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The local impacts of coal and oil power plant retirements on air pollution and cardiorespiratory health in California: an application of generalized synthetic control method

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Abstract

Background: This study capitalized on coal and oil facility retirements to quantify their potential effects on fine particulate matter ($PM_{2.5}$) concentrations and cardiorespiratory hospitalizations in affected areas using a generalized synthetic control method.

Methods: We identified 11 coal and oil facilities in California that retired between 2006 and 2013. We classified zip code tabulation areas (ZCTA) as exposed or unexposed to a facility retirement using emissions information, distance, and a dispersion model. We calculated weekly ZCTA-specific $PM_{2.5}$ concentrations based on previously estimated daily time-series $PM_{2.5}$ concentrations from an ensemble model, and weekly cardiorespiratory hospitalization rates based on hospitalization data collected by the California Department of Health Care Access and Information. We estimated the average differences in weekly average $PM_{2.5}$ concentrations and cardiorespiratory hospitalization rates in four weeks after each facility retirement between the exposed ZCTAs and the synthetic control using all unexposed ZCTAs (i.e., the average treatment effect among the treated [ATT]) and pooled ATTs using meta-analysis. We conducted sensitivity

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Conflicts of interest: None declared

Data access: Data on facility closures can be obtained from US Energy Information Administration (EIA), US Environmental Protection Agency Air Markets Program, and the California Environmental Protection Agency Air Resources Board. Health data was obtained from the California Department of Health Care Access Information. R code for the main analysis and figures are available online: https://github.com/suthlam/facility_closure_ca.git

analyses to consider different classification schemes to distinguish exposed from unexposed ZCTAs, including aggregating outcomes with different time intervals and including a subset of facilities with reported retirement date confirmed via emission record.

Results: The pooled ATTs were 0.02μg/m^3 (95% confidence interval (CI): −0.25 to 0.29μg/m^3) and 0.34 per 10,000 person-weeks (95%CI: −0.08 to 0.75 per 10,000 person-weeks) following the facility closure for weekly $PM_{2.5}$ and cardiorespiratory hospitalization rates, respectively. Our inferences remained the same after conducting sensitivity analyses..

Conclusions: We demonstrated a novel approach to study the potential benefits associated with industrial facility retirements. The declining contribution of industrial emissions to ambient air pollution in California may explain our null findings. We encourage future research to replicate this work in regions with different industrial activities.

Keywords

Quasi-experimental methods; air pollution; industrial facility; cardiorespiratory health

1. Introduction

It is well documented that air pollution contributes to the onset and exacerbation of cardiovascular and respiratory conditions (Alexeeff et al., 2021; Chen and Hoek, 2020; Dominici et al., 2006; Hoek et al., 2013; Orellano et al., 2021). Fine particulate matter ($PM_{2.5}$) specifically, can be inhaled and enter cardiovascular and respiratory organ systems and trigger inflammation and oxidative stress (Brook et al., 2010; Pope and Burnett, 2007; Rajagopalan et al., 2018). Acute exposures to high levels of $PM_{2.5}$ can exacerbate existing conditions and result in hospitalizations and increased mortality risk (Apte et al., 2015; Dominici et al., 2006; Hayes et al., 2020; Kioumourtzoglou et al., 2016; Orellano et al., 2021; Shi et al., 2016). The chemical composition of $PM_{2.5}$ varies substantially by emission source (e.g., vegetative burning, motor vehicles, and coal and oil facilities) and affects the toxicity of the pollution (Kim et al., 2003; Krall et al., 2013; Rohr and Wyzga, 2012; Thurston et al., 2016). Environmental regulatory policies, for example policies regulating energy sources for electricity production, can result in varying health benefits depending on the targeted emission source. Historically, coal and oil facilities fuel the majority of electricity production in the United States and emit hazardous air pollutants, including $PM_{2.5}$. Over the last two decades, a combination of abundant and low-cost natural gas, changes in the economy, and environmental regulations have resulted in the closure of many coal and oil facilities nationwide (Lueken et al., 2016). Research that quantifies the change in health burden due to a well-defined intervention on air pollution, such as the closure of coal and oil facilities, can inform targeted interventions to improve population health (Zigler and Dominici, 2014).

Limited public health research has quantified the effect of real-world interventions on air quality and health effects of real-world interventions (Bell et al., 2011; Burns et al., 2019; Henneman et al., 2017). Previous epidemiologic studies of air pollution and cardiorespiratory outcomes typically use more traditional environmental epidemiologic methods to estimate a concentration-response function (e.g., the change in risk of the outcome per unit change in air pollution exposure). Translating such results to evidence-based action is challenging because of the heterogeneity in $PM_{2.5}$ sources. Furthermore, these studies are subject to unmeasured confounding due to lifestyle behaviors like exercise, socioeconomic characteristics, and neighborhood characteristics which are difficult to sufficiently characterize with available data (Pope and Burnett, 2007).

Quasi-experimental methods offer a solution to some of these challenges in more traditional study designs and can isolate a causal effect due to a well-defined intervention (Bor, 2016; Craig et al., 2017; O'Neill et al., 2020). The retirement of coal and oil facilities can be leveraged as a quasi-experiment (Remler and Van Ryzin, 2014, chap. 15). In this observational setting, we can capitalize on the difference between pre- and post- retirement changes between exposed and control areas to evaluate the effect of the intervention using quasi-experimental methods like difference-in-differences and generalized synthetic control (O'Neill et al., 2020).

