



Mediating Role of Fine Particles Abatement on Pediatric Respiratory Health During COVID-19 Stay-at-Home Order in San Diego County, California

Key Points:

- We assessed changes in pediatric respiratory emergency department (ED) visits and PM_{2.5} in 2020 with respect to the preceding 4 years
- We observed a sustained decline in pediatric respiratory ED visits, while decreases in PM_{2.5} concentrations were short-lived
- We estimated a 4% contribution of PM_{2.5} changes on the reduction in pediatric respiratory ED visits during the stay-at-home period

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Lower respiratory tract infections disproportionately affect children and are one of the main causes of hospital referral and admission. COVID-19 stay-at-home orders in early 2020 led to substantial reductions in hospital admissions, but the specific contribution of changes in air quality through this natural experiment has not been examined. Capitalizing on the timing of the stay-at-home order, we quantified the specific contribution of fine-scale changes in PM_{2.5} concentrations to reduced respiratory emergency department (ED) visits in the pediatric population of San Diego County, California. We analyzed data on pediatric ED visits ($n = 72,333$) at the ZIP-code level for respiratory complaints obtained from the ED at Rady Children's Hospital in San Diego County (2015–2020) and ZIP-code level PM_{2.5} from an ensemble model integrating multiple machine learning algorithms. We examined the decrease in respiratory visits in the pediatric population attributable to the stay-at-home order and quantified the contribution of changes in PM_{2.5} exposure using mediation analysis (inverse of odds ratio weighting). Pediatric respiratory ED visits dropped during the stay-at-home order (starting on 19 March 2020). Immediately after this period, PM_{2.5} concentrations, relative to the counterfactual values based in the 4-year baseline period, also decreased with important spatial variability across ZIP codes in San Diego County. Overall, we found that decreases in PM_{2.5} attributed to the stay-at-home order contributed to explain 4% of the decrease in pediatric respiratory ED visits. We identified important spatial inequalities in the decreased incidence of pediatric respiratory illness and found that brief decline in air pollution levels contributed to a decrease in respiratory ED visits.

Plain Language Summary Children are commonly affected by respiratory tract infections, which can lead to hospitalization in some cases. During the COVID-19 lockdown in early 2020, pediatric cases of respiratory illnesses decreased substantially. We examined the contribution in the lower levels of fine particle pollution observed in San Diego County, over the lockdown period, on the decreased number of visits to pediatric Emergency Department facilities.

1. Introduction

Respiratory illnesses disproportionately affect children worldwide (Zar & Ferkol, 2014). Lower respiratory tract infections are one of the main causes of hospital referral and admission in young children (Nair et al., 2013), resulting in a major burden on health services. In early 2020, mitigative measures implemented to reduce coronavirus disease 2019 (COVID-19) effectively prevented the transmission of viruses that cause respiratory infections (Chu et al., 2020). Measures such as social distancing, mask-wearing, frequent handwashing, and school closures greatly reduced respiratory illness cases among infants and young children in the US (Graciano et al., 2020; Hatoun et al., 2020; Kenyon et al., 2020; Nolen et al., 2020; Sheehan et al., 2021; Simoneau et al., 2021; Ulrich et al., 2021) and worldwide (Angoulvant et al., 2021; Chan et al., 2021; Kishimoto et al., 2021; Trenholme et al., 2021). For instance, Simoneau et al. (2021) and Nolen et al. (2020) observed a sharp drop in pediatric respiratory visits and hospitalizations during the period of stay-at-home orders in their respective US states. Graciano et al. (2020) observed a striking decline in pediatric intensive care unit admissions during lockdown in Maryland, US, mostly due to a decrease in respiratory infections.

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In parallel, COVID-19 pandemic restrictions caused an unprecedented reduction in economic and transport activity across the world. This in turn resulted in a short-lived decrease in air pollution levels in some regions (Bekbulat et al., 2021; de Maria et al., 2021; Gkatzelis et al., 2021; He et al., 2021; Hernández-Paniagua et al., 2021; Venter et al., 2020). Venter et al. (2020) found that particulate matter (PM) levels were reduced by 31% in 34 countries (including the US), however Bekbulat et al. (2021) observed a large variability in changes in PM concentrations following COVID-19 stay-at-home order in the US. Air pollution is known to cause adverse effects on human health (Mills et al., 2009; Pope & Dockery, 2006). Children, being at a crucial stage of growth and development, are particularly vulnerable to air pollution (WHO, 2005), even to short-term increases in pollutant levels (Dales et al., 2009; Friedman et al., 2001; Horne et al., 2018; Zhu et al., 2017). The period in 2020 when major restrictions were in place created an unprecedented opportunity, and natural experiment, to better understand the effects of air pollution on children's respiratory health and the potential benefits of policies targeting traffic emissions.

