

# Do Environmental Markets Cause Environmental Injustice? Evidence from California's Carbon Market

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## Abstract

Market-based environmental policies are widely adopted on the basis of allocative efficiency. However, there is growing concern that market-induced spatial reallocation of pollution could widen existing pollution concentration gaps between disadvantaged and other communities. We estimate how this “environmental justice” (EJ) gap changed following the 2013 introduction of California’s carbon market, the world’s second largest and most subjected to EJ critiques. Embedding a pollution dispersal model within a program evaluation framework, we find that previously widening EJ gaps in PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> from facilities subject only to the carbon market began narrowing as a consequence of the program. By 2017, the program returned these EJ gaps back to 2008 levels. We demonstrate that explicit modeling of pollution dispersal is critical for detecting these results.

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# 1 Introduction

Over the last three decades, policy makers have increasingly relied on market-based environmental policies - such as pollution trading and taxes - to address environmental problems. Expanded use of market-based policies followed each major amendment to the U.S. Clean Air Act since the 1970s (Schmalensee and Stavins, 2019). Widespread adoption has occurred in other environmental domains: today, market-based policies cover 30% of global fisheries (Costello et al., 2016), account for over \$36 billion in global ecosystem service payments (Salzman et al., 2018), and govern 20% of global greenhouse gas (GHG) emissions (World Bank Group, 2019).

The central appeal of market-based environmental policies is allocative efficiency. In theory, such policies reduce the total abatement cost of meeting an environmental objective by inducing less abatement from polluters with higher abatement costs (Crocker, 1966; Dales, 1968; Montgomery, 1972). At the same time, the reallocation of emissions induced by market-based policies also spatially alters who is harmed by pollution. This is of particular concern as a growing “environmental justice” (EJ) literature has documented that communities with lower income, higher minority share, and/or otherwise disadvantaged, systematically experience higher pollution concentrations than other communities, a statistic we refer to as the environmental justice gap (or EJ gap).<sup>1</sup> While all environmental policies can generate pollution inequities, market-based policies, by emphasizing allocative efficiency, have raised questions about whether they present a distinct equity-efficiency trade-off.

Whether a market-based policy widens or narrows the EJ gap depends on the joint spatial distribution of polluting facilities, their abatement costs, and disadvantaged communities. Market-based policies induce relatively less abatement from facilities with steeper marginal abatement cost curves. If these facilities are upwind of disadvantaged communities, such policies will widen an existing EJ gap. Conversely, if these facilities are upwind of non-disadvantaged communities, a market-based policy will narrow the EJ gap (Burtraw et al., 2005).<sup>2</sup> Unfortunately, facility-level marginal abatement cost curves are usually unobserved, making it hard to anticipate the direction of EJ gap effects ex-ante. This underscores the need for ex-post empirical approaches, for which prior studies have found mixed EJ gap effects across different settings (Fowlie, Holland and Mansur, 2012; Grainger and Ruangmas, 2018; Shapiro and Walker, 2021).

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<sup>1</sup>EJ gaps across many settings have been shown through case (Bullard, 2000; Bowen, 2002; Ringquist, 2005; Mohai, Pellow and Roberts, 2009; Banzhaf, Ma and Timmins, 2019) and population-level (Tessum et al., 2019; Colmer et al., 2020; Currie, Voorheis and Walker, 2020) studies.

<sup>2</sup>Additionally, for a policy regulating global pollutants like greenhouse gases, the EJ gap effect depends on the extent in which GHG and local pollutants are co-produced.

This paper estimates the EJ gap consequences across California due to the state’s greenhouse gas (GHG) cap-and-trade (C&T) program, which since 2013 has created the world’s second largest carbon market. This program has also been a focal point of EJ concerns, as local air pollution emissions are typically co-produced with GHG emissions.<sup>3</sup> The possibility that the program could widen California’s existing EJ gaps in local air pollution has, among other critiques, led to political opposition that temporary paused the program’s initial development in 2011 and nearly halted renewal efforts in 2017. However, to date, there has been limited evidence on whether emissions reallocation due to the program has caused EJ gaps to widen.

Quantifying the EJ gap consequences of a market-based climate policy requires overcoming two empirical challenges. First, one must isolate how the policy altered emissions of regulated facilities apart from potentially confounding macroeconomic conditions and other “overlapping” climate policies that may interfere with market-based allocation. Second, policy effects on pollution emissions at the facility-level must be converted to location-level changes pollution concentrations. We develop a statistical framework that jointly addresses these two challenges for California’s C&T program.

To overcome the first challenge, we exploit the program’s facility-level eligibility rule based on historical emissions to estimate a break in differential emission trends between C&T-regulated and unregulated facilities after 2013. To inform the central distributional concern that market-based emissions allocation may have altered EJ gaps across California, we focus on facilities subject only to C&T. Abatement from facilities additionally regulated by overlapping climate programs - such as renewable portfolio and low carbon fuel standards - may be induced by those programs and not by the carbon market.

We find that C&T reduced emissions annually at an average rate of 3-9% across GHG and criteria air pollutants between 2012-2017 across sample facilities. These emissions effects are robust across various model specification and sample restriction choices; to concerns about differential trends across sectors; and to the possibility of regulatory spillover effects. In a placebo test that systematically imposes trend breaks across sample years, we generally detect the largest trend break in the year when the program was actually introduced. In a heterogeneity analysis, we find that larger emitting facilities undergo more abatement under C&T.

To address the second challenge, we explicitly embed an atmospheric dispersal model to determine how program-driven changes in facility-level pollution *emissions* alter the spatial

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<sup>3</sup>Similar EJ concerns have arisen for market-based climate policies elsewhere. Recent efforts to introduce state-level U.S. carbon pricing and to renew the European Union Emissions Trading System were opposed on EJ grounds (Leber, 2016; Herron, 2019; Transnational Institute, 2013).

distribution of pollution *concentrations*. The canonical framework for evaluating environmental policies requires knowing the link between pollution “source” and “receptors” (Baumol and Oates, 1988). In practice, however, this mapping is rarely characterized. Instead, one typically assumes simple spatial patterns such as assigning pollution concentrations only to areas within a facility’s geographic unit or within a surrounding distance-based circle (Banzhaf, Ma and Timmins, 2019). This contrasts with actual patterns of pollution dispersal which are far more spatially and temporally complex and depend on topography and time-varying atmospheric conditions. Failure to accurately account for dispersal can lead to bias estimates even in otherwise valid quasi-experimental settings (Deschenes and Meng, 2018).

Our approach combines estimates of C&T emissions effects (and its uncertainty) at the facility level with an analysis of resulting EJ gap changes at the location level, as determined by the atmospheric dispersal model. This computationally-intensive procedure, involving over two million pollution trajectories, builds on two prior approaches using dispersal models (e.g., Sullivan (2017); Grainger and Ruangmas (2018)). Location-only studies typically insert observed emissions into a dispersal model and thus can not quantify policy-induced changes in pollution concentration. Facility-only studies examine whether a policy’s effect on emissions varies with demographic characteristics of downwind locations from a facility. We formally demonstrate that estimates from such facility-level analyses are not generally informative of the EJ gap effect: they not only differ in value but may not even be positively correlated or have the same sign.

Employing a definition of a “disadvantaged” zip code that serves as a basis for California’s EJ policies, we report three EJ gap findings from our sample facilities. First, consistent with EJ concerns in the lead up to the C&T program’s introduction, we find not only were there baseline EJ gaps across criteria air pollutants in 2008, but that gaps were widening in the 2008-2012 period before the program. Second, the C&T program has slowed down these previously widening EJ gaps so much that they have been narrowing since 2013. Third, while EJ gaps have narrowed, they have not been eliminated: by 2017, the C&T program returned EJ gaps roughly to 2008 levels. An important caveat is that these EJ gap effects come from facilities only subject to C&T, which are more suitable for examining whether emissions allocation induced by a market-based policy altered pollution disparities. In a robustness check, we include facilities that are additionally subject to overlapping climate policies, finding similar EJ gap effects. However, for this augmented sample, it is difficult to discern how much of these results are due to C&T and how much to overlapping policies.

We subject our benchmark EJ gap effects to a variety of robustness checks. In particular, we find that allowing for heterogeneous emissions effects as a function of a facility’s aver-

age emissions does not meaningfully alter EJ gap effects. We further demonstrate similar EJ gap effects when employing an alternative atmospheric dispersal model that generates secondary PM<sub>2.5</sub> concentrations as well as when using a finer scale definition of disadvantaged communities at the census tract-level. An analysis of spatial heterogeneity reveals that EJ gaps narrowed most for disadvantaged areas in California's Central Valley, while a few disadvantaged areas in Los Angeles County experienced widening gaps.

Finally, we demonstrate the importance of modeling pollution dispersal for our results. Our EJ gap effects become unstable if instead of modeling pollution dispersal, we were to employ more conventional approaches for assigning pollution emissions to concentrations. We posit that our empirical approach may have broader applicability as many environmental policy settings require researchers to track how policy-driven changes in pollution emissions alter the spatial distribution of pollution concentration (Greenstone and Gayer, 2009; Graff Zivin and Neidell, 2013; Deschenes and Meng, 2018).

The paper is structured as follows: Section 2 considers a conceptual framework for how a C&T program could widen or narrow an existing EJ gap and offers background on California's GHG C&T program. Section 3 summarizes our data. Section 4 details our empirical approach. Section 5 presents our results. Section 6 provides a discussion.

## 2 Background

We begin by discussing how the introduction of a cap-and-trade (C&T) program can either widen or narrow existing pollution concentration gaps between disadvantaged and other communities. We then review California's greenhouse gas (GHG) cap-and-trade program.

### 2.1 Cap-and-trade and the environmental justice gap

In a textbook C&T program, the regulator establishes a limit (or cap) on total emissions within a jurisdiction by issuing a fixed supply of emission permits. Regulated facilities are then either given, or must purchase, permits to cover their emissions. Permit trading allows the marginal abatement cost (MAC) of emissions to be equalized among regulated facilities to the permit price.<sup>4</sup>

Two key consequences of C&T are often emphasized. First, by placing a price on pollution, a C&T program induces polluting facilities to internalize (some of) the social costs of their emissions.<sup>5</sup> Second, by equalizing MACs across facilities, a C&T program allocates

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<sup>4</sup>The modern C&T framework was initially developed by Crocker (1966) and Dale (1968).

<sup>5</sup>Whether social costs are fully internalized depends on if the cap is set at the socially optimal level.

emissions by inducing relatively less abatement from facilities with steeper MAC curves and more abatement from facilities with flatter MAC curves. In theory, the resulting allocation of abatement achieves the aggregate emissions cap at the lowest total abatement cost across regulated facilities (Montgomery, 1972).

What is less clear is how the allocative efficiency achieved by C&T alters the spatial distribution of pollution concentration. In particular, there is growing concern that the same market forces resulting in allocative efficiency may also be altering the difference in pollution concentrations experienced between disadvantaged and other communities. This difference, which we call the “environmental justice gap” (or EJ gap) has been shown to be positive in the many settings (Bullard, 2000; Bowen, 2002; Ringquist, 2005; Mohai, Pellow and Roberts, 2009; Banzhaf, Ma and Timmins, 2019; Tessum et al., 2019; Colmer et al., 2020; Currie, Voorheis and Walker, 2020).

The introduction of C&T can either widen or narrow an existing EJ gap. Figure 1 illustrates this ambiguous effect for a stylized two-facility setting with emissions ( $e$ ) on the horizontal axis and permit prices ( $\tau$ ) on the vertical axis. The first facility is upwind of a disadvantaged community (DAC) with a marginal abatement curve labeled “DAC” (in orange). The second facility is upwind of a non-disadvantaged community and has a marginal abatement curve labeled “non-DAC” (in gray).<sup>6</sup> To establish an existing positive EJ gap prior to the introduction of C&T, we allow the DAC facility to have larger emissions in the absence of C&T, or when  $\tau = 0$ . When C&T is introduced, each facility’s MAC is equated to the equilibrium permit price  $\tau = \tau^*$ . What happens to the EJ gap?

In the left panel of Figure 1, the DAC facility has a steeper MAC curve than the non-DAC facility, causing the DAC facility to abate less than the non-DAC facility under C&T. In this case, C&T widens the EJ gap. The right panel of Figure 1 shows an alternative case whereby the DAC facility has a flatter MAC curve than the non-DAC facility. Following C&T, the DAC facility abates more than the non-DAC facility, narrowing the EJ gap.

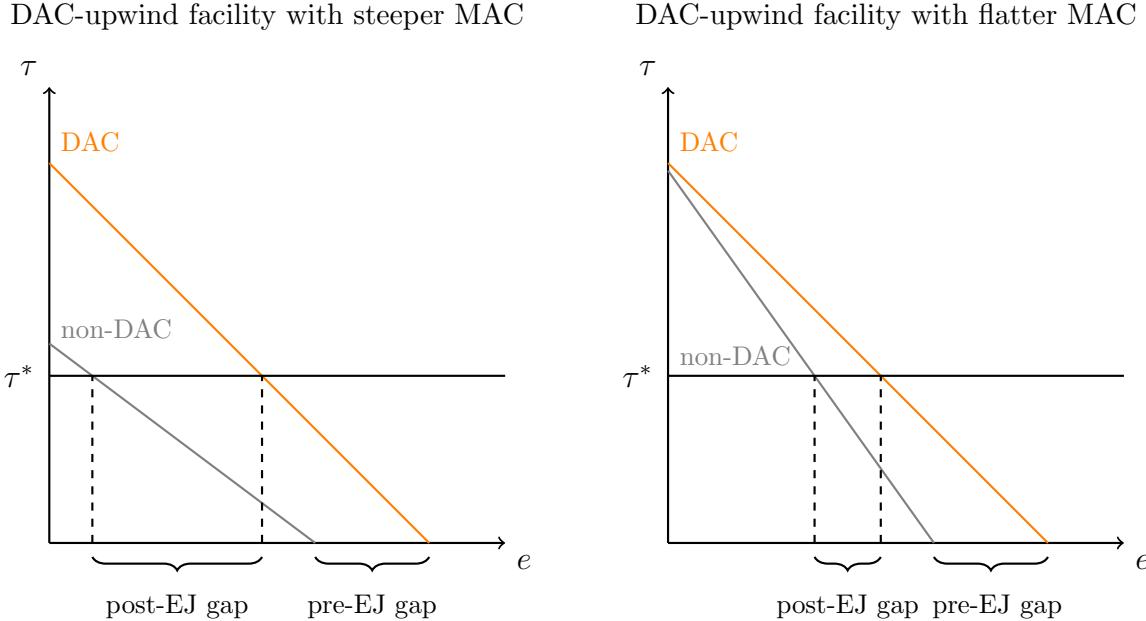
Thus, in settings with an existing positive EJ gap, whether C&T widens or narrows the EJ gap depends on whether facilities upwind of DAC communities have relatively steeper or flatter MAC curves. Furthermore, for a cap-and-trade system regulating a global pollutant such as greenhouse gases, the EJ gap effect depends on the extent in which GHG and local air pollutants are co-produced.

Unfortunately, facility-level MAC curves are rarely observed, which limits the ability to anticipate EJ gap effects of proposed C&T programs. Ex-post studies also face several empirical challenges. First, to remove the influence of macroeconomic conditions, one needs

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<sup>6</sup>The horizontal axes in Figure 1 indicates emissions rather than abatement in order to illustrate emissions levels prior to C&T when  $\tau = 0$ .

**Figure 1:** EJ gap under cap-and-trade



NOTES: Panels illustrate how the introduction of a C&T program can widen or narrow an existing EJ gap in a two facility setting. Horizontal axes indicate emissions. Vertical axes indicate marginal abatement costs, and equivalently the permit price under C&T. The marginal abatement cost curve for facility upwind of a disadvantaged community (labeled DAC) is shown in orange. The marginal abatement cost curve for facility upwind of a non-disadvantaged community (labeled non-DAC) is shown in gray.  $\tau^*$  indicates the permit price under C&T. In the left panel, the DAC-upwind facility has a relatively steeper MAC curve. In the right panel, the DAC-upwind facility has a relatively flatter MAC curve.

to estimate the effect of cap-and-trade for regulated facilities relative to unregulated facilities. Second, isolating the effect of reallocation from cap-and-trade requires restricting attention to facilities that are only regulated by cap-and-trade and not additionally by overlapping climate programs such as renewable portfolio or low carbon fuel standards.<sup>7</sup> Third, estimated C&T-driven facility emissions must be mapped onto location-level pollution concentrations in order to examine resulting EJ gap changes. Section 4 details how we overcome these challenges.

## 2.2 California’s GHG cap-and-trade program

California’s has one of the world’s most sophisticated and ambitious climate policies. In 2006, California passed Assembly Bill 32 (AB 32), requiring total GHG emissions across

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<sup>7</sup>Returning to Figure 1, suppose an overlapping climate program binds for one facility. Any subsequent change in the EJ gap following cap-and-trade now depends on the overlapping program, and in particular whether it binds for the DAC or non-DAC facility and at what emissions level.

the state to decline gradually, reaching 1990 emissions level by 2020.<sup>8</sup> AB 32's central program is cap-and-trade, introduced in 2013 and administered by the California Air Resources Board (CARB). The program requires participation by all stationary GHG-emitting facilities producing at least 25,000 metric tons of annual carbon dioxide equivalent emissions, or CO<sub>2</sub>e, during any year between 2009-2012.<sup>9,10</sup> The program becomes more stringent over time, mandating a declining cap on aggregate emissions across eligible facilities.

California's GHG C&T program has since created the world's second largest carbon market by permit value, following the European Union Emissions Trading System (EU-ETS). AB 32 remains the only economy-wide climate policy in the U.S.: all other state or national climate policies regulate specific sectors, whereas AB 32 covers all GHG emission sources. In 2016, California met AB 32's 2020 GHG target four years early. That same year, the state extended its GHG target to 40% below 1990 levels by 2030. This was shortly followed by a 2030 extension of the C&T program.

Cap-and-trade, however, is not California's only climate program. The adoption of C&T occurred against a backdrop of various sector-specific climate programs that overlap with the economy-wide C&T, including a renewable portfolio standard for electricity generators and a low carbon fuel standard for refiners. When overlapping policies bind - i.e., induce sector-specific abatement that the economy-wide C&T would not on its own - it becomes hard to attribute emission changes in these facilities to market-based allocation under C&T.<sup>11</sup> Indeed, an ex-ante analysis of California's GHG C&T program demonstrated a potentially large role played by these overlapping programs (Borenstein et al., 2019).

### 3 Data

Our analysis involves two primary datasets: 1) GHG and criteria air pollution emissions at the facility-by-year level and 2) an indicator of whether a zip code is considered to be "disadvantaged" according to California legislation.

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<sup>8</sup>Greenhouse gases covered by AB 32 are CO<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub>O, HFCs, PFCs, SF6, NF3 and other fluorinated GHGs.

<sup>9</sup>The 2013 timing of the C&T program is also unique. Most other AB 32 climate programs were introduced earlier.

<sup>10</sup>The GHG C&T program does not directly regulate local criteria air pollution emissions. Any changes in the spatial distribution of local air pollution concentration due to the program is driven by the program's reallocation of local air pollution emissions that is co-produced with GHG emissions.

<sup>11</sup>Note that the emissions allocation under C&T includes the use of offset credits which allow a regulated facility to meet up to 8% of its emissions with credits purchased from GHG abatement projects originating in sectors not covered by the cap. Our estimated C&T effects are therefore inclusive of the use of offsets.

**Facility emissions** We obtain 2008-2017 facility-level annual emissions of GHG (or CO<sub>2</sub>e), PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, all in metric tons, from CARB’s Pollution Mapping Tool.<sup>12</sup> We observe GHG as well as criteria air pollution emissions for both C&T-regulated and non-regulated stationary facilities, before and after the introduction of the C&T program.<sup>13</sup>

Several additional facility-level variables serve as inputs for the atmospheric dispersal model. CARB provides facility latitude and longitude as well as pollution-specific stack heights for a subset of facilities. For other facilities, we impute missing pollution-specific stack heights using sector averages constructed from non-missing observations.