In California, several coal and oil facilities closed between 2006 and 2014; these closures can be considered a quasi-experiment to quantify the effect of facility retirements on ambient levels of $PM_{2.5}$ and cardiorespiratory hospitalizations in communities affected by the facility emissions. We implement a generalized synthetic control study design to create a synthetic control community that is unaffected by the facility emission and subsequent closure, and comparable to the communities affected in outcomes of interest after accounting for confounding (Xu, 2017). This approach allows us to isolate the effect of a specific source of air pollution, emissions from coal and oil facilities. The objective of this study is to estimate the effects of coal and oil facility retirements on ambient levels of $PM_{2.5}$ and cardiorespiratory hospitalizations to inform the public health relevance of environmental regulatory policy.

2. Methods

2.1. Measurement of Key Variables

We identified 15 coal and oil facilities in California that retired between January 1st 2006 and December 31st, 2013 using data from US Energy Information Administration (EIA), US Environmental Protection Agency Air Markets Program (EPA AMPD), and the California Environmental Protection Agency Air Resources Board (California Air Resources Board, n.d.; US Energy Information Administration, n.d.; US Environmental Protection Agency, n.d.). Agency-reported retirement dates were used to define retirement dates for analysis. We used data from EIA for information on fuel type and the AMPD for facility geographic coordinates (US Energy Information Administration, n.d., n.d.).

The health outcome of interest for this study was cardiorespiratory hospitalizations. We obtained daily cardiovascular and respiratory hospitalizations in all California zip code tabulation areas (ZCTA) 2006 to 2013 from the California Department of Health Care Access and Information (formally known as the Office of Statewide Health Planning and Development) ("HCAI - Department of Health Care Access and Information," n.d.). We combined cardiovascular and respiratory hospitalization counts for each ZCTA and retrieved population sizes from the 2010 U.S. Decennial Census to estimate weekly cardiorespiratory hospitalization rates for each ZCTA. We used a weekly time interval for our main analyses to provide sufficient sample size.

We also included weekly ambient total $PM_{2.5}$ concentrations as an outcome of interest for facility retirement. We calculated weekly ambient total $PM_{2.5}$ concentrations from 2006 to 2013 at the ZCTA level using previously estimated ZCTA level daily $PM_{2.5}$ concentrations from an ensemble model that integrated multiple machine learning algorithms with a R^2 of 0.86 in 10-fold cross-validation (Aguilera et al., 2021). The ensemble model incorporated a large set of predictors such as meteorological variables, land-use variables and satellite-derived variables to estimate ZCTA level daily $PM_{2.5}$ concentrations in California (Aguilera et al., 2021). This exposure dataset has been utilized in other epidemiological studies (Aguilera et al., 2022; Letellier et al., 2022).

We used values from a dispersion-based exposure model, the HYSPLIT Average Dispersion (HyADS) model in our ZCTA exposure definition. (L. R. F. Henneman et al., 2019). HyADS estimates ZCTA-specific, monthly exposure to facility sulfur dioxide (SO_2) emissions after considering meteorological conditions using the HYSPLIT transport and dispersion model (L. R. F. Henneman et al., 2019). For each facility location, HyADS tracks 100 air parcels starting at four times through the day (12:00am, 6:00am, 12:00pm, and 6:00pm) as they travel through the atmosphere for 7 days, selected as a reasonable atmospheric lifetime of sulfur. Wind speed and direction are taken from NCEP/NCAR Reanalysis data (Kalnay et al., 1996). SO_2 emission data are obtained from the Environmental Protection Agency and Energy Information Administration (US Energy Information Administration, n.d.; US Environmental Protection Agency, n.d.). Air parcel locations are aggregated by month and weighted by monthly emissions (parcels within the first 1 hour of emissions and those that reach a height of zero are removed). The model output is unitless (air parcel counts weighted by emissions) and is interpreted as a relative metric that quantifies the influences of emitted $PM_{2.5}$ precursors from each facility on ZCTAs and their change over time. The model performs well against air pollution regulatory monitors and more sophisticated chemical transport models and has been applied in epidemiological studies (Casey et al., 2020a; Daouda et al., 2021; L. R. Henneman et al., 2019; Henneman et al., 2021). The HyADS model is appropriate in this study because of its ability to model exposure to emissions from a large number of facilities over long periods. Facilities without emission data were excluded from the main analysis (n = 4).

2.2. Statistical Analysis

We applied the generalized synthetic control (GSC) design, a quasi-experimental method recently proposed by Xu et al. to estimate the impact of each facility retirements on two outcomes separately (weekly $PM_{2.5}$ concentration and weekly cardiorespiratory hospitalizations) in the four weeks after the facility retirement (Xu, 2017). To conduct these analyses, we 1) defined and classified ZCTAs as *exposed* or *control* for each facility retirement and obtained outcome data for these ZCTAs in 26 weeks before and 4 weeks after the facility retirements, 2) estimated the average treatment effect among the treated (ATT) by estimating the mean differences in outcomes during four weeks after facility retirement between the observed exposed ZCTAs and the imputed synthesized control for each facility closure with GSC, and 3) combined ATTs across all facility retirements with meta-analysis.