Fine particulate matter, composed of airborne particles with diameters of 2.5 μm or less ($\text{PM}_{2.5}$), small enough to enter the deep recesses of the lungs and bloodstream, is one of the main components of air pollution affecting public health (Landrigan et al., 2018; Lelieveld et al., 2015). The adverse effects of $\text{PM}_{2.5}$ air pollution on children's health are well documented (Garcia, Urman, et al., 2019; Gauderman et al., 2004; Horne et al., 2018; Khreis et al., 2017). Short-term impacts associated with $\text{PM}_{2.5}$ exposure include asthma exacerbations and pneumonia (Darrow et al., 2014; Mann et al., 2010; Nhung et al., 2018) and other upper and lower respiratory tract infections (Bayer-Oglesby et al., 2005; Horne et al., 2018; Zhu et al., 2017). Thus, day-to-day fluctuations in air pollution can be associated with changes in pediatric hospital admissions (Schwartz, 2004). In the long term, exposure to air pollution can cause reductions in lung function (Dales et al., 2009; Gauderman et al., 2000; Xu et al., 2020), as well as adverse neurobehavioral effects during childhood and adolescence (Cserbik et al., 2020).

$\text{PM}_{2.5}$ and other air pollutants in Southern California and across the US have decreased during the past two decades because of regulatory efforts to curtail traffic and industrial emissions (Schwarzman et al., 2021), though significant spatial variability of $\text{PM}_{2.5}$ exists (e.g., attainment of air quality standards vs. non-attainment areas; Lee & Park, 2020). Decreases in air pollution levels have been associated with lower pediatric asthma incidence (Garcia, Berhane, et al., 2019) and improvements in respiratory symptoms in children with or without asthma overall (Berhane et al., 2016).

Here, we aimed to quantify changes in air pollution levels, particularly of $\text{PM}_{2.5}$, attributable to COVID-19 stay-at-home order, and to assess their specific contribution to reduced respiratory emergency department (ED) visits in the pediatric population of San Diego County, California, during 2020. We examine the changes in 2020 with respect to the preceding four years (2016–2019). Furthermore, we consider the spatio-temporal patterns in $\text{PM}_{2.5}$ and pediatric respiratory ED visits within our study area and quantify their association at weekly and ZIP code spatiotemporal resolution.

2. Data

2.1. Respiratory Health Visits

Data on pediatric ED visits for respiratory complaints (Table S1 in Supporting Information S1) were obtained from Rady Children's Hospital, the only freestanding children's hospital with the largest emergency department in San Diego County. The Rady Children's ED cares for approximately 90,000 children annually. Data from the medical record included date of visit, date of birth and ZIP code of patient's self-reported home residence. Respiratory visits were defined by the following ICD10 codes: asthma (J45.XX, R06.2 and J98.01), allergic rhinitis (J30.9), upper respiratory tract infection (J06.9) and pneumonia (J18.9).

2.2. Fine Particulate Matter ($\text{PM}_{2.5}$)

Daily ZIP code-specific concentrations of $\text{PM}_{2.5}$ were estimated from 2016 to 2020 by using 24-hr daily means sampled and analyzed by the US Environmental Protection Agency (EPA) Air Quality System (<https://www.epa.gov/aqs>) at ground monitoring stations. We used an ensemble machine learning model to predict daily $\text{PM}_{2.5}$ at each population-weighted ZIP code centroid in San Diego County (Aguilera et al., 2021). Briefly stated, we fitted a series of machine learning models (including gradient boosting machine, random forest and deep learning) using $\text{PM}_{2.5}$ concentrations and a wide range of predictors for $\text{PM}_{2.5}$, such as aerosol optical depth, land use

and meteorological conditions, to estimate daily concentrations of $PM_{2.5}$ at the ZIP code level, a relevant spatio-temporal resolution for epidemiological studies. Our ensemble model of the above machine learning algorithms produced high model prediction capabilities (R^2 of 0.86). The detailed methodology is presented in Aguilera et al. (2021).

2.3. Meteorological Covariates

Meteorological conditions such as minimum and maximum temperature, and wind velocity were extracted from the high-resolution Gridded Surface Meteorological data set (gridMET; Abatzoglou, 2013). The gridMET data set blends the high-resolution spatial data from PRISM with the high temporal resolution data from the National Land Data Assimilation System (NLDAS) to produce spatially and temporally continuous, complete, high-resolution (1/24th degree \sim 4-km) gridded data set of surface meteorological variables across the contiguous United States. Values for these meteorological covariates were extracted at the location of ZIP code population-weighted centroids in San Diego County.

3. Materials and Methods

3.1. Weekly Differentials

To assess the impacts of COVID-19 pandemic restrictions, we quantified weekly differentials between January and September 2020 with respect to the preceding period (2016–2019) for each of the variables involved in our study: $PM_{2.5}$ and respiratory ED visits. In this way, we examine the changes on a given week in 2020, before, during and after the stay-at-home period, relative to the recorded observations during that same given week in the preceding four years. Specifically, we calculated the robust differences, a metric recently proposed by Bekbulat et al. (2021), by subtracting the temporally corrected median of the preceding period from weekly median value in 2020 from the normalized to the interquartile range (IQR). For the preceding period (2016–2019), we also considered the 2 weeks before and after a given 7-day week (i.e., a 5-week window) to calculate the median. This allowed us to increase the sample size, consider a broader comparison window, and help smooth atypical weeks in the data set for the preceding period (Bekbulat et al., 2021).