**Definition of a disadvantaged community** There is no established definition of a “disadvantaged” community. Previous papers in other settings use a location’s median income or minority share of population as proxy measures (Fowlie, Holland and Mansur, 2012; Grainger and Ruangmas, 2018; Mansur and Sheriff, 2019). For our setting, we select a policy-relevant definition of a “disadvantaged” community. Senate Bill 535 (SB 535), passed in 2012, requires a portion of the revenue from the auction of C&T permits to be directed towards benefiting disadvantaged communities. SB 535 formally defines a “disadvantaged community” using CalEnviroScreen, a scoring system based on multiple pollution exposure and socioeconomic indicators developed by the California Environmental Protection Agency.<sup>14</sup> In our benchmark analysis, we use CalEnviroScreen v1.1 which assigns disadvantaged status at the zip code-level and is constructed using pre-2013 indicators, mitigating concerns that C&T may directly impact disadvantaged community designation. Specifically, a zip code is considered disadvantaged if it contains all or part of a census tract with a CalEnviroScreen score above the top 25th percentile. Zip codes designated as disadvantaged are shaded in dark blue in Figure 2a. As a robustness check, we also use a later CalEnviroScreen v3.0 which has the benefit of defining a disadvantaged community at a finer census tract-level

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<sup>12</sup>Available here: [https://ww3.arb.ca.gov/ei/tools/pollution\\_map/](https://ww3.arb.ca.gov/ei/tools/pollution_map/)

<sup>13</sup>Stationary facilities with annual emissions past a certain threshold must report emissions. For GHGs, the data reporting threshold is 10,000 metric tons of CO<sub>2</sub>e, set by CARB. For criteria air pollutants, CARB sets a reporting threshold of 10 metric tons per year, but each air district can set lower data reporting thresholds. As a consequence, we observe criteria air pollution emissions below 10 metric tons, with no evidence of bunching at 10 tons (see histograms of sample facility-year emissions in Figure S1). We confirmed that emissions data in CARB’s Pollution Mapping Tool matches values found in source datasets: CARB’s Mandatory Reporting Regulation (MRR) dataset for GHG emissions and the California Emissions Inventory Development and Reporting System (CEIDARS) for criteria air pollution emissions. Details on California’s emissions reporting requirements can be found: [https://ww3.arb.ca.gov/ei/tools/pollution\\_map/doc/caveats%20document12\\_22\\_2017.pdf](https://ww3.arb.ca.gov/ei/tools/pollution_map/doc/caveats%20document12_22_2017.pdf)

<sup>14</sup>The socioeconomic indicators used to construct CalEnviroScreen do not explicitly include a location’s racial and/or ethnic composition, though many included indicators such as poverty levels, educational attainment, unemployment rate, are correlated with racial and/or ethnic composition (CalEPA, 2018). In a robustness check, we use a location’s minority share of population as a measure of a disadvantaged community.

but at the cost of being constructed using post-2013 indicators. We further augment our zip code level data with average 2008-2012 population obtained from the U.S. Census Bureau.

## 4 Empirical approach

Our analysis proceeds along three steps. First, we use facility-by-year-level data to estimate how the GHG C&T program altered GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> emissions. Second, we feed C&T-driven PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> emissions predicted from the first step into an atmospheric dispersal model to generate zip code-by-year-level concentrations of these pollutants due to the program. Finally, we examine whether the C&T program changed the concentration gap for these pollutants between disadvantaged and other communities following its 2013 introduction.

**Step 1: Estimating C&T effects on emissions** We exploit the facility-level eligibility criteria based on pre-program GHG emissions and the 2013 timing of the C&T program to identify its effects on GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> facility-level emissions during 2008-2017.<sup>15</sup> Because the program's eligibility criteria is based on pre-C&T GHG emissions, we expect regulated and unregulated facilities to differ in pre-program emissions levels and perhaps also in pre-program emission trends. Our empirical test therefore examines whether differential emission trends exhibit a break after 2013. Identification requires that any existing differential emission pre-trends to have continued if not for the introduction of the C&T program.<sup>16</sup>

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<sup>15</sup>Data availability for facility GHG and criteria air pollution emissions for both regulated and unregulated facilities and for periods before and after the program's introduction is not common across cap-and-trade programs. For example, facility-level pre-program emissions are not directly observed for the European Union Emissions Trading System (EU-ETS), the world largest carbon market (Petrick and Wagner, 2014; Martin, Muûls and Wagner, 2016; Colmer et al., 2020). Even in settings where emissions data is available, emissions-based eligibility thresholds can sometimes be too low for there to be sufficient control units within the same jurisdiction, as in the case of Southern California's RECLAIM NO<sub>x</sub> C&T program (Fowlie, Holland and Mansur, 2012). We are able to compare regulated and unregulated units within the same jurisdiction. Note that because there is no overlap in pre-program GHG emissions for regulated and unregulated facilities, we are unable to implement a matching estimator that matches on pre-program emissions, as is done in Fowlie, Holland and Mansur (2012) and Martin, Muûls and Wagner (2016). Implementing such a matching approach would require emissions data from facilities outside of California. That comparison, however, may be confounded by systematic unobserved differences between California and non-California facilities.

<sup>16</sup>The identifying assumption in our differential trend-break model is similar to that of a standard difference-in-difference (D-i-D) model. In a D-i-D setting, identification requires that the average pre-policy difference in outcome *levels* between treated and control units continue if not for the policy. In a differential trend-break model, one assumes that the average pre-policy difference in outcome *trends* between treated and control units continue if not for the policy. Note that identification does not require pre-treatment trends for treated and control units to be parallel, only that any differential pre-trends would have continued if not for the policy.

Specifically, let  $j$  index facilities.  $C_j \in \{0, 1\}$  is GHG C&T regulatory status with  $C_j = 1$  indicating facility  $j$  is regulated.<sup>17</sup> For facility  $j$  in year  $t$ ,  $Y_{jt}^p$  is annual emissions of pollutant  $p \in \{GHG, PM_{2.5}, PM_{10}, NO_x, SO_x\}$ . Because emissions exhibit a skewed distribution and contain zero values, we apply an inverse hyperbolic sine transformation, which like a log transformation lends a percentage effect interpretation, but with the added advantage of retaining zero-valued observations (Bellemare and Wichman, 2020). To examine differential emission trends driven by the C&T program, we estimate the following specification:

$$\text{asinh}(Y_{jt}^p) = \kappa_1^p[C_j \times t] + \kappa_2^p[C_j \times \mathbf{1}(t \geq 2013) \times t] + \phi_j^p + \gamma_t^p + \nu_{jt}^p \quad (1)$$

Facility-specific dummy variables  $\phi_j^p$  removes time-invariant determinants of pollution  $p$  for facility  $j$ . Year-specific dummy variables  $\gamma_t^p$  remove common determinants of emissions affecting all sample facilities in year  $t$ , such as California-wide economic conditions.

$\kappa_1^p$  captures the differential emission pre-trend for pollutant  $p$  between facilities that would and would not eventually be regulated by the C&T program during 2008-2012, reported in annual percentage point changes. Our parameter of interest is  $\kappa_2^p$ , the change, or break, in the differential emission trend after the program's introduction during 2013-2017. While we are primarily interested in  $\kappa_2^p$ , we also report  $\kappa_1^p + \kappa_2^p$ , the post-C&T differential emission trend.  $\nu_{jt}^p$  is clustered at the county-level to allow for arbitrary forms of heteroskedasticity and serial correlation within a county.

We employ two sample restrictions. First, despite the C&T program's unique eligibility criteria and timing, the presence of overlapping climate programs, such as the renewable portfolio standard for electricity generators and the low carbon fuel standard for refineries, imply that emission changes from facilities further regulated by these programs may not reflect abatement induced by the carbon market. Since our central interest is to understand how the carbon market altered EJ gaps, we remove electricity generators and refineries from our sample.<sup>18</sup> Second, to ensure better comparability between treated and control facilities, we restrict our sample to facilities with sample average annual GHG emissions below the

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<sup>17</sup>All but 39 facilities that emit local air pollution found in CARB's Pollution Mapping Tool have time-invariant GHG C&T regulatory status between 2008-2017. These 39 facilities all switched status in 2017. Under the C&T program, a regulated (unregulated) facility can become unregulated (regulated) if annual GHG emissions fall below (above) the 25,000 metric tons threshold in any year during a prior compliance period. Of the 39 facilities that switched status in 2017, 8 switched even though annual GHG emissions during the previous 2015-2016 compliance period should not have permitted a regulatory status change. Because we do not know if these switches are due to actual changes in regulatory status or coding errors, we retain these 39 facilities in our sample and re-assign them their previous (time-invariant) regulatory status for 2017. In a robustness check, we drop observations from these 39 facilities in our estimation.

<sup>18</sup>This restriction also addresses concerns about the the 2013 closure of the San Onofre Nuclear Generating Station, a power plant in southern California (Davis and Hausman, 2016).

75th percentile.<sup>19</sup> As robustness checks, we consider estimating samples with smaller and larger cutoff percentiles, as well as the inclusion of electricity generators and refineries.

Our benchmark sample contains 106 regulated and 226 unregulated facilities. Each regulated facility is shown as a black dot in Figure 2a. Table S1 shows average 2008-2012 annual GHG and criteria emissions and sectoral distribution for sample regulated and unregulated facilities. Since C&T regulatory status is defined by historical GHG emissions, it is unsurprising that regulated and unregulated facilities exhibit different average pre-program emissions, nor does this invalidate our differential emissions trend break design, per se. Table S1 also shows a slight sectoral imbalance between regulated and unregulated facilities, with more regulated facilities in extraction and more unregulated facilities in services. In a robustness check, we replace year fixed effects in equation (1) with sector-by-year fixed effects to address concerns that this sectoral imbalance may confound our estimates.

C&T generates heterogeneous emission abatement levels across regulated facilities. To model this heterogeneity along an observable dimension, we turn to a recent literature building on Melitz (2003)'s heterogeneous firm model that emphasizes heterogeneity in abatement levels as a function of a facility's baseline emissions level, with more productive firms having both higher baseline emission levels and lower pollution intensities (Forslid, Okubo and Ulltveit-Moe, 2018; Shapiro and Walker, 2018). We implement this abatement level heterogeneity by applying a hyperbolic sine transformation to the first two terms of equation (1) and the estimated facility-level fixed effect.<sup>20</sup> Because facilities differ by average emission levels, this approach allows us to translate a common percentage effect into heterogeneous C&T-driven abatement levels, as is shown in Figure S4.<sup>21</sup>

Whether a common percentage effect is appropriate in our setting is an empirical matter. To explore this, we estimate variants of equation (1) that interact the post-C&T trend break with linear and quadratic functions of each facility's average annual emissions, allowing the data to determine whether the C&T percentage effect varies with emission levels. These models consistently reveal that larger emitting facilities abate more in levels under C&T, slightly more so than is assumed with a common percentage effect (see Table S3). However,

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<sup>19</sup>The 75th percentile corresponds to average annual emissions of 62,770 metric tons of CO<sub>2</sub>e.

<sup>20</sup>Specifically, C&T-driven emissions is:

$$\hat{Y}_{jt}^p = \sinh \left( \hat{\kappa}_1^p [C_j \times t] + \hat{\kappa}_2^p [C_j \times \mathbf{1}(t \geq 2013) \times t] + \hat{\phi}_j^p \right) * e^{(RMSE)^2 / 2}$$

where hat notation indicates estimated parameters and RMSE is the root mean squared error from equation (1). In theory, the hyperbolic sine transformation can generate negative emission values. In practice, our benchmark model predicts negative emissions for 1%, 1%, 0.2%, and 0.3% of sample observations for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, respectively. We replace these negative values with zeros.

<sup>21</sup>For example, a 10% abatement effect implies 10 tons of abatement for a facility with 100 tons of average annual emissions and 5 tons of abatement for a facility with 50 tons of average annual emissions.

predicted emissions that allow for this heterogeneity do not meaningfully alter pollution disparity results (see col. 6 of Table S7).

**Step 2: Modeling pollution dispersal** Our second step determines how C&T-driven criteria air pollution disperses spatially across California. The standard approach is for the researcher to prescribe the set of locations affected by emissions from a particular source, either by assuming emissions only disperses within areas in the same administrative unit of the source or within a radially uniform distance from the source. For example, one may assume emissions from a facility in Los Angeles County only affect Los Angeles County or areas within a certain radial distance of that facility. Actual affected areas, however, may not conform to these assumptions and instead may vary depending on topography or time-varying meteorological conditions. To fully capture the complexity of pollution dispersal, we turn to an atmospheric dispersal model that employs topography and real-time meteorological conditions to generate spatial distributions of criteria pollution concentrations driven by C&T.

We feed predicted facility-by-year PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> emissions from step 1, together with the location and stack height of each facility, into the Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPPLIT), an atmospheric dispersal model developed by the U.S. National Oceanographic and Atmospheric Administration (NOAA) with real-time meteorological conditions from NOAA's 40-km resolution North American Model Data Assimilation System (NAMDAS) (Draxler and Hess, 1998). An emerging literature uses HYSPPLIT to convert pollution emissions to concentrations (Grainger and Ruangmas, 2018; Henneman, Mickley and Zigler, 2019; Casey et al., 2020).

We choose HYSPPLIT because it provides a middle-of-the-road approach for our application, balancing atmospheric realism with computational tractability. HYSPPLIT is more reliable for modeling pollution dispersal beyond distances of 50 kilometers, which less computationally-intensive Gaussian-plume models like AERMOD or APEEP do poorly (EPA, 2015). At the same time, it is less computationally intensive than chemical dispersal models such as WRF-Chem, but at the cost of not incorporating atmospheric chemistry, which is important for modeling secondary pollutant formation. To see if secondary PM<sub>2.5</sub> concentrations exhibits a different spatial pattern than primary PM<sub>2.5</sub> concentrations, in a robustness check, we replace HYSPPLIT with InMAP, a reduced-complexity dispersal model based on the WRF-Chem model that models secondary PM<sub>2.5</sub> concentrations (Tessum, Hill and Marshall, 2017). InMap, however, has a major disadvantage: while HYSPPLIT's underlying meteorological inputs cover our 2008-2017 sample period, InMap only models dispersal patterns in 2005.

We note several features of our HYSPPLIT implementation. First, to account for high-

frequency variation in meteorological conditions, we run forward particle trajectories at four hour intervals, implicitly assuming that annual emissions are distributed uniformly within the year. In a robustness check, we relax this assumption by distributing C&T-driven annual emissions at the monthly level according to sector-specific monthly output shares.<sup>22</sup> Each trajectory runs for 24 hours, a duration long enough to ensure most emitted particles leave California.<sup>23</sup> Second, because HYSPLIT does not explicitly account for particle decay, we apply half-life parameters from the atmospheric chemistry literature set at 24 hours for PM<sub>2.5</sub> and PM<sub>10</sub>(U.S. EPA, 2018), 3.8 hours for NO<sub>x</sub> (Liu et al., 2016), and 13 hours for SO<sub>x</sub> (Lee et al., 2011). Third, we assume that a particle no longer contributes to surface pollution concentrations once it exits the planetary boundary layer, beyond which there is far less turbulent mixing. We conservatively set the boundary layer height at 1 km above the surface, which is about double the typical height for California (Rahn and Mitchell, 2016). As a robustness check, we also consider boundary layer heights of 0.5 and 2 km. As an illustration of pollution dispersal modeled by HYSPLIT, Figure 2b shows the distribution of trajectories of pollution emitted by a regulated facility in Los Angeles during 2016. In total, we compute over 2 million particle trajectories from the roughly one hundred regulated facilities in our sample during the 2008-2017 period. This procedure takes about 24 hours to complete using over one thousand facility-by-year parallelized nodes on a high-performance computing cluster.

Following common HYSPLIT practice, we convert the distribution of trajectories generated by HYSPLIT into concentration units by summing HYSPLIT trajectories for each zip code and year and divide by the volume of the atmosphere between a zip code's surface and the boundary layer. We further divide by 365 days. This gives us a zip code-by-year measure of average daily C&T-driven pollution concentration for the 1 km-high air column above each zip code in units of  $\mu\text{g}/\text{m}^3/\text{day}$ .<sup>24</sup> Figure 2c shows our benchmark HYSPLIT-generated daily concentration (in  $\mu\text{g}/\text{m}^3/\text{day}$ ) for each zip code, averaged across 2008-2017 for PM<sub>2.5</sub>. Figure S2 similarly shows average 2008-2017 zip-code concentrations for PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>.<sup>25</sup> Note that pollution concentration levels in Figure S2 are generally below

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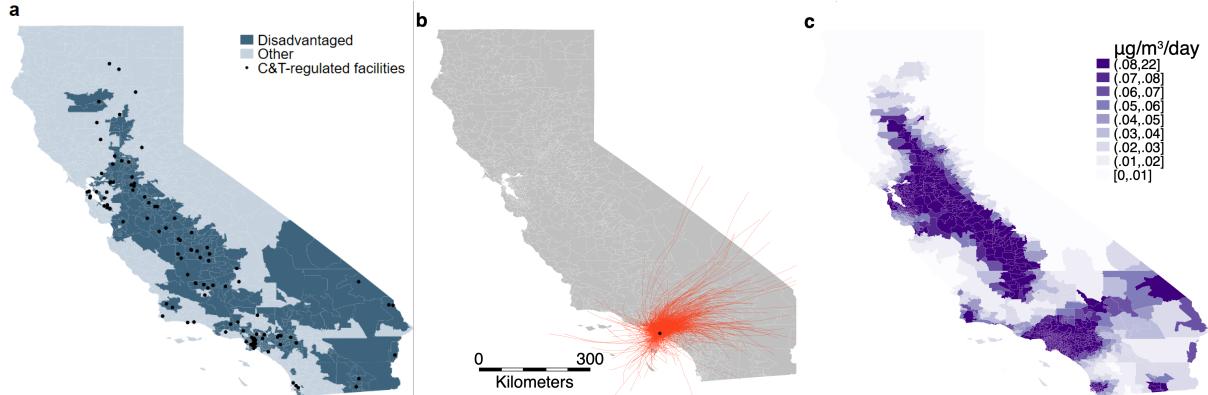
<sup>22</sup>Specifically, using Federal Reserve Economic Data, we obtain U.S. aggregate monthly output for manufacturing (NAICS 31-33) and 2-digit NAICS level monthly output for extraction (NAICS 21) during the 2008-2017 period. We then distribute C&T-driven annual emissions according to these monthly output shares when feeding emissions into HYSPLIT.

<sup>23</sup>Unlike Henneman et al. (2019), we do not discard the first hour of each particle trajectory because doing so may omit highly localized pollution concentrations that may be important for our distributional analysis.

<sup>24</sup>Other HYSPLIT applications convert HYSPLIT particles into concentration units by regressing HYSPLIT output onto concentration output from a different atmospheric dispersal model using the same emissions sources (see for example: Henneman, Choirat and Zigler (2019)) to obtain predicted concentrations using that fitted relationship. We are unable to perform that adjustment as there are no alternative measures of C&T-driven pollution concentrations in the literature.

<sup>25</sup>Figure 2, Figure S2, and Table S6 show that criteria air pollution from GHG C&T-regulated facilities

**Figure 2:** Modeling air pollution concentrations driven by the cap-and-trade program



NOTES: Panels illustrates how facility-level emissions is converted to zip code-level pollution concentrations using an atmospheric dispersal model. Shading in panel (a) shows California zip codes that are designated as disadvantaged (dark blue) and zip codes that are not (light blue) according to California policy. Black dots show sample facilities regulated by California’s GHG C&T program. Panel (b) shows the spatial distribution of HYSPLIT-generated particle trajectories every 4-hours from a regulated facility during 2016. Panel (c) shows zip code-level average daily PM<sub>2.5</sub> concentrations (in  $\mu\text{g}/\text{m}^3/\text{day}$ ) during 2008-2017 driven by facilities regulated by the C&T program as modeled by HYSPLIT.

those recorded in ambient monitors because we are only considering pollution concentrations driven by C&T-driven emissions from sample regulated facilities.

