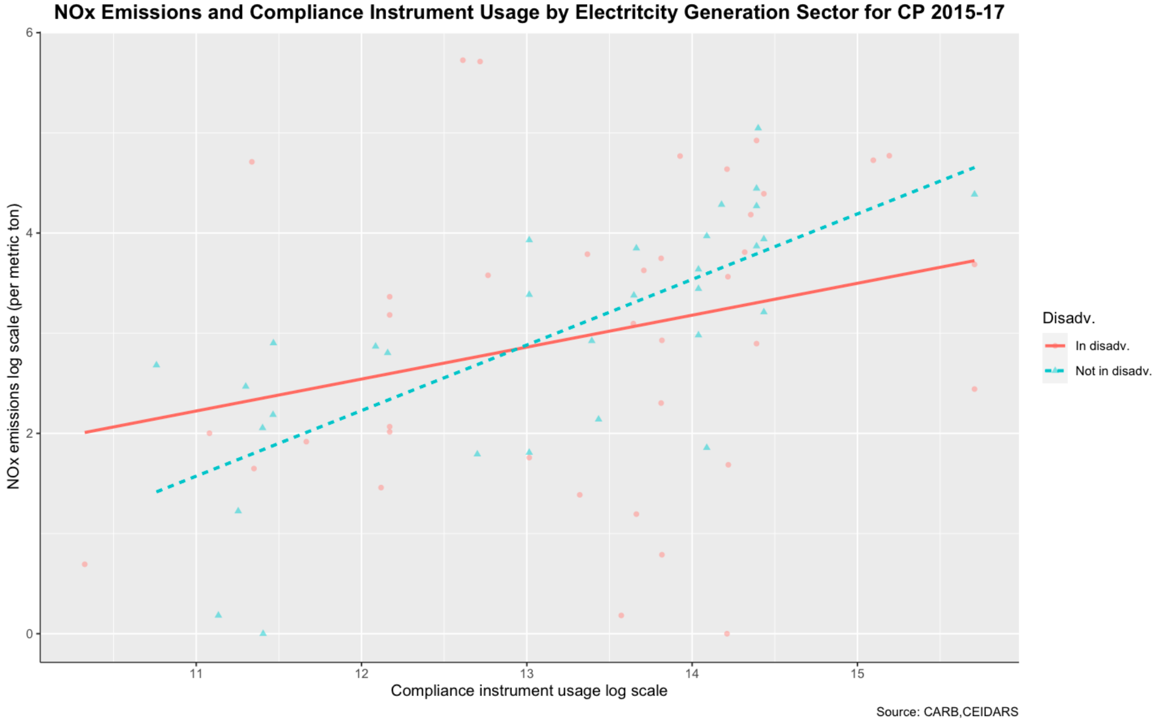

GHG Emissions and Compliance Instrument Usage by Electritcity Generation Sector for CP 2015-17
GHG emissions log scale (per metric ton)
Compliance instrument usage log scale
colour
Primary Sector
Disadv.
In disadv.
Not in disadv.
Source: CARB,CEIDARS

