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Impact of the COVID-19 induced lockdown measures on PM$_{2.5}$ concentration in USA

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HIGHLIGHTS

• We examine the impact of the COVID-19 lockdown measures on the PM2.5 concentration level in USA.
• We also investigate if there is any spatio-temporal heterogeneity in the effect of lockdown on air quality.
• We use Linear mixed effects models and functional regression methods as primary tools of our analysis.
• We adjust for local meteorological variables to remove their confounding effect on PM2.5 concentration.

ARTICLE INFO

Keywords:
COVID-19
Lockdown
PM$_{2.5}$
Air quality
Mixed effects model
Functional regression

ABSTRACT

In 2020, most countries around the world have observed varying degrees of public lockdown measures to mitigate the transmission of SARS-CoV-2. As an unintended consequence of reduced transportation and industrial activities, air quality has dramatically improved in many major cities around the world. In this paper, we analyze the environmental impact of the lockdown measures on PM$_{2.5}$ concentration levels in 48 core-based statistical areas (CBSA) of the United States, during the pre and post-lockdown period of January to June 2020. We model the effect of lockdown on the PM$_{2.5}$ concentration in different CBSAs while adjusting for various meteorological factors like temperature, wind-speed, precipitation and snow. Linear mixed effects models and functional regression methods with random intercepts are employed to capture the heterogeneity of the effect across different regions. Our analysis shows there is a statistically significant reduction in levels of PM$_{2.5}$ across most of the regions during the lock-down period, although interestingly, this effect is not uniform across all the CBSAs under consideration.

1. Introduction

The global pandemic caused by the outbreak of the novel coronavirus SARS-CoV-2 in 2020 have resulted in various degrees of public lockdown measures being implemented by local and national governments in different countries. These measures aimed at mitigating the transmission of the novel coronavirus disease, imposed restrictions on public and/or private transportation and led to temporary shut down of various industrial activities. Along with several important public health (Heymann and Shindo, 2020) and socio-economic impacts (McKibbin and Fernando, 2020; Nicola et al., 2020), the lockdown itself, presumably has had a significant environmental effect as well (Liu et al., 2020a, b; Saadat et al., 2020; Rodríguez-Urrego and Rodríguez-Urrego, 2020), with reports of “nature healing itself” coming out from around the world (Rupani et al., 2020; Archer et al., 2020). In populous countries like China and India, researchers have identified drastic improvement in air quality (Liu et al., 2020a; Lokhandwala and Gautam, 2020) in terms of concentration levels of various primary air pollutants such as PM$_{2.5}$, PM$_{10}$, Carbon Monoxide (CO), Nitrogen dioxide (NO$_2$), Sulphur dioxide (SO$_2$), etc. Rodríguez-Urrego and Rodríguez-Urrego (2020) found around 12% reduction in PM$_{2.5}$ levels in the 50 most contaminated capital cities around the world during the period of lockdown.

In the United States as well, several studies were conducted scrutinizing the impact of the COVID-19 lockdown measures on the environment. The Rhodium Group estimated that this drastic drop in economic activity led to a 10.3% drop in US greenhouse gas emissions in...
2020, which is the “single largest drop in annual emissions in the post-World War II era” (Larsen et al., 2021). Interestingly, in spite of the drop in CO$_2$ emissions, CO$_2$ levels determined in 2020 were higher than in 2021, with a peak in May. In fact, the latest data show that global emissions were 2% higher in December 2020 than they were in the same month a year earlier. Many major economies are observing a sharp resurgence in CO$_2$ levels as a result of accelerated economic activities pushing energy demand higher and a general lack of significant policy measures in promoting clean energy (iea.org, 2021). In California, USA (first state to implement a stay-at-home order), a sudden drop (and increment) in air pollution, in terms of concentration levels of major pollutants such as NO$_2$, PM$_{2.5}$ and CO, were found to be concurrent (Liu et al., 2020b) with the shutdown (and reopening) dates in the state. Archer et al. (2020) examined the spatial variability of air quality changes in the USA during the COVID-19 pandemic in terms of two pollutants: PM$_{2.5}$ and NO$_2$. They compared these pollutant levels in April 2020 with the corresponding pollutant levels observed over the past five years. Although they found significant decrease in NO$_2$-level across various ground weather stations, no such effect of lockdown measures was observed in the level of PM$_{2.5}$ for the month of April. In contrast, Chen et al. (2020) identified a nonuniform impact of lockdown on air quality including concentration level of PM$_{2.5}$ across the USA.

