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Who Wins from Emissions Trading? Evidence from California

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Abstract Researchers and environmental policy advocates have raised questions regarding the distributional impacts of emissions trading programs, a.k.a. "cap-and-trade". While previous research has been careful to identify the causal effect of emissions trading on emissions reductions (Fowlie et al. in Am Econ Rev 102(2):965–993, 2012, hereafter FHM), we argue that existing estimates of differential impacts on demographic groups have relied on unrealistic assumptions regarding pollution dispersion. In this paper, we estimate the emissions reduction due to the RECLAIM cap-and-trade program in Southern California following the identification strategy of FHM, but we relax the assumption of uniform dispersion surrounding point sources. We model the transport of effluents using a state-of-the-science dispersion model to determine the areas impacted by emissions from each source. Importantly, conditional on race and ethnicity, we find that higher income areas receive larger reductions in pollution under cap-and-trade. Furthermore, conditional on income (or poverty rates), we find that Blacks benefit while Hispanics lose relative to whites under RECLAIM.

Keywords Cap-and-trade · Emissions trading · Environmental justice · Distribution · Pollution dispersion

1 Introduction

Market-based environmental policies such as cap-and-trade (a.k.a. "emissions trading") are being used increasingly to regulate emissions of airborne pollutants. Cap-and-trade is often touted for cost-effectiveness, as it achieves an emissions reduction by allowing firms to buy and sell the right to emit the target pollutant. Under cap-and-trade, individual firms are

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allocated permits for some level of emissions (either through freely allocated permits or an auction), and firms that can achieve the emissions reduction determined by their allocation at a low cost may decide to sell permits to other firms for which it is more costly to reduce emissions. This policy has been criticized, however, because the efficiency gain may come at some cost to equity. Because cap-and-trade policies allow firms to trade the right to emit, it may lead to an uneven reduction in pollution for different socioeconomic groups.

Critics of cap-and-trade have argued that it can have harmful distributional consequences, as the cost-effective reduction in pollution may be unevenly distributed over space. A common argument is that cap-and-trade can lead to hotspots of pollution, which may disproportionately affect minority and economically-disadvantaged communities. This claim is so prevalent among advocacy groups that it has led to an academic literature that looks for distributional impacts of cap-and-trade, focusing primarily on these claims surrounding hotspots and disadvantaged communities. Whether or not this reduction is correlated with demographic characteristics has been the subject of recent research by economists and other social scientists (e.g. Fowlie et al. 2012; Ringquist 2011).

One emissions trading program that has received recent attention is the Regional Clean Air Incentives Market (RECLAIM), a Los Angeles-based cap-and-trade program that began in 1994. It targeted NO_x and SO_2 emissions and included almost all facilities in the area emitting more than four tons of NO_x and SO_2 a year. Fowlie et al. (2012, hereafter FHM) estimate the impact of RECLAIM on NO_x emissions relative to the pre-existing command-and-control program. They obtain a causal estimate of the regulation on emissions using a matching estimator, but their estimates of distributional impacts rely on the assumption that the "treated" area for each polluter is a circle surrounding the regulated polluting facility. This simplifying assumption is prevalent in the environmental economics literature, as well as across the social sciences (e.g. Banzhaf and Walsh 2008; Ringquist 2011).[1] However, the dispersion of pollution from a point source (e.g. a coal-fired power plant, or an industrial manufacturing facility) is far from uniformly distributed. Indeed, determining dispersion patterns and the chemical and physical interactions that lead to ambient pollution is the focus of much research by atmospheric scientists. This literature describes, typically with models and monitoring data, the physical forces and chemical reactions that eventually translate emissions of an effluent to ground-level ambient pollution concentrations.

As shown by FHM, the RECLAIM cap-and-trade program has had a significant impact on emissions in Los Angeles, but they find no correlation between the reduction in pollution and neighborhood demographic characteristics. We argue that previous papers, including FHM, may not have adequately identified distributional impacts of cap-and-trade due to simplifying assumptions regarding the dispersion of pollution. In this paper, we employ the matching identification strategy in FHM to obtain a causal estimate of the policy on facility-level emissions. However, in order to determine the effect of the regulation on different demographic groups (or communities defined spatially), we rely on a pollution dispersion model to determine how emissions affect eventual exposure. We use the Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT; see Draxler and Hess 1997, 1998; Draxler 1999) to determine the weighted treatment area for each facility. In contrast to previous studies, we find evidence of distributional effects of emissions trading. That is, the efficiency gains of cap-and-trade may come at some cost to equity: areas with the lower incomes tend to receive a smaller reduction in pollution under emissions trading, holding constant race and ethnicity. Furthermore, conditional on income (or poverty rates), we find

[1] An exception is a working paper by Sullivan (2016), who also uses a dispersion model in the LA Basin. He also finds that poorer households benefit less from air quality improvements.

that emissions trading leads to differential reductions by race and ethnicity, with Blacks receiving a larger reduction and Hispanics receiving a smaller reduction than whites.

2 Background

There is a long history in economics studying the incidence of taxes, subsidies, and policies, but until recently the incidence of environmental regulations has been largely understudied. There are many channels through which environmental regulations, such as emissions trading, could have distributional impacts (e.g. Fullerton 2011; Parry et al. 2006). These channels include changes in product prices (e.g. Grainger and Kolstad 2010), changes in land prices and rents (e.g. Grainger 2012), or changes in labor or capital input prices (Fullerton and Heutel 2007). One area that has received increased attention from environmental advocacy groups, and increasingly from researchers, is the potential creation of hotspots of pollution from market-based environmental policies (Ringquist 2011; Fowlie et al. 2012).

Though environmental justice advocacy groups often oppose cap-and-trade programs due to concerns about "hotspots", the academic literature typically finds no evidence that the reduction in pollution is correlated with demographic characteristics. However, the majority of these studies treat the area immediately surrounding an emissions source as the treatment area. While this is convenient empirically, the actual dispersion patterns of pollution are often significantly different, which creates difficulties for researchers interested in distributional impacts of environmental policy. In order to define the treated area for each emitting source, we use a dispersion model, which in turn allows us to characterize who wins (or loses) from cap-and-trade.

There are many plausible reasons that emissions trading would deliver differential reductions in emissions for different demographic groups. Because emissions trading allows firms to buy and sell the right to emit, there is an incentive for firms with high marginal abatement costs to purchase emissions permits from firms with low marginal abatement costs. Therefore, any correlation between demographic characteristics and the marginal abatement costs of firms could lead to differential reductions in pollution for some groups under emissions trading. For example, if marginal abatement costs (perhaps through facility age or industrial composition) are negatively correlated with income in a given region, then emissions trading may disproportionately benefit high income groups. Alternatively, if sorting occurs on race (e.g. Sethi and Somanathan 2004; Card et al. 2008) or race and public goods (Banzhaf and Walsh 2013), there could be a correlation between the reduction in pollution and demographic characteristics under emissions trading.

As another example, we note that including areas within one mile (or some other distance) of a polluting firm ignores topography, so both high- and low-elevation areas could fall within a mile of a polluting firm. This may be problematic, as hilltop areas in Los Angeles tend to have higher median incomes than surrounding areas as shown in Fig. 1, and pollution may tend to settle in lower lying areas. In this paper, we make no attempt to empirically disentangle the mechanisms through which emissions trading causes disproportionate reductions for some demographic groups. Instead, we take the first step at carefully modeling the reduction in pollution over space in a prominent emissions trading program and test the hypothesis that the reduction in pollution is distributed evenly across income and demographic groups.