Temporally corrected differences account for trends observed in the data within the preceding years, particularly for $PM_{2.5}$. The temporal correction for a given ZIP-code-week is the 4-year slope (2016–2019) of weekly median concentrations within the preceding period 15. Thus, we compared the observed year-2020 values to the “expected” level for a given week in year-2020, accounting for 4-year trends for that week-of-year at that location.

We also quantified weekly anomalies, that is, an additional measure of weekly differentials, in $PM_{2.5}$ and respiratory visits for each ZIP-code-week, as a sensitivity analysis (see details in appendix). Anomalies for a given ZIP code and week were defined as the difference between a 7-day mean value in 2020 and the average of those for the same week (plus/minus ± 2 weeks) for a 4-year baseline (2016–2019). We contrasted the resulting set of differentials (robust differences and anomalies) with the measures taken as a response to the COVID-19 pandemic within San Diego County and the State of California, US (Table 1). We classified weeks based on these measures, as follows: weeks <12 , before stay-at-home order; weeks 12–15, during stay-at-home-order, and weeks >15 corresponded to the period after the stay-at-home order in our study region. Only the weeks before and during were considered in the analyses describe in Sections 3.2 and 3.3.

3.2. Mediation Analysis

We hypothesized that the total effect of the stay-at-home mandate on pediatric respiratory ED visits partially occurred through decreases in $PM_{2.5}$ concentrations (due to a change in traffic emissions and population mobility). When a mediator, that is, $PM_{2.5}$ concentration, is hypothesized, the total effect can be decomposed into two parts: the direct effect, which is the natural direct effect of the stay-at-home mandate on the drop in respiratory visits (setting the mediator to a fixed value), and the natural indirect effect of the stay-at-home mandate on respiratory visits that works through the mediator (i.e., $PM_{2.5}$ concentrations). The main identification assumptions are that there were no unmeasured confounders and no mediator-outcome confounders induced by the exposure. We dealt with seasonal confounding and trends within the 4-year preceding period by estimating directly weekly differentials for the outcome and the mediator (see details above).

Table 1

Timeline of Measures Taken in 2020 in Response to the COVID-19 Pandemic in San Diego County and California

Week of the year	Date in 2020	Measures taken in response to COVID-19
10	March 9	Declaration of Local Health Emergency by County of San Diego
11	March 13	County of San Diego issues its initial public health order for COVID-19
12	March 19	California stay-at-home order
16	April 14	Stay-at-home order loosens statewide
17	April 27	Some San Diego-area beaches and open spaces reopen for limited use
18	May 1	Mask mandate put in place
19	May 7	Some businesses begin reopening
20	May 18	New criteria allowing some counties, including San Diego, to reopen more of their economies
21	May 21	Indoor dining resumes
24	June 12	County of San Diego allows certain gyms, bars, museums, hotels and other businesses to reopen.
25	June 18	Face-covering guidance, mandate to wear masks indoors
27	July 5	Bars and indoor dining closing
28	July 13	Closing of all indoor activities
32	August 6	San Diego hits second wave peak of 652 new daily cases
35	August 31	San Diego placed in Red Tier under the “Blueprint for a Safer Economy”

To quantify the proportion mediated by $PM_{2.5}$ concentrations, we estimated the total (TE), natural direct (NDE) and indirect (NIE) effects as detailed below. In this way, we isolated the underlying contribution of reductions in $PM_{2.5}$ by which the stay-at-home and associated measures affected respiratory visits in our study area. We included weekly robust differences, estimated as described above in Section 3.1 and shown in Figure S2 in Supporting Information S1, in minimum and maximum temperature and in wind velocity as controls. The stay-at-home variable was defined as binary where 0 was assigned to weeks before (weeks <12) and 1 corresponded to weeks 12–15. We did not adjust for traffic or population mobility in our mediation analysis, as these variables represent the main mechanism through which we expect a change in $PM_{2.5}$ due to the stay-at-home order.

We implemented the inverse odds ratio-weighted (IORW; Tchetgen Tchetgen, 2013) approach to estimate total, direct and indirect effects. Such approach is particularly well fitted when multiple mediators are considered simultaneously (or to handle potential mediator-outcome confounders induced by the exposure) by capitalizing on the odds ratio's invariance property. IORW synthesizes information on the odds ratio between the exposure (which is the dependent variable here) and mediators into a weight (similar to inverse probability weighting). The obtained weight is then used to estimate natural direct effects via a weighted outcome regression analysis. Then, indirect effects are estimated by subtracting direct effects from total effects (outcome model without weights). Confidence intervals are obtained via bootstrapping (1,000 replications).

3.3. Spatial Analysis

We assessed whether weekly changes in $PM_{2.5}$ and respiratory ED visits were spatially clustered across San Diego County before (weeks <12) and during (weeks 12–15) the stay-at-home order. Specifically, we aimed to measure the spatial correlation and capture how much bivariate associations are spatially clustered, while accounting for the spatial distribution of the two variables involved. For this purpose, we used Lee's L statistic (Lee, 2001), which combines Pearson's r as a spatial bivariate association measure and Moran's I as a univariate spatial association measure. Local L statistics can help investigate bivariate spatial heterogeneity by detecting the local instability

in relationships between two variables (Kim et al., 2018). In addition, local statistics are important because the magnitude of spatial autocorrelation typically present in environmental and health datasets is not uniform over a study area (Kim et al., 2018). Weekly local Lee's L statistics are shown as maps highlighting clustering of spatial correlation between high $PM_{2.5}$ concentrations and of high number of respiratory visits (High-High), and clusters with low $PM_{2.5}$ spatially correlated with low respiratory visits (Low-Low).