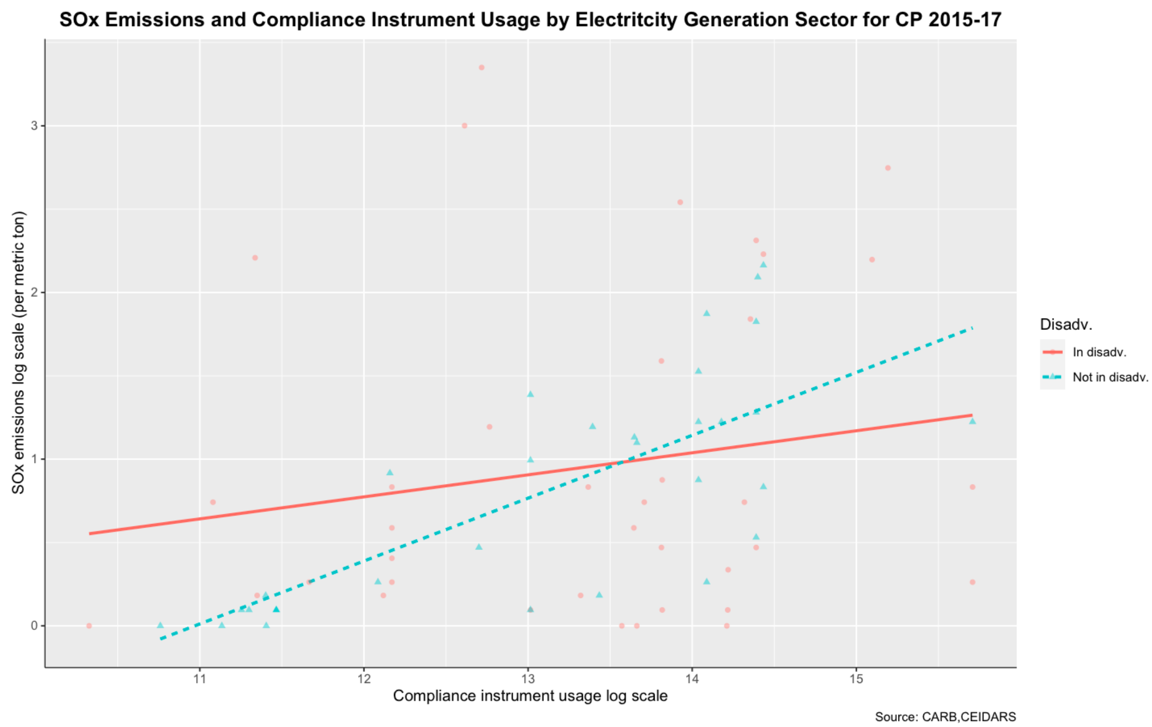

PM2.5 Emissions and Compliance Instrument Usage by Electritcity Generation Sector for CP 2015-17
PM2.5 emissions log scale (per metric ton)
Compliance instrument usage log scale
Disadv.
In disadv.
Not in disadv.
Source: CARB,CEIDARS

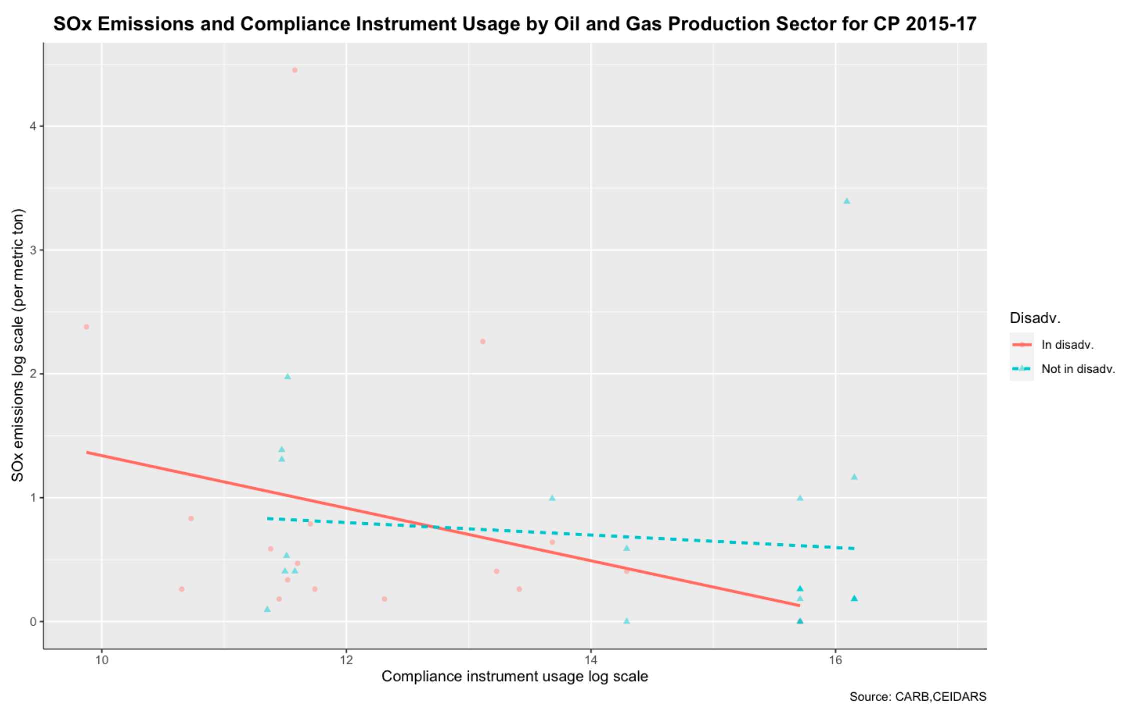
NOx Emissions and Compliance Instrument Usage by Oil and Gas Production Sector for CP 2015-17



NOx Emissions and Compliance Instrument Usage by Electritcity Generation Sector for CP 2015-17







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