In this paper, we investigate the impact of lockdown on air quality across the USA, by comparing the level of PM$_{2.5}$ during the pre-lockdown and lockdown period of January to June 2020. As reported in recent studies, the concentration level of PM$_{2.5}$ is found to be associated with higher mortality rate and increased severity of COVID-19 infections (Wu et al., 2020; Yongjian et al., 2020). PM$_{2.5}$ is one of the six major pollutants monitored by the United States Environmental Protection Agency (EPA). It is emitted from domestic heating, by airplanes and various motor vehicles, including commercial heavy-duty diesel trucks and also by fossil-fuel power plants. Besides these primary emissions, PM$_{2.5}$ can also be of secondary origin, formed during chemical reactions of other pollutants and gases e.g., SO$_2$, nitrogen oxides (NO and NO$_2$), volatile organic compounds (VOCs) and Ammonia (NH$_3$) (Hao et al., 2020; Wu et al., 2007). Given the reduced operations of airplanes (Monmousseau et al., 2020) and commercial heavy-duty diesel trucks, as a result of lockdown measures across the states, we should expect to see a decrease in the level of PM$_{2.5}$ during the lockdown period. Our goal is to quantify this effect and study its spatio-temporal heterogeneity, if present.

Instead of comparing the average pollutant levels in 2020 with the past years, we focus our attention to the pre-lockdown and lockdown period in 2020 only, so that the impact of lockdown does not get confounded by the “decreasing multi-annual concentration trends” in PM$_{2.5}$ (Archer et al., 2020). However any comparison among the levels of PM$_{2.5}$ over several consecutive months needs to be suitably adjusted for the local weather patterns because these concentration levels are heavily dependent on individual meteorological factors (Liu et al., 2017). Therefore, in order to properly identify and isolate the effect of lockdown on PM$_{2.5}$ levels, we adjust for the seasonal and local weather effects e.g. temperature, wind speed, precipitation and snow. Without such adjustments, any decrease in pollutant levels might be statistically void as one might just be capturing the natural seasonal fluctuations in the pollutant level.

Another important factor to take into account while investigating the environmental impact of the COVID-19 lockdown measures, is the spatial variability in these effects across various regions of the United States. Such variability is expected due to the variability in population density and industrial activities across states and also because of the varied measures of public lockdown e.g., stay-at-home, shelter-in-place to none at all. Moreover the effective dates of the lockdown also varied extensively across the states. Therefore careful statistical analysis addressing the heterogeneity among the states, and over time is necessary in order to identify and understand the environmental effects of COVID-19 lockdown across USA. In this paper, we focus on the environmental impact of the lockdown measures during the COVID-19 pandemic on 48 core-based statistical areas (CBSA) in the United States. Specifically, we consider particulate matter 2.5 (PM$_{2.5}$) concentration between January 1, 2020 to June 29, 2020 as the primary environmental indicator of air quality in our study. We employ linear mixed effects models and functional regression techniques for analyzing the effects of lockdown on PM$_{2.5}$ levels while adjusting for various meteorological factors and region-specific effects.

Fig. 1 displays the time-varying pattern of lockdown and daily mean of PM$_{2.5}$ concentration levels in four representative CBSA: (i) New York-Newark-Jersey City, NY-NJ-PA; (ii) Los Angeles-Long Beach-Anaheim, CA; (iii) Manchester-Nashua, NH; and (iv) Jacksonville, FL respectively.