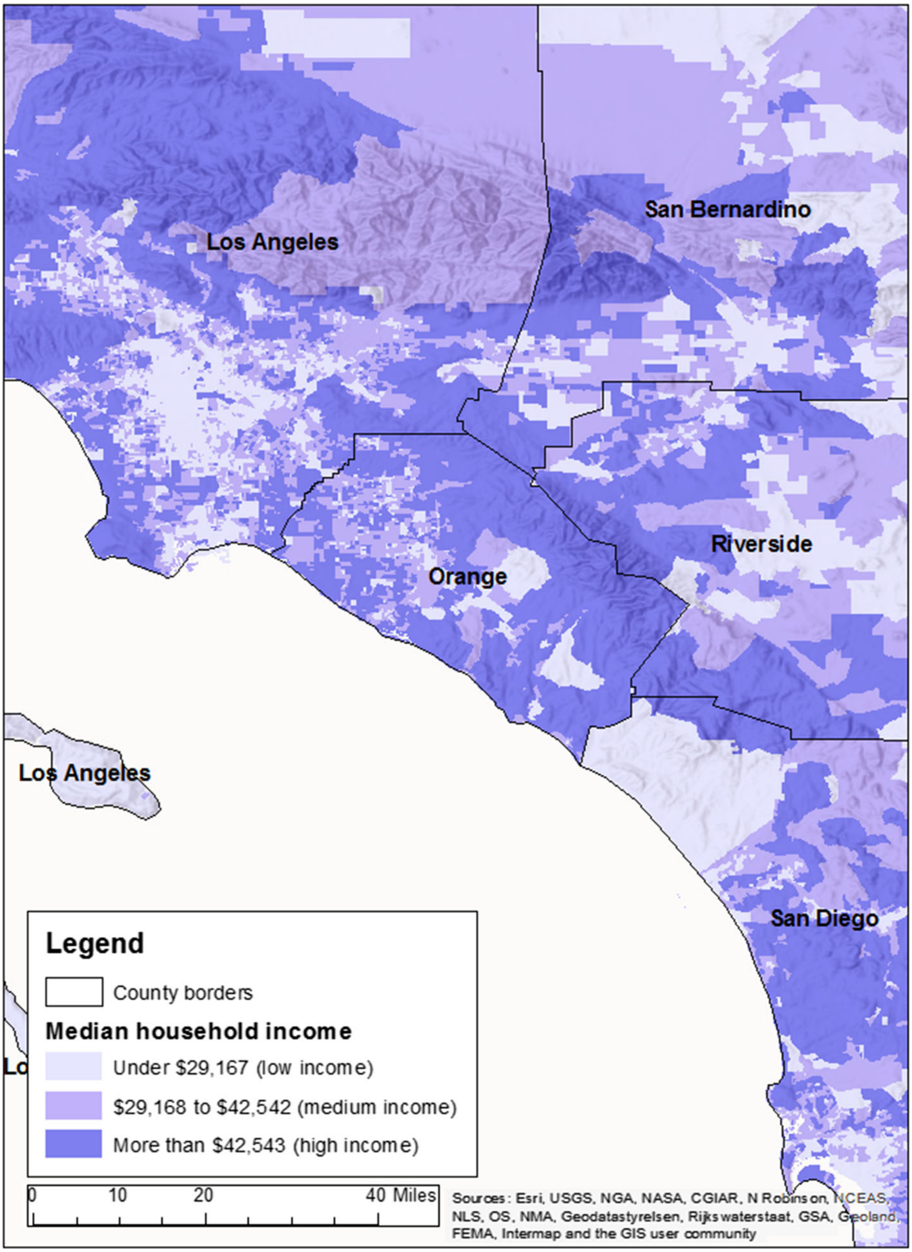

Fig. 1 Block-level median household income from the 1990 Census and topography in southern California. See text for details. This figure compares household median income to topography in southern California to show that that hilltop areas in Los Angeles tend to have higher median incomes than surrounding areas. We categorize each block into one of three categories based on the median household income of each block. Census blocks with median household income in the lowest tertile (less than $29,161 in year 1990) are categorized as low-income. Census blocks with a median household income between $29,167 and $42,542 are categorized as medium-income. Census blocks with a median household income higher than $42,554 are categorized as high-income

3 Empirical Design

As we are trying to compare the pollution distribution under cap-and-trade to a command-and-control counterfactual, a realistic control group is created to resemble emission trajectories of each RECLAIM facility had it been regulated under command-and-control. There is limited overlap between the controls of the treatment and the control group, so we follow FHM's strategy by using the matching algorithm introduced by Abadie and Imbens (2006). We match each RECLAIM facility with a minimum of three similar facilities that are exempted from RECLAIM. The control facilities are selected on three criteria: (1) it must have the same four-digit industry SIC code as the RECLAIM facility, (2) it must be in a non-SCAQMD,[2] ozone nonattainment area in California, and (3) it must emit similar quantities of NO_x to the RECLAIM facility prior to implementation of the program. This allows our control group to resemble the RECLAIM facility with respect to the state, technology, and size.

Following FHM, we estimate the following equation:

$$Y_{it'} - Y_{it^0} = \delta_j + \beta' X_i + \theta' X_i D_i + \alpha D_i + \epsilon_i, \tag{1}$$

where $Y_{it'} - Y_{it^0}$ is the emissions change from period 1 (1990 and 1993) to period 2 (2004 and 2005), D_i is a dummy variable indicating RECLAIM participation, and δ_j are group-specific fixed effects, where group j is comprised of facility j and its m_j closest matches. The regressions are weighted by $1/m_j$ and standard errors are clustered at the zip code level.

For each polluting facility, the treatment area is determined by HYSPLIT, which in turn is used to obtain the demographic characteristics included in X_i. To preview our results, we find that the distributional impacts of RECLAIM are different than as modeled by FHM for two main reasons: 1) the dispersion of pollution is not uniform around point sources, and 2) the inclusion or exclusion of electrical generating units is critical to the distributional results.

3.1 Data

Our main data come from the annual emissions report from the California Air Resources Board (CARB), which details facility level NO_x emissions, the facility's physical address, and its industry classification. Emissions reductions are calculated for each firm and represent changes in emissions prior to RECLAIM (1990 and 1993, a.k.a. "Period 1") and 10 years after RECLAIM was implemented (2004 and 2005, a.k.a. "Period 2").[3] Demographic data are from the 1990 Census at the block group. These data include median household income and population by poverty status, ethnicity, and race.

Unlike FHM, we exclude power producers from our analysis, which were not regulated under RECLAIM over the entire time period of our study. Increased electricity production during the California electricity crisis led major power producers to buy more RECLAIM trading credits, which led to a large spike in allowance prices. To stabilize the market, fourteen power producers were removed from the market in 2001 and they were required by SCAQMD to install "best available control technology"; they were not subsequently re-introduced until 2007 (Burtraw and Szambelan 2009). As our period of study spans from 1990 to 2005, we

[2] South Coast Air Quality Management District.

[3] Emission levels in Period 1 is an average of 1990 and 1993 had data from both years are available. Otherwise, emissions levels from either 1990 or 1993 are used. The same is done for year 2004 and 2005 in Period 2. In addition, we independently geocoded each facility, and when replicating the results in FHM, our coefficient estimates are slightly different. Furthermore, there are ten sources that were dropped in FHM's analysis because they are offshore, do not intersect census blocks, or are uninhabited, but when we model the dispersion of pollution from these sites there are affected communities. These ten firms are included in our analysis.

Table 1 Summary statistics of NO_x emissions from facilities in California

Observations	Period 1 emissions	Period 2 emissions	Change in emissions
Non-electric RECLAIM firms			
199	74.65	30.70	−43.95
	(272.60)	(120.98)	(162.49)
Electric RECLAIM firms			
13	525.59	35.18	−490.41
	(450.09)	(25.94)	(448.18)
Non-electric control firms			
366	74.33	43.11	−31.22
	(295.10)	(193.12)	(137.73)

See the text for details. Standard deviations in parentheses. “Period 1” includes 1990–1993, and “Period 2” includes 2004–2005. Emissions are measured in tons

exclude electric firms from our analysis.[4] Table 1 summarizes emissions (in tons) during our period of study for the three firm categories.[5]

3.2 Modeling Dispersion

We use HYSPLIT to determine the treatment area from each regulated entity under RECLAIM. It is well-suited for our purposes, as its primary use in the scientific and regulatory communities is to determine whether ambient pollution at one site is caused by the transport of airborne contaminants emitted from a given source. HYSPLIT computes air parcel trajectories and the dispersion or deposition of atmospheric pollutants such as NO_x.[6]

Because pollution dispersion patterns are critically sensitive to meteorological conditions, HYSPLIT is run two times a day for each day of the year using 1990 weather to determine how emissions from each regulated source eventually affect exposure over space. For each run, HYSPLIT gives the gridded average air pollution concentrations, where each grid cell is roughly one square kilometer.[7] For each firm, we scale the concentration levels such that the total concentrations from a firm over the year sum to unity. To illustrate dispersion patterns throughout the year, Fig. 2 shows the dispersion patterns for ten representative RECLAIM firms in the Los Angeles area.

Compared to the one-half, one, and two mile radii modeled in FHM, HYSPLIT gives a more realistic dispersion pattern to determine the areas of treatment. We note that not only is

[4] When we include the power plants into our regression, we do not find significant correlation between any socioeconomic group and NO_x reduction. The results can be found in the Appendix Table 6. Appendix Table 7 show results excluding electric generating units, under the assumption that NO_x disperses uniformly within a 1-mile radius around each facility.

