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Stringency of COVID-19 Containment Response Policies and Air Quality Changes: A Global Analysis across 1851 Cities

Jiawei Zhang, Youn-Hee Lim, Zorana Jovanovic Andersen, George Napolitano, Seyed Mahmood Taghavi Shahri, Rina So, Maude Plucker, Mahdieh Danesh-Yazdi, Thomas Cole-Hunter, Jeanette Therming Jørgensen, Shuo Liu, Marie Bergmann, Amar Jayant Mehta, Laust H. Mortensen, Weeberb Requia, Theis Lange, Steffen Loft, Nino Kuenzli, Joel Schwartz, and Heresh Amini*

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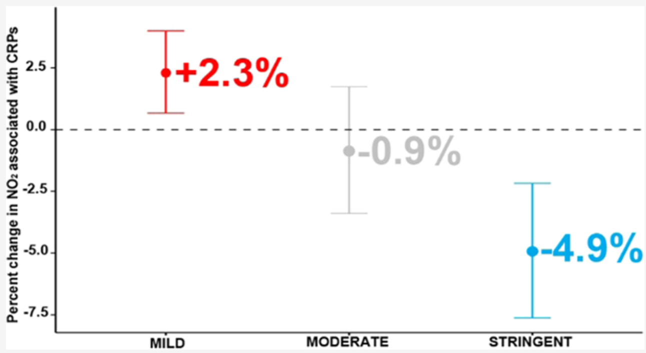

ABSTRACT: The COVID-19 containment response policies (CRPs) had a major impact on air quality (AQ). These CRPs have been time-varying and location-specific. So far, despite having numerous studies on the effect of COVID-19 lockdown on AQ, a knowledge gap remains on the association between stringency of CRPs and AQ changes across the world, regions, nations, and cities. Here, we show that globally across 1851 cities (each more than 300 000 people) in 149 countries, after controlling for the impacts of relevant covariates (e.g., meteorology), Sentinel-5P satellite-observed nitrogen dioxide (NO_2) levels decreased by 4.9% (95% CI: 2.2, 7.6%) during lockdowns following stringent CRPs compared to pre-CRPs. The NO_2 levels did not change significantly during moderate CRPs and even increased during mild CRPs by 2.3% (95% CI: 0.7, 4.0%), which was 6.8% (95% CI: 2.0, 12.0%) across Europe and Central Asia, possibly due to population avoidance of public transportation in favor of private transportation. Among 1768 cities implementing stringent CRPs, we observed the most NO_2 reduction in more populated and polluted cities. Our results demonstrate that AQ improved when and where stringent COVID-19 CRPs were implemented, changed less under moderate CRPs, and even deteriorated under mild CRPs. These changes were location-, region-, and CRP-specific.

KEYWORDS: *SARS-CoV-2, air pollution, lockdown, policies, worsened*

1. INTRODUCTION

To contain and control the transmission of COVID-19, diverse policies have been adopted by governments across the world, such as limiting public transportation, encouraging or mandating working from home, and enforced closure of public services, which profoundly affect people's daily lives.[1] The impact of the COVID-19 pandemic on air quality (AQ) has been heavily reported worldwide. Dozens of researchers used in situ ground monitoring information,[2,3] satellite observations,[4,5] and model simulations[6,7] to depict the change in air pollution during the pandemic (Table S1). Venter et al. reported that concentrations of ground monitored nitrogen dioxide (NO_2), a pollutant mainly emitted from the transportation sector, had declined by ~60% across 34 countries due to COVID-19 lockdown.[8] Bao et al. reported an ~25% reduction in NO_2 across 44 cities in China,[9] and Sharma et al. observed an 18% reduction in NO_2 from March to April 2020 across 22 Indian cities compared to previous years.[10] In addition, greater than 50% reductions in NO_2 were observed in Sao Paulo, Brazil[11] and Delhi, India.[12]

While numerous studies have reported AQ changes due to COVID-19 lockdown, challenges still exist in most studies. Arguably, most studies neglected the impacts of other determinants of AQ, such as meteorological conditions and time trend.[13,14] Without proper adjustment for these covariates, attributing the AQ changes to COVID-19 lockdown per se might not necessarily be correct, and previous studies have not addressed these well, especially on a global scale.[7−9] Besides, the inconsistent definition of lockdown also constrains current global and cross-region comparisons. The COVID-19

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containment response policies (CRPs) have been diverse and time varying across countries; in other words, dynamic policies