Different patterns of PM$_{2.5}$ concentration with and without lockdown can be observed in the four CBSAs. While there is a visible decrease in the peak PM$_{2.5}$ concentration in New-York and Los Angeles, the effect of the lockdown is not so evident in Manchester-Nashua and Jacksonville. Therefore in order to properly model the impact of lockdown on PM$_{2.5}$, it becomes essential to address region-specific heterogeneity and adjust for local weather effects. Our analysis in this paper attempts to present a deeper understanding and impact of lockdown measures on PM$_{2.5}$ levels across USA, which might assist the policy makers in implementing tailored interventions for curbing air pollution levels in the future.

2. Material and methods

2.1. Study area

Our study focuses on PM$_{2.5}$ concentration levels across 48 core-based statistical areas (CBSA) (also known as Metro/Micropolitan Statistical Areas) in the United States from January 1 to June 29. The complete list of the CBSAs can be found in supplementary Table A3. The 48 core-based statistical areas (as defined in https://www.epa.gov/outdoor-air-quality-data/air-quality-index-report) were chosen to represent all the major cities from the 50 states across USA. Air pollution in the United States has been getting worse over the years, and can be attributed to: booming economic activity, increase in number of wildfires (Westerling and Bryant, 2008), and relaxed enforcement of clean air regulations. The degree and the intensity of the air pollution also varies regionally depending on these factors. Early studies analyzing the effects of the lockdown on levels of air pollutants in the USA have identified a nonuniform impact across the states (Chen et al., 2020). Specifically, majority of the reduction was found to be taking place in densely populated areas across the Northeast and California/Nevada regions. We intend to capture this heterogeneity through analyzing the PM$_{2.5}$ concentration levels in the 48 CBSAs that cover the most populous cities across all 50 states in USA.

2.2. Data

Data on daily mean of PM$_{2.5}$ concentration levels across the 48 CBSAs were obtained from https://www.epa.gov/outdoor-air-quality-data/air-quality-index-report for the study period of January 1-June 29, 2020. Daily weather data on minimum temperature, maximum temperature, average wind speed, precipitation, snow and daily max 2 min wind speed were obtained from https://www.ncdc.noaa.gov/cdo-web/datassets and aggregated over the sites within every CBSA under consideration.

2.3. Methods and statistical analysis

We use three different statistical models with increasing hierarchy of complexity to model the effect of lockdown on PM$_{2.5}$ concentration levels while accounting for region specific heterogeneity and adjusting for local weather effects.

First, we use a mixed effects model for longitudinal data with random intercepts for region-specific effects to model the effect of lockdown on
PM$_{2.5}$ concentration levels given by,

\[
Y_{ij} = \beta_0 + aT_{ij} + \sum_{j=1}^{6} \beta_j X_{ij} + \gamma_0 Z_{ij} + b_i + \epsilon_{ij},
\]

(1)

Here the response $Y_{ij}$ is the daily mean of PM$_{2.5}$ concentration levels (log-transformed) in region $i$ on day $t$. The corresponding weather variables minimum temperature, maximum temperature, average wind speed, precipitation, snow and daily max 2 min wind speed are denoted by $X_{ij}$ ($j = 1,...,6$) and their fixed effect is captured by $\beta_j$. The time since the beginning of the study is denoted by $T_{ij}$ and its effect is captured via fixed effect $a$. $Z_{ij}$ is the binary lockdown status of region $i$ on day $t$ (coded as 1 during the time of the lockdown; and coded as 0 otherwise). This is the main predictor of interest in our analysis. The effect of the lockdown is captured via the fixed effect $\gamma_0$. The region-specific impact is captured by the random effect $b_i$. The region-specific impact is captured by the random effect $b_i \sim N(0, \sigma^2_b)$. Finally, $\epsilon_{ij} \sim N(0, \sigma^2_\epsilon)$, is the region and day specific residual error. The random intercept model is a multi-level model which essentially allows each region to have it’s own linear regression function, against a particular predictor of interest. These region-specific regression lines with random intercept, are parallel to the average population-level regression line (corresponding to fixed intercept $\beta_0$).