[5] Although there are fourteen power producers, Table 1 summarizes only thirteen power producers as one firm, Riverside Canal Power Company, did not report emissions after 2001.

[6] A selection of papers that have used HYSPLIT to find sources of high NO_x concentrations in different countries include Baker (2010), Gebhart et al. (2011) and Junker et al. (2009).

[7] To be specific, HYSPLIT gives the average air pollution concentration level at every 0.01 latitude and longitude grid cell, which is roughly equivalent to a 1 by 1 km^2. We assume that NO_x is being emitted at 65 m above ground level. This is the minimum smokestack height required by the EPA. For each HYSPLIT run, the output concentration level is the average concentration level from 0 to 100 m above ground level, 12 h after a puff of air is emitted from a given source.

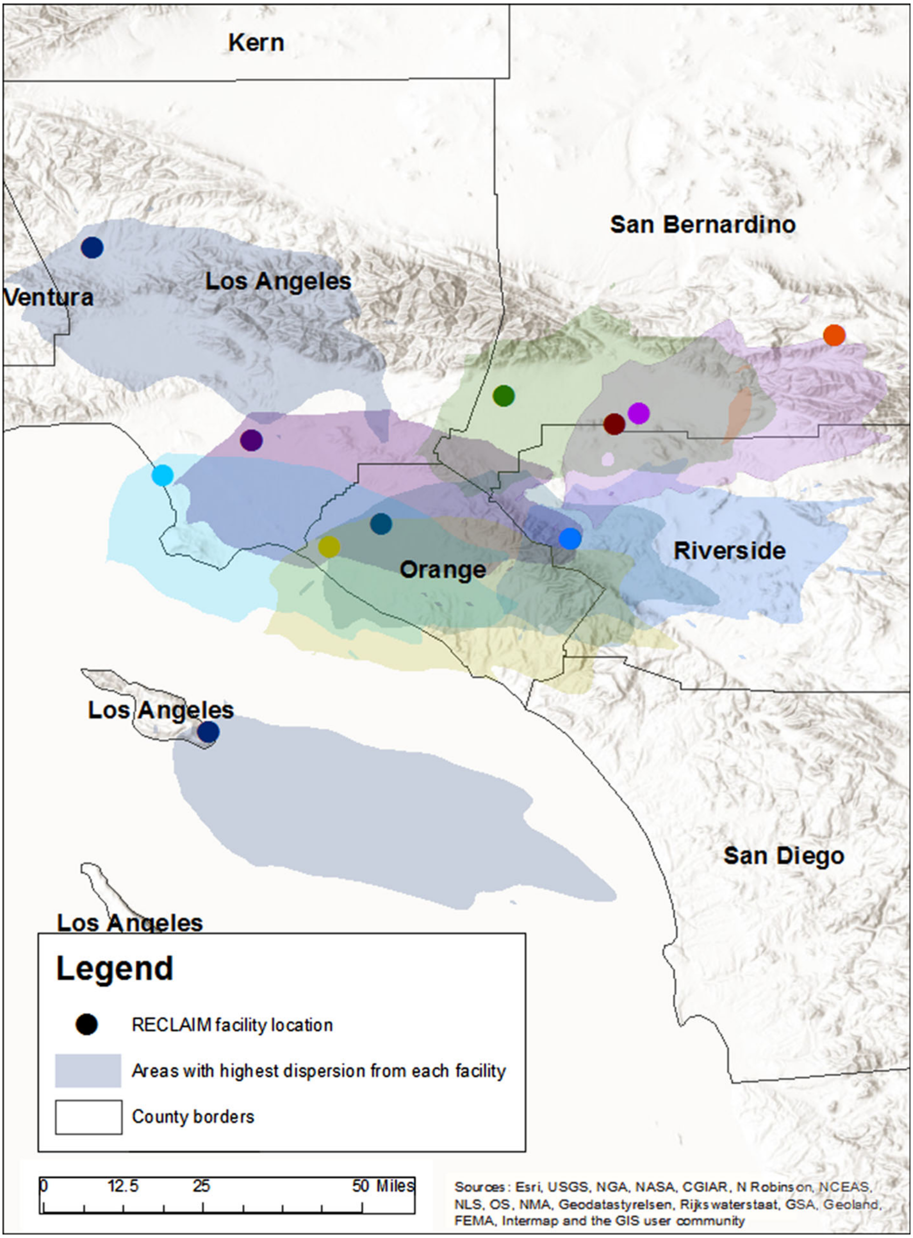

Fig. 2 Pollution dispersion for ten RECLAIM firms. *Notes* the dispersion patterns are shown for ten representative firms regulated by RECLAIM in the Los Angeles area. Polluted areas from each firm are separated into 100 bins based on their concentration levels. Only areas with the highest concentration bin (100th percentile concentration) from each facility are shown figure

the pattern far from uniform around a source, but the affected areas also branch out far from the effluent's origin.[8]

The ratio of NO and NO_2 emitted from each firm depends on the heat and air ratio of combustion (de Nevers 2010). We use the default gas dispersion option in HYSPLIT. We also note that HYSPLIT takes into account the dispersion but does not model interactions with sunlight radiation. With more sunlight radiation in the summer, NO_x may react with volatile organic compounds to form ozone, which is critical to health and mortality. Thus seasonal differences in NO_x dispersion may have different implications due to atmospheric chemistry.

3.2.1 Relative Changes Across Neighborhoods

To determine the treatment area for each firm, we first determine how a "puff" of emissions is transformed into ambient concentrations over a one square kilometer grid covering the Los Angeles area. We scale the concentrations initially such that the sum over all grid cells is unity; that is, we determine the proportion of emissions from source i that falls in each grid cell. Affected demographics from source i are the product of the number of people in each grid and the proportion of emissions from each source to each grid, summed across every grid cells.[9] Table 2 summarizes affected demographics and emissions change of treatment and control groups.

Following FHM, relative changes are defined as the difference between actual and counterfactual emissions. Average relative change in emissions, weighted by each demographic group, are shown in Fig. 3.[10] Blacks see the largest reductions, followed by Asians, Hispanics, whites, and Native Americans.[11]

Community-level effects of RECLAIM relative to the counterfactual increase in stringency of command-and-control can be measured in two ways; the population weighted relative change (in tons), or the population density weighted relative change (in people $\times$ tons per square feet) that each community sees from RECLAIM. Population weighted relative changes at the census block level are calculated the same way as in Fig. 3, but the total number of people living in each census block is used instead.[12] Figure 4 shows block-level relative changes for southern California. Although most census blocks benefit from cap-and-trade relative to command-and-control, some blocks appear to experience a net increase in pollution under cap-and-trade.

To illustrate, we plot which neighborhoods are most affected by RECLAIM relative to a command-and-control policy. Because the population-weighted relative change at the census block level is the same between two different demographic groups in the same census

[8] While dispersion patterns vary over the year, in estimates not shown here we find no significant difference in the estimates by season. Results estimated separately by season are available from the authors.

[9] See "Appendix" section for a detailed description of how HYSPLIT simulation results are combined with census block data to calculate affected neighborhoods.

[10] Average relative change in emissions, weighted by each demographic group, are calculated from $\sum_f (R_f D_f)/\sum_f D_f$ where R_f is relative change for each facility f, and D_f are affected people in each demographic group from facility f.

[11] Similar patterns are found for actual changes, but at a much larger magnitude. A full set of results, including actual and relative changes of all demographic groups are displayed in Tables 4 and 5 in the "Appendix" section.

[12] For each census block b with D_{fb} people affected by each firm f, the block-level, population-weighted relative change is $\sum_f (R_f D_{fb})/D_{fb}$.