4. Results

4.1. Weekly Differentials in Respiratory ED Visits and $PM_{2.5}$ Concentrations

Weekly $PM_{2.5}$ concentrations (Figure 1a) in 2020, relative to the expected values based in the 4-year baseline, decreased particularly between weeks 10 and 12, at the beginning of the COVID-19 pandemic in San Diego County. The decrease in $PM_{2.5}$ roughly extends until week 15, after which an ease in stay-at-home order restrictions was gradually implemented (Table 1 and Table S2 in Supporting Information S1). As economic activities resumed with the ease of restrictions, $PM_{2.5}$ robust differences were closer to or higher than the expected values based on the 4-year baseline. The highest positive robust differences were observed by the end of our study period due to the presence of smoke from wildfires burning in the County and in California. The initial decline in $PM_{2.5}$ was short-lived, as mentioned above. Weekly differences for rates of pediatric respiratory ED visits dropped around week 12, when California issued a statewide stay-at-home order. This drop was maintained throughout all following weeks in 2020, with a few exceptions (Figure 1b). Overall, lowest values of differences in respiratory visits were observed immediately after the stay-at-home order was issued in Week 12.

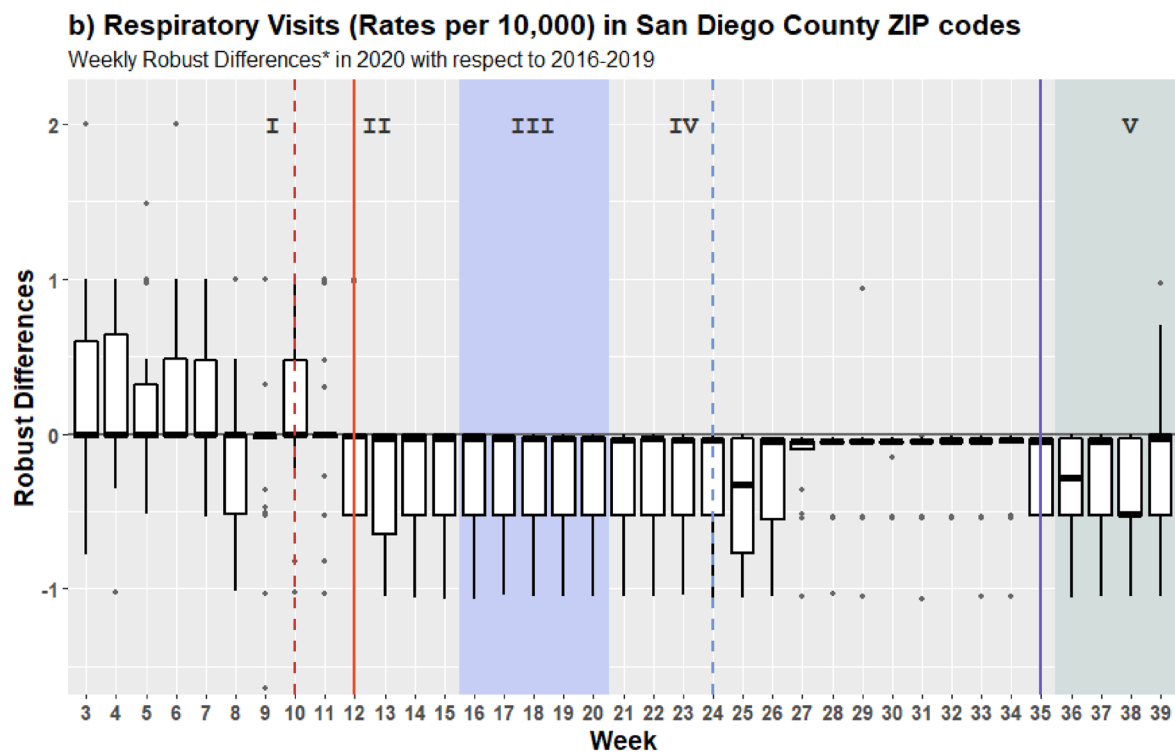
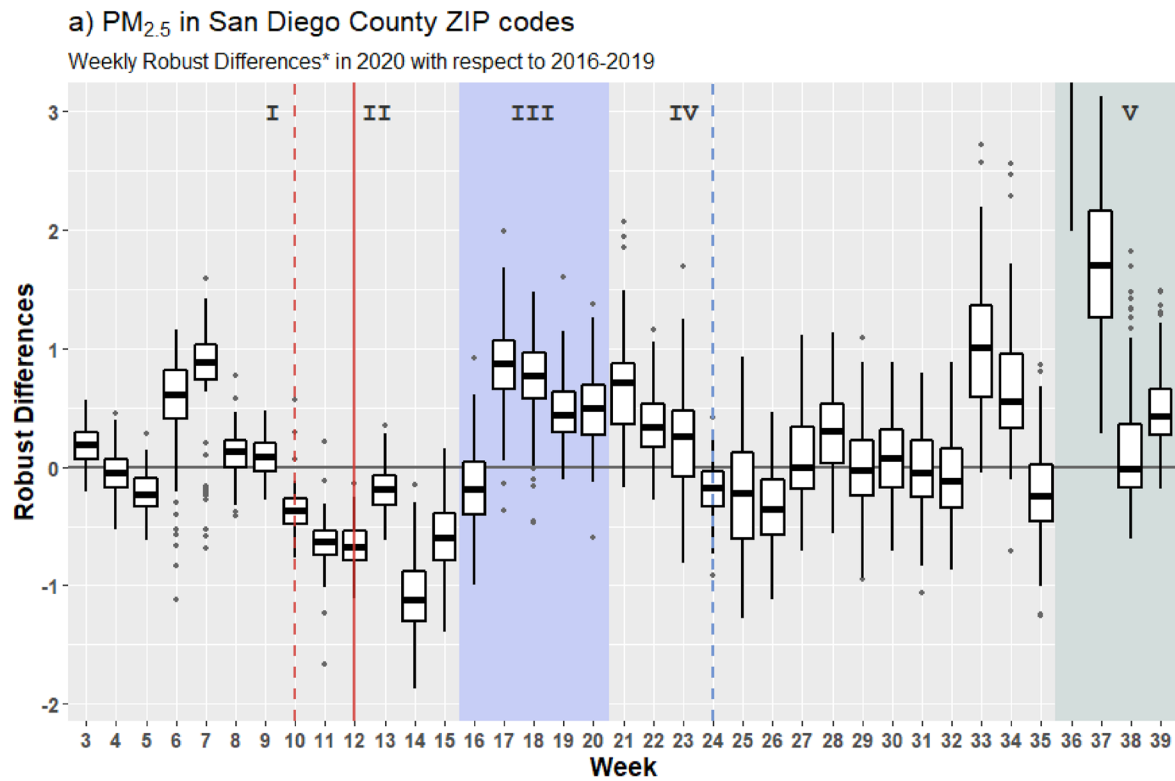
In addition to temporal variation, robust differences in $PM_{2.5}$ concentrations for a given week in 2020 varied spatially across ZIP codes (Figure 2). During early 2020 and prior to the stay-at-home period (weeks 12–15), most ZIP codes had slightly higher $PM_{2.5}$ concentrations than the expected values (Figure 2a). These areas corresponded mainly to the more densely populated coastal ZIP codes, which is also where highways are found. During the stay-at-home period, $PM_{2.5}$ slightly decreased in the above areas (Figure 2b). Spatial differences in weekly respiratory ED visits showed that the lowest values during the stay-at-home period were found in southern ZIP codes in San Diego County (Figure 3).