2.2.1. Identification of the exposed and control ZCTAs—We classified California ZCTAs as "exposed" and "control" to facility retirements, a proxy for presence or absence of influence from facility-related emissions, respectively. Our primary exposure definition combined the distance to facility and the monthly ZCTA-specific HyADS values from 2005 to 2013. The distance to facility restricts exposed ZCTAs to those relatively close (i.e., 40 kilometers) to the facility, where emissions like primary $PM_{2.5}$ are more likely to influence outcomes. The monthly HyADS value quantifies the influences of emitted $PM_{2.5}$ precursors from each facility on ZCTAs.

First, we calculated the annual average HyADS value as the average of monthly values over the calendar year before the closure for each retired facility. Second, we used the median annual average HyADS value of ZCTAs within 40 kilometers of the retired facility as the threshold value (see Table A.1). Distance to a retired facility was calculated using 2010 population weighted ZCTA centroids and GPS location of the facility. Third, ZCTAs were classified as exposed to a facility retirement if they 1) are located within 40 kilometers of the retired facility and 2) had annual HyADS value greater than the threshold. Finally, ZCTAs were classified as controls if they 1) are located more than 40 kilometers from the retired facility and 2) had annual HyADS values less than the threshold value. For example, if a facility closed on April 26, 2012, we first calculated the annual average HyADS as the average of values from January to December of 2011 for each ZCTA. Next, we calculated the threshold as the median of 2011-HyADS values of ZCTAs within 40 kilometers if the retired facility. Then we categorized ZCTAs within 40 kilometers of the facility as exposed if their 2011-HyADS value was greater than the threshold. We also categorized ZCTAs more than 40 kilometers from the facility as control if their annual HyADS value was less than the threshold value.

This approach classified ZCTAs as exposed to the influence of facility-related emissions or not (Figure 1). Similar approaches to dichotomize neighborhoods as exposed and unexposed using HyADS data have been previously described (Casey et al., 2020a). We aggregated the HyADS value for the year prior to closure date for calculation of threshold value to represent the average influence from facility emissions for an entire year. Since the computation burden for GSC increases with the number of exposed ZCTAs, we also included a distance buffer of 40 kilometers to restrict the number of exposed ZCTAs to below 100.

2.2.2. Estimation of the Average Treatment Effect among the Treated—Application of the GSC estimates an average treatment effect among the treated (ATT); we consider facility retirement as the treatment in this study. The day of retirement was included as the first day of the post-retirement period. The analysis was restricted to ZCTAs with at least three weekly values of both outcomes in four weeks before and after the retirement date, respectively. For each facility retirement and outcome combination, we ran a GSC analysis with 26 weeks of data before the retirement and four weeks of data after the retirement. We selected 26 weeks because we expect half a year before facility retirement should capture the trend in outcome pre-retirement. We selected 4 weeks after facility retirement because we hypothesized an acute effect on air pollution levels and hospitalizations.

Using the GSC approach, we first constructed a “synthetic” control for the ZCTAs exposed to each facility retirement using data prior to the retirement from the exposed ZCTAs and all data from the control ZCTAs after accounting for time-fixed and time-varying confounding. Using a combination of the traditional synthetic control (weighting scheme) and an interactive fixed-effects model, the GSC estimated latent factors, factor loadings, and coefficients for measured time-varying confounders that approximate outcomes of the ZCTAs exposed to the facility retirement in the pre-retirement period. For more information on how these factors were estimated, please see the original article by Xu (Xu, 2017). Specifically, we accounted for weekly average temperature and dew point temperatures in the construction of synthetic control, given their known association with cardiovascular outcomes and potential spatial variation across ZCTAs (Green et al., 2019; Son et al., 2019; Song et al., 2017). For facility retirements with multiple exposed ZCTAs, we allowed the pre-treatment outcomes to vary for each ZCTA. Next, we imputed the hypothetical trend in the exposed ZCTAs had there been no facility retirement using factors estimated above and observed time-varying confounders in the exposed ZCTAs post retirement. We evaluated the performance of GSC by visually inspecting the alignment of pre-treatment outcomes between the exposed and control ZCTAs. We estimated the ATT as the mean differences in outcomes during four weeks after facility retirement between the observed exposed ZCTAs and the imputed synthesized control. We reported the weekly differences in outcomes after facility retirement. We estimated 95% confidence intervals using parametric bootstrapping. Finally, we calculated ATT for each facility retirement and pooled the mean ATTs across facilities using random-effect meta-analysis (“meta” package in R).

This study design accounts for measured and unmeasured time-fixed confounders (e.g., potential confounders that do not vary remarkably within months like age composition, socioeconomic status, and behavior characteristics of the population) and unmeasured time-varying confounders that vary with calendar time through the latent factors and factor loadings. The GSC approach also considers measured time-varying confounding by including covariates in the imputation of counterfactual trends in the exposed ZCTAs (Xu, 2017). More details about this approach applied to environmental epidemiological settings and a discussion of differences with methods like difference-in-differences and traditional synthetic control have been previously described (O’Neill et al., 2020; Sheridan et al., 2022).