Table 2 Facility-level summary statistics

Variable	Mean	SD	Min.	Max.
Change in NO_x (in tons) for treated facilities	−43.95	162.49	−1450.53	41.79
Change in NO_x (in tons) for control facilities	−24.79	130.14	−1264.22	165.33
Period 1 NO_x (in tons) for treated facilities	74.65	272.6	0.35	2492.3
Period 1 NO_x (in tons) for control facilities	62.35	272.13	0.10	2973.35
Median household income (in thousand dollars) for treated facilities	42.78	3.23	35.97	50.1
Median household income (in thousand dollars) for control facilities	42.21	5.59	22.52	56.36
%Population below poverty line affected by treated facilities	10.33	1.83	6.88	15.82
%Population below poverty line affected by control facilities	10.54	2.96	6.10	28.08
%Black affected by treated facilities	6.99	2.81	2.98	19.48
%Black affected by control facilities	6.59	2.68	2.22	14.49
%Asian affected by treated facilities	9.9	2.38	3.71	16.49
%Asian affected by control facilities	9.99	3.40	1.62	21.75
%Hispanic affected by treated facilities	28.54	6.48	15.95	42.8
%Hispanic affected by control facilities	24.31	8.31	10.06	69.97
%Native American affected by treated facilities	0.65	0.12	0.46	1.06
%Native American affected by control facilities	0.80	0.65	0.47	11.56
%Other groups, excluding whites, affected by treated facilities	14	4.4	6.55	24.54
%Other groups, excluding whites, affected by control facilities	12.14	5.16	3.78	41.26

This table include observations that are used in our regressions. There are 199 unique observations for the treated group and 366 unique observations for the control group. Each observation represents a facility or people affected by each facility's emissions. Each treated facility is matched with a minimum of three control facility that are not regulated under SCAQMD, in a non-attainment county, in the same industry, and emit similar quantities of NO_x as a treated firm. Each demographic variable is a product of number people in each area and the proportion of emissions from each facility that falls into that area, summed across all areas

block,[13] we use the product of population density and relative change to measure the effect

[13] Within each census block, the fraction of number of people affected by a single firm relative to the number of people affected by all firms is the same regardless of demographic group. For example, in census block b, the fraction of blacks affected by firm 1 relative to blacks affected by all firms is equal to the fraction of Hispanics affected by firm 1 relative to all firms. For example, $\frac{Black_{1b}}{\sum_f Black_{fb}} = \frac{Hispanic_{1b}}{\sum_f Hispanic_{fb}}$. Let $D_{fb} = F_{fb} \sum_f D_f b$ where F_{fb} is a constant fraction representing firm f's effect on census block b. Therefore, census block level population weighted relative change can be expressed as $\frac{\sum_f (R_f F_{fb} \sum_f D_f b)}{\sum_f D_{fb}} = \sum_f R_f F_{fb}$ which is independent of the number of people living within each census block. Differences in rankings between top beneficiaries or losers from cap-and-trade are only due to the fact that same census blocks do not have certain demographic groups living in them, $D_{fb} = 0$, and are omitted from the analysis.

Table 3 Heterogeneous treatment effect results where change in NO_x (in tons) is the dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	−11.04	−14.08	−11.94	−14.42	−12.69	−15.88
	(3.69)***	(4.43)***	(3.74)***	(4.15)***	(4.31)***	(4.81)***
	[4.24]***	[3.30]***	[3.94]***	[3.01]***	[4.46]***	[3.62]***
Treatment × Period 1 NO_x		−0.18		−0.18		−0.18
		(0.10)*		(0.10)*		(0.10)*
		[0.06]***		[0.06]***		[0.06]***
Treatment × Income (in thousands)			−3.20	−5.03		
			(3.07)	(3.04)*		
			[2.40]	[2.60]*		
Treatment × %Poverty					12.61	16.64
					(7.56)*	(8.37)**
					[5.58]**	[6.78]**
Treatment × %Black	−1.88	−1.55	−3.33	−3.97	−4.06	−4.46
	(1.97)	(1.50)	(2.65)	(2.38)*	(2.64)	(2.39)*
	[1.11]*	[0.86]*	[1.79]*	[1.79]**	[1.75]**	[1.75]**
Treatment × %Asian	−0.80	2.54	−0.57	2.11	−0.89	2.39
	(3.55)	(2.32)	(3.40)	(2.31)	(3.51)	(2.39)
	[2.31]	[1.45]*	[2.22]	[1.21]*	[2.32]	[1.34]*
Treatment × %Hispanic	6.76	2.37	6.24	1.22	7.29	2.97
	(4.05)*	(2.07)	(4.32)	(1.99)	(4.17)*	(2.21)
	[2.84]**	[1.53]	[2.81]**	[1.34]	[2.76]***	[1.51]**
Treatment × %Native American	5.91	39.64	−49.28	−62.79	−15.50	11.83
	(54.48)	(49.60)	(54.32)	(53.92)	(53.45)	(48.16)
	[30.89]	[25.85]	[40.08]	[41.90]	[31.31]	[24.27]

Table 3 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × %Other race	−8.25	−3.06	−9.29	−4.25	−13.42	−9.69
	(5.16)	(3.39)	(4.87)*	(3.31)	(6.47)**	(5.22)*
	[3.84]**	[2.31]	[3.59]***	[2.13]**	[4.75]***	[3.91]**
Period 1 NO_x	−0.45	−0.46	−0.46	−0.46	−0.46	−0.46
	(0.21)**	(0.18)**	(0.21)**	(0.18)**	(0.21)**	(0.18)**
	[0.12]***	[0.10]***	[0.11]***	[0.10]***	[0.12]***	[0.10]***
Income (in thousands)			0.77	0.17		
			(1.38)	(1.48)		
			[0.94]	[1.18]		
%Poverty					−1.97	−2.04
					(2.73)	(2.79)
					[1.78]	[2.02]
%Black	−0.95	0.06	−0.61	0.21	−0.58	0.47
	(1.29)	(1.30)	(1.58)	(1.61)	(1.58)	(1.63)
	[0.95]	[0.92]	[1.21]	[1.25]	[1.12]	[1.19]
%Asian	−2.80	−2.73	−3.41	−2.95	−3.18	−3.15
	(1.83)	(1.66)	(1.85)*	(1.68)*	(1.99)	(1.79)*
	[1.29]**	[1.17]**	[1.30]***	[1.09]***	[1.35]**	[1.23]**
%Hispanic	−1.57	−0.34	−1.64	−0.30	−1.71	−0.48
	(1.12)	(1.10)	(1.12)	(1.10)	(1.08)	(1.02)
	[0.50]***	[0.48]	[0.50]***	[0.54]	[0.47]***	[0.46]

Table 3 continued

	(1)	(2)	(3)	(4)	(5)	(6)
%Native American	−4.50	−5.83	−2.77	−5.77	−3.00	−4.45
	(5.92)	(5.49)	(7.44)	(6.87)	(7.06)	(6.36)
	[4.13]	[3.98]	[4.96]	[5.07]	[4.32]	[4.24]
%Other race	1.79	0.36	2.24	0.36	2.84	1.43
	(1.84)	(1.90)	(1.80)	(1.93)	(1.75)	(1.71)
	[0.91]**	[0.94]	[0.91]**	[1.14]	[0.98]***	[1.00]
Observations	832	832	832	832	832	832
Adjusted R^2	0.79	0.83	0.79	0.83	0.79	0.83

Standard errors with zip code clustering are shown in parentheses. Conley's (1999) standard errors in brackets.
*, ** and *** denote significance at the 10, 5 and 1% levels, respectively

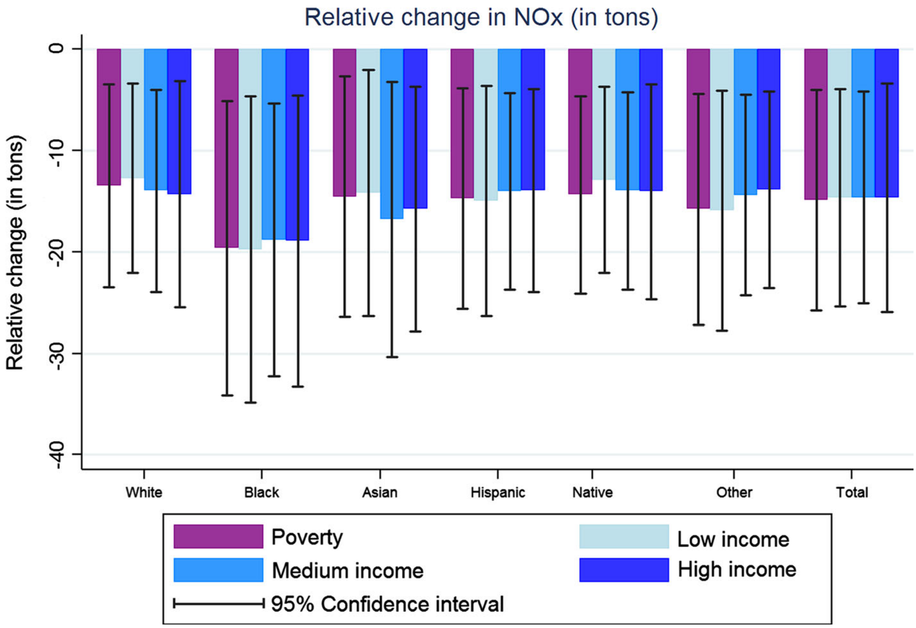

Fig. 3 Relative changes in NO_x across socioeconomic groups. See text for details. Each bar represents the average relative change in NO_x emissions (in tons), weighted by each demographic group. Relative changes weighted by demographics are calculated from $\sum_f (R_f D_f)/\sum_f D_f$ where R_f is relative change for each facility f, and D_f are affected people in each demographic group from facility f. Relative change is the difference between the actual change in emissions and counterfactual change in emissions, which is the average change in emissions of control firms. Relative changes were calculated for 199 treated facilities

of RECLAIM for each demographic group in each census block.[14] Most winners and losers from cap-and-trade relative to command-and-control are clustered in the southern part of Los Angeles county. Figure 5 shows census blocks in the greater Los Angeles area that are the top ten winners and losers from cap-and-trade relative to the command-and-control counterfactual. We see that Hispanics and population below the poverty line in Southeast division of Los Angeles county benefit from RECLAIM relative to command-and-control, while other top beneficiaries from each demographic group are scattered around Los Angeles county. Top losers from all demographic groups are clustered in the southern part of Los Angeles.[15]