**Step 3: Estimating C&T-driven change in EJ gap trends** In our third step, we examine whether the C&T program altered the difference in pollution concentrations between disadvantaged and other communities, or the EJ gap. Let  $D_i \in \{0, 1\}$  denote disadvantaged status, with  $D_i = 1$  indicating that zip code  $i$  contains all or part of a “Disadvantaged Community Census Tract,” as defined by Senate Bill 535. For zip code  $i$  in year  $t$ , we take C&T-driven pollution concentration from HYSPLIT,  $E_{it}^p$ , for criteria air pollutant  $p \in \{PM_{2.5}, PM_{10}, NO_x, SO_x\}$ , and estimate the following specification:

$$E_{it}^p = \beta_1^p[D_i \times t] + \beta_2^p[D_i \times \mathbf{1}(t \geq 2013) \times t] + \psi_i^p + \delta_t^p + \epsilon_{it}^p \quad (2)$$

where  $\psi_i^p$  are zip code-specific dummies and  $\delta_t^p$  are year-specific dummies.  $\beta_1^p$ , or the pre-C&T EJ gap trend, captures the linear trend in the EJ gap (from facilities that would eventually be regulated by the C&T program) during 2008-2012, before the program was introduced. A positive trend (i.e.,  $\beta_1^p > 0$ ) would indicate that the EJ gap was widening prior to the C&T program. Our main parameter of interest is  $\beta_2^p$ , which captures the change in the EJ gap trend after the program’s introduction, or the post-C&T EJ gap trend break. Conditional on  $\beta_1^p > 0$ ,  $\beta_2^p < 0$  implies that the introduction of the C&T program slowed the previous disperses across all of California and not just zip codes designated as disadvantaged.

positive EJ gap trend. We consider two additional trend break statistics. The first statistic asks whether the post C&T EJ gap trend break is sufficiently large such that the EJ gap has actually narrowed in level terms after the C&T program. This would be captured by  $\beta_1^p + \beta_2^p$ , or the post-C&T EJ gap trend, with  $\beta_1^p + \beta_2^p < 0$  indicating that the EJ gap is narrowing.<sup>26</sup> A second statistic examines the relative degree in which C&T program has slowed the prior EJ gap trend. Specifically,  $\frac{\beta_2^p}{\beta_1^p} * 100 = (\frac{(\beta_1^p + \beta_2^p) - \beta_1^p}{\beta_1^p}) * 100$  captures the percentage change in the EJ gap trend following the introduction of the C&T program.

C&T-driven pollution concentration,  $E_{it}^p$ , the outcome variable in equation (2), is predicted C&T-driven emissions from equation (1) via HYSPLIT. As a consequence,  $\epsilon_{it}^p$ , the error term in equation (2), does not account for statistical uncertainty in C&T emission effects from equation (1). Instead,  $\epsilon_{it}^p$  may capture residuals that arise when estimating an average EJ effect in the presence of heterogeneous EJ effects. To address inference concerns, we conduct two standard error adjustments. First, we cluster  $\epsilon_{it}$  at the county level to allow for arbitrary forms of heteroskedasticity and serial correlation when heterogeneous treatment effects are not independent and identically distributed. Second, to incorporate statistical uncertainty in predicted C&T-driven emissions from equation (1), we conduct a bootstrap procedure drawing multiple vectors of C&T-driven emissions from the estimated empirical distributions of  $\kappa_1^p$  and  $\kappa_2^p$ , which are then fed into steps 2 and 3. In practice, we implement 250 bootstrap draws to generate a component of the standard error for  $\beta_1^p$  and  $\beta_2^p$  that accounts for statistical uncertainty in equation (1). We add this component to the standard error from directly estimating equation (2) when reporting uncertainty for  $\beta_1^p$  and  $\beta_2^p$ .<sup>27</sup> Appendix A.1 provides more details on this bootstrap procedure.

Finally, to estimate an average EJ gap effect across individuals in California, we weight each zip code-by-year observation in equation (2) by average zip code population during 2008-2012, the period prior to the program.

**Comparison with prior uses of pollution dispersal models** Our empirical approach is part of a broader effort across natural and social sciences to use atmospheric dispersal models to map pollution emissions to concentrations. Prior studies can be broadly classified into two groups: whether the analysis is done at the location-level or at the facility-level.

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<sup>26</sup>Observe that while  $\beta_2^p < 0$  alone implies that the C&T program resulted in EJ gap benefits by slowing the growth in the EJ gap, it does not necessarily imply that this post-trend break effect is strong enough to offset the magnitude of the pre-trend such that EJ gap is narrowing in absolute terms following the program. For that to occur, one needs  $\beta_2^p < -\beta_1^p$ , or  $\beta_1^p + \beta_2^p < 0$ .

<sup>27</sup>As with prior literature, we omit uncertainty associated with atmospheric dispersal, or the mapping between facility-level emissions and zip code-level concentration. One possibility involves resampling meteorological conditions in HYSPLIT via a bootstrapping algorithm. Given that our use of HYSPLIT takes 24 hours, overlaying such an approach to the existing 3-step procedure is currently unrealistic under available computational resources.

Location-level analyses typically feed observed emissions into a dispersal model, but without first estimating the emissions effects of environmental policies (Ash and Fetter, 2004; Morello-Frosch and Jesdale, 2006; Sullivan, 2017; Cummiskey et al., 2019; Henneman et al., 2019; Henneman, Choirat and Zigler, 2019; Kim et al., 2020). Because these studies omit estimation of policy-driven emissions (i.e., our Step 1), they cannot attribute changes in pollution concentrations to specific policies.<sup>28</sup>

Facility-level studies examine whether a policy's effect on emissions varies with the demographic characteristics of households downwind of facilities, as determined by the atmospheric dispersal model (Grainger and Ruangmas, 2018; Mansur and Sheriff, 2019). This approach augments the facility-level in equation (1) by adding a term that interacts the policy treatment with demographic characteristics of downwind locations. However, given the complex spatial nature of pollution dispersal whereby concentrations in each location may be affected by emissions from multiple facilities, it is not obvious whether one can recover EJ gap changes, the estimand of interest, from such an approach.

In Appendix A.2, we formally demonstrate that the coefficient on the interaction term from such dispersal-augmented facility-level regressions is not generally informative of the EJ gap effect. Not only can this coefficient differ in value from the true EJ gap effect, but it is also not necessarily positively correlated or have the same sign as the EJ gap effect. The reason is that a facility-level analysis fails to account for the full complexity of pollution dispersal patterns by overlooking the possibility that a facility can alter pollution concentrations in both disadvantaged and other locations. For example, a facility-level analysis may recognize that emissions from facilities in Los Angeles and San Francisco affect air quality in both disadvantaged and other receptor locations, but it does not undergo the additional exercise of tallying up pollution from Los Angeles and San Francisco at each receptor location.

To illustrate this, Appendix A.2 shows the restrictions on pollution dispersal patterns required in order for estimates from a facility-level analysis to equal the true EJ gap effect: emissions from each facility can *only* affect disadvantaged communities or *only* affect non-disadvantaged communities. This assumption is readily rejected in our setting. For each sample C&T regulated facility-year observation, we calculate the share of downwind affected locations containing disadvantaged communities. Figure S3 shows that this share is always within the unit interval. That is, emissions from every sample C&T regulated facilities alters pollution concentrations in both disadvantaged and non-disadvantaged communities.

In summary, our approach combines both facility- and location-level analyses. This

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<sup>28</sup>For example, Henneman et al. (2019) and Henneman, Choirat and Zigler (2019) insert observed air pollution emissions from coal-fired power plants into a version of HYSPLIT to examine how much U.S. PM<sub>2.5</sub> concentrations are due emissions from these plants, but cannot speak to the policies that are affecting coal-fired power plant emissions.

enables us to attribute changes in emissions due to the C&T program and quantify the resulting change in the EJ gap as a consequence of these emissions.

## 5 Results

This section presents our results. Section 5.1 shows the effect of C&T on differential emission trends between regulated and unregulated facilities. Section 5.2 examines how these C&T-driven emissions altered trends in the pollution concentration gap between disadvantaged and other communities across California.

### 5.1 Cap-and-trade effects on emissions

**Main results** Table 1 reports the pre-C&T differential emissions trend (i.e.,  $\kappa_1^p$  from equation (1)) and the post-C&T differential emissions trend break (i.e.,  $\kappa_2^p$  from equation (1)) for GHG and criteria air pollutants. Column 1 shows a statistically significant trend break in GHG emissions, indicating that the C&T program led to a reduction in GHG emissions. Prior to the program, the gap in GHG emissions between regulated and unregulated facilities increased at an annual rate of 19 percentage points. Following the introduction of the program, this trend slowed by 30 percentage points leading the gap in GHG emissions to fall at an annual rate of 11 percentage points between 2012-2017. For criteria air pollutants, columns 2-4 show a statistically significant, negative emissions trend break following the program's introduction for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>. For SO<sub>x</sub>, the trend break is negative but not statistically significant, suggesting that all subsequent SO<sub>x</sub> results should be interpreted with caution.

We predict C&T-driven emissions using estimates in Table 1 together with facility-level fixed effects. This generates heterogeneous facility-level C&T-driven abatement between 2012-2017, or  $\widehat{Y}_{j,2017}^p - \widehat{Y}_{j,2012}^p$  as defined in footnote 20, and shown in Figure S4 for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>. Averaged across sample regulated facilities, between 2012 and 2017, the C&T program reduced emissions annually at a rate of 9%, 5%, 4%, 3%, and 9% for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, respectively.<sup>29</sup> In total, sample regulated facilities reduced 3.2 million tons of CO<sub>2</sub>e between 2012-2017.<sup>30</sup>

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<sup>29</sup>This is calculated by averaging  $(\frac{\widehat{Y}_{j,2017}^p - \widehat{Y}_{j,2012}^p}{\widehat{Y}_{j,2012}^p})/5$ , as defined in footnote 20, across regulated sample facilities for each pollutant  $p$ .

<sup>30</sup>This amounts to an average abatement of 6,740 tons per facility per year during a period with permit prices between \$12-15 per ton. While this may be a surprising amount of abatement at such permit prices, Colmer et al. (2020) find that the EU-ETS lowered emissions by 28,830 tons per firm per year under a \$21 per ton price.

**Table 1:** Trend break in emissions

	Outcome is (asinh) emissions				
	(1) GHG	(2) PM <sub>2.5</sub>	(3) PM <sub>10</sub>	(4) NO <sub>x</sub>	(5) SO <sub>x</sub>
$\kappa_1^p$	0.187 (0.052) [0.001]	0.058 (0.043) [0.183]	0.083 (0.033) [0.016]	0.075 (0.039) [0.061]	0.006 (0.035) [0.875]
$\kappa_2^p$	-0.297 (0.077) [0.000]	-0.097 (0.048) [0.053]	-0.117 (0.039) [0.005]	-0.104 (0.050) [0.042]	-0.037 (0.043) [0.393]
$\kappa_1^p + \kappa_2^p$	-0.111 (0.036) [0.004]	-0.039 (0.018) [0.039]	-0.034 (0.018) [0.068]	-0.029 (0.019) [0.138]	-0.031 (0.019) [0.108]
Facilities	316	302	302	303	303
Counties	41	40	40	40	40
Observations	2,054	1,968	1,968	1,970	1,965

NOTES: Estimates of pre-C&T differential emissions trend (i.e.,  $\kappa_1^p$  from equation (1)) and post-C&T differential emissions trend break (i.e.,  $\kappa_2^p$  from equation (1)) for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> across columns. All models include facility-specific and year-specific dummy variables. Standard errors clustered at the county-level in parentheses, p-value in brackets.

**Robustness checks** We subject these emission effects to several robustness checks. First, Figure S5 considers placebo program start years, plotting  $\kappa_2^p$  for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> emissions from variants of equation (1) that impose alternative C&T start years across 2009-2016. Generally, we detect the strongest trend break coefficient when we assign the treatment year to its actual occurrence in 2013.

Table S2 considers several alternative specification and sample restriction choices. Table S1 shows that regulated and unregulated facilities are not perfectly balanced across sectors. To address concerns that differential trends across sectors may confound our estimates, column 1 of Table S2 replaces year fixed effects with sector-by-year fixed effects. Column 2 drops the handful of facilities whose treatment status switched only in 2017. Columns 3 and 4 change the 75th percentile average GHG emissions cutoff to the 70th and 80th percentiles.<sup>31</sup> None of these robustness checks produces estimates that differ meaningfully from our benchmark estimates in Table 1.

<sup>31</sup>The 70th and 80th percentiles for sample average annual GHG emissions corresponds to 48,834 and 82,173 tons of CO<sub>2</sub>e, respectively.

Our C&T-driven emissions which includes facility fixed effects, implicitly assumes more pollution abatement from facilities that emit more on average. To examine whether this assumption is reasonable, column 2 of Table S3 reports a variant of equation (1) that further includes an interaction between the trend break term and a linear function of facility-level average emissions. A positive interaction coefficient would imply that larger emitting facilities are abating less, contradicting our assumption. With the exception of GHG emissions for which the linear interaction term is positive but of very small magnitude, the coefficient on this interaction term for every criteria air pollution is negative. This specification confirms that large emitting facilities are indeed abating more in levels and that our benchmark model, which estimates an average trend break coefficient across facilities (regardless of size) is conservatively understating this dimension of emissions abatement heterogeneity. Column 3 of Table S3 shows that heterogeneity by average emissions does not exhibit nonlinearity, as indicated by statistically imprecise quadratic interaction terms.

Finally, there may be a Stable Unit Treatment Value Assumption (SUTVA) violation as pollution may shift from a regulated to unregulated facilities following the introduction of C&T. If so, the resulting increase in unregulated facility emissions may lead to more negative estimates of the trend break parameter  $\kappa_2^p$ . Following Fowlie, Holland and Mansur (2012), we consider two robustness checks in Table S4 to examine this possibility. In the first test, note that a facility located in a county under U.S. Clean Air Act nonattainment for a particular pollutant may be more constrained from increasing pollution levels. This idea is implemented in column 2, which restricts the sample of unregulated facilities to those located in nonattainment counties for that pollutant under the Clean Air Act.<sup>32</sup> Our second test notes that firms with multiple facilities can more readily reallocate pollution across their facilities. In column 3, we restrict the control group of unregulated facilities to those whose parent company only operates a single plant.<sup>33</sup> If treatment spillovers were present, the trend break coefficient  $\kappa_2^p$  should be of smaller magnitude in columns 2 and 3 than in our benchmark estimate, shown in column 1. This is not the case.

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<sup>32</sup>In Table S4, column 2 does not apply to GHG emissions because it is not a criteria pollutant regulated under the Clean Air Act. For  $\text{SO}_x$ , there are no counties in nonattainment during our sample period. For  $\text{NO}_x$ , because there were not enough counties under  $\text{NO}_2$  nonattainment to construct a control group, we follow Fowlie, Holland and Mansur (2012) by looking at nonattainment under Clean Air Act's one-hour ozone standard as  $\text{NO}_x$  is a precursor pollutant to ozone.

<sup>33</sup>We link each facility from CARB with its parent company as indicated by the EPA. We employ a fuzzy string matching algorithm as facility names are not standardized across the two datasets.

## 5.2 Cap-and-trade effects on EJ gaps

**Validating pollution dispersal modeling** We consider two sensibility checks for our measure of C&T-driven pollution concentrations via HYSPLIT before turning to our main EJ gap results. First, we examine whether HYSPLIT-generated criteria air pollution concentrations correlate with monitored ambient air pollution concentrations. Specifically, we match zip code-level HYSPLIT-generated pollution concentration averaged over 2008-2017 to the average ambient pollution concentration of that zip code as recorded by pollution monitors averaged over the same period, obtained from the U.S. Environmental Protection Agency.<sup>34</sup> We do not expect a perfect fit between these two variables as ambient pollution at any location is composed of emissions originating from many more sources (i.e., stationary and non-stationary, within and beyond California) than our subset of stationary sources regulated by California’s GHG C&T program. However, a positive correlation between the two pollution concentration measures would provide reassurance that HYSPLIT-generated pollution concentration from C&T regulated facilities is detected by ambient pollution monitors. The positive correlations shown in Table S5 indicate that is indeed the case.<sup>35</sup>

Next, we examine the EJ gap in 2008 driven by facilities that would eventually be regulated by the C&T program. Prior work documented strong baseline EJ gaps in California (Cushing et al., 2018). Indeed, this baseline EJ gap informed initial EJ concerns regarding California’s C&T program. Table S6 shows that steps 1 and 2 of our approach reproduces EJ gaps in 2008. Disadvantaged communities experienced higher levels of PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> concentrations in 2008 than other communities on average due to emissions from facilities that would eventually be regulated by the C&T program.

**Main results** We now turn to our main results examining the time evolution of EJ gaps between 2008-2017, shown in Table 2 and Figure 3. Across PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, the EJ gap widens during 2008-2012, the period prior to the C&T program, as indicated by the positive pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)). Following 2013, the EJ gap trend falls: the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)) is negative and statistically significant. This drop in the EJ gap trend is sufficiently large such that the EJ gap is actually narrowing following C&T, as indicated by the negative post-C&T EJ gap trend across pollutants (i.e.,  $\beta_1^p + \beta_2^p$ ). In percentage terms (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ), the EJ gap trend fell between 140-270% across pollutants after the program’s introduction. Figure 3

<sup>34</sup>Available here: [https://aqs.epa.gov/aqsweb/airdata/download\\_files.html](https://aqs.epa.gov/aqsweb/airdata/download_files.html)

<sup>35</sup>We are interested in modeling where C&T-driven pollution is dispersed. As such, we do not directly use ambient pollution data (either from ground-based monitoring stations or remotely-sensed satellites) in our analysis as it is often difficult to determine which component of any location’s ambient pollution originates from C&T-regulated facilities. Such “backwards” atmospheric modeling often yield indeterminate results.

**Table 2:** Trend break in the environmental justice gap

	(1) PM <sub>2.5</sub>	(2) PM <sub>10</sub>	(3) NO <sub>x</sub>	(4) SO <sub>x</sub>
$\beta_1^p$	0.042 (0.015) [0.006]	0.065 (0.017) [0.000]	0.085 (0.037) [0.026]	0.037 (0.025) [0.151]
$\beta_2^p$	-0.063 (0.022) [0.006]	-0.090 (0.029) [0.003]	-0.143 (0.074) [0.060]	-0.101 (0.051) [0.053]
$\beta_1^p + \beta_2^p$	-0.021 (0.015) [0.159]	-0.026 (0.020) [0.203]	-0.058 (0.050) [0.252]	-0.064 (0.027) [0.024]
$(\beta_2^p / \beta_1^p) * 100$	-149.699 (36.369) [0.000]	-139.739 (29.971) [0.000]	-168.282 (53.377) [0.002]	-272.291 (66.044) [0.000]
Zip codes	1649	1649	1649	1649
Counties	58	58	58	58
Observations	16,416	16,416	16,416	16,416

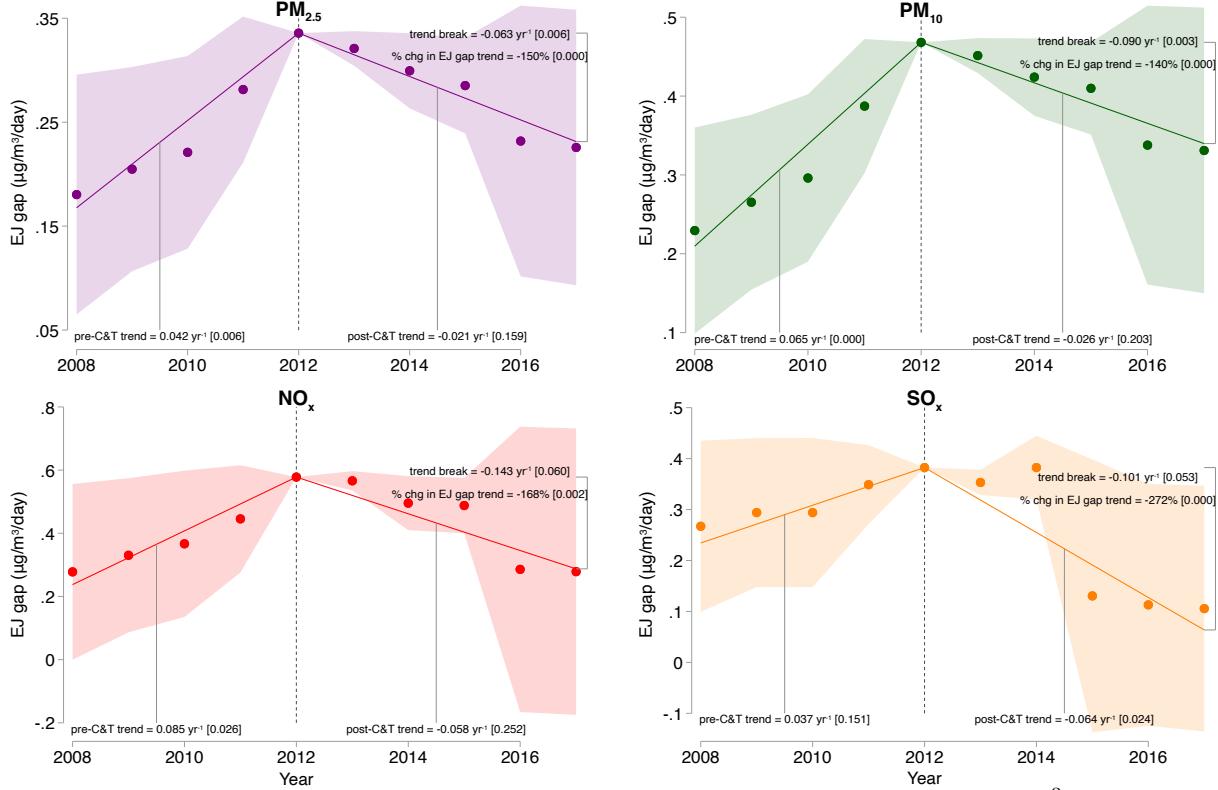
NOTES: Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), the post-C&T EJ gap trend (i.e.,  $\beta_1^p + \beta_2^p$ ), and the percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, across columns. All models include zip code-specific and year-specific dummy variables. Observations weighted by zip code-level average population during 2008-2012. Parentheses indicate standard errors that account for statistical uncertainty in C&T predicted emissions ( $\nu_{it}^p$  from equation (1) via the bootstrap procedure in Appendix A.1) and shown in Figure S6, and county-level heterogeneity in EJ gap effects of arbitrary form ( $\epsilon_{it}^p$  from equation (2)). P-value in brackets.

plots this trend break as well as annual EJ gap coefficients from a more flexible version of equation (1) using year-specific EJ gap coefficients.<sup>36</sup> Figure 3 also highlights that while the C&T program has led EJ gaps to narrow since 2012, it has not eliminated them. By 2017, EJ gaps are roughly at 2008 levels across pollutants.