2.3. Sensitivity analyses

We conducted extensive sensitivity analyses to test the robustness of our results. First, we aggregated outcomes with different time intervals: daily and two weeks. Second, we explored different classification schemes to distinguish exposed from unexposed ZCTAs. We used the HyADS values in the same month of the retirement date during the year before instead of the annual average HyADS values to test any potential differential influence of emissions related to seasonal variations in metrological conditions. We also used a distance only approach to define exposure status. ZCTAs with a population-weighted centroid within 5 kilometers of the retired facility were considered exposed and ZCTAs with centroids outside of the 10km buffer of any retired facility were considered control. Finally, since the reported retirement date might not align with the date when emission stopped, we repeated the main analysis subset to facilities whose reported retirement date approximately aligns with the time when emissions was reported to be zero in the same or next month using data from the Environmental Protection Agency and the Energy Information Administration.

All analyses were conducted in RStudio with R version 4.1.0 (R Core Team, 2021; RStudio Team, 2021). Packages used are “gsynth” and “meta” (Balduzzi et al., 2019; Yiqing and Licheng Liu, 2021).

3. Results

We constructed a dataset with 11 facility retirements in California between 2006–01-01 and 2013–12-31 (Figure 2). These facilities had a total facility-specific net generation capacity that ranges from 19 MW to 156 MW (Table A.1). The median number of exposed and control ZCTAs are 22 (min and max: 6 and 64 ZCTAs) and 1304 (min and max: 1203 and 1382 ZCTAs), respectively. Table 1 summarizes the observed changes in average weekly outcome values in exposed and control ZCTAs during 26 weeks before and four weeks after facility retirement without adjusting for time-fixed or time-varying confounding, for each facility. Compared to control ZCTAs, we observed larger decreases in weekly average $PM_{2.5}$ concentrations among exposed ZCTAs. There was no consistent pattern in change of weekly hospitalization rates; changes (post minus pre) in cardiorespiratory hospitalizations ranged from −0.7 to 1.0 in exposed ZCTAs and from −1.5 to 1.2 in control ZCTAs. We also included the average $PM_{2.5}$ concentration and cardiovascular hospitalization rates before and after facility retirements separately in Table A.1.

Accounting for time-varying confounders with GSC method, we estimated facility-specific ATTs to evaluate the impact of each facility closure on weekly $PM_{2.5}$ concentration and cardiorespiratory hospitalization rates separately. The GSC performs well with overlapping trends pre-retirement between the exposed ZCTAs and synthetic control, suggested by our facility-specific results (Figure 3, Figure A.1). Seven out of 11 facilities demonstrated negative ATTs for weekly $PM_{2.5}$ concentration, suggesting a reduction in average weekly $PM_{2.5}$ concentration during the four weeks post retirement of facility (Figure 4). Individual facility ATTs for weekly $PM_{2.5}$ concentration ranged from −0.42 to 0.80 μg/m^3. We also estimated the pooled ATT across all facility retirements, which is 0.02 μg/m^3 (95% confidence interval (CI): −0.25 to 0.29 μg/m^3) for weekly $PM_{2.5}$ concentration. In analyses exploring the impact of facility closures on cardiorespiratory outcomes, nine out of 11 facilities demonstrated positive ATT for weekly cardiorespiratory hospitalization rate, suggesting an increase in cardiorespiratory hospitalization rates post retirement (Figure 4). Individual facility ATTs ranged from −0.58 to 1.29 per 10,000 person-time. The pooled ATT across all facility retirements is 0.34 per 10,000 person-time (95% CI: −0.08 to 0.75 per 10,000 person-time) for weekly cardiorespiratory hospitalization rate.

Our sensitivity analyses led to minor changes in numerical results, but inferences remained the same as main analysis. Compared to the HyADS exposure definition, we found slightly larger positive ATT with distance approach and negative ATT with the closure month

HyADS approach for weekly $PM_{2.5}$ concentration. ATTs for weekly cardiorespiratory hospitalization rate are smaller but positive for both alternative approaches (Table A.2). Using daily or bi-weekly outcomes instead of weekly outcomes did not change the direction of ATTs for cardiorespiratory hospitalization rate, while the ATTs for $PM_{2.5}$ concentration became negative (Table A.2). Considering the subset of facilities where the administrative retirement date aligned with emissions data also led to no change in direction of ATTs for cardiorespiratory hospitalization rate but the ATTs for weekly $PM_{2.5}$ concentration became more negative (Table A.2).

4. Discussion

In this study, we examined the effect of oil and coal facility retirement on weekly ambient levels of $PM_{2.5}$ and on weekly cardiorespiratory hospitalization rates. This study demonstrates the use of a novel quasi-experimental study design, the generalized synthetic control, in environmental epidemiology. Our results suggest that facility closures did not result in either a measurable change in $PM_{2.5}$ concentrations or cardiorespiratory hospitalization rates in California, 2006–2013.