4 Results

We present our heterogeneous treatment effect estimates in Table 3.[16] The first column includes a treatment indicator, race/ethnicity variables and treatment interactions, and baseline NO_x levels. We subsequently add income or poverty rates (and column (2) includes a

[14] Population density weighted relative change for each census block b is $\sum_f R_f D_{fb}/A_b$ where R_f is the relative change of firm f, D_{fb} is the number of people in block b affected by facility f, and A_b is the area of block b.

[15] A list of census blocks that benefit or lose from cap-and-trade relative to command-and-control is available from the authors.

[16] Our results correspond to specifications (3), (5), (6), and (7) in FHM's Table 7.

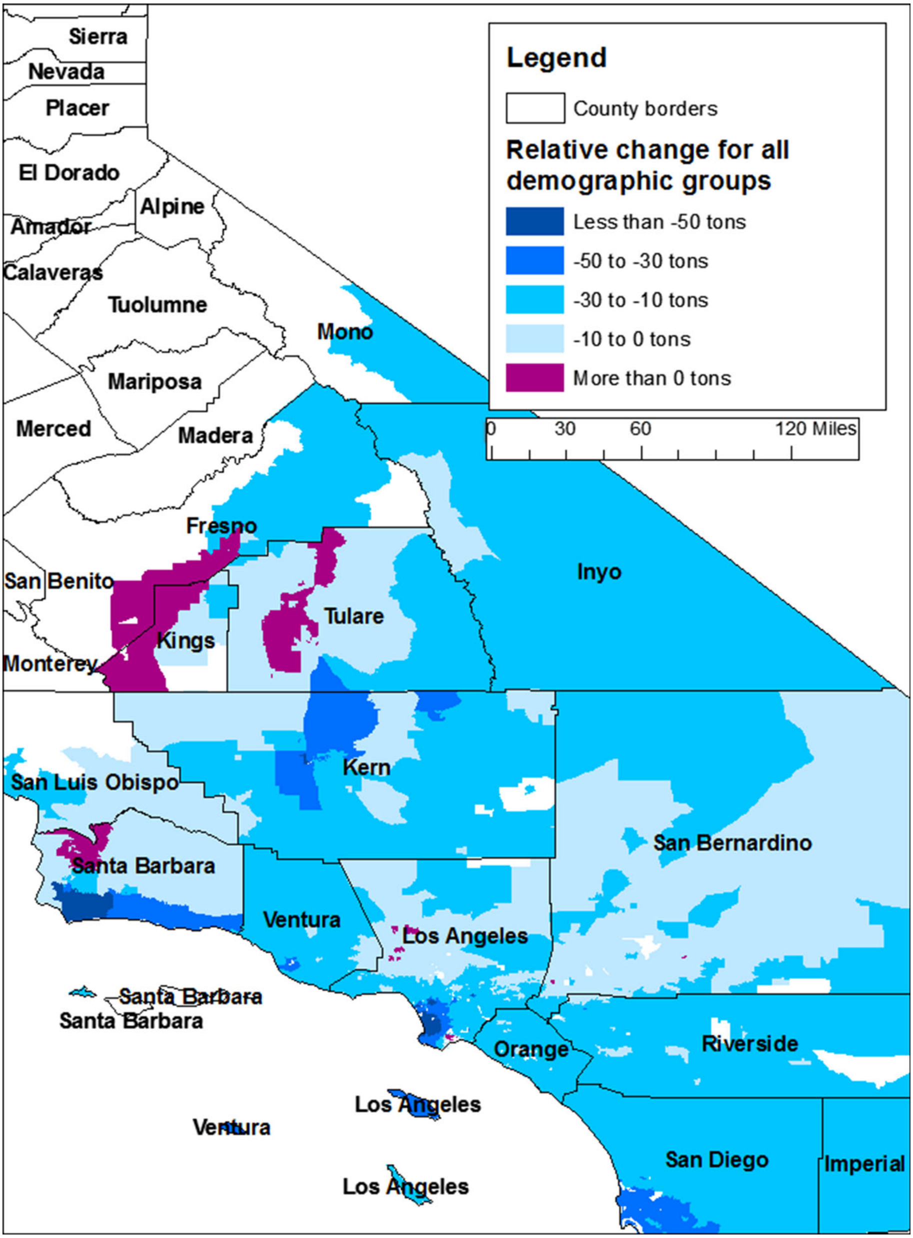

Fig. 4 Block-level relative change (in tons) for all demographic groups. See text for details. This figure shows population weighted relative change (in tons of NO_x) for each census block in California. For each census block b with D_{fb} people affected by each facility f, the census block level relative change is $\sum_f (R_f D_{fb})/D_{fb}$. *White shaded* areas represent census blocks that are not affected by any treated firm