The mixed effects model 1 considers different intercept for every region, which allows each region to have its own baseline level of PM$_{2.5}$. This is essential since industrial regions with higher population density (e.g. California) are likely to have elevated levels of PM$_{2.5}$, compared to regions with sparser population density and/or lower economic activity. A natural hierarchical extension of this model would be to allow random slopes along with random intercepts. Region-specific random slopes for “lockdown status” $Z_{ij}$ might be important if the lockdown tends to have varying degrees of impact on different regions. As we already discussed in section 1, different states in USA observed different degrees of public lockdown measures ranging over “stay-at-home”, “shelter-in-place” to none at all. This disparity might result in a non-homogeneous degree of reduction in PM$_{2.5}$ level across different regions. To check this hypothesis, we now extend the mixed effects model 1, allowing region-specific random slopes for the lockdown effect $Z_{ij}$. Specifically, the model is given by,

\[
Y_{ij} = \beta_0 + aT_{ij} + \sum_{j=1}^{6} \beta_j X_{ij} + (\gamma_0 + \gamma_j) Z_{ij} + b_i + \epsilon_{ij},
\]

(2)

Here $\gamma_j$ is a random effect, capturing different region-specific effect of lockdown on PM$_{2.5}$ concentration levels (log-transformed). The random slope model allows the regression line for each region to have a different slope, hence allowing the explanatory variable lockdown-status to have a different effect in each region. If in reality, there is no such heterogeneity across regions, we should expect the variance of these random intercepts to be very close to zero, which would essentially reduce model 2 to the simpler constant-slope model 1. The model specification is completed by assuming,

\[
\begin{pmatrix}
\gamma_0 \\
\gamma_1 \\
\gamma_2 \\
\gamma_3 \\
\gamma_4 \\
\gamma_5 \\
\gamma_6
\end{pmatrix} \sim N_6(0, \Omega), \quad \Omega = \begin{pmatrix}
\sigma^2_0 & \sigma_{01} & \sigma_{02} & \sigma_{03} & \sigma_{04} & \sigma_{05} & \sigma_{06} \\
\sigma_{10} & \sigma^2_1 & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{15} & \sigma_{16} \\
\sigma_{20} & \sigma_{21} & \sigma^2_2 & \sigma_{23} & \sigma_{24} & \sigma_{25} & \sigma_{26} \\
\sigma_{30} & \sigma_{31} & \sigma_{32} & \sigma^2_3 & \sigma_{34} & \sigma_{35} & \sigma_{36} \\
\sigma_{40} & \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma^2_4 & \sigma_{45} & \sigma_{46} \\
\sigma_{50} & \sigma_{51} & \sigma_{52} & \sigma_{53} & \sigma_{54} & \sigma^2_5 & \sigma_{56} \\
\sigma_{60} & \sigma_{61} & \sigma_{62} & \sigma_{63} & \sigma_{64} & \sigma_{65} & \sigma^2_6
\end{pmatrix}
\quad \text{and} \quad \epsilon_{ij} \sim N(0, \sigma^2_\epsilon).
\]

Third, we use a functional concurrent regression model (Leroux et al., 2018) allowing region specific functional intercept and smooth time-varying effect of the lockdown status and the weather variables. The effect of lockdown is captured by a time-varying effect $\gamma_0(t)$. Specifically, the model is given by,

\[
Y_{ij}(t) = \beta_0(t) + \sum_{j=1}^{6} \beta_j(t)X_{ij}(t) + (\gamma_0(t) + \gamma_j(t)) Z_{ij}(t) + b_i(t) + \epsilon_{ij}(t).
\]

(3)

Here the response $Y_{ij}(t)$ again represents the daily mean of PM$_{2.5}$ con-
Results from the linear mixed effects model 1 of Table 1

The region-specific deviation is captured by the functional random effect $b_i(t) \sim \mathcal{N}(0, \sigma_i^2)$. Finally, $s_i(t) \sim \mathcal{N}(0, s^2_i)$, denotes the region and day specific residual error. The above model 3 can be seen as a generalization of random intercept model 1 allowing time-varying dynamic effects of both lockdown status and the adjusting weather factors. In addition, a region-specific dynamic deviation is captured by the functional random effects $b_i(t)$.