Previous studies have looked at the closure of oil and coal facilities in relation to medium- or long-term change in perinatal outcomes, asthma outcomes and air pollution (Casey et al., 2020b, 2018). A prior study used quasi-experimental designs to look at the closure and retrofit of coal facilities with higher net generation capacity near Louisville, Kentucky and found a reduction in air pollution and asthma burden (Casey et al., 2020b, 2020a). In California, researchers used a difference-in-differences method and found that annual preterm was reduced and fertility rates increased after facility retirements, potentially due to reductions in air pollution (Casey et al., 2018).Here, we use a GSC method that is advantageous over other quasi-experimental designs like difference-in-differences but did not find an effect of facility retirements on ambient levels of $PM_{2.5}$ or cardiorespiratory hospitalization rates in the month immediately after facility closure in California. The GSC can flexibly account for time-varying confounding instead of assuming a “parallel trend” (i.e., no time-varying confounding) (Sheridan et al., 2022). Furthermore, GSC can accommodate settings where there are multiple treated units (i.e., multiple ZCTAs affected by one facility closure) (Xu, 2017). However, like all controlled pre-post designs, GSC assumes no additional event coinciding with the facility retirement that affects only the exposed or majority of the controls. For example, a relatively small wildfire near the facility would likely affect the exposed zip codes only but we did not observe any wildfire smoke events in California around the facility closure periods. We do not expect any major events, including wildfire smoke events, in California during the study period.

Our largely null findings can be interpreted in different ways. First, the contribution of active oil and coal power plant to ambient $PM_{2.5}$ in California might be minimal, especially given the relatively low net generation capacity of our retired facilities. The contribution of industrial emissions to ambient air pollution in the U.S. has declined while other major emitting sources like wildfires increased (Ford et al., 2018; Tschofen et al., 2019). Thus, low $PM_{2.5}$ level pre-retirement might make detecting a small effect more challenging. Second, we focused on the impact of facility closure during the month immediately after facility closure, while the impact might emerge after a longer period, especially in health outcomes like hospitalization. Third, evaluating impacts of facility retirement on ambient air pollution and health outcomes requires careful evaluation of the facility closure information. For example, our study design relies on the reported facility closure date to define the time after which we expect a change in air pollution and health outcomes due to emission reduction from the closure. However, true emissions changes may not coincide with these administrative dates, for example, plants may ramp down production in the lead-up to shutting down completely. To address this, we repeated the analyses among a subset of facilities where the trends in emissions approximately aligned with the administrative retirement date and found a more pronounced decrease in air pollution after closure of these facilities (Table A.2), suggesting that the discrepancy between administrative and true closure date may partly explain the null results in the main analysis.

Next, defining the exposed spatial unit is challenging. We classified ZCTAs as exposed or unexposed based on estimates from annual average HyADS values. Although HyADS values incorporate meteorological conditions to evaluate transport of pollutants in the air, utilizing the annual average might neglect the seasonal change in chemical transformations of emitted sulfur dioxide to sulfate $PM_{2.5}$. However, when we conducted sensitivity analyses employing a similar definition that used the average HyADS value in the same month of facility retirement during the year prior to the retirement, results changed only minimally (Table A.2). Similarly, we found minimal change in the results when basing exposure on distance from the facility rather than HyADS values (Table A.2). Furthermore, because we only evaluated the impact of facility closure within a month, we might have missed potential long-term effects on exposure and health. Finally, we used changes in $PM_{2.5}$ concentration to represent changes in ambient air pollution while other harmful air pollutants could have changed as well. For example, decreases in nitrogen oxides titration due to decreases in nitrogen oxides emission (which were not directly addressed here) might lead to increases in ground level ozone in ZCTAs nearby facilities with high nitrogen oxides concentrations (Qian et al., 2019). Such increases in ground level ozone might partly explain the observed small increase in cardiorespiratory hospitalization rates due to facility retirements.

Estimating the impact of a specific intervention like facility closure on ambient levels of $PM_{2.5}$ and health outcomes with quasi-experimental methods still provides important information to policymakers (Burns et al., 2019; Health Effects Institute, 2003). Industrial activity and environmental policies have dramatically changed what constitutes air pollution in a local area. As we embark on an energy transition, we encourage future researchers to replicate our work in other regions and settings and have provided code to facilitate future applications.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Declaration of interests

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- We examined the impact of facility closures on air pollution and hospitalizations.
- We used a generalized synthetic control method to control for confounding.
- We observed no change in average weekly fine particulate matter due to closure.
- We observed no change in average weekly hospitalizations due to closure.