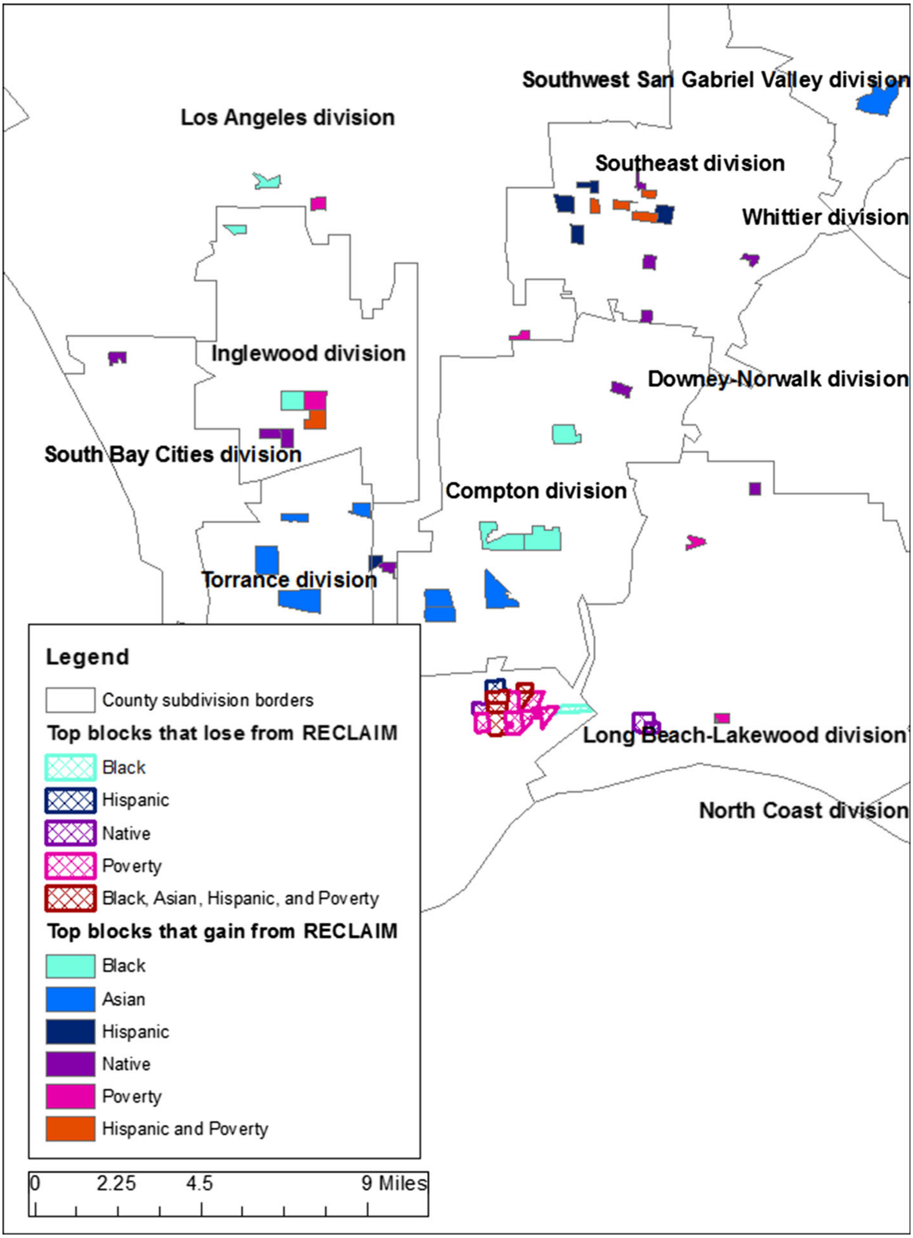

Fig. 5 *Top* census blocks that gain and lose from RECLAIM based on population density weighted relative change. See text for details. This figure shows *top* ten census blocks that gain and lose from RECLAIM based on population density weighted relative change. Population density weighted relative change for each census block b is $\sum_f R_f D_{fb}/A_b$ where R_f is the relative change of firm f, D_{fb} is the number of people in block b affected by facility f, and A_b is the area of block b. Most, but not all, census blocks that gain and lose from RECLAIM are located in the southern part Los Angeles county. *Top* census blocks that gain or lose from RECLAIM, but are located outside of the southern part of Los Angeles county are not shown

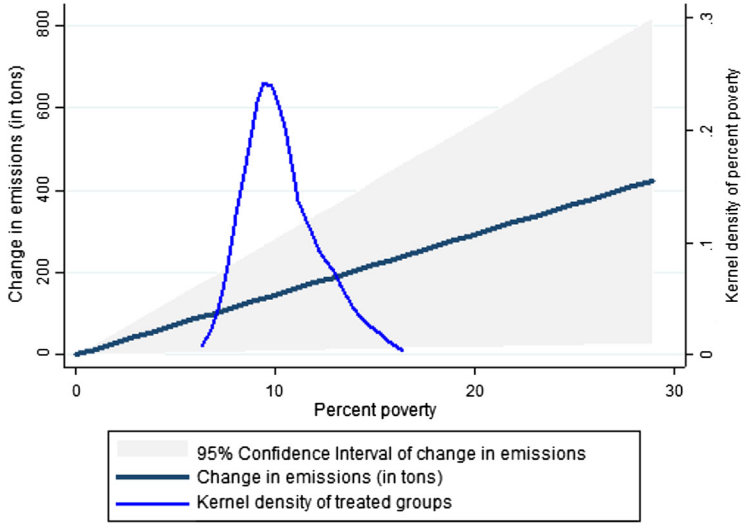

Fig. 6 Marginal effects of percentage poverty on change in emissions. This figure shows the correlation between each treated facility's change in emissions under RECLAIM and the fraction of people below the poverty line that each facility affects. We see that higher proportion of population below the poverty is correlated with less emissions reduction, such that a one percentage point increase in the poverty rate corresponds to an additional 14.60 tons of NO_x

treatment interaction with baseline NO_x and treatment).[17] We also note the standard errors shown here are clustered at the zip code level, which is different than in the original analysis by FHM.[18] We also present Conley (1999) standard errors as an alternative to account for cross-sectional dependence.

The results in column (4) of Table 3 suggest that areas with higher income experience a larger reduction in pollution, controlling for race and ethnicity. Similarly, in column (6), an increase in the poverty rate is associated with a smaller reduction in pollution, again holding race and ethnicity constant. In what follows, we will use (6) as our preferred specification. Figure 6 shows the marginal effect of the poverty ratio on emissions change from our preferred specification. We see that higher poverty rate is correlated with a smaller pollution reduction, such that a one percentage point increase in the poverty rate corresponds to an additional 14.60 tons of NO_x.[19]

Importantly, conditional on income or poverty rates, race and ethnicity explain differences in the emissions reduction observed. Notably, on average Blacks receive a significantly larger reduction in pollution under cap-and-trade. Figure 7 shows the marginal effect of an increase in the percentage Black on the reduction based on annual average dispersion from our pre-

[17] Additional results are shown in the Appendix to contrast our results with FHM's main specification, including estimates that include electric generating units in the sample, and including their definition of Minority (Hispanic and Blacks).

[18] FHM cluster at a higher level, but the result is only ten cluster groups, which may be too few, particularly in unbalanced cases (Cameron and Miller 2015).

[19] 14.60 is a linear combination of 16.64 and -2.04 which are the coefficients on Treatment $\times$ %Poverty and %Poverty, respectively.

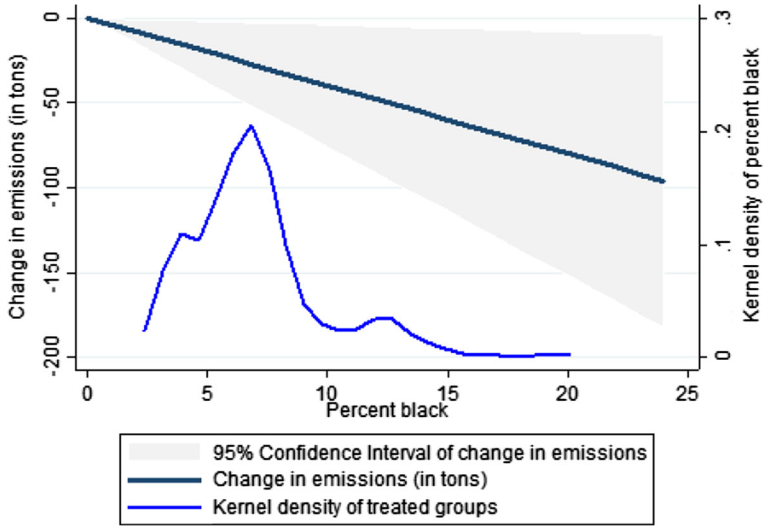

Fig. 7 Marginal effects of percentage black on change in emissions. This figure shows the correlation between each treated facility's change in emissions under RECLAIM and the fraction of Blacks that each facility affects. We see that a one percentage point increase in the percentage of the population that is Black corresponds to 3.99 tons of emission reduction

ferred specification. We see that a one percentage point increase in the percentage of the population that is Black corresponds to 3.99 tons of emission reduction.[20]

On the contrary, on average, Hispanics receive a smaller pollution reduction under cap-and-trade (relative to whites). We see that a one percentage point increase in the percentage of Hispanic population corresponds to an additional 2.49 tons of emissions.[21] Figure 8 shows the marginal effect for Hispanic population percentages, where the average treated community is roughly 28% Hispanic. Other variables of interest are generally not statistically significant.

5 Discussion

Using the same identification strategy as FHM, but explicitly modeling pollution dispersion to define each facility's treatment area, we find that the reduction in pollution due to the RECLAIM program in Los Angeles varied significantly with income and race and ethnicity.

Our results suggest that there may be important equity-efficiency tradeoffs in the case of emissions trading, but these effects are complicated. Controlling for race and ethnicity, we find that higher income areas tend to receive larger reductions in emissions under cap-and-trade; similarly, an increase in the poverty rate is associated with a *smaller* emissions reduction under emissions trading relative to command-and-control. Furthermore, conditional on the poverty rate, Blacks received a larger reduction, while Hispanics experienced a smaller reduction relative to whites. Future research is needed to determine whether these results generalize to other emissions trading programs.

[20] 3.99 is a linear combination of -4.46 and 0.47 which are the coefficients on Treatment $\times$ %Black and %Black, respectively.

[21] 2.49 is a linear combination of 2.97 and -0.48 which are the coefficients on Treatment $\times$ %Hispanic and %Hispanic, respectively.