<sup>36</sup>Specifically, the annual coefficients in Figure 3 are  $\beta_\tau^p$  from

$$E_{it}^p = \sum_{\substack{2008 \leq \tau \leq 2017 \\ \tau \neq 2012}} \beta_\tau^p [D_i \times \mathbf{1}(t = \tau)] + \psi_i^p + \delta_t^p + \epsilon_{it}^p$$

**Figure 3:** Environmental justice gap before and after the cap-and-trade program



NOTES: Panels show the estimated average daily pollution concentration gap (in  $\mu\text{g}/\text{m}^3/\text{day}$ ) between disadvantaged and other zip codes (i.e., “EJ gap”) during 2008–2017 for  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ ,  $\text{NO}_x$ , and  $\text{SO}_x$ , respectively. Dots show year-specific EJ gap. Solid lines show linear fit for EJ gap trend before (2008–2012) and after (2013–2017) the C&T program. Estimates centered at the 2008 EJ gap shown in Table S6. Associated text indicates point estimates and standard errors for the pre-C&T linear trend, post-C&T trend break, post-C&T linear trend, and the percentage change in the EJ gap trend (i.e.,  $\beta_1^p$ ,  $\beta_2^p$ ,  $\beta_1^p + \beta_2^p$ ,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ). 95% confidence interval and p-values (in brackets) account for statistical uncertainty in C&T predicted emissions ( $\nu_{it}^p$  from equation (1) via the bootstrap procedure in Appendix A.1) and shown in Figure S6, and county-level heterogeneity in EJ gap effects of arbitrary form ( $\epsilon_{it}^p$  from equation (2)). Trend break estimates also reported in Table 2.

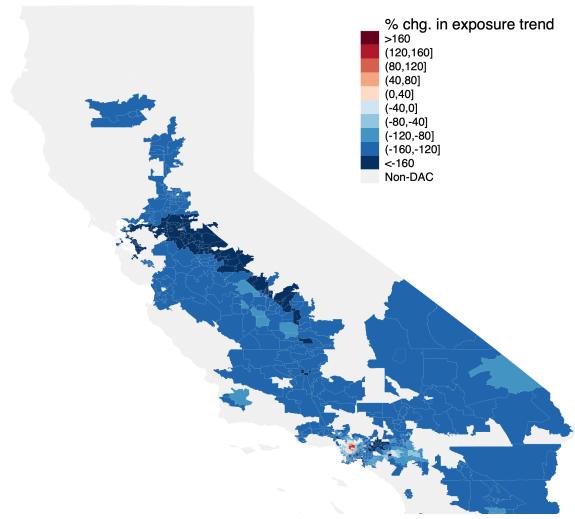
**Spatial heterogeneity** Estimates from equation (2) shown in Table 2 and Figure 3 examine the time evolution of EJ gaps averaged across disadvantaged and other zip codes. Additionally, one may be interested in how EJ gap effects vary spatially, particularly given the localized nature of EJ concerns. To examine spatial heterogeneity in trend break effects across disadvantaged zip codes, we estimate a variant of equation (2) allowing zip code-specific post-C&T EJ gap trend break coefficients.<sup>37</sup> Figure 4 shows the percentage change in the EJ gap trend following the introduction of C&T for each disadvantaged zip code for

<sup>37</sup>Specifically, we estimate the following variant of equation (2)

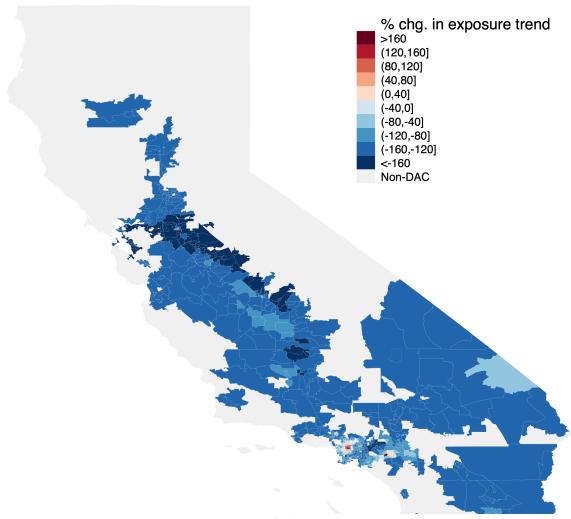
$$E_{it}^p = \beta_1^p[D_i \times t] + \sum_i \beta_{2i}^p[D_i \times \mathbf{1}(t \geq 2013) \times t] + \psi_i^p + \delta_t^p + \epsilon_{it}^p$$

**Figure 4:** Spatial heterogeneity in EJ gap effects

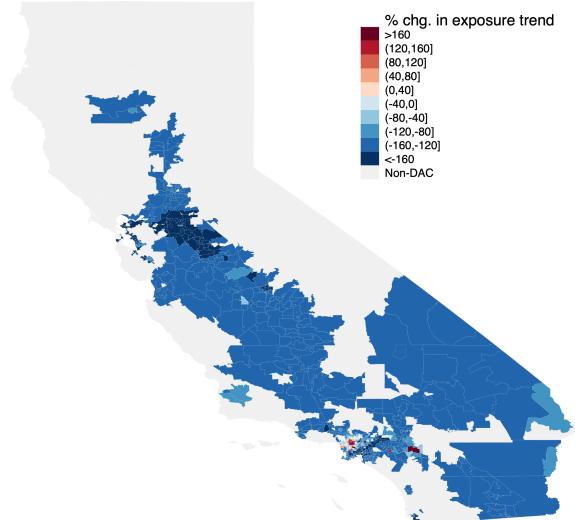
$\text{PM}_{2.5}$



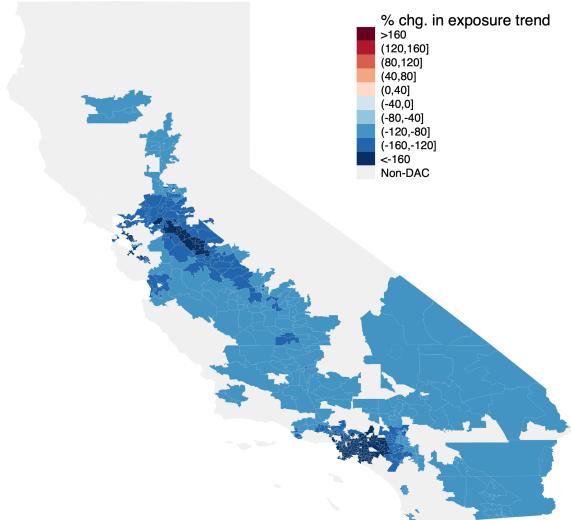
$\text{PM}_{10}$



$\text{NO}_x$



$\text{SO}_x$



NOTES: Panels maps the zip code-specific percentage change in the EJ gap trend following the introduction of the C&T program for disadvantaged zip codes across  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ ,  $\text{NO}_x$ , and  $\text{SO}_x$ . Blue (red) shading indicates reduced (increased) EJ gap trends following C&T for disadvantaged zip codes. Gray shading shows non-disadvantaged zip codes.

$\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ ,  $\text{NO}_x$ , and  $\text{SO}_x$ . Across pollutants, post-C&T EJ gaps narrowed the most for disadvantaged zip codes in California's Central Valley. For  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ , and  $\text{NO}_x$ , Figure 4 also shows a cluster of zip codes in Los Angeles County that experienced widening post-C&T EJ gaps. Figure S7 shows histograms for the distribution of percentage changes in EJ gap trends across disadvantaged zip codes.

where  $\beta_{2i}^p$  is the post-C&T trend break for zip code  $i$ . Figures 4 and S7 plot  $\frac{\beta_{2i}^p}{\beta_1^p} * 100$ , the percentage change in the EJ gap trend following the introduction of the C&T program for zip code  $i$  relative to the average pre-C&T EJ gap trend across disadvantaged zip codes.

**Robustness checks** We subject our EJ gap trend effects to several robustness checks. Most robustness checks forgo the bootstrap procedure across steps 1-3 (detailed in Appendix A.1) given the computational demands of that procedure. Instead, Figure 5 presents only point estimates of the percentage change in the EJ gap trend following C&T (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for each robustness check and compares that with the point estimate and 95% confidence interval of our benchmark result for which inference does account for statistical uncertainty from equation (1) via our bootstrap procedure.<sup>38</sup>

Within step 1, we conduct eight EJ gap robustness checks, drawing on C&T emissions effects shown in Tables S2-S4. Equation (1) models changes in the emissions difference between C&T regulated and non-regulated facility as linear trends. We find a similar result when we estimate a more flexible version of equation (1) with year-specific emission differences (M2 of Figure 5 and column 1 of Table S7); when we replace year fixed effects with sector-by-year fixed effects in equation (1) (M3 of Figure 5 and column 2 of Table S7); and when we drop facilities that switched regulatory status in 2017 (M4 of Figure 5 and column 3 of Table S7). Next, we consider restricting facilities to those with sample average annual GHG emissions below the 70th and 80th percentiles, respectively (M5-6 of Figure 5 and columns 4-5 of Table S7). These alternative facility sample restrictions do not alter EJ gap trend effects.

We further allow the post C&T emissions trend break to vary as a linear function of sample average emissions. Recall from the heterogeneous emissions effects shown in column 2 of Table S3 that large-emitting facilities are abating more than is assumed in our baseline model which assumes a common percentage emissions change. For PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>x</sub>, allowing for heterogeneity in emissions effects results in a slightly larger, though not statistically different, percentage change in the EJ gap trend (M7 of Figure 5 and column 6 of Table S7). That is, our baseline model without heterogeneous emissions effects is slightly understating the EJ gap fall as a consequence of C&T. For SO<sub>x</sub>, this dimension of heterogeneity implies much larger drops in the post-C&T EJ gap trend. Lastly, we examine EJ gap effects after restricting the set of unregulated C&T facilities to those in counties under Clean Air Act nonattainment and those whose parent company only operates a single facility (M8-9 of Figure 5 and columns 7 and 8 of Table S7). SUTVA concerns do not alter EJ gap trend effects.

We conduct five robustness checks within step 2. For sample facilities in some sectors, we are able to obtain monthly output data during our 2008-2017 sample period. For those facilities, we distribute C&T-driven annual emissions using the monthly share of annual out-

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<sup>38</sup>Coefficients  $\beta_1^p$  and  $\beta_2^p$  in accompanying Tables S7 and S8 cluster standard errors  $\epsilon_{it}^p$  from equation (2) at the county-level but are not adjusted for statistical uncertainty in equation (1).

put when feeding emissions into HYSPLIT and show that accounting for monthly variability in these sectors does not alter EJ gap results (M10 of Figure 5 and column 1 Table S8). We use pollution half-life parameters taken from the atmospheric chemistry literature because HYSPLIT does not model pollution decay over time. Our results are relatively stable to whether we allow for a 10% larger half-life parameter which implies a slower decay rate (M11 of Figure 5 and column 2 Table S8) or a 10% smaller half-life parameter which implies a faster decay rate (M12 of Figure 5 and column 3 of Table S8). Likewise our results are little affected when we lower the height of the planetary boundary layer to 0.5 km (M13 of Figure 5 and column 4 Table S8) or raise it to 2 km (M14 of Figure 5 and column 5 Table S8).

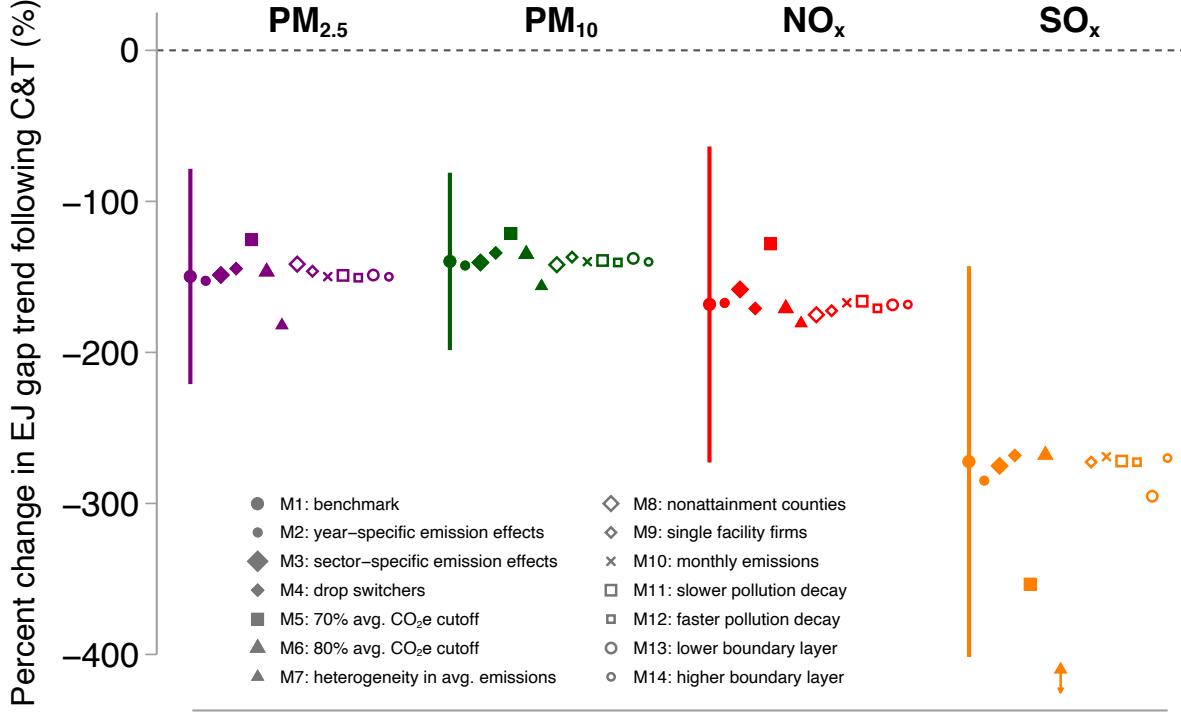
We also conduct multiple robustness checks within step 3. The first set of checks consider alternative error structures for  $\epsilon_{it}^p$ . We find that precision increases when we allow  $\epsilon_{it}^p$  to be spatially correlated within a uniform kernel across a distance of 500 km distance (Conley, 1999), roughly the longitudinal width of California, and serially correlated across 5 years (Newey and West, 1987) (column 6 of Table S8). Likewise, precision increases when we allow for error terms to be correlated across the four local pollutants using a Seemingly Unrelated Regression (SUR) procedure (column 7 of Table S8).

Equation (2) examines the EJ gap in daily pollution levels of  $\mu\text{g}/\text{m}^3/\text{day}$ , the concentration unit typically used for air pollution policy and by the public health literature. In Table S9, we detect a post-C&T EJ gap trend break after applying an inverse hyperbolic sine transformation to our outcome variable, showing C&T-driven concentrations in disadvantaged communities decreased as a percentage of concentration in other communities after 2013. Standard errors reported in Table S9 are adjusted for statistical uncertainty from equation (1) using our bootstrap procedure.

In Table S10, we employ CARB's CalEnviroScreen v3.0, an updated designation for disadvantaged communities at the census tract-level, the finest spatial scale for which California defines disadvantaged status. A census tract better captures local variation in socio-economic characteristics that underlie EJ concerns. However, this and all census tract-level versions of the CalEnviroScreen present endogeneity concerns as some underlying indicators were observed after the start of the C&T program and thus may itself be affected by C&T. Table S10 shows similar EJ gap effects across criteria pollutants when conducting census tract-level analysis using CalEnviroScreen v3.0 as compared with our benchmark zip code-level analysis.

The socioeconomic indicators used to construct CalEnviroScreen does not include an explicit measure of racial and/or ethnic composition, though many included indicators are correlated with racial and/or ethnic composition. In Table S11, we replace our CalEnviroScreen-based indicator for a disadvantaged community with a dummy for whether a zip code's av-

**Figure 5:** Robustness checks for EJ gap effects



NOTES: Percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^P}{\beta_1^P} * 100$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> across robustness checks. M1: benchmark model point estimate and 95% confidence interval accounting for uncertainty in equations (1) and (2). Point estimate shown for all other models. M2: using year-specific effects to estimate C&T-driven emissions. M3: C&T-driven emissions effects estimated using sector-by-year fixed effects. M4: C&T-driven emissions effects estimated without facilities that switched status in 2017. M5: restricting sample to facilities with average annual GHG emissions below the 70th percentile. M6: restricting sample to facilities with average annual GHG emissions below the 80th percentile. M7: allowing heterogeneous emissions effects by average annual emissions. M8: restricting unregulated facilities to those in counties under Clean Air Act nonattainment. M9: restricting unregulated facilities to those whose parent company only operates a single plant. M10: distributes annual C&T-driven emissions by monthly output. M11: applying a slower pollution decay (i.e., 10% larger half-life parameter). M12: applying a faster pollution decay (i.e., 10% smaller half-life parameter). M13: applying a planetary boundary layer set at 0.5 km. M14: applying planetary boundary layer set at 2 km. Point estimates also reported in Tables S7-S8.

verage 2008-2012 minority share of population according to the U.S. Census (defined as the sum of Black and Hispanic share of population) is above the median value across California zip codes. We find similar EJ gap effects when using this alternative definition of a disadvantaged community.

In our benchmark sample, we exclude electricity generators and refineries from our sample because the presence of overlapping climate programs applied to those facilities imply that their emission abatement are likely driven by these programs and not by the carbon

market. We also excluded facilities with sample average annual GHG emissions above the 75th percentile to ensure comparability between treated and control facilities. Table S12 shows EJ gap effects when we add these facilities into our sample. Their inclusion does not qualitatively change our main findings.