There are three questions at the heart of our analysis: (i) is there any impact of the lockdown measures imposed during the COVID-19 pandemic, on the level of PM$_{2.5}$ concentration in USA? and (ii) if present, how does this impact vary across different regions? and (iii) does this effect vary over time as well? Model 1 addresses the first question while Model 2 digs deeper into the data to investigate possible region-specific heterogeneity that might help answer the second question. Finally Model 3 tries to answer the third question by extending the model 1 to a functional data analysis (FDA) framework that allows the impact of both lockdown status and local weather conditions to vary smoothly over time.

3. Results

Table 1 presents the results from the random intercept model 1, analyzing the effect of lockdown on PM$_{2.5}$ concentration levels. The estimated fixed effect $\gamma_0$ corresponding to lockdown is reported to be $-0.030$ (with P-value 0.0008) illustrating a significant negative impact of lockdown on PM$_{2.5}$ concentration levels across USA after adjusting for the local weather conditions. The effect of all the weather variables, as intuitively expected, are found to have a significant impact on daily PM$_{2.5}$ concentration. Specifically, daily PM$_{2.5}$ concentration level is found to be positively associated with maximum temperature and snow, and negatively associated with minimum temperature, average wind speed, precipitation, and daily max 2 min wind speed. The conditional $R^2$ (Nakagawa and Schielzeth, 2013) of the model (representing the proportion of variance explained by both the fixed and random factors) is reported to be 0.377. Fig. 2 displays the observed and predicted trajectories of PM$_{2.5}$ concentration levels from model 1 for the four CBSA regions considered in Fig. 1.

Although the daily variation in PM$_{2.5}$ concentration levels is captured well in the CBSA corresponding to New York and Jacksonville, for Los Angeles or Manchester-Nashua the predictions are quite a bit off. This suggests that there might be other region-specific factors that might influence the variation in the PM$_{2.5}$ concentration, which are not accounted for by local weather effects and lockdown measures. Interestingly, Los Angeles is one of the most polluted cities in our sample and Manchester-Nashua is towards the lower end in terms of typical daily PM$_{2.5}$ concentration, while both New York and Jacksonville fall somewhere in between.

To explore the regional effect of lockdown on PM$_{2.5}$ concentration levels across USA we fit model 2 with region-specific random slopes for lockdown. Table 2 presents the results from the analysis. The estimated fixed effect $\gamma_0$ corresponding to lockdown is reported to be $-0.023$ (with P-value 0.1271), indicating a negative (although not statistically significant) population level impact of lockdown on PM$_{2.5}$ concentration levels. We perform a likelihood ratio test to test whether the additional variance components corresponding to the random effects of model 2 are significant. The P-value of the test is calculated to be $< 0.0001$. This demonstrates that there is significant region-specific heterogeneity in the effect of lockdown on PM$_{2.5}$ concentration levels across USA.