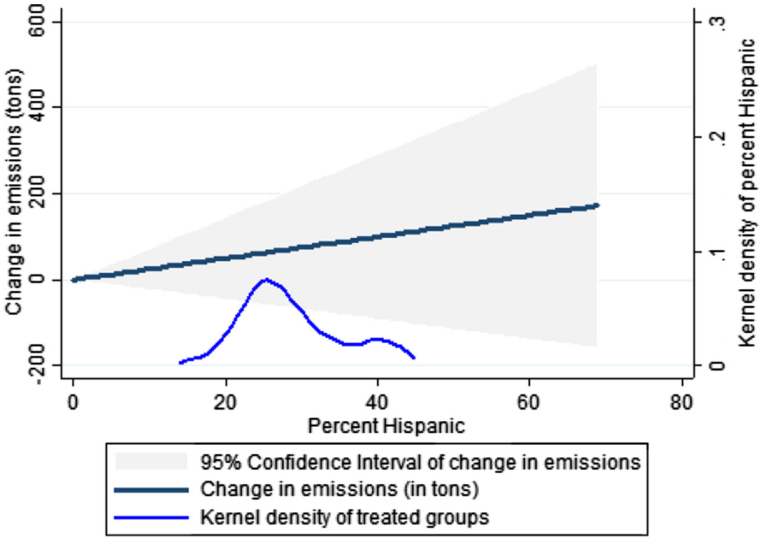

Fig. 8 Marginal effects of percentage Hispanic on change in emissions. This figure shows the correlation between each treated facility's change in emissions under RECLAIM and the fraction of Hispanics that each facility affects. We see that a one percentage point increase in the percentage of Hispanic population corresponds to an additional 2.49 tons of emissions

Moving forward, this paper highlights the need to carefully account for exposure and the dispersion of pollution when estimating distributional effects of regulations. Our weighted annual average effects are significantly different than estimates under a uniform dispersion assumption surrounding point sources. Importantly for policy, the common environmental justice claim—that cap-and-trade disproportionately favors high income groups—appears to be at least partially supported by our estimates for RECLAIM. Similarly, conditional on income (or the poverty rate), some minority groups saw significantly different reductions in pollution under cap-and-trade than did their white counterparts.[22] We also stress that pollution exposure is only one mechanism through which emissions trading can have distributional impacts; to make more general statements, more research is required. However, our results suggest that part of the overall research agenda should be to carefully account for exposure and not assume that pollution falls where it is emitted.

Appendix

Calculating Affected Neighborhoods

A puff of air that is being emitted from a facility affects G 0.01 latitude and 0.01 longitude grid points. Each grid point g receives an aggregate impact of c_g. Emissions from each facility affect B census blocks in California.

Figure 9 illustrates a sample puff of air that disperses to 9 grids (shown in the squares) and affects 3 census blocks (shown in the hexagons). In order to calculate demographic groups

[22] In results not shown here, we estimated similar specifications but including interactions of income with indicators for different racial/ethnic compositions. These results are generally insignificant.

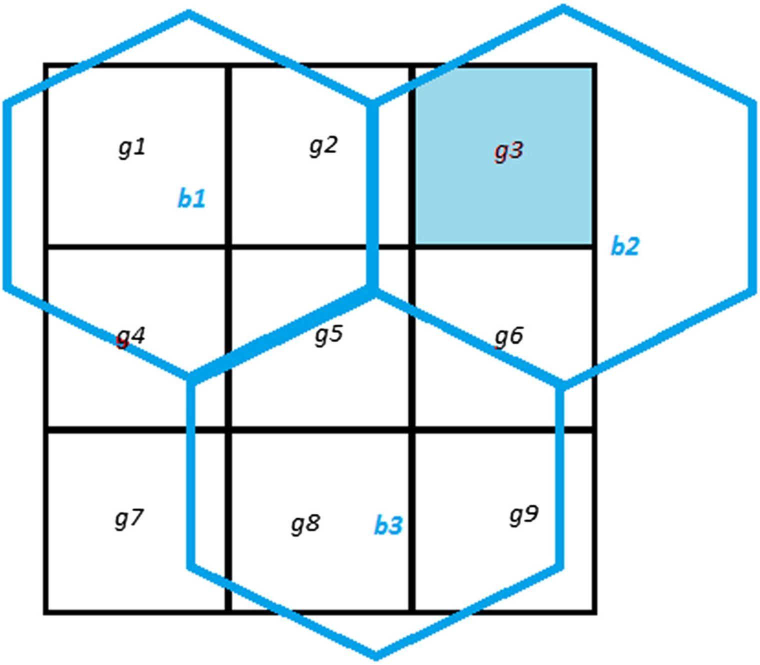

Fig. 9 Sample HYSPLIT grids and census blocks. *Notes* the *squares* show sample 0.01 latitude and 0.01 longitude grid points affected by a sample dispersion. The hexagons show sample census blocks

that are affected by this puff of air, we have to calculate affected groups within each grid - census block intersecting area; such as the blue area where grid $g3$ and block $b2$ intersects.

Let $area(g \cap b)$ represent the size of an area in census block b that is affected by grid point g. The effect of emissions in grid g that affects census block b is $c_g \times \dfrac{area(g \cap b)}{area(g)}$.

The net effect of grid g on all census blocks is $\sum_{b=1}^{B} \left\{ c_g \times \dfrac{area(g \cap b)}{area(g)} \right\}$.

When a facility affects G grids, the total effect of that facility on all census blocks is $\sum_{g=1}^{G} \sum_{b=1}^{B} \left\{ c_g \times \dfrac{area(g \cap b)}{area(g)} \right\}$.

We scale this effect such that $\sum_{g=1}^{G} \sum_{b=1}^{B} \left\{ \hat{c}_g \times \dfrac{area(g \cap b)}{area(g)} \right\} = 1$. Hence, $\hat{c}_g \times \dfrac{area(g \cap b)}{area(g)}$ would represent the fraction of the effect of a facility's emissions on a concentration grid-census block intersecting area.

Assume that demographic of interest has D_b people in census block b. Under the assumption that people distributes uniformly within census block b, $D_b \times \dfrac{area(g \cap b)}{area(b)}$ people are affected by grid g in census block b.

The number of people affected by a facility's emission on the concentration grid g - census block b intersecting area is the product of number of people living in that area and the fraction of effect that it receives from that facility, $D_b \times \dfrac{area(g \cap b)}{area(b)} \times \hat{c}_g \times \dfrac{area(g \cap b)}{area(g)}$.

Table 4 Change in emissions (in tons) weighted by demographic group from the 1990 census

	Actual change	Relative change
White, below poverty line	−42.72***	−13.45***
	(10.88)	(5.07)
White, low income	−42.27***	−12.72***
	(10.21)	(4.75)
White, medium income	−42.28***	−13.95***
	(11.22)	(5.07)
White, high income	−44.13***	−14.29**
	(12.38)	(5.65)
Black, below poverty line	−51.85***	−19.59***
	(15.35)	(7.37)
Black, low income	−51.99***	−19.73**
	(15.71)	(7.66)
Black, medium income	−49.75***	−18.78***
	(14.71)	(6.82)
Black, high income	−51.06***	−18.91**
	(16.80)	(7.30)
Asian, below poverty line	−45.79***	−14.53**
	(13.29)	(6.03)
Asian, low income	−46.27***	−14.15**
	(13.17)	(6.16)
Asian, medium income	−48.36***	−16.80**
	(16.04)	(6.88)
Asian, high income	−46.23***	−15.77**
	(13.93)	(6.13)
Hispanic, below poverty line	−43.61***	−14.72***
	(11.25)	(5.52)
Hispanic, low income	−44.40***	−14.93**
	(11.37)	(5.76)
Hispanic, medium income	−40.51***	−14.00***
	(10.42)	(4.90)
Hispanic, high income	−41.58***	−13.93***
	(10.95)	(5.08)
Native American, below poverty line	−42.90***	−14.36***
	(10.58)	(4.95)
Native American, low income	−41.72***	−12.88***
	(9.99)	(4.67)
Native American, medium income	−42.47***	−13.95***
	(11.01)	(4.94)
Native American, high income	−43.51***	−14.03***
	(11.83)	(5.38)
Other race, excluding white, below poverty line	−44.54***	−15.76***
	(11.69)	(5.79)

Table 4 continued

	Actual change	Relative change
Other race, excluding white, low income	−44.88***	−15.90***
	(11.77)	(6.02)
Other race, excluding white, medium income	−41.15***	−14.37***
	(10.50)	(5.02)
Other race, excluding white, high income	−40.97***	−13.82***

There are 199 observations. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Change in emissions (in tons) weighted by demographic group from the 1990 census

	Actual change	Relative change
White	−43.18***	−13.90***
	(11.52)	(5.27)
Black	−51.07***	−19.24***
	(15.51)	(7.23)
Asian	−46.88***	−15.83**
	(14.40)	(6.33)
Hispanic	−42.28***	−14.35***
	(10.78)	(5.21)
Native American	−42.57***	−13.65***
	(10.86)	(4.96)
Other race, excluding white	−42.82***	−14.98***
	(10.95)	(5.38)
Total, below poverty line	−44.57***	−14.89***
	(11.68)	(5.52)
Total, low income	−44.55***	−14.63***
	(11.27)	(5.43)
Total, medium income	−43.15***	−14.60***
	(11.68)	(5.29)
Total, high income	−44.50***	−14.64**
	(12.63)	(5.71)
Total	−44.06***	−14.62***
	(11.89)	(5.46)