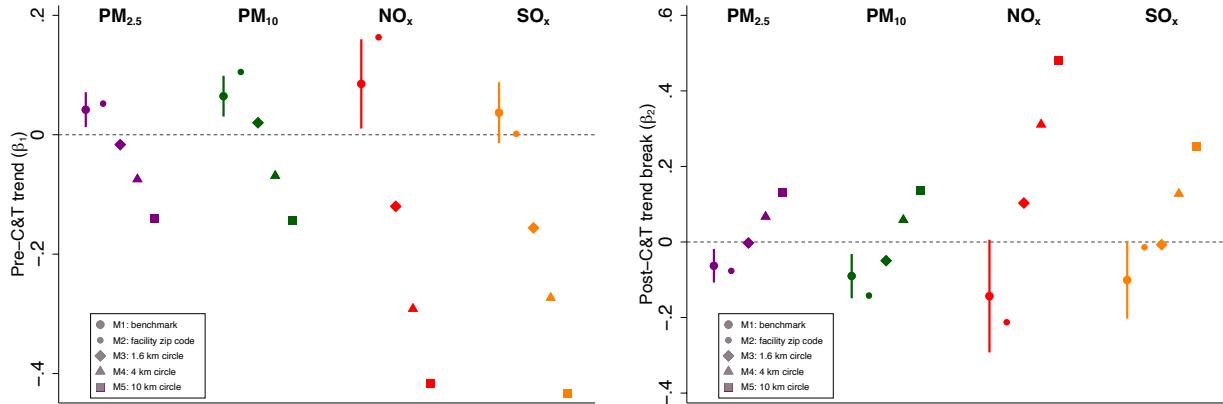
Finally, to examine the potential role of secondary PM<sub>2.5</sub>, we replace HYSPLIT in step 2 of our procedure with InMAP, a reduced-complexity dispersal model based on output from WRF-Chem, which incorporates atmospheric chemistry in order to model total (i.e., primary and secondary) PM<sub>2.5</sub> concentrations from C&T-driven facility-level PM<sub>2.5</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, emissions (Tessum, Hill and Marshall, 2017).<sup>39</sup> InMAP, however, has one major limitation: unlike HYSPLIT which employs real-time meteorological conditions during our 2008-2017 sample period, InMap only models dispersal patterns in 2005. Because InMAP does not model dispersal patterns during our sample period, we are unable to directly compare estimates using InMAP-generated concentrations with that using HYSPLIT-generated concentrations. Furthermore, there is a difference in units between HYSPLIT and InMap. For any given location, HYSPLIT produces the stock of pollution concentration during a given period, whereas InMAP produces that period's average flow of pollution concentration. Instead, we examine the role of secondary PM<sub>2.5</sub> by comparing how EJ gap trend estimates differ between InMAP-generated primary PM<sub>2.5</sub> concentration and InMAP-generated total PM<sub>2.5</sub> concentrations. If these two InMap estimates are similar, it is plausible that the true EJ gap effect for secondary PM<sub>2.5</sub> is similar to effects using HYSPLIT-generated primary PM<sub>2.5</sub> concentrations. Table S13 replicates the structure of Table 2. Column 1 examines InMAP-generated primary PM<sub>2.5</sub> concentrations while column 2 examines InMAP-generated total PM<sub>2.5</sub> concentrations. Both show similar EJ gap effects.

**Importance of modeling pollution dispersal** Our empirical approach explicitly embeds an atmospheric dispersal model within a causal inference framework. Compared with conventional methods for assigning pollution concentration from emission sources, this approach lends two benefits. It accounts for actual pollution dispersal patterns as dictated by topography and time-varying meteorological conditions. It also determines resulting pollution concentrations across all locations in California, rather than a subset of locations assumed to be exposed to policy-driven emissions. To demonstrate the importance of accounting for pollution dispersal for our results, we compare estimates from using our approach with that of more conventional methods of assigning pollution concentrations from emission

<sup>39</sup>In addition to the inputs used in HYSPLIT, InMap requires the diameter, temperature, and emissions velocity for each smokestack. We obtain these inputs from CARB. In the case of facilities with more than one stack, we use the mean value across stacks. In the case of facilities with missing observations, we use the industry-level average.

sources.

**Figure 6:** Importance of modeling pollution dispersal



NOTES: Left panel shows estimates of pre-C&T trend (i.e.,  $\beta_1^p$ ) and right panel shows estimates of post-C&T trend break (i.e.,  $\beta_2^p$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> across different methods for assigning pollution concentrations from emissions. M1: benchmark model with point estimate and 95% confidence interval accounting for uncertainty in equations (1) and (2). Point estimate shown for all other models. M2: pollution concentration assigned only to zip code of emitting facility. M3-5: pollution concentration assigned to zip codes with centroid within 1.6 km, 4 km and 10 km circle of emitting facility, respectively. Point estimates also reported in Table S14.

Figure 6 plots estimates of the pre-C&T trend, or  $\beta_p^1$  (left panel), and the post-C&T trend break, or  $\beta_p^2$  (right panel), across criteria pollutants under different assumptions about how facility-level emissions alter location-specific concentrations.<sup>40</sup> In M1, we show our benchmark estimate where pollution dispersal is modeled by HYSPLIT. In M2 (and column 1 of Table S14), we assume that the area affected by a facility's emissions is limited to the zip code of that facility, referred to in the literature as “unit-hazard coincidence” (Banzhaf, Ma and Timmins, 2019). In M3-5 (and columns 2-4 of Table S14), we employ a distance-based measure by assuming that the area affected by a facility's emissions is limited to zip codes with centroids that are within 1.6, 4, and 10 km circles around the facility. These radial distances appear in the literature but nonetheless are chosen largely arbitrarily. Point estimates of  $\beta_p^1$  and  $\beta_p^2$  vary greatly across these alternative methods for assigning pollution concentrations. Not only do some estimates fall well outside the 95% confidence intervals of our benchmark results, but they also have different signs.

<sup>40</sup>Unlike Figure 5, Figure 6 does not plot  $\frac{\beta_2^p}{\beta_1^p} * 100$  because  $\beta_1^p$  and  $\beta_2^p$  do not have consistent sign across the different methods for assigning emissions to concentrations.

## 6 Discussion

Many market settings are characterized by efficiency-equity tradeoffs. We find that disparities in local air pollution concentrations from facilities subject only to California's carbon market fell following its introduction. This result brings causal evidence to a debate that continues to shape one of the world's most ambitious climate policies and climate policies elsewhere. Moreover, the integration of pollution dispersal modeling and causal inference employed in this paper may have broader applications across a variety of environmental policy settings.

Equity concerns regarding California's cap-and-trade program remain. First, while we show that the program has led the pollution concentration gap between disadvantaged and other communities from sample facilities to fall, this gap has not been eliminated five years into the program. Second, pollution concentration constitutes only one component of the many distributional concerns regarding the program. Questions remain over how the program may have altered the distribution of health outcomes as well as the distribution of the program's cost burden, including changes in energy prices and wages. A comprehensive understanding of welfare inequality must also account for other pollutants such as toxins (Sheriff, 2022), sorting as households move in response to changes in pollution concentrations (Depro, Timmins and O'Neil, 2015; Banzhaf, Ma and Timmins, 2019) and entry decisions by polluters (Weber, 2020). Third, a broader notion of equity must also consider the ability of disadvantaged communities to partake in decision-making around environmental policies. Such procedural justice issues remain in California though recent policies such as AB 617 are beginning to engage disadvantaged communities directly in the design of local pollution regulations (Fowlie, Walker and Wooley, 2020).

More generally, despite these findings for California, market-based environmental policies should not be used explicitly to address environmental justice concerns. Market-based policies are intended for allocative efficiency and not distributional objectives, *per se*. The EJ gap consequences detected in California emerges from the state's spatial distribution of polluting facilities and demographic characteristics. In other settings where facilities with steeper marginal abatement cost curves may be upwind of disadvantaged communities, an environmental market could widen the environmental justice gap. Difficulties with observing facility-level marginal abatement cost curves make it hard to anticipate ex-ante how proposed market-based policies will alter existing EJ gaps. As a safeguard against potential widening EJ gaps, policies that specifically address environmental justice concerns should be considered in tandem with market-based policies. In short, environmental justice problems need environmental justice policies.

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# A Appendix

## A.1 Bootstrap procedure for incorporating uncertainty in C&T emission effects

This section details our bootstrap procedure over steps 1-3 to account for statistical uncertainty in C&T-driven emission effects from equation (1), reproduced here:

$$\text{asinh}(Y_{jt}^p) = \kappa_1^p[C_j \times t] + \kappa_2^p[C_j \times \mathbf{1}(t \geq 2013) \times t] + \phi_j^p + \gamma_t^p + \nu_{jt}^p$$

We obtain point estimates  $\widehat{\kappa}_1^p$ ,  $\widehat{\kappa}_2^p$  and standard errors  $\widehat{\sigma}_{\kappa_1^p}$  and  $\widehat{\sigma}_{\kappa_2^p}$  from equation (1). We then iterate the following procedure for draws  $b = 1\dots 250$ :

1. Draw  $\widehat{\kappa}_1^p(b) \sim N(\widehat{\kappa}_1^p, \widehat{\sigma}_{\kappa_1^p})$  and  $\widehat{\kappa}_2^p(b) \sim N(\widehat{\kappa}_2^p, \widehat{\sigma}_{\kappa_2^p})$
2. Construct  $\widehat{Y}_{jt}^p(b) = \sinh \left( \widehat{\kappa}_1^p(b)[C_j \times t] + \widehat{\kappa}_2^p(b)[C_j \times \mathbf{1}(t \geq 2013) \times t] + \widehat{\phi}_j^p \right) * e^{(\text{RMSE})^2/2}$ , where RMSE is the root mean squared error from equation (1)
3. Feed  $\widehat{Y}_{jt}^p(b)$  into HYSPLIT to generate zip code-by-year pollution concentration,  $E_{it}^p(b)$
4. Estimate equation (2) using  $E_{it}^p(b)$  as the outcome variable to obtain  $\widehat{\beta}_1^p(b)$  and  $\widehat{\beta}_2^p(b)$

Figure S6 plots the empirical distributions for  $\widehat{\beta}_1^p(b)$  and  $\widehat{\beta}_2^p(b)$  for  $p \in \{PM_{2.5}, PM_{10}, NO_x, SO_x\}$ . Denote standard errors across 250 bootstrap runs as  $\widehat{\sigma}_{\beta_1^p}(\nu_{jt}^p)$  and  $\widehat{\sigma}_{\beta_2^p}(\nu_{jt}^p)$  where the  $\nu_{jt}^p$  argument indicates the dependence on statistical uncertainty from equation (1). Denote  $\widehat{\sigma}_{\beta_1^p}(\epsilon_{jt}^p)$  as the estimated standard error arising from heterogeneity in  $\beta_1^p$  obtained by directly estimating equation (2) with county-level clustered errors. Our reported standard error for  $\beta_1^p$  is  $\widehat{\sigma}_{\beta_1^p} = \widehat{\sigma}_{\beta_1^p}(\epsilon_{jt}^p) + \widehat{\sigma}_{\beta_1^p}(\nu_{jt}^p)$ . Likewise, for  $\beta_2^p$ .  $\widehat{\sigma}_{\beta_1^p}$  and  $\widehat{\sigma}_{\beta_2^p}$  are reported in Table 2 and used to construct the confidence intervals displayed in Figure 3.

## A.2 Can the EJ gap effect be recovered using only dispersal-augmented facility-level regressions?

In Section 4, we detailed a multi-step procedure to estimate the change in the EJ gap as a consequence of the the C&T policy. In this section we discuss how our procedure differs from an alternative approach found in the literature.

### A.2.1 Estimand

We begin by first formalizing our estimand. Let  $j$  index polluting facilities. The (heterogeneous) change in emissions due to C&T is  $\Delta Y_j$  for regulated facility  $j$ , with regula-

tion status denoted by  $C_j = 1$  and  $C_j = 0$  otherwise. Locations are indexed by  $i$ , with  $D_i = 1$  indicating if location  $i$  is a disadvantaged community and  $D_i = 0$  otherwise. For simplicity, we assume the same number of disadvantaged and non-disadvantaged locations,  $N = \sum_{i:D_i=1} D_i = \sum_{i:D_i=0} (1 - D_i)$  and that population is constant across locations. Let  $\mathbf{W}$  be the source-receptor matrix obtained by the atmospheric dispersal model, with element  $w_{ji} = 1$  if emissions from facility  $j$  disperses to location  $i$  and  $w_{ji} = 0$  otherwise.<sup>41</sup>

The EJ gap effect, our estimand, is the difference in the average change in pollution concentration between disadvantaged and other communities due to C&T-driven emission changes from regulated facilities. Formally, this is

$$\begin{aligned}\theta &= \underbrace{\frac{1}{N} \sum_{i:D_i=1} \sum_{j:C_j=1} \Delta Y_j w_{ji}}_{\text{avg. DAC concentration from C\&T-driven emissions}} - \underbrace{\frac{1}{N} \sum_{i:D_i=0} \sum_{j:C_j=1} \Delta Y_j w_{ji}}_{\text{avg. non-DAC concentration from C\&T-driven emissions}} \\ &= \frac{1}{N} \sum_{j:C_j=1} \Delta Y_j \left( \sum_{i:D_i=1} w_{ji} \right) - \frac{1}{N} \sum_{j:C_j=1} \Delta Y_j \left( \sum_{i:D_i=0} w_{ji} \right) \\ &= \frac{1}{N} \sum_{j:C_j=1} \Delta Y_j \left( \sum_{i:D_i=1} w_{ji} - \sum_{i:D_i=0} w_{ji} \right)\end{aligned}\tag{A.1}$$

Note that our procedure in Section 4 is designed to recover  $\theta$ : equation (1) estimates  $\widehat{\Delta Y}_j$ , the pollution dispersal model provides the source-receptor matrix  $\mathbf{W}$ , and equation (2) takes these inputs to obtain the estimate  $\widehat{\theta}$ .

### A.2.2 Alternative approach: dispersal-augmented facility-level regressions

Previous studies argue that  $\theta$  can be estimated with only a facility-level analysis, augmented with information from the dispersal model. This approach typically examines how a facility's emission effect from the policy varies with the share of its downwind locations that are disadvantaged, as provided by the dispersal model (Grainger and Ruangmas, 2018; Mansur and Sheriff, 2019). Specifically, this approach estimates

$$\Delta Y_j = \phi_0 C_j + \phi_1 C_j s_j + \phi_2 s_j + \varepsilon_j\tag{A.2}$$

where  $s_j = N_j^D / (N_j^D + N_j^O)$  is the share of affected downwind locations that is disadvantaged, with  $N_j^D = \sum_{i:D_i=1} w_{ji}$  and  $N_j^O = \sum_{i:D_i=0} w_{ji}$  being the total number of disadvantaged and

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<sup>41</sup>We assume  $w_{ji}$  to be dichotomous in order to match the literature's definition of the share of affected locations that are disadvantaged, or  $s_j$  below. In our actual implementation, we apply spatial decay rates to pollution dispersal patterns which allows  $w_{ji}$  to vary continuously within the unit interval.

other locations affected by facility  $j$ , respectively. The coefficient of interest is typically  $\widehat{\phi}_1$ , the additional emissions effect for facilities that disproportionately affect disadvantaged locations.

Unfortunately,  $\widehat{\phi}_1$  is not generally informative of  $\theta$ . First, it may be that equation (A.2) is misspecified in the sense that  $s_j$  is not the relevant dimension of heterogeneity for  $\Delta Y_j$ . In that case, estimates from equation (A.2) cannot be inserted into equation (A.1). Even when  $s_j$  is the relevant dimension of heterogeneity, recovery of  $\theta$  may still not be possible. To see why, note that when  $s_j$  is the relevant dimension of heterogeneity, we have  $\widehat{\Delta Y}_j = \widehat{\phi}_0 + \widehat{\phi}_1 s_j$ . Inserting into equation (A.1) yields

$$\widehat{\theta} = \frac{1}{N} \sum_{j:C_j=1} (\widehat{\phi}_0 + \widehat{\phi}_1 s_j)(2s_j - 1)(N_j^D + N_j^O) \quad (\text{A.3})$$

showing that  $\widehat{\phi}_1$  in general does not equal  $\widehat{\theta}$ .<sup>42</sup>

But are  $\widehat{\theta}$  and  $\widehat{\phi}_1$  systematically related? Consider first whether  $\widehat{\theta}$  and  $\widehat{\phi}_1$  move in the same direction. The derivative of  $\widehat{\theta}$  with respect to  $\widehat{\phi}_1$  is

$$\frac{d\widehat{\theta}}{d\widehat{\phi}_1} = \frac{1}{N} \sum_{j:C_j=1} \underbrace{(2s_j - 1)}_{\geq 0} \underbrace{s_j(N_j^D + N_j^O)}_{\geq 0} \gtrless 0$$

which shows no systematic correlation. Next, consider whether  $\widehat{\phi}_1$  and  $\widehat{\theta}$  consistently have the same sign. We can reject this with the following example. Assume  $\widehat{\phi}_0 = 0$  and the normalization  $N_j^D + N_j^O = N \forall j$ . Next, suppose  $s_1 = 1$  for the first facility and  $s_{j>1} < 0.5$  for all other facilities. Equation (A.3) becomes

$$\widehat{\theta} = \widehat{\phi}_1 \underbrace{\left( 1 + \sum_{j>1} s_j(2s_j - 1) \right)}_{\leq 0}$$

indicating that  $\widehat{\theta}$  and  $\widehat{\phi}_1$  can be of different signs. This implies that simply showing emissions are relatively higher for facilities that disproportionately affect disadvantaged communities (i.e.,  $\widehat{\phi}_1 > 0$ ) does not necessarily conclude that the EJ gap has widened (i.e.,  $\widehat{\theta} > 0$ ).

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<sup>42</sup>Observe also that having  $\widehat{\phi}_0$ ,  $\widehat{\phi}_1$ , and  $s_j$  does not recover  $\widehat{\theta}$ . One also needs either  $N_j^D$  or  $N_j^O$ , which is typically missing from equation (A.2).

### A.2.3 Source of bias

Why do  $\hat{\theta}$  and  $\hat{\phi}_1$  differ? The issue is that a facility-level analysis does not account for the full complexity of pollution dispersal patterns. In particular, it overlooks the possibility that each facility can alter pollution concentrations in both disadvantaged and other locations. Equation (A.2) may recognize, for example, that emissions from facilities in Los Angeles and San Francisco affect air quality in both disadvantaged and other receptor locations, but it does not undergo the additional exercise of tallying up pollution from Los Angeles and San Francisco at each receptor location.