The sensitivity analyses and results, where anomalies were estimated as alternative weekly differential measures instead of the robust differences proposed by Bekbulat et al. (2021) are presented in the Supplemental Information. Overall, weekly anomalies in 2020, relative to the 4-year baseline, showed similar patterns to those seen in weekly robust differences: anomalies in $PM_{2.5}$ were lowest following the stay-at-home mandate on week 12 (though briefly) and anomalies in respiratory ED visits dropped after week 12 and stayed low throughout our study period (Figure S1 in Supporting Information S1).

The natural indirect effect (NIE) (Table 2) corresponds to the effect of the stay-at-home order on robust differences for respiratory ED visits that is specifically related to robust differences in $PM_{2.5}$ concentrations. This reduction value of -0.016 ($-0.041, 0.0041$) based on IORW, though slightly imprecise, corresponds to 3.8% of the total effect estimate of -0.43 ($-0.52, -0.35$). Said differently, decreases in $PM_{2.5}$ attributed to the stay-at-home order contributed to explain approximately 4% of the decrease in pediatric respiratory ED visits.

In addition to the results for the stay-at-home period (weeks 12–15), we performed a sensitivity analysis with alternative time periods including week 10 (local health emergency declared in San Diego) and week 11 (local health order). We also extended the period to week 16 and week 17, immediately after the stay-at-home order was loosened and some restrictions were lifted in the County of San Diego and/or state-wide. We found that, for the most part, the proportion mediated actually increased (Table 2), especially during weeks 10–16 and 11–16 (12.3% and 12.4%, respectively). These increases potentially indicate the presence of lagged effects and that behaviors may have changed before the statewide stay-at-home order starting at Week 12.