There are 199 observations. Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The total effect of a facility on demographic group D is the sum of such effects across all concentration grid - census block intersecting areas.

$$\sum_{g=1}^{G}\sum_{b=1}^{B}\left\{D_b \times \frac{area(g \cap b)}{area(b)} \times \hat{c}_g \times \frac{area(g \cap b)}{area(g)}\right\}$$

Table 6 Heterogeneous treatment effect results including electric firms

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	−18.77***	−20.88***	−17.69***	−19.24***	−17.18***	−19.89***
	(6.19)	(5.83)	(5.78)	(5.39)	(6.09)	(6.24)
Treatment × Period 1 NO_x		−0.18**		−0.19**		−0.19**
		(0.08)		(0.08)		(0.08)
Treatment × Income (in thousands)			0.17	−1.73		
			(3.97)	(3.62)		
Treatment × %Poverty					4.54	10.11
					(8.12)	(8.31)
Treatment × %Black	0.17	−0.07	0.12	−1.10	−0.74	−1.94
	(2.44)	(1.86)	(3.36)	(2.79)	(3.05)	(2.58)
Treatment × %Asian	−1.68	1.53	−2.41	0.14	−2.15	1.03
	(4.29)	(3.10)	(4.42)	(3.35)	(4.25)	(3.15)
Treatment × %Hispanic	7.27*	1.72	7.06	0.92	7.32	1.91
	(4.38)	(2.73)	(4.49)	(2.58)	(4.47)	(2.83)
Treatment × %Native American	24.36	29.73	13.66	−28.63	16.81	13.27
	(60.44)	(56.54)	(79.63)	(71.31)	(61.13)	(56.97)
Treatment × %Other race	−7.54	−1.72	−7.16	−1.58	−8.86	−5.18
	(5.53)	(4.10)	(5.53)	(4.33)	(7.05)	(5.94)
Period 1 NO_x	−0.50***	−0.49***	−0.50***	−0.49***	−0.50***	−0.49***
	(0.18)	(0.16)	(0.18)	(0.16)	(0.18)	(0.16)
Income (in thousands)			−0.92	−1.43		
			(1.86)	(1.80)		
%Poverty					1.90	1.27
					(3.41)	(3.22)
%Black	−2.01	−1.21	−2.36	−1.74	−2.32	−1.39
	(1.68)	(1.54)	(2.14)	(2.02)	(2.03)	(1.93)
%Asian	−3.25	−2.75	−2.59	−1.75	−2.98	−2.62
	(2.16)	(1.82)	(2.22)	(1.96)	(2.30)	(1.98)
%Hispanic	0.75	1.37	0.82	1.48	0.78	1.37
	(1.96)	(1.82)	(1.97)	(1.83)	(1.93)	(1.81)
%Native American	4.59	1.56	2.19	−2.31	2.39	−0.19
	(6.09)	(5.62)	(8.24)	(7.75)	(7.43)	(6.71)
%Other race	−1.84	−2.56	−2.36	−3.40	−2.65	−3.05
	(3.14)	(3.15)	(3.45)	(3.41)	(3.57)	(3.41)
Observations	885	885	885	885	885	885
Adjusted R^2	0.85	0.87	0.85	0.87	0.85	0.87

Change in NO_x (in tons) is the dependent variable. Zip code clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Heterogeneous treatment effect results using 1-mile uniform dispersion, excluding electric firms

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	−9.61**	−11.61**	−9.77**	−12.09***	−9.78**	−12.50***
	(4.37)	(4.68)	(4.07)	(4.28)	(3.89)	(4.17)
Treatment × Period 1 NO_x		−0.18*		−0.18*		−0.18*
		(0.10)		(0.10)		(0.10)
Treatment × Income (in thousands)			−0.41	−0.67		
			(0.62)	(0.52)		
Treatment × %Poverty					0.27	0.84
					(0.70)	(0.66)
Treatment × %Black	0.69	0.37	0.57	0.18	0.63	0.16
	(0.51)	(0.36)	(0.59)	(0.37)	(0.59)	(0.34)
Treatment × %Asian	0.59	−0.09	0.57	−0.08	0.57	−0.14
	(0.66)	(0.42)	(0.70)	(0.47)	(0.68)	(0.44)
Treatment × %Hispanic	1.23**	1.31***	1.16**	1.19**	1.19**	1.18***
	(0.49)	(0.49)	(0.51)	(0.48)	(0.49)	(0.45)
Treatment × %Native American	3.01	1.60	1.37	−0.73	2.23	−0.47
	(4.47)	(2.87)	(5.35)	(3.02)	(4.80)	(2.93)
Treatment × %Other race	−0.93	−1.37**	−1.00	−1.46**	−0.97	−1.47**
	(0.62)	(0.63)	(0.64)	(0.64)	(0.64)	(0.66)
Period 1 NO_x	−0.47**	−0.47***	−0.47**	−0.47**	−0.47**	−0.47***
	(0.22)	(0.18)	(0.22)	(0.18)	(0.21)	(0.18)
Income (in thousands)			0.09	0.25		
			(0.47)	(0.44)		
%Poverty					−0.09	−0.41
					(0.62)	(0.64)
%Black	−0.57**	−0.48*	−0.54**	−0.41	−0.55*	−0.37
	(0.24)	(0.27)	(0.27)	(0.27)	(0.29)	(0.24)
%Asian	−0.81**	−0.42	−0.83**	−0.47	−0.82**	−0.44
	(0.39)	(0.30)	(0.36)	(0.30)	(0.39)	(0.31)
%Hispanic	−0.54*	−0.45	−0.52	−0.41	−0.52	−0.39
	(0.30)	(0.30)	(0.32)	(0.31)	(0.33)	(0.29)
%Native American	−0.45	−1.64	−0.40	−1.44	−0.39	−1.35
	(2.59)	(1.95)	(2.63)	(2.05)	(2.48)	(1.94)
%Other race	0.36	0.44	0.36	0.45	0.37	0.48
	(0.46)	(0.48)	(0.46)	(0.48)	(0.46)	(0.49)
Observations	821	821	821	821	821	821
Adjusted R^2	0.79	0.83	0.79	0.83	0.79	0.83

Change in NO_x (in tons) is the dependent variable. Zip code clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 Heterogeneous treatment effects with alternative minority definition, excluding electric firms

	1-mile dispersion	HYSPLIT (1)	HYSPLIT (2)	HYSPLIT (3)	HYSPLIT (4)
Treatment	−11.67***	−11.71***	−13.70***	−10.31***	−12.43***
	(4.26)	(4.17)	(4.49)	(3.84)	(4.18)
Treatment × Period 1 NO_x	−0.18*		−0.18*		−0.18*
	(0.10)		(0.11)		(0.10)
Treatment × Income (in thousands)	−0.49			−0.46	−1.11
	(0.46)			(2.23)	(2.56)
Treatment × %Minority	0.35	−0.06	−0.56	−0.15	−0.83
	(0.23)	(0.59)	(0.37)	(0.80)	(0.69)
Period 1 NO_x	−0.47***	−0.46**	−0.46***	−0.46**	−0.46***
	(0.18)	(0.21)	(0.18)	(0.21)	(0.18)
Income (in thousands)	0.23			−0.80	−0.71
	(0.40)			(1.21)	(1.18)
%Minority	−0.18	−0.42	0.02	−0.63	−0.16
	(0.11)	(0.36)	(0.23)	(0.46)	(0.24)
Observations	821	832	832	832	832
Adjusted R^2	0.83	0.79	0.83	0.79	0.83

Change in NO_x (in tons) is the dependent variable. Zip code clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional Results

Table 6 shows our main specifications but including electric firms in the sample. Table 7 shows results using FHM's 1-mile data specification but excluding electric firms. Table 6 shows results using HYSPLIT-simulated data, but Blacks and Hispanics are included as a single minority group (the first column shows results using FHM's 1-mile radius for comparison).[23]

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[23] We independently geocoded the sources regulated by RECLAIM, and when replicating the results in FHM our coefficient estimates are slightly different from FHM. Note that we have 821 observations in Table 7 and column (1) Table 8 whereas FHM have 822 observations in their regressions excluding electric facilities. We independently geocoded each facility and finds no population living within a 1-mile radius of Raisch Products located on 1444 Borregas Avenue, Sunnyvale CA 94089. This observation is omitted from our analysis.

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