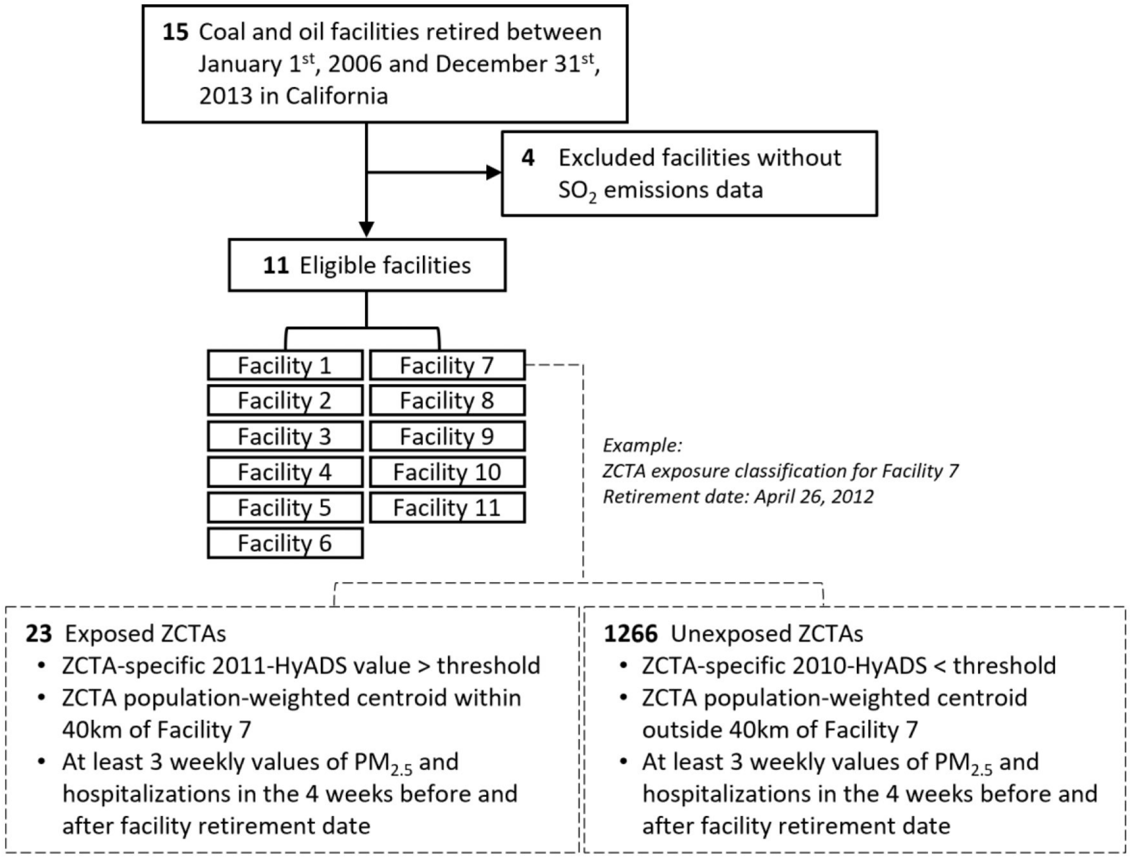

Figure 1. Flowchart describing the identification of exposed and unexposed ZCTAs for eligible coal and oil facilities in California, 2006–2013.

This figure demonstrates exposure classification for Facility 7. This classification scheme is repeated for each eligible facility. Note: threshold HyADS value is defined as the median of annual average HyADS values of all ZCTAs within 40km of the facility the year before reported retirement date. We use 2011-HyADS for Facility 7 exposure definitions. Abbreviations: Sulfur dioxide, SO_2; zip code tabulation area, ZCTA; fine particulate matter, $PM_{2.5}$; HYSPLIT Average Dispersion, HyADS.

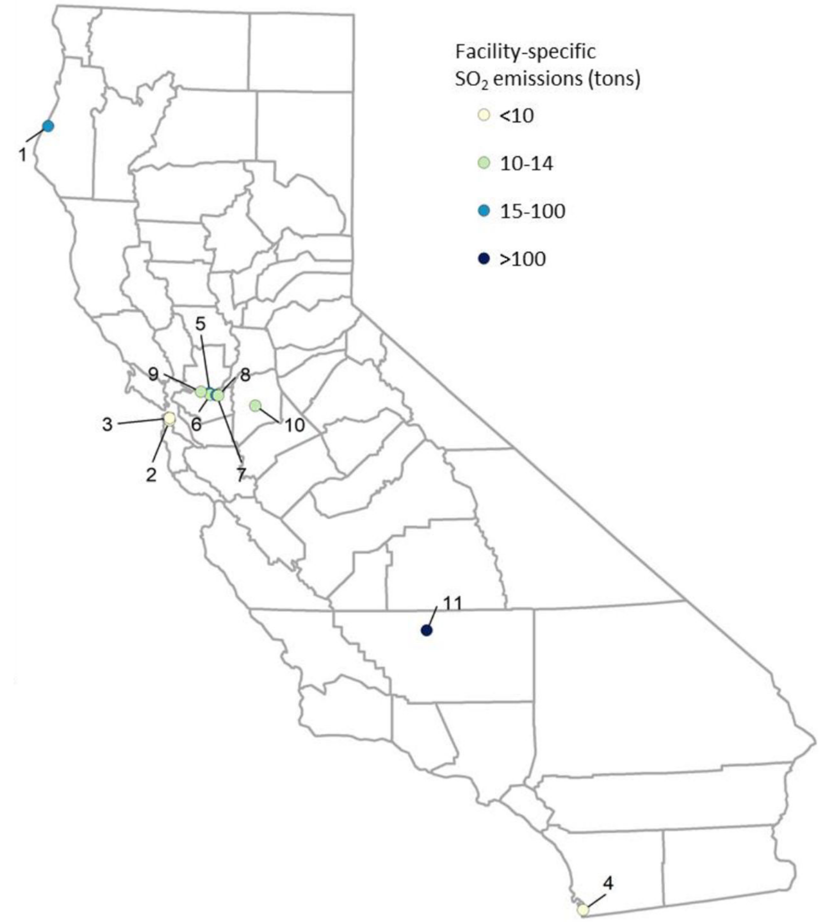

Figure 2. Map of retired facilities in California, 2006–2013 and SO_2 emissions the year prior to facility retirement.