To get a sense of the degree of heterogeneity in region-specific effects of lockdown, we report the empirical BLUP (best linear unbiased predictor) estimates of the region-specific random effects from model 2, in ascending order of the random slopes in Supplementary Table A3. We notice that 22 out of 48 CBSAs have a negative random slope corresponding to lockdown status and if we consider region specific regression lines, the slope ($\gamma_0 + \gamma_i$) is negative for 32 out of the 48 regions, indicating a decrease of PM$_{2.5}$ concentration level in these regions during lockdown. In terms of the magnitude of the effect, we notice a substantial decrease in PM$_{2.5}$ levels during the lockdown period, in densely populated areas such as New York and Baltimore. The severity of lockdown measures might have contributed to this effect as well, for example New York was one of the worst hit regions from COVID-19 and had therefore enforced stricter lockdown policies. A somewhat counter-intuitive phenomenon is observed in the Los-Angeles-Long Beach-Anaheim region, one of the most populated and polluted regions in USA. We observe a very small negative slope ($-$0.029), corresponding to the lockdown status in this region, even though it had strict lockdown measures in place during the study period (Liu et al., 2020b; COVID19.CA.GOV, 2020). As LA times reported in May (Barboza, 2020), the pandemic had hindered the enforcement of clean air rules which might have aided this effect. Chauhan and Singh (2020) also found marginal decrease in PM$_{2.5}$ concentration in Los-Angeles and this was attributed to local weather conditions e.g., rainfall over the lockdown period. Another factor that can potentially interfere with the atmospheric PM$_{2.5}$ concentration, thereby diminishing the effect of lockdown is the emission of volatile organic compounds (VOC) by automobiles (Hodan and Barnard, 2004). In a similar study in the Sao Paulo region, Cruvinel Brando Fonseca Marinho (2021) found negligible change in PM$_{2.5}$ level, that can be ascribed to the high number of fire burnings in the Southeast region.

A non-negative slope corresponding to the lockdown status was estimated for 16 out of the 48 CBSAs under consideration including Jacksonville, FL. Interestingly 14 of these 16 CBSAs are in republican states that did not observe strict lockdown measures. The only two democrat regions having non-negative slopes were Portland-South Portland, ME (slope = 0.007) which had a slope very close to zero and Albuquerque, NM (slope = 0.035), which imposed its first lockdown

### Table 1

| Dependent variable: Daily PM$_{2.5}$ concentration (log-transformed) | Value | Std.Error | P-value |
|---|---|---|---|
| Intercept | 2.174 | 0.0357 | $< 10^{-4}$ |
| TMIN | -0.002 | 0.0007 | 0.0067$^{**}$ |
| TMAX | 0.006 | 0.0006 | $< 10^{-4}$ |
| AWND | -0.022 | 0.0018 | $< 10^{-4}$ |
| PRCP | -0.211 | 0.0133 | $< 10^{-4}$ |
| SNOW | 0.036 | 0.0086 | $< 10^{-4}$ |
| WSF2 | -0.003 | 0.0010 | 0.0037$^{**}$ |
| Time | -0.001 | 0.0001 | $< 10^{-4}$ |
| Lockdown | -0.030 | 0.0090 | 0.008$^{***}$ |

Observations: 8605
Groups: 48
$\bar{\sigma}_i$: 0.205
$\bar{\tau}_i$: 0.318
Conditional R$^2$: 0.377
AIC: 4996.116

Note: +$p<0.05$; **+$p<0.01$; ***+$p<0.001$. 

measures in early May. The observed and predicted trajectories of PM$_{2.5}$ concentration levels from model 2 for the four representative CBSA regions considered in Fig. 1 are shown in Supplementary Figure A4.

Next, we fit model 3, restricting our attention to the 32 CBSAs (out of 48 CBSAs considered in model 1 and model 2), for which the slope corresponding to the lockdown status was negative in model 2. The objective is to investigate how the influence of lockdown evolved over the lockdown period, in regions where such a negative impact was indeed present. The time-varying effect of lockdown on PM$_{2.5}$ concentration is found to be statistically significant (P-value = 1.05 x 10^{-7}) during the lockdown period. However, since these lockdown measures were initiated during mid March to late March, in most of these 32 regions, before this period, the effect of lockdown is captured to be not significant by model 3. We display the estimated effect of lockdown $\hat{\gamma}_0(t)$ between the time March 21 to June 29, 2020 (last day considered in our study) in Fig. 3. We notice the effect of lockdown to be negative and significant in late March up to first two weeks of April (corresponding to ~ 85-th to 100-th day of the study). This can be attributed to the initial change in the environment that was introduced due to the lockdown measures such as reduced industrial activity, restricted transportation etc. Interestingly, we observe a positive but non-significant effect of the lockdown status during the end of our study. One possible reason behind this could be a gradual decrease in the severity of the lockdown measures, in several of the regions by the start of July.