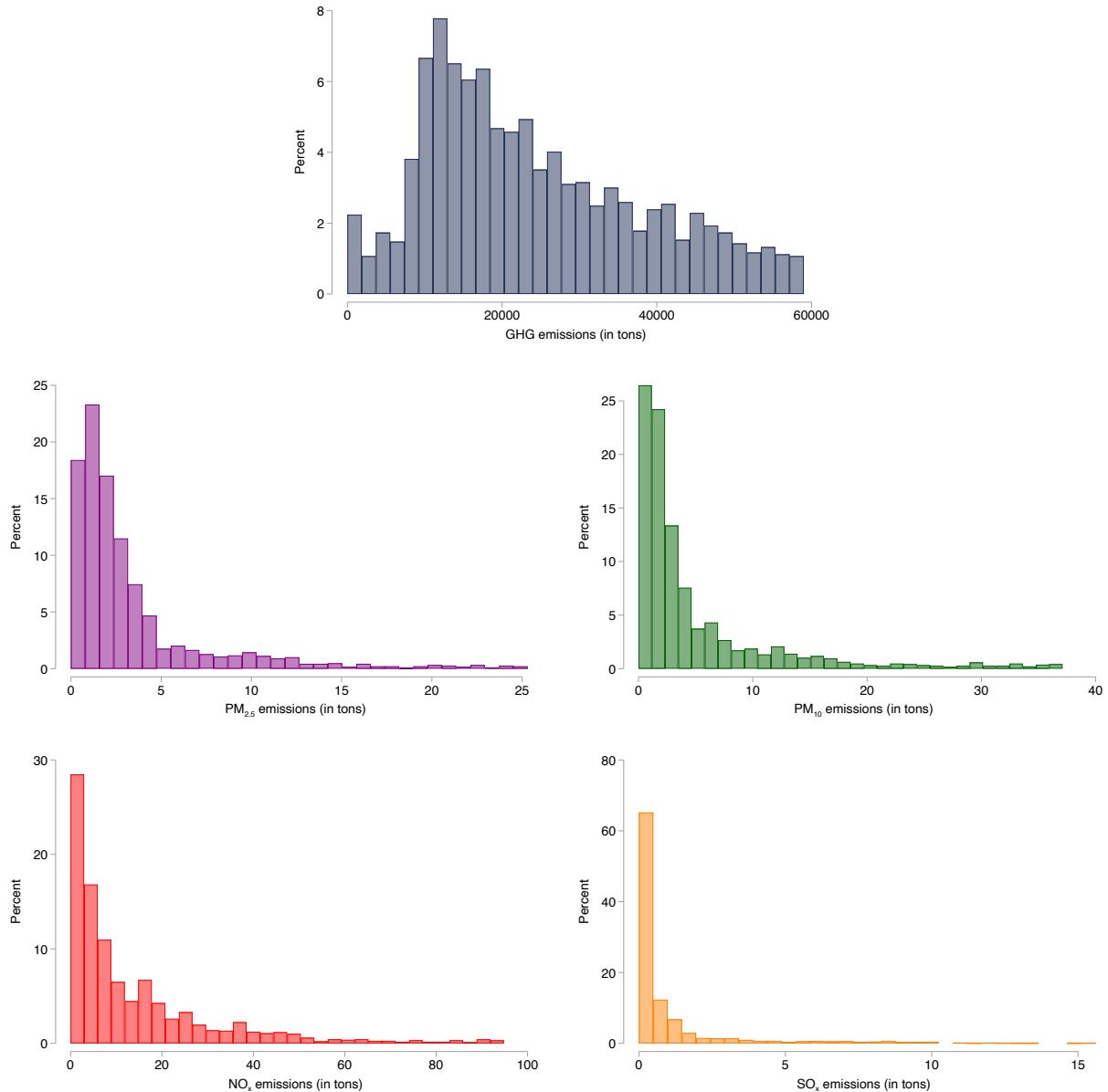
To see this formally, we show that  $\hat{\phi}_1$  can equal  $\hat{\theta}$  if one assumes pollution from each facility *only* affects one type of location. Let  $J$  facilities only affect disadvantaged communities (i.e.,  $s_j = 0$ ) and another  $J$  facilities only affect non-disadvantaged communities (i.e.,  $s_j = 1$ ). Further imposing the normalization  $(N_j^D + N_j^O) = \frac{N}{J} \forall j$ , we have

$$\begin{aligned}\theta &= \frac{1}{N} \left( \sum_{j:C_j=1,s_j=0} -\hat{\phi}_0(N_j^D + N_j^O) + \sum_{j:C_j=1,s_j=1} (\hat{\phi}_0 + \hat{\phi}_1)(N_j^D + N_j^O) \right) \\ &= \frac{N}{NJ} (-J\hat{\phi}_0 + J\hat{\phi}_0 + J\hat{\phi}_1) \\ &= \hat{\phi}_1\end{aligned}$$

Observe the restrictions on pollution dispersal considered here: facilities can *only* affect disadvantaged communities or *only* affect non-disadvantaged communities, that is  $s_j \in \{0, 1\} \forall j$ . Facilities cannot alter pollution concentrations in both types of locations. Our California setting violates this assumption. For each sample C&T regulated facility-year observation, we calculate the share of downwind affected locations containing disadvantaged communities. Figure S3 shows that this share is always within the unit interval. That is, emissions from sample C&T regulated facilities always alter pollution concentrations in both disadvantaged and non-disadvantaged communities. Recovery of  $\theta$  therefore requires the extra step of converting facility-level emissions changes onto location-level concentration changes, as is done with our approach, detailed in Section 4.

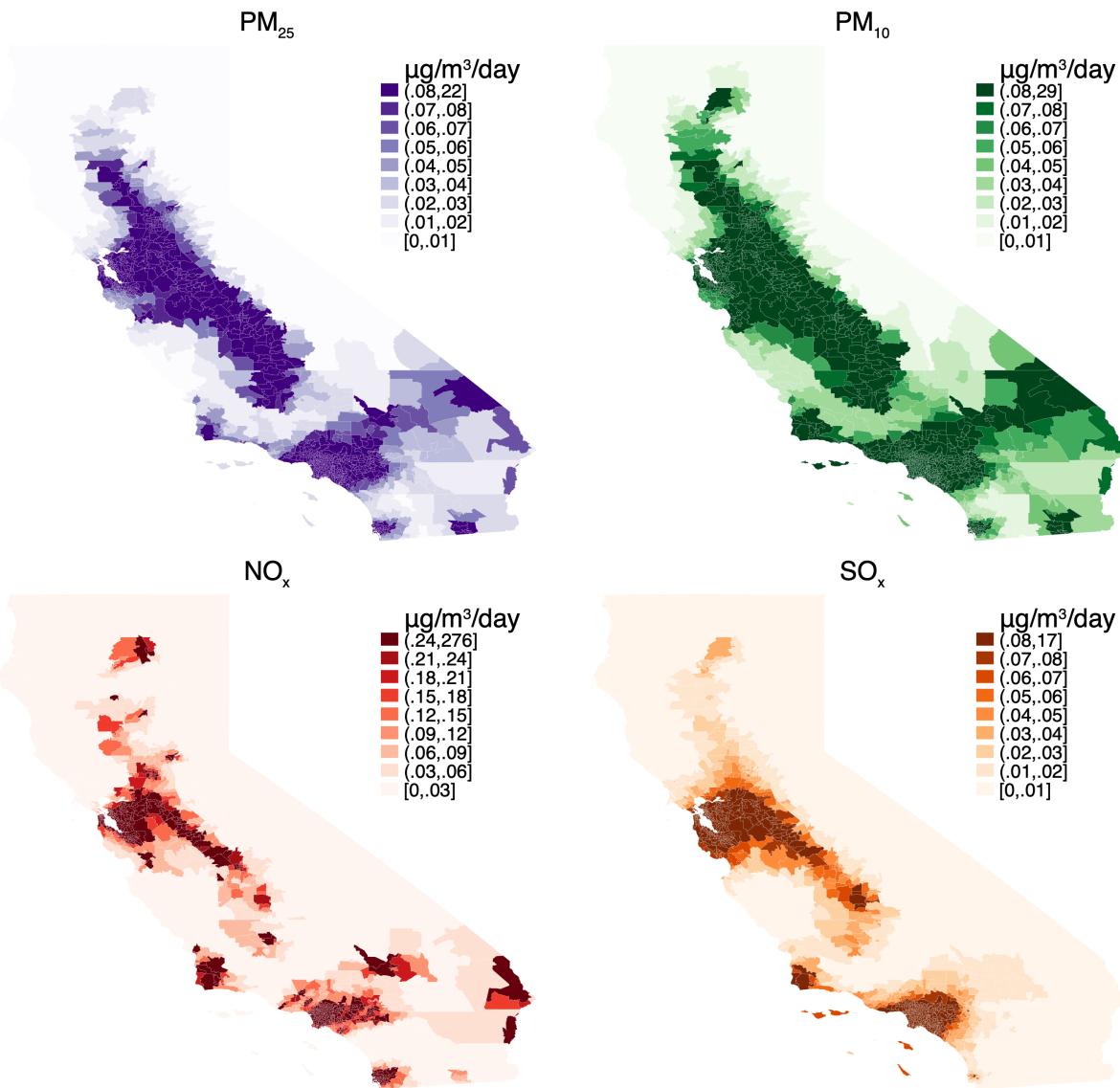
## Appendix Figures

**Figure S1:** Distribution of sample facility-year emissions



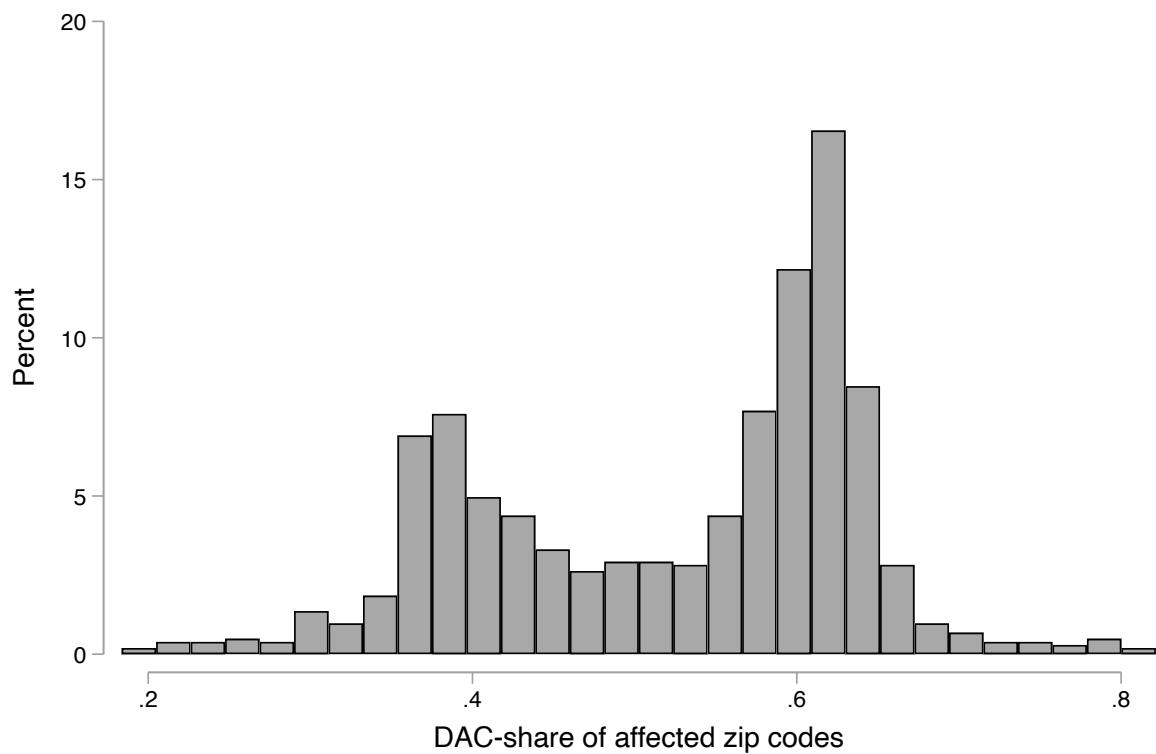
NOTES: Panels show the distribution of facility-year GHG,  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ ,  $\text{NO}_x$ , and  $\text{SO}_x$  emissions for sample observations. Observations above the 95th percentile are truncated.

**Figure S2:** Average pollution concentrations driven by C&T regulated facilities



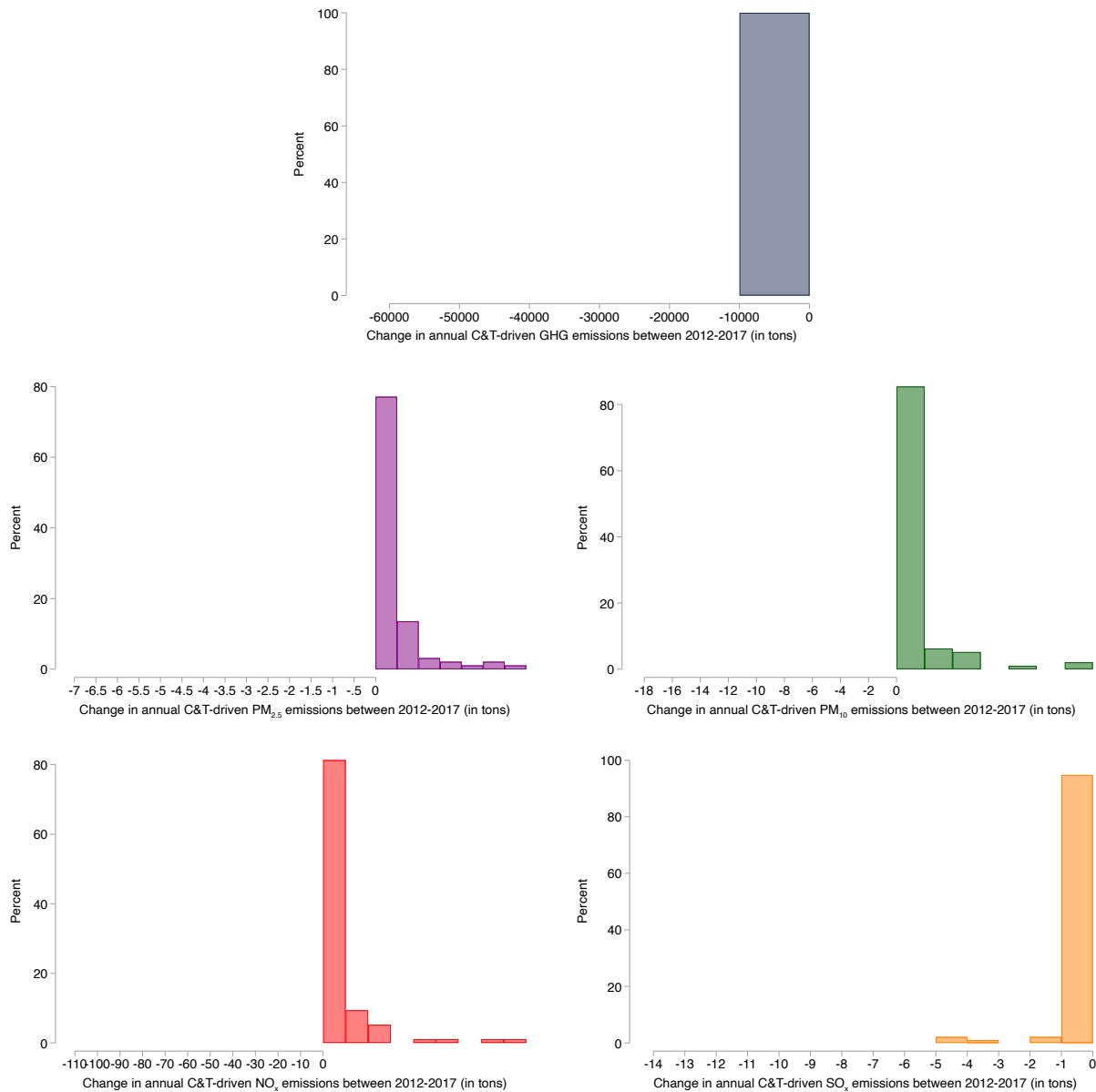
NOTES: Panels show daily concentrations (in  $\mu\text{g}/\text{m}^3/\text{day}$ ) for each zip code averaged across 2008-2017 from GHG C&T-regulated facilities as modeled in step 2 by HYSPLIT for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, respectively.

**Figure S3:** Share of zip codes affected by sample regulated facilities that contains DACs



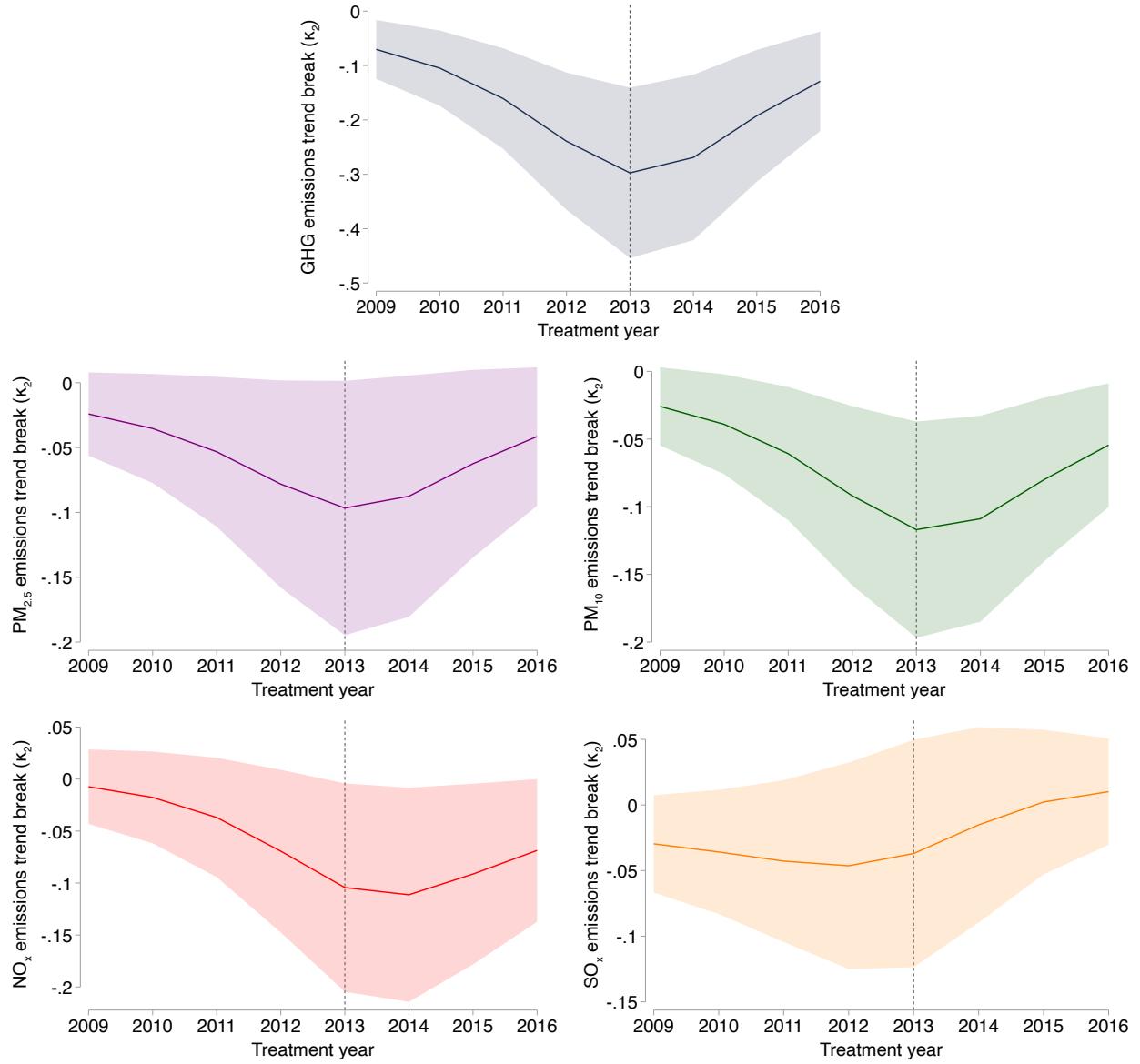
NOTES: Figure plots the distribution of the share of downwind affected zip codes that is designated as DAC across sample C&T regulated facility-year observations.