Facilities retired in 2006 (Facility 2), 2010 (Facilities 1 and 4), 2011 (Facilities 3 and 11), and 2012 (Facilities 5 through 10).

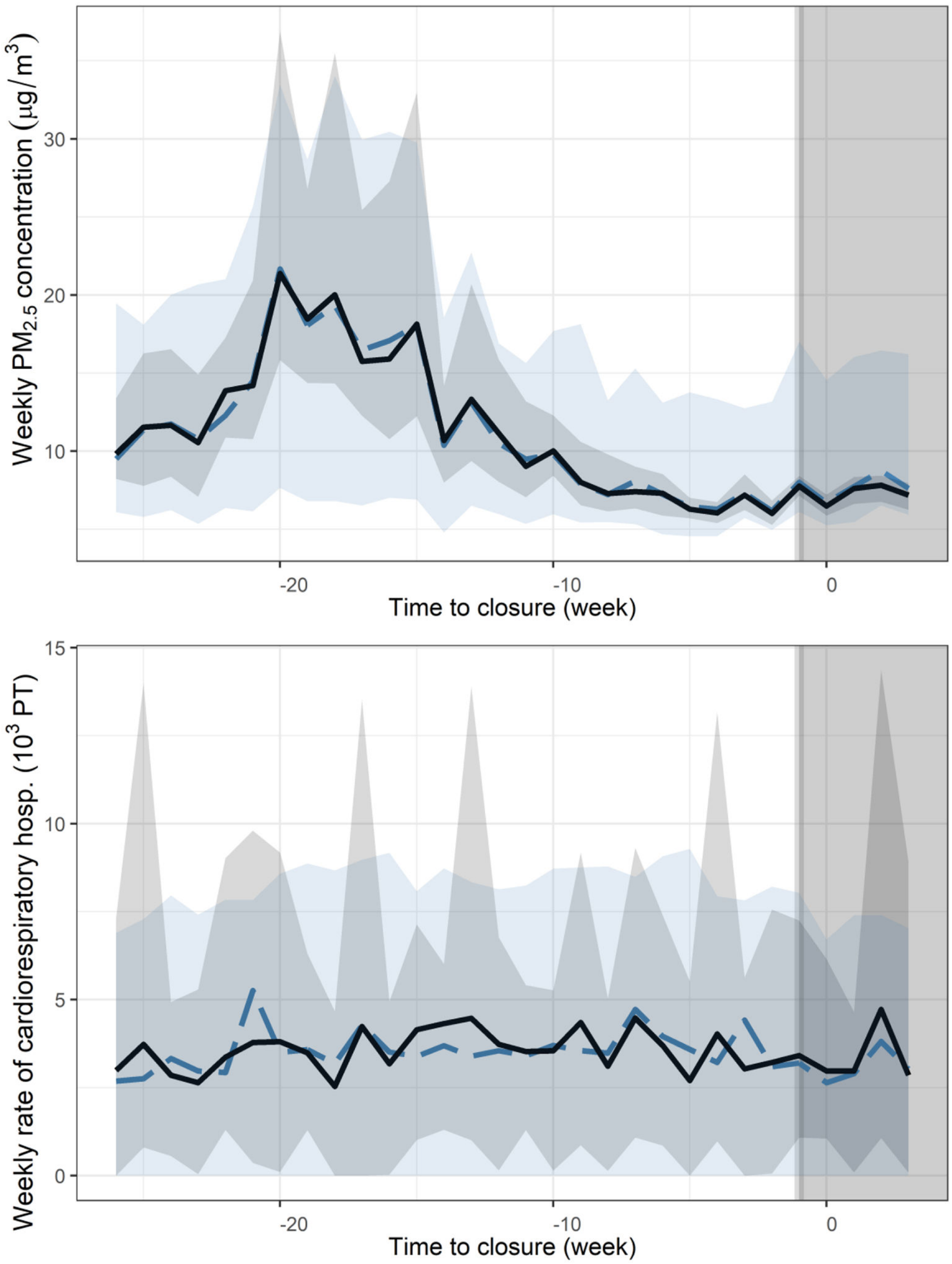

Figure 3. Estimated trends in weekly average $PM_{2.5}$ concentration and cardiorespiratory hospitalization rates of exposed and synthesized control before and after closure of example facility (Facility 7).

Black line indicates the estimated outcome for exposed ZCTAs, while blue dotted line indicates the counterfactual outcome estimated with synthetic control ZCTAs. Shades represent middle 90% of exposed (grey) and control (blue) ZCTAs.