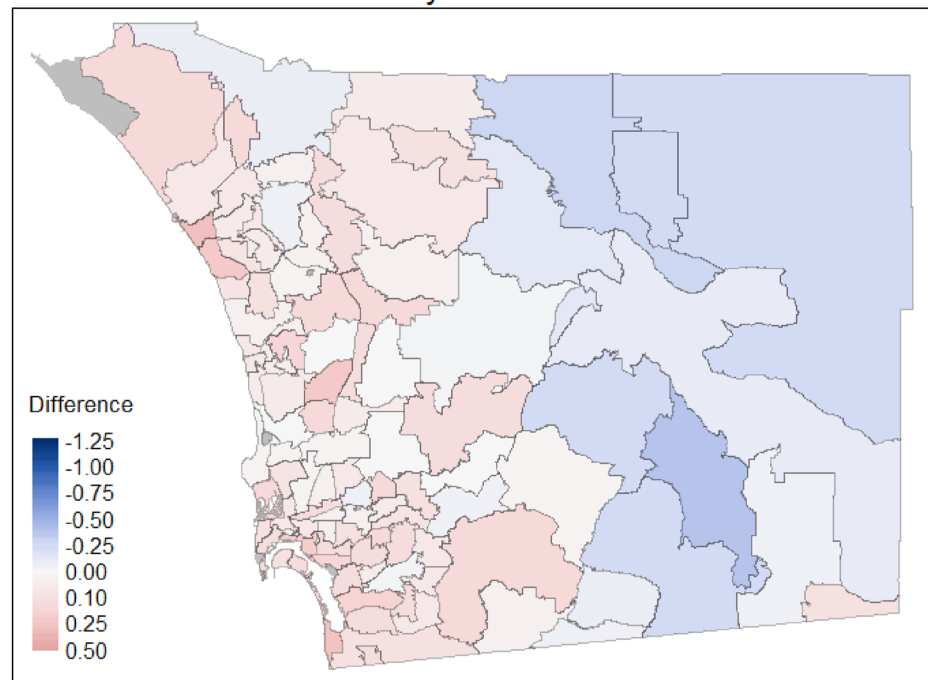
Lastly, Figure S3 in Supporting Information S1 shows several High-High and Low-Low clusters for the bivariate association between robust differences in $PM_{2.5}$ concentrations and pediatric respiratory visits in San Diego County, along with other areas displaying inverse associations between them. These bivariate associations are described by means of Lee's L and translated into clustering patterns. Once the stay-at-home order was implemented at week 12, Low-Low clusters were predominantly found in southern San Diego County. Here, lower than



*Bekbulat et al., 2021

Figure 1. Weekly robust differences for (a) PM_{2.5} and (b) respiratory visits in 2020 with respect to a 4-year baseline (2016–2019). Highlighted COVID-19 measures: I = Local Health Emergency (San Diego County); II = Stay-at-Home Order; III = Ease of Restrictions, IV = Businesses Reopening, V = Wildfire Smoke. *PM_{2.5} robust differences observed for week 36 were higher than any other observations during the year and are not displayed in the figure.

a) Mean Weekly Robust Differences in PM_{2.5}
Before Stay-at-Home Order



b) Mean Weekly Robust Differences in PM_{2.5}
During Stay-at-Home Order

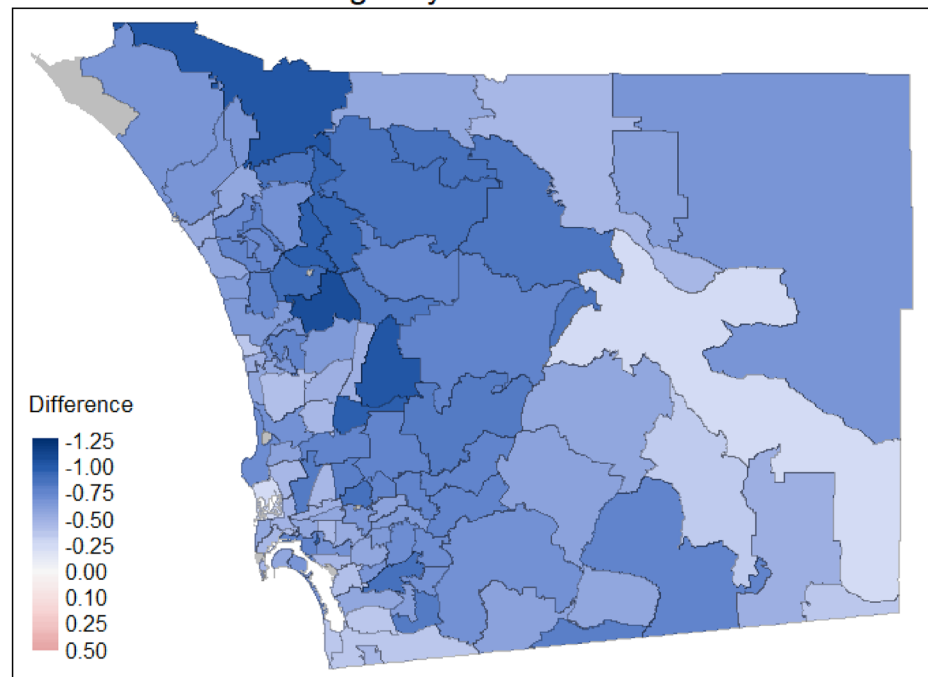
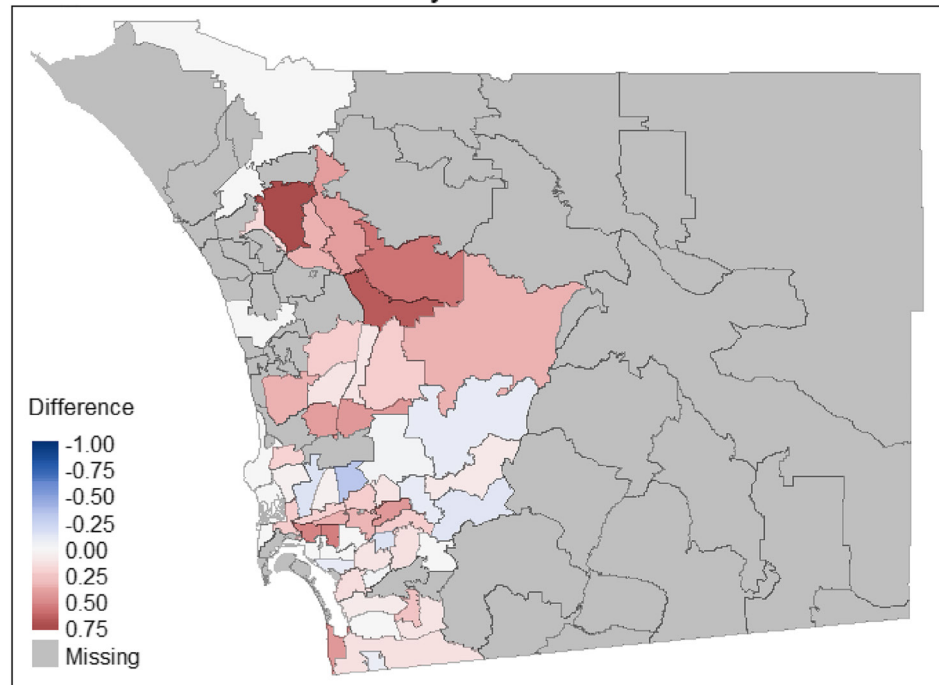