**Figure S4:** Facility-level C&T-driven abatement between 2012-2017



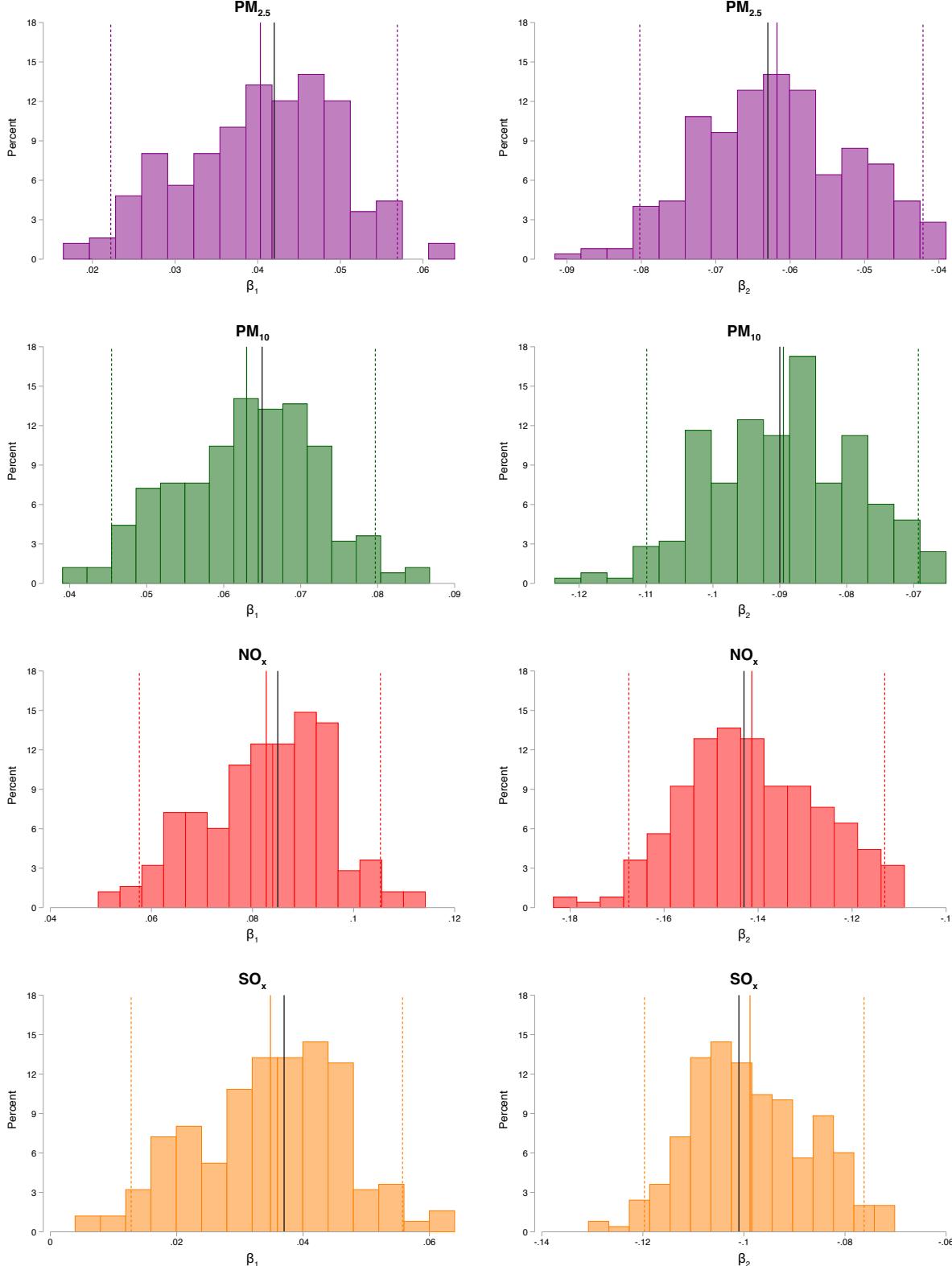
NOTES: Panels show the distribution of facility-level change in C&T-driven pollution between 2012-2017 (or abatement) predicted from step 1 for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> emissions, respectively.

**Figure S5:** Emissions robustness: placebo C&T program timing



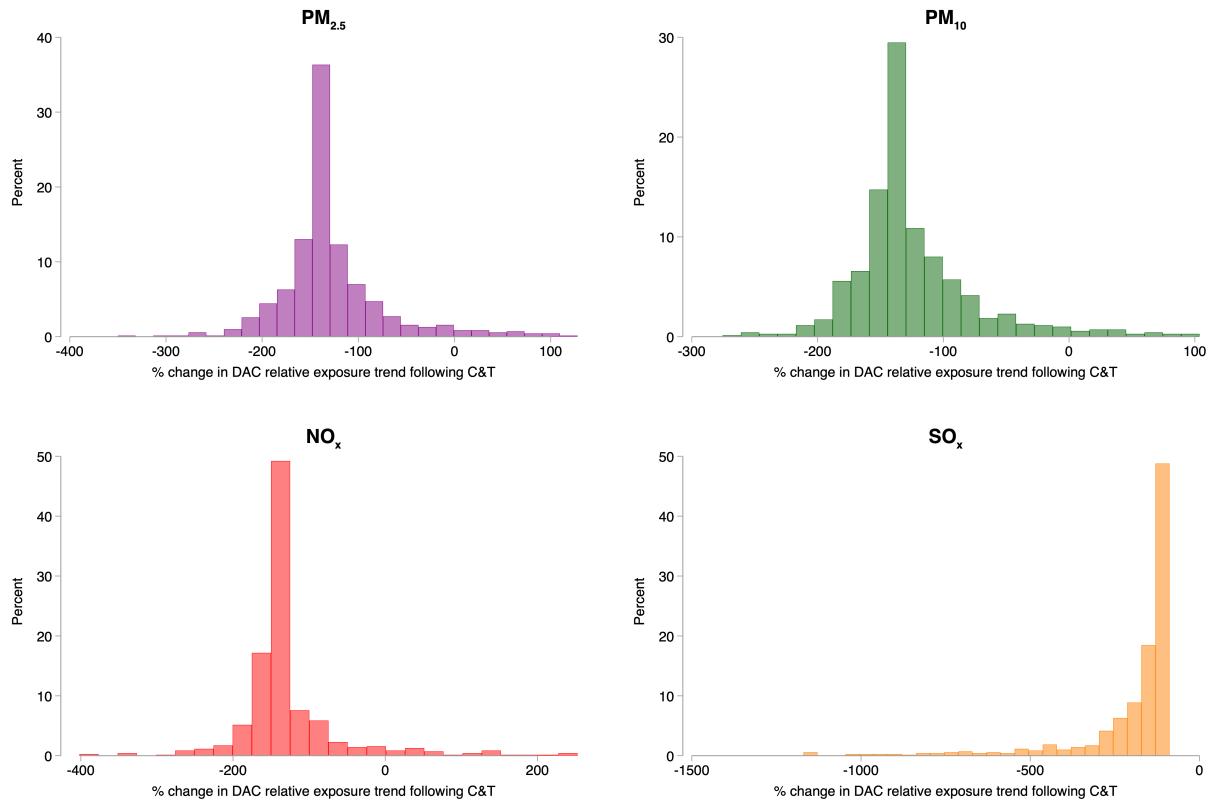
NOTES: Panels show estimated (true and placebo) emissions trend break coefficients (i.e.,  $\kappa_2$  from eq. (1)) for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> emissions from varying the start year of the C&T program. Vertical line at 2013 indicates actual introduction of the program. Shaded areas indicate 95% confidence intervals.

**Figure S6:** Empirical distribution of  $\beta_1^p$  and  $\beta_2^p$  from bootstrapping step 1



NOTES: Panels show the empirical distribution of  $\beta_1^p$  and  $\beta_2^p$  from equation (1) (across columns) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> (across rows) using the bootstrap procedure detailed in Section A.1 with 250 draws. Solid black line shows parameter from directly estimating equation (1). Solid colored line shows the mean parameter value from the empirical bootstrapped distribution. Dotted colored lines show the 2.5% and 97.5% percentiles of the empirical bootstrap distributions.

**Figure S7:** Zip code-level percent change in EJ gap trend following C&T



NOTES: Panels show the distribution of zip code-level percentage change in the EJ gap trend following the introduction of the C&T program, for each disadvantaged zip code across PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>. Solid line shows the average percentage change across disadvantaged zip codes, or  $\frac{\beta_2^P}{\beta_1^P} * 100$  from equation (2). Dashed line marks zero.

## Appendix Tables

**Table S1:** GHG cap-and-trade regulated and non-regulated facilities

	C&T regulated facilities	non-C&T regulated facilities
Number of facilities	106	226
Avg. 2008-2012 emissions (in metric tons):		
CO <sub>2</sub>	38192.62	17566.48
PM <sub>2.5</sub>	8.08	3.74
PM <sub>10</sub>	14.47	6.25
NO <sub>x</sub>	53.42	16.03
SO <sub>x</sub>	10.86	2.8
Shares by sector:		
Agriculture	0	.018
Manufacturing	.623	.5
Mining, oil and gas extraction	.151	.097
Services	.066	.23
Transportation	.075	.053
Utilities	.075	.093
Wholesale	.009	.009

NOTES: Sample C&T regulated and non-regulated facilities by count, average 2008-2012 GHG and criteria air pollution emissions, and by sector shares. Sectors shown adhere to the following definitions: Agriculture: NAICS 11; Manufacturing: NAICS 31-33; Mining, oil, and gas extraction: NAICS 21; Services: NAICS 51, 54, 56, 61, 62, 71, 81, 92; Transportation: NAICS 48, 49; Utilities: NAICS 22; Wholesale: NAICS 42.

**Table S2:** Emissions robustness: specification and sample restrictions

	(1) sector-year FEs	(2) Drop switchers	(3) Baseline CO <sub>2</sub> e cutoff (%) 70	(4) Baseline CO <sub>2</sub> e cutoff (%) 80
Outcome is asinh(CO <sub>2</sub> e) emissions				
$\kappa_1^p$	0.172 (0.058) [0.005]	0.220 (0.054) [0.000]	0.194 (0.055) [0.001]	0.174 (0.050) [0.001]
$\kappa_2^p$	-0.273 (0.095) [0.006]	-0.317 (0.079) [0.000]	-0.307 (0.085) [0.001]	-0.260 (0.072) [0.001]
Facilities	315	298	294	337
Observations	2,052	1,924	1,863	2,234
Outcome is asinh(PM <sub>2.5</sub> ) emissions				
$\kappa_1^p$	0.059 (0.043) [0.176]	0.065 (0.045) [0.156]	0.071 (0.043) [0.111]	0.046 (0.043) [0.298]
$\kappa_2^p$	-0.099 (0.048) [0.046]	-0.092 (0.051) [0.081]	-0.105 (0.050) [0.044]	-0.079 (0.050) [0.121]
Facilities	301	285	281	323
Observations	1,966	1,847	1,780	2,147
Outcome is asinh(PM <sub>10</sub> ) emissions				
$\kappa_1^p$	0.086 (0.034) [0.014]	0.088 (0.035) [0.016]	0.097 (0.034) [0.008]	0.075 (0.035) [0.039]
$\kappa_2^p$	-0.124 (0.040) [0.003]	-0.108 (0.043) [0.017]	-0.129 (0.043) [0.005]	-0.103 (0.042) [0.018]
Facilities	301	285	281	323
Observations	1,966	1,847	1,780	2,147
Outcome is asinh(NO <sub>x</sub> ) emissions				
$\kappa_1^p$	0.085 (0.042) [0.048]	0.057 (0.039) [0.158]	0.085 (0.033) [0.015]	0.058 (0.037) [0.128]
$\kappa_2^p$	-0.117 (0.053) [0.035]	-0.079 (0.050) [0.123]	-0.126 (0.047) [0.010]	-0.091 (0.048) [0.066]
Facilities	302	286	282	324
Observations	1,968	1,849	1,782	2,149
Outcome is asinh(SO <sub>x</sub> ) emissions				
$\kappa_1^p$	0.005 (0.038) [0.902]	0.008 (0.036) [0.817]	-0.005 (0.038) [0.890]	-0.004 (0.035) [0.912]
$\kappa_2^p$	-0.040 (0.048) [0.407]	-0.040 (0.046) [0.386]	-0.025 (0.048) [0.600]	-0.020 (0.045) [0.657]
Facilities	302	286	282	324
Observations	1,961	1,847	1,777	2,142

NOTES: Estimates of pre-C&T differential emissions trend (i.e.,  $\kappa_1^p$  from equation (1)) and post-C&T differential emissions trend break (i.e.,  $\kappa_2^p$  from equation (1)) for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> across panels. All models include facility-specific and year-specific dummy variables (except for column 1). Column 1 replaces year fixed effects with sector-by-year fixed effects with sectors defined as shown in Table S1. Column 2 drops facilities that switched C&T regulatory status in 2017. Columns 3 and 4 restrict facilities to those with sample average annual GHG emissions below the 70th and 80th percentile, respectively. Standard errors clustered at the county-level in parentheses, p-value in brackets.

**Table S3:** Emissions effect robustness: heterogeneity by average emissions

	(1)	(2)	(3)
Outcome is asinh(GHG) emissions			
$\kappa_1^p$	0.187 (0.052) [0.001]	0.176 (0.052) [0.002]	0.172 (0.052) [0.002]
$\kappa_2^p$	-0.297 (0.077) [0.000]	-0.361 (0.092) [0.000]	-0.354 (0.097) [0.001]
trend break $\times$ avg. emissions	0.000 (0.000) [0.053]	0.000 (0.000) [0.090]	0.000 -0.000 (0.000) [0.158]
Outcome is asinh(PM <sub>2.5</sub> ) emissions			
$\kappa_1^p$	0.058 (0.043) [0.183]	0.060 (0.042) [0.167]	0.060 (0.043) [0.165]
$\kappa_2^p$	-0.097 (0.048) [0.053]	-0.133 (0.051) [0.012]	-0.146 (0.068) [0.040]
trend break $\times$ avg. emissions	-0.004 (0.003) [0.197]	-0.005 (0.004) [0.249]	-0.005 0.000 (0.000) [0.661]
Outcome is asinh(PM <sub>10</sub> ) emissions			
$\kappa_1^p$	0.083 (0.033) [0.016]	0.084 (0.033) [0.015]	0.086 (0.033) [0.012]
$\kappa_2^p$	-0.117 (0.039) [0.005]	-0.143 (0.042) [0.002]	-0.172 (0.048) [0.001]
trend break $\times$ avg. emissions	-0.002 (0.001) [0.080]	-0.003 (0.002) [0.073]	-0.003 0.000 (0.000) [0.197]
Outcome is asinh(NO <sub>x</sub> ) emissions			
$\kappa_1^p$	0.075 (0.039) [0.061]	0.079 (0.038) [0.046]	0.080 (0.039) [0.046]
$\kappa_2^p$	-0.104 (0.050) [0.042]	-0.143 (0.045) [0.003]	-0.157 (0.079) [0.054]
trend break $\times$ avg. emissions	-0.001 (0.000) [0.002]	-0.001 (0.001) [0.294]	-0.001 0.000 (0.000) [0.793]
Outcome is asinh(SO <sub>x</sub> ) emissions			
$\kappa_1^p$	0.006 (0.035) [0.875]	0.013 (0.035) [0.715]	0.013 (0.035) [0.705]
$\kappa_2^p$	-0.037 (0.043) [0.393]	-0.110 (0.048) [0.026]	-0.074 (0.077) [0.345]
trend break $\times$ avg. emissions	-0.004 (0.002) [0.017]	-0.002 (0.003) [0.455]	-0.002 0.000 (0.000) [0.438]
trend break $\times$ avg. emissions <sup>2</sup>			-0.000 (0.000) [0.438]

NOTES: Estimates of pre-C&T differential emissions trend (i.e.,  $\kappa_1^p$  from equation (1)) and post-C&T differential emissions trend break (i.e.,  $\kappa_2^p$  from equation (1)) for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> across panels. Columns 1 shows benchmark model. Column 2 (3) further interacts post C&T differential trend break with a linear (quadratic) function of sample average annual emissions. All models include facility-specific and year-specific dummy variables. Standard errors clustered at the county-level in parentheses, p-value in brackets.

**Table S4:** Emissions effect robustness: restricting treatment spillovers

	(1) Benchmark	(2) Nonattainment	(3) Single facilities
Outcome is $\text{asinh}(\text{GHG})$ emissions			
$\kappa_1^P$	0.187 (0.052) [0.001]	- - -	0.210 (0.053) [0.000]
$\kappa_2^P$	-0.297 (0.077) [0.000]	- - -	-0.322 (0.078) [0.000]
Facilities	316	-	310
Observations	2,054	-	2,029
Outcome is $\text{asinh}(\text{PM}_{2.5})$ emissions			
$\kappa_1^P$	0.058 (0.043) [0.183]	0.085 (0.049) [0.092]	0.066 (0.043) [0.137]
$\kappa_2^P$	-0.097 (0.048) [0.053]	-0.119 (0.052) [0.029]	-0.101 (0.049) [0.046]
Facilities	302	260	299
Observations	1,968	1,729	1,952
Outcome is $\text{asinh}(\text{PM}_{10})$ emissions			
$\kappa_1^P$	0.083 (0.033) [0.016]	0.101 (0.034) [0.006]	0.091 (0.033) [0.008]
$\kappa_2^P$	-0.117 (0.039) [0.005]	-0.145 (0.054) [0.012]	-0.121 (0.040) [0.004]
Facilities	302	140	299
Observations	1,968	1,080	1,952
Outcome is $\text{asinh}(\text{NO}_x)$ emissions			
$\kappa_1^P$	0.075 (0.039) [0.061]	0.057 (0.041) [0.173]	0.065 (0.039) [0.101]
$\kappa_2^P$	-0.104 (0.050) [0.042]	-0.090 (0.054) [0.102]	-0.098 (0.050) [0.060]
Facilities	303	287	300
Observations	1,970	1,879	1,954
Outcome is $\text{asinh}(\text{SO}_x)$ emissions			
$\kappa_1^P$	0.006 (0.035) [0.875]	- - -	0.005 (0.036) [0.892]
$\kappa_2^P$	-0.037 (0.043) [0.393]	- - -	-0.036 (0.044) [0.423]
Facilities	303	-	300
Observations	1,965	-	1,950

NOTES: Estimates of pre-C&T differential emissions trend (i.e.,  $\kappa_1^P$  from equation (1)) and post-C&T differential emissions trend break (i.e.,  $\kappa_2^P$  from equation (1)) for GHG, PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> across panels. Columns 1 shows benchmark model. Column 2 restricts unregulated facilities to those in counties under Clear Air Act nonattainment for pollutant of interest. Nonattainment does not apply for GHG emissions and there were no counties under SO<sub>x</sub> nonattainment during our sample period. For NO<sub>x</sub>, we use nonattainment in the one-hour ozone standard, for which NO<sub>x</sub> is a precursor pollutant. Column 3 restricts unregulated facilities to those whose parent company only operates a single facility. All models include facility-specific and year-specific dummy variables. Standard errors clustered at the county-level in parentheses, p-value in brackets.

**Table S5:** Correlation between HYSPLIT-driven and ambient pollution concentrations

	(1)	(2)	(3)	(4)
Outcome is ambient asinh(concentration)				
PM <sub>2.5</sub>	PM <sub>10</sub>	NO <sub>x</sub>	SO <sub>x</sub>	
HYSPLIT-driven asinh(concentration)	0.860 (0.154) [0.000]	0.625 (0.137) [0.000]	0.436 (0.148) [0.004]	0.231 (0.207) [0.272]
Zip codes	133	160	121	39

NOTES: Linear coefficient from zip code-level regressions of asinh daily HYSPLIT-driven pollution concentrations (in  $\mu\text{g}/\text{m}^3/\text{day}$ ) averaged across 2008-2017 on asinh daily pollution concentrations in zip codes with ambient pollution monitors (in  $\mu\text{g}/\text{m}^3/\text{day}$ ) averaged across 2008-2017. We employ a asinh-asinh specification because ambient pollution readings, which capture the average daily instantaneous stock of pollution, are not directly comparable to our concentration measure, which capture average daily pollution flow from C&T-driven emissions. Ambient pollution are assumed to be uniformly distributed within a monitor's zip code. Standard errors clustered at the county-level in parentheses, p-value in brackets.

**Table S6:** Pollution concentration difference between disadvantaged and other zip codes in 2008

	(1) Disadvantaged	(2) Other	(3) Difference
PM <sub>2.5</sub>	0.256 (0.888)	0.093 (0.572)	0.163 (0.038) [0.000]
PM <sub>10</sub>	0.322 (1.066)	0.109 (0.532)	0.214 (0.043) [0.000]
NO <sub>x</sub>	0.451 (2.842)	0.387 (6.856)	0.064 (0.243) [0.792]
SO <sub>x</sub>	0.364 (1.092)	0.091 (0.217)	0.273 (0.041) [0.000]
Zip codes	722	984	1,706

NOTES: Column 1 shows average 2008 pollution concentration ( $\mu\text{g}/\text{m}^3/\text{day}$ ) across disadvantaged zip codes, with standard deviation in parentheses. Column 2 shows average 2008 pollution concentration ( $\mu\text{g}/\text{m}^3/\text{day}$ ) across other zip codes, with standard deviation in parentheses. Column 3 shows the average difference in 2008 pollution concentrations between disadvantaged and other zip codes, with standard error in parentheses and p-value in brackets. All pollution concentrations generated by HYSPPLIT from facilities that would eventually be regulated by the GHG C&T program.