The adjusted R$^2$ from model 3 is reported to be 0.537 indicating improved predictive performance (compared to model 1 and model 2) due to the time-varying effect of lockdown and local weather effects. All the local weather effects are also found to be significant. Figure A5 in the supplementary material, displays the observed and predicted trajectories of PM$_{2.5}$ concentration levels from model 3 for the CBSAs of New York, Los Angeles-Long Beach-Anaheim and Manchester-Nashua, NH. We observe the daily PM$_{2.5}$ concentration levels, particularly for Los Angeles-Long Beach-Anaheim, are captured more closely compared to the mixed effects models (Fig. 2 and A.4), highlighting the efficacy of the functional concurrent regression model (3).

4. Discussion

In this paper we have examined the influence of the lockdown measures imposed due to the COVID-19 pandemic, on the PM$_{2.5}$ concentration level, in the most densely populated core based statistical areas in each of the 50 states in USA. We chose PM$_{2.5}$ as a proxy for the overall air quality in these regions as PM$_{2.5}$ is one of the six most common air pollutants monitored by EPA and has important implications on public health. After comparing the pollutant level in the pre-lockdown and lockdown period in 2020 through a longitudinal and a functional analysis perspective, we conclude that the various lockdown measures implemented across USA had a significant impact in bringing down the PM$_{2.5}$ concentration level. Moreover, there is considerable heterogeneity in this effect across different regions, the common pattern being: the more severe the lockdown measures, the more pronounced reduction in the pollutant level. This corroborates the consensus among the majority of the emerging studies on the environmental impact of COVID-19 pandemic, that the different degrees of public lockdown measures imposed during the pandemic can be associated to an improvement in air quality in various major cities. This environmental rejuvenation,
Table 2
Results from linear mixed effects model 2 of PM$_{2.5}$ concentration levels on lockdown status and local weather effects. Reported are the estimated fixed effects along with their standard error and P-values. TMIN: minimum temperature, TMAX: maximum temperature, AWND: average wind speed, PRCP: precipitation, SNOW: snow, WSF2: daily max 2 min wind speed.

|                             | Value | Std.Error |   P-value |
|-----------------------------|-------|-----------|-----------|
| Intercept                   | 2.178 | 0.0348    | < 10$^{-4}$ |
| TMIN                        | -0.002| 0.0007    | 0.0083    |
| TMAX                        | 0.006 | 0.0006    | < 10$^{-4}$ |
| AWND                        | -0.022| 0.0018    | < 10$^{-4}$ |
| PRCP                        | -0.211| 0.0132    | < 10$^{-4}$ |
| SNOW                        | 0.035 | 0.0085    | < 10$^{-4}$ |
| WSF2                        | -0.003| 0.0010    | 0.0025    |
| Time                        | -0.001| 0.0001    | < 10$^{-4}$ |
| Lockdown                    | -0.023| 0.0163    | 0.1271    |
| Observations                | 8605  |           |           |
| Groups                      | 48    |           |           |
| \(\hat{\sigma}_u\)         | 0.198 |           |           |
| \(\hat{\sigma}_r\)         | 0.087 |           |           |
| \(\hat{\tau}_{\text{aw}}\) | 0.352 |           |           |
| \(\hat{\tau}_{\text{pr}}\) | 0.316 |           |           |
| Conditional R²              | 0.385 |           |           |
| AIC                          | 4945.512 |       |           |

Note: *p<0.05; **p<0.01; ***p<0.001.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2021.118388.

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