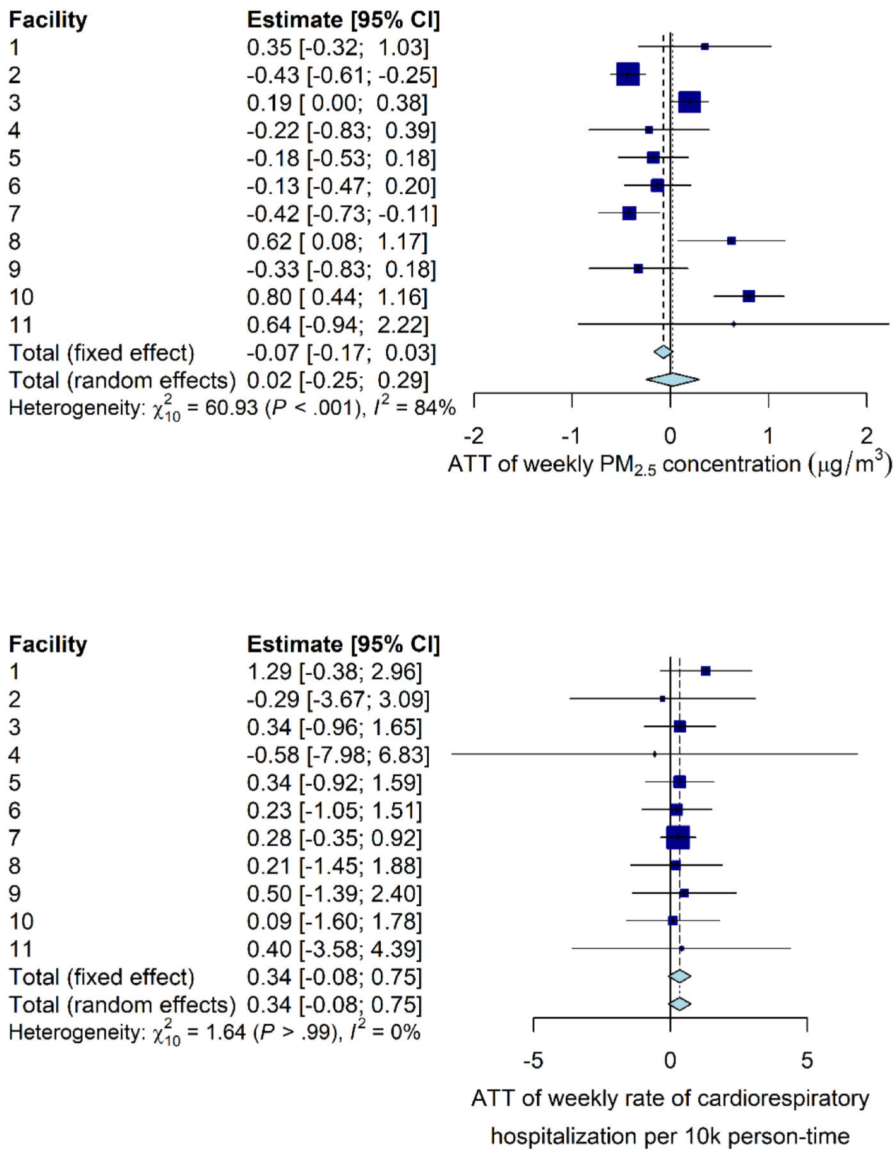

Figure 4.

Forest plot of estimated average treatment effect among exposed (ATT) for weekly average $PM_{2.5}$ concentration and cardiorespiratory hospitalization rates, across all facilities.

Table 1.

Observed changes (SD) in $PM_{2.5}$ and hospitalizations in exposed and control ZCTAs during 26 weeks before and four weeks after facility retirements

Facility ID	Retirement i Date	# of exposed ZCTAs	# of control ZCTAs	Change in $PM_{2.5}$[a,b]		Change in cardiorespiratory hospitalization rate[a,c]	
				Exposed	Control	Exposed	Control
1	09-24-2010	6	1382	0.5 (0.09)	0.9 (1.10)	1.0 (2.27)	−0.3 (3.10)
2	05-15-2006	54	1203	−0.4 (0.55)	0.5 (2.33)	−0.7 (0.72)	−0.7 (4.93)
3	02-28-2011	64	1254	−3.3 (0.71)	−2.5 (2.18)	0.6 (2.74)	0.5 (3.04)
4	12-31-2010	18	1337	0.5 (1.50)	2.6 (3.79)	0.7 (1.09)	1.2 (13.25)
5	04-26-2012	23	1274	−3.3 (0.89)	−0.5 (3.14)	−0.1 (2.01)	−1.5 (3.62)
6	04-26-2012	27	1271	−3.4 (1.00)	−1.5 (3.62)	−0.3 (1.89)	−0.5 (3.14)
7	04-26-2012	23	1266	−4.2 (1.90)	−1.5 (3.62)	−0.2 (2.01)	−0.5 (3.14)
8	04-26-2012	21	1323	−5.2 (2.64)	−1.6 (3.61)	−0.3 (2.09)	−0.5 (3.10)
9	04-26-2012	14	1304	−3.7 (0.81)	−1.7 (3.73)	0.0 (2.54)	−0.5 (3.10)
10	03-31-2012	22	1348	−7.9 (1.89)	−2.9 (3.24)	0.1 (1.11)	−0.1 (3.76)
11	11-01-2011	9	1378	6.5 (2.59)	1.3 (3.20)	0.4 (0.74)	0.1 (5.45)

[a] Observed change=average outcome after retirement – average quantity before retirement, where outcome is $PM_{2.5}$ or hospitalization rate

[b] $PM_{2.5}$ per μg/m^3; hospitalization rate per 10,000 person-weeks

Abbreviations: SD, standard deviation; $PM_{2.5}$, fine particulate matter; ZCTA zip code tabulation area