**Table S7:** EJ gap effect robustness: step 1

	(1) Year-specific effects	(2) Sector-year FEs	(3) Drop switchers	(4) GHG cutoff: 70%	(5) GHG cutoff: 80%	(6) Hetero by avg. emissions	(7) SUTVA NA	(8) SUTVA Single fac.
Panel a: PM <sub>2.5</sub>								
$\beta_1^p$	0.040 (0.011) [0.001]	0.041 (0.011) [0.001]	0.040 (0.013) [0.003]	0.025 (0.006) [0.000]	0.043 (0.010) [0.000]	0.041 (0.012) [0.001]	0.048 (0.012) [0.000]	0.043 (0.012) [0.000]
$\beta_2^p$	-0.061 (0.019) [0.003]	-0.061 (0.019) [0.002]	-0.058 (0.021) [0.007]	-0.031 (0.008) [0.000]	-0.063 (0.019) [0.001]	-0.075 (0.021) [0.001]	-0.067 (0.021) [0.002]	-0.064 (0.020) [0.002]
$(\beta_2^p/\beta_1^p) * 100$	-152.583	-148.723	-144.528	-125.385	-146.581	-182.096	-141.543	-146.262
Observations	16,416	16,416	16,413	16,387	16,426	16,416	16,416	16,416
Panel b: PM <sub>10</sub>								
$\beta_1^p$	0.062 (0.014) [0.000]	0.063 (0.014) [0.000]	0.059 (0.017) [0.001]	0.038 (0.008) [0.000]	0.069 (0.013) [0.000]	0.064 (0.014) [0.000]	0.074 (0.016) [0.000]	0.066 (0.015) [0.000]
$\beta_2^p$	-0.089 (0.027) [0.002]	-0.089 (0.026) [0.001]	-0.079 (0.028) [0.007]	-0.046 (0.009) [0.000]	-0.093 (0.026) [0.001]	-0.100 (0.028) [0.001]	-0.105 (0.030) [0.001]	-0.091 (0.028) [0.002]
$(\beta_2^p/\beta_1^p) * 100$	-142.447	-140.455	-134.110	-121.310	-134.948	-156.155	-141.932	-136.905
Observations	16,416	16,416	16,413	16,387	16,426	16,416	16,416	16,416
Panel c: NO <sub>x</sub>								
$\beta_1^p$	0.079 (0.033) [0.019]	0.091 (0.037) [0.015]	0.077 (0.032) [0.021]	0.043 (0.026) [0.108]	0.087 (0.031) [0.006]	0.079 (0.033) [0.021]	0.079 (0.032) [0.018]	0.082 (0.034) [0.018]
$\beta_2^p$	-0.132 (0.066) [0.051]	-0.145 (0.070) [0.043]	-0.132 (0.069) [0.061]	-0.055 (0.031) [0.084]	-0.149 (0.069) [0.035]	-0.142 (0.075) [0.062]	-0.138 (0.070) [0.052]	-0.141 (0.071) [0.053]
$(\beta_2^p/\beta_1^p) * 100$	-167.212	-158.315	-170.919	-128.157	-170.878	-180.760	-175.096	-172.408
Observations	16,416	16,416	16,413	16,387	16,426	16,416	16,416	16,416
Panel d: SO <sub>x</sub>								
$\beta_1^p$	0.036 (0.022) [0.108]	0.036 (0.022) [0.109]	0.038 (0.023) [0.104]	0.023 (0.015) [0.141]	0.037 (0.020) [0.077]	0.011 (0.012) [0.349]	- -	0.037 (0.023) [0.108]
$\beta_2^p$	-0.103 (0.050) [0.045]	-0.099 (0.049) [0.047]	-0.102 (0.050) [0.046]	-0.080 (0.045) [0.084]	-0.099 (0.046) [0.037]	-0.114 (0.058) [0.054]	- -	-0.100 (0.049) [0.047]
$(\beta_2^p/\beta_1^p) * 100$	-284.826	-275.129	-268.202	-353.380	-267.896	-1003.707	-	-272.630
Observations	16,416	16,416	16,413	16,387	16,426	16,416	-	16,416

NOTES: Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), and the percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> down panels. All models include zip code-specific and year-specific dummy variables. Observations weighted by zip code-level average population during 2008–2012. Column 1 uses year-specific effects to estimate C&T-driven emissions. Column 2 estimates C&T-driven emissions with sector-by-year fixed effects (see column 1 of Table S2). Column 3 estimates C&T-driven emissions after dropping facilities that switched regulatory status in 2017 (see column 2 of Table S2). Columns 4 and 5 restrict facilities to those with sample average GHG emissions below the 70th and 80th percentile, respectively to estimate C&T-driven emissions (see columns 3 and 5 of Table S2). Column 6 uses C&T-driven emissions that allow the C&T differential trend break to vary as a linear function of sample average emissions (see column 2 of Table S3). Column 7 restricts unregulated facilities to those in counties under Clear Air Act nonattainment for pollutant of interest (see column 2 of Table S4). Column 8 restricts unregulated facilities to those whose parent company only operates a single facility (see column 3 of Table S4). Standard errors, in parentheses, cluster  $\epsilon_{it}^p$  from equation (2) at the county-level but are not adjusted for statistical uncertainty from equation (1). P-value in brackets. Observations apply to all panels.

**Table S8:** EJ gap effect robustness: steps 2 and 3

	(1) Monthly emissions	(2) Slower decay	(3) Faster decay	(4) Lower boundary	(5) Higher boundary	(6) Spatial corr. err.	(7) Pollution corr. err.
Panel a: PM_2.5							
$\beta_1^p$	0.043 (0.011) [0.000]	0.043 (0.011) [0.000]	0.041 (0.011) [0.000]	0.037 (0.010) [0.001]	0.043 (0.011) [0.000]	0.042 (0.004) [0.000]	0.042 (0.006) [0.000]
$\beta_2^p$	-0.064 (0.020) [0.002]	-0.064 (0.020) [0.002]	-0.062 (0.020) [0.003]	-0.055 (0.019) [0.007]	-0.064 (0.020) [0.002]	-0.063 (0.009) [0.000]	-0.063 (0.010) [0.000]
$(\beta_2^p/\beta_1^p) * 100$	-149.824	-149.007	-150.533	-148.764	-149.992	-149.699	-149.699
Observations	16,416	16,416	16,416	16,359	16,430	16,417	16,417
Panel b: PM_10							
$\beta_1^p$	0.066 (0.015) [0.000]	0.066 (0.015) [0.000]	0.063 (0.014) [0.000]	0.057 (0.013) [0.000]	0.066 (0.014) [0.000]	0.065 (0.006) [0.000]	0.065 (0.008) [0.000]
$\beta_2^p$	-0.092 (0.028) [0.002]	-0.092 (0.027) [0.001]	-0.089 (0.027) [0.002]	-0.079 (0.027) [0.005]	-0.092 (0.027) [0.001]	-0.090 (0.011) [0.000]	-0.090 (0.013) [0.000]
$(\beta_2^p/\beta_1^p) * 100$	-139.896	-139.150	-140.448	-137.785	-140.161	-139.739	-139.739
Observations	16,416	16,416	16,416	16,359	16,430	16,417	16,417
Panel c: NO <sub>x</sub>							
$\beta_1^p$	0.088 (0.037) [0.019]	0.089 (0.036) [0.018]	0.081 (0.034) [0.020]	0.083 (0.035) [0.020]	0.085 (0.035) [0.018]	0.085 (0.039) [0.030]	0.085 (0.021) [0.000]
$\beta_2^p$	-0.147 (0.075) [0.056]	-0.148 (0.073) [0.048]	-0.139 (0.073) [0.063]	-0.140 (0.073) [0.060]	-0.144 (0.073) [0.054]	-0.143 (0.050) [0.004]	-0.143 (0.033) [0.000]
$(\beta_2^p/\beta_1^p) * 100$	-167.136	-166.117	-170.804	-168.674	-168.261	-168.282	-168.282
Observations	16,416	16,416	16,416	16,359	16,430	16,417	16,417
Panel d: SO <sub>x</sub>							
$\beta_1^p$	0.038 (0.023) [0.104]	0.037 (0.023) [0.109]	0.037 (0.022) [0.107]	0.030 (0.019) [0.133]	0.038 (0.023) [0.103]	0.037 (0.007) [0.000]	0.037 (0.006) [0.000]
$\beta_2^p$	-0.102 (0.050) [0.047]	-0.102 (0.050) [0.047]	-0.100 (0.049) [0.047]	-0.087 (0.044) [0.053]	-0.102 (0.050) [0.045]	-0.101 (0.012) [0.000]	-0.101 (0.010) [0.000]
$(\beta_2^p/\beta_1^p) * 100$	-269.062	-271.967	-272.688	-295.166	-270.107	-272.291	-272.291
Observations	16,416	16,416	16,416	16,359	16,430	16,417	16,417

NOTES: Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), and the percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> down panels. All models include zip code-specific and year-specific dummy variables. Observations weighted by zip code-level average population during 2008–2012. Column 1 distributes annual facility-level C&T-driven emissions according to monthly share of annual sectoral output. Column 2 applies a slower pollution decay to HYSPLIT pollution trajectories (i.e., 10% larger half-life parameter). Column 3 applies a faster pollution decay to HYSPLIT pollution trajectories (i.e., 10% smaller half-life parameter). Column 4 applies a lower planetary boundary layer set at 0.5 km. Column 5 applies a higher planetary boundary layer set at 2 km. Column 6 adjusts standard errors for spatial (500 km uniform kernel) and serial correlation (5 years). Column 7 adjusts standard errors allowing correlation across pollutants using a Seemingly Unrelated Regression (SUR) procedure. Standard errors, in parentheses, cluster  $\epsilon_{it}^p$  from equation (2) at the county-level but are not adjusted for statistical uncertainty from equation (1). P-value in brackets. Observations apply to all panels.

**Table S9:** EJ gap effect robustness: asinh concentration

	(1)	(2)	(3)	(4)
	Outcome is (asinh) concentration			
	PM <sub>2.5</sub>	PM <sub>10</sub>	NO <sub>x</sub>	SO <sub>x</sub>
$\beta_1^p$	0.027 (0.013) [0.045]	0.037 (0.014) [0.009]	0.032 (0.021) [0.137]	0.017 (0.017) [0.336]
$\beta_2^p$	-0.032 (0.014) [0.026]	-0.042 (0.015) [0.009]	-0.038 (0.023) [0.102]	-0.051 (0.030) [0.095]
$\beta_1^p + \beta_2^p$	-0.006 (0.005) [0.302]	-0.004 (0.007) [0.551]	-0.005 (0.008) [0.487]	-0.034 (0.015) [0.029]
Zip codes	1649	1649	1649	1649
Counties	58	58	58	58
Observations	16,416	16,416	16,416	16,416

NOTES: Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), and the post-C&T EJ gap trend (i.e.,  $\beta_1^p + \beta_2^p$ ) for asinh(PM<sub>2.5</sub>), asinh(PM<sub>10</sub>), asinh(NO<sub>x</sub>), and asinh(SO<sub>x</sub>), across columns. All models include zip code-specific and year-specific dummy variables. Observations weighted by zip code-level average population during 2008-2012. Parentheses indicate standard errors that account for statistical uncertainty in C&T predicted emissions ( $\nu_{it}^p$  from equation (1) via the bootstrap procedure in Appendix A.1) and county-level heterogeneity in EJ gap effects of arbitrary form ( $\epsilon_{it}^p$  from equation (2)). P-value in brackets.

**Table S10:** EJ gap effect robustness: census tract-level DAC definition

	(1) PM <sub>2.5</sub>	(2) PM <sub>10</sub>	(3) NO <sub>x</sub>	(4) SO <sub>x</sub>
$\beta_1^p$	0.057 (0.016) [0.001]	0.082 (0.019) [0.000]	0.152 (0.043) [0.001]	0.063 (0.029) [0.036]
$\beta_2^p$	-0.083 (0.026) [0.002]	-0.113 (0.037) [0.003]	-0.245 (0.104) [0.022]	-0.131 (0.047) [0.007]
$\beta_1^p + \beta_2^p$	-0.026 (0.019) [0.180]	-0.031 (0.026) [0.231]	-0.094 (0.075) [0.220]	-0.068 (0.020) [0.001]
$(\beta_2^p/\beta_1^p) * 100$	-144.708 (33.612) [0.000]	-137.866 (29.323) [0.000]	-161.746 (43.279) [0.000]	-207.392 (31.638) [0.000]
Census Tracts	8023	8023	8023	8023
Counties	58	58	58	58
Observations	80,230	80,230	80,230	80,230

NOTES: Data at the census tract-year level. Disadvantaged community defined at the census tract using CalEnviroScreen v3.0. Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), the post-C&T EJ gap trend (i.e.,  $\beta_1^p + \beta_2^p$ ), and the percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, across columns. All models include census tract-specific and year-specific dummy variables. Observations weighted by census tract-level population from the 2010 census. Parentheses indicate standard errors that account for statistical uncertainty in C&T predicted emissions ( $\nu_{it}^p$  from equation (1) via the bootstrap procedure in Appendix A.1) and shown in Figure S6, and county-level heterogeneity in EJ gap effects of arbitrary form ( $\epsilon_{it}^p$  from equation (2)). P-value in brackets.

**Table S11:** EJ gap effect robustness: minority-share DAC definition

	(1) PM <sub>2.5</sub>	(2) PM <sub>10</sub>	(3) NO <sub>x</sub>	(4) SO <sub>x</sub>
$\beta_1^p$	0.032 (0.013) [0.020]	0.049 (0.016) [0.003]	0.084 (0.034) [0.016]	0.029 (0.022) [0.190]
$\beta_2^p$	-0.049 (0.022) [0.027]	-0.069 (0.028) [0.017]	-0.139 (0.070) [0.053]	-0.073 (0.043) [0.093]
$\beta_1^p + \beta_2^p$	-0.017 (0.014) [0.230]	-0.020 (0.019) [0.278]	-0.055 (0.046) [0.238]	-0.044 (0.023) [0.059]
$(\beta_2^p / \beta_1^p) * 100$	-152.201 (42.970) [0.000]	-141.658 (35.481) [0.000]	-165.554 (46.534) [0.000]	-248.045 (64.826) [0.000]
Zip codes	1649	1649	1649	1649
Counties	58	58	58	58
Observations	16,416	16,416	16,416	16,416

NOTES: Disadvantaged community defined at whether a zip code has 2008-2012 average minority share of population above the median across California zip codes. Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), the post-C&T EJ gap trend (i.e.,  $\beta_1^p + \beta_2^p$ ), and the percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, across columns. All models include census tract-specific and year-specific dummy variables. Observations weighted by census tract-level population from the 2010 census. Parentheses indicate standard errors that account for statistical uncertainty in C&T predicted emissions ( $\nu_{it}^p$  from equation (1) via the bootstrap procedure in Appendix A.1) and shown in Figure S6, and county-level heterogeneity in EJ gap effects of arbitrary form ( $\epsilon_{it}^p$  from equation (2)). P-value in brackets.

**Table S12:** EJ gap effect robustness: including large emitters, electricity generators, and refineries

	(1) PM <sub>2.5</sub>	(2) PM <sub>10</sub>	(3) NO <sub>x</sub>	(4) SO <sub>x</sub>
$\beta_1^p$	0.209 (0.137) [0.132]	0.223 (0.147) [0.134]	0.084 (0.092) [0.366]	0.139 (0.096) [0.154]
$\beta_2^p$	-0.431 (0.188) [0.026]	-0.477 (0.201) [0.021]	-0.348 (0.134) [0.012]	-0.199 (0.094) [0.039]
$\beta_1^p + \beta_2^p$	-0.222 (0.059) [0.000]	-0.254 (0.063) [0.000]	-0.264 (0.062) [0.000]	-0.060 (0.021) [0.007]
$(\beta_2^p/\beta_1^p) * 100$	-206.402 (48.897) [0.000]	-213.745 (54.661) [0.000]	-414.288 (314.152) [0.187]	-143.527 (36.385) [0.000]
Zip codes	1650	1650	1650	1650
Counties	58	58	58	58
Observations	16,488	16,488	16,488	16,488

NOTES: Sample augments benchmark sample with large emitters (i.e., >75th percentile average annual emissions), electricity generators, and refineries. Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), the post-C&T EJ gap trend (i.e.,  $\beta_1^p + \beta_2^p$ ), and the percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub>, across columns. All models include zip code-specific and year-specific dummy variables. Observations weighted by zip code-level average population during 2008-2012. Parentheses indicate standard errors that account for county-level heterogeneity in EJ gap effects of arbitrary form ( $\epsilon_{it}^p$  from equation (2)). P-value in brackets.

**Table S13:** EJ gap effect robustness: total PM<sub>2.5</sub> concentration using InMAP

	(1)	(2)
	Primary PM <sub>2.5</sub>	Total PM <sub>2.5</sub>
$\beta_1^p$	0.002 (0.001) [0.001]	0.003 (0.001) [0.001]
$\beta_2^p$	-0.003 (0.001) [0.000]	-0.004 (0.001) [0.000]
$\beta_1^p + \beta_2^p$	-0.001 (0.000) [0.004]	-0.002 (0.001) [0.001]
$(\beta_2^p / \beta_1^p) * 100$	-150.559 (16.261) [0.000]	-172.948 (16.415) [0.000]
Zip codes	1648	1648
Counties	58	58
Observations	16,480	16,480

NOTES: Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)), the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)), the post-C&T EJ gap trend (i.e.,  $\beta_1^p + \beta_2^p$ ), and the percentage change in the EJ gap trend following the introduction of the C&T program (i.e.,  $\frac{\beta_2^p}{\beta_1^p} * 100$ ) for InMAP-modeled primary PM<sub>2.5</sub> concentration (column 1) and for InMAP-modeled total (i.e., primary and secondary) PM<sub>2.5</sub> concentration (column 2). InMAP employs dispersal patterns for 2005 and not for the 2008-2017 sample period. All models include zip code-specific and year-specific dummy variables. Observations weighted by zip code-level average population during 2008-2012. Standard errors, in parentheses, cluster  $\epsilon_{it}^p$  from equation (2) at the county-level but are not adjusted for statistical uncertainty from equation (1). P-value in brackets.

**Table S14:** Importance of modeling pollution dispersal

	(1)	(2)	(3)	(4)
	Facility zip code	1.6 km circle	4 km circle	10 km circle
	Panel a: PM <sub>2.5</sub>			
$\beta_1^p$	0.052 (0.036) [0.157]	-0.017 (0.026) [0.527]	-0.075 (0.040) [0.075]	-0.140 (0.079) [0.084]
$\beta_2^p$	-0.076 (0.049) [0.134]	-0.003 (0.023) [0.912]	0.067 (0.036) [0.075]	0.132 (0.072) [0.076]
Observations	785	1,831	3,573	7,545
	Panel b: PM <sub>10</sub>			
$\beta_1^p$	0.105 (0.070) [0.142]	0.020 (0.030) [0.509]	-0.069 (0.047) [0.155]	-0.143 (0.089) [0.116]
$\beta_2^p$	-0.142 (0.091) [0.132]	-0.049 (0.036) [0.177]	0.059 (0.055) [0.294]	0.137 (0.095) [0.157]
Observations	785	1,831	3,573	7,545
	Panel c: NO <sub>x</sub>			
$\beta_1^p$	0.163 (0.188) [0.391]	-0.120 (0.110) [0.285]	-0.292 (0.096) [0.005]	-0.417 (0.175) [0.022]
$\beta_2^p$	-0.213 (0.247) [0.396]	0.103 (0.132) [0.442]	0.311 (0.110) [0.008]	0.480 (0.179) [0.011]
Observations	785	1,831	3,573	7,545
	Panel d: SO <sub>x</sub>			
$\beta_1^p$	0.001 (0.004) [0.688]	-0.156 (0.122) [0.210]	-0.273 (0.183) [0.145]	-0.433 (0.250) [0.091]
$\beta_2^p$	-0.014 (0.009) [0.125]	-0.007 (0.030) [0.813]	0.128 (0.103) [0.223]	0.253 (0.143) [0.085]
Observations	783	1,823	3,553	7,535

NOTES: Estimates of the pre-C&T EJ gap trend (i.e.,  $\beta_1^p$  from equation (2)) and the post-C&T EJ gap trend break (i.e.,  $\beta_2^p$  from equation (2)) for PM<sub>2.5</sub>, PM<sub>10</sub>, NO<sub>x</sub>, and SO<sub>x</sub> down panels. All models include zip code-specific and year-specific dummy variables. Observations weighted by zip code-level average population during 2008-2012. Column 1 assigns pollution concentration to only the zip code of the emitting facility. Columns 2-4 assign pollution concentration to zip codes with centroid within a 1.6, 4 km and 10 km circle of emitting facility, respectively. Standard errors in parentheses cluster  $\epsilon_{it}^p$  from equation (2) at the county-level but are not adjusted for statistical uncertainty from equation (1). P-value in brackets.