Figure 2. Spatial patterns of mean weekly robust differences in PM_{2.5} in 2020 with respect to a 4-year baseline (2016–2019). (a) Differences in weeks prior to the stay-at-home period (week <12). (b) Differences during the stay-at-home mandate (weeks 12–15).

a) Mean Weekly Robust Differences in Respiratory Visits
Before Stay-at-Home Order



b) Mean Weekly Robust Differences in Respiratory Visits
During Stay-at-Home Order

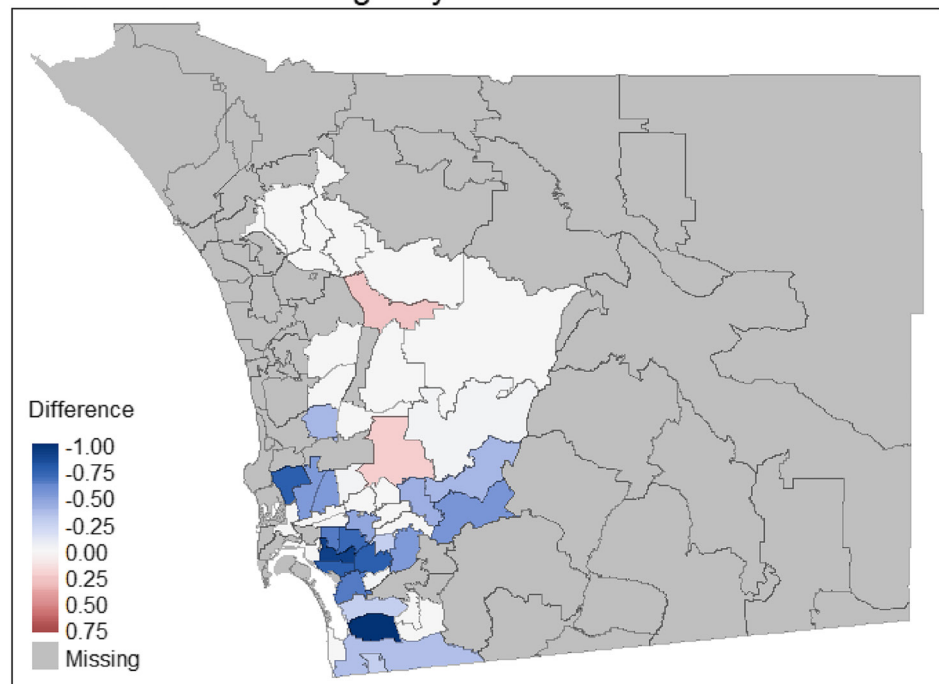


Figure 3. Spatial patterns of mean weekly robust differences in respiratory visits (rates per 10,000) in 2020 with respect to a 4-year baseline (2016–2019). (a) Differences in weeks prior to the stay-at-home period (week <12). (b) Differences during the stay-at-home order (weeks 12–15).

Table 2
Mediation Analysis

Period (Weeks)	Total effect (TE)	Natural direct effect (NDE)	Natural indirect effect (NIE)	Proportion mediated (%)
12–15	−0.43 (−0.52, −0.35)	−0.41 (−0.50, −0.34)	−0.016 (−0.041, 0.0041)	3.8
Alternative periods				
12–16	−0.21 (−0.29, −0.14)	−0.19 (−0.26, −0.12)	−0.027 (−0.050, −0.0052)	12.5
12–17	−0.25 (−0.33, −0.19)	−0.23 (−0.30, −0.16)	−0.024 (−0.049, −0.0020)	9.5
11–15	−0.36 (−0.44, −0.28)	−0.34 (−0.42, −0.26)	−0.017 (−0.045, 0.0065)	4.9
11–16	−0.21 (−0.29, −0.14)	−0.19 (−0.26, −0.12)	−0.026 (−0.052, −0.0063)	12.4
11–17	−0.26 (−0.33, −0.18)	−0.23 (−0.30, −0.16)	−0.025 (−0.050, −0.0042)	9.9
10–15	−0.30 (−0.38, −0.22)	−0.28 (−0.36, −0.20)	−0.021 (−0.052, 0.0051)	7.1
10–16	−0.21 (−0.29, −0.14)	−0.19 (−0.26, −0.11)	−0.026 (−0.050, −0.0052)	12.3
10–17	−0.26 (−0.34, −0.19)	−0.23 (−0.31, −0.16)	−0.025 (−0.052, −0.0027)	9.7

expected values with respect to the 4-year baseline were observed both in $PM_{2.5}$ concentrations and respiratory visits.

5. Discussion and Conclusions

We found a considerable drop in pediatric respiratory ED visits in the wake of the COVID-19 pandemic in 2020, based on our assessment of robust differences in relation to the preceding 4-year baseline. Following unprecedented public health interventions in early 2020, similar findings have been reported worldwide, both for the pediatric (Angoulvant et al., 2021; Fan et al., 2021; Kishimoto et al., 2021; Nolen et al., 2020; Trenholme et al., 2021) and general populations (Jeffery et al., 2020; Olsen et al., 2021).

Decreases in $PM_{2.5}$ concentrations were also observed in our study and elsewhere (Bekbulat et al., 2021; Gkatzelis et al., 2021; Liu et al., 2021; Venter et al., 2020). Our weekly estimation of robust differences showed a short-lived decrease in $PM_{2.5}$ concentrations immediately after the stay-at-home order was issued in California (19 March 2020; Week 12). This drop in $PM_{2.5}$ was maintained until the most restrictive measures were loosened on Week 16.

We hypothesized that decreases in air pollutants like $PM_{2.5}$ played a role in the observed decreases in pediatric respiratory ED visits in our study region. Through IORW mediation analysis, we estimated $PM_{2.5}$ decreases contributed 4% to the total observed decrease in ED visits (see Table 2). Since part of the mechanism involved in the abatement of $PM_{2.5}$ concentrations is linked to reductions in traffic and population mobility, we did not explicitly consider traffic as a mediator in our analysis.

Reduced $PM_{2.5}$ pollution clearly contributed to the decreases in respiratory ED visits among children in our study, which suggests an abrupt sudden change in exposure (Simoneau et al., 2021). However, the decrease in respiratory ED visits may have largely been a direct consequence of social distancing and school closures in preventing the spread of respiratory illnesses among children. Similar studies in other regions in the US and worldwide anecdotally attribute the dramatic decline in respiratory visits to measures such as universal masking, social distancing, and school closures during stay-at-home order periods in 2020 (Chu et al., 2020; Hatoun et al., 2020; Kishimoto et al., 2021; Nolen et al., 2020). Other potential explanations would be an increased adherence to medication for the asthmatic population, avoidance of healthcare settings due to fear of contracting COVID-19, as well as lower exposure to outdoor aero-allergens (Simoneau et al., 2021).

Limitations of our work include the use of patient's residence address (ZIP code) to estimate exposure and using community-level $PM_{2.5}$ to assess and quantify individual $PM_{2.5}$ exposures. We also acknowledge that other pollutants such as nitrogen dioxide (NO_2) and ozone would also be of interest in the study of air pollution effects on children's health, because of this unprecedented intervention associated with the COVID-19 pandemic. Other mediators besides additional air pollutants, such as changes in population mobility, also exist. In the future, it

would be interesting to compare the specific role of multiple mediators to better understand the mechanisms through which COVID-19 restrictions may have benefited children's health.

Lastly, we observed a considerable spatial variability in robust differences for both respiratory visits and PM_{2.5} concentrations in San Diego County ZIP codes. The spatial distribution of weekly differentials changed within our study period and was not uniform or entirely spatially correlated among the variables considered here. However, concomitant decreases observed for both variables are encouraging in an environmental justice perspective in certain areas of the County that are otherwise characterized by poor air quality and high incidence of respiratory illness (see Figure S4 in Supporting Information S1). The cluster analysis presented helps in identifying areas where air pollutants like PM_{2.5} can be targeted for regionally specific intervention in the context of public health, paying special attention to pediatric health. Being able to prevent pediatric respiratory infections through public health interventions, such as mask-wearing, staying home when sick and frequent handwashing, as well as reducing traffic emissions, could provide an opportunity to control future pediatric respiratory burden.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All data, except for the Emergency Department (ED) visits data set, are available at <https://doi.org/10.5281/zenodo.6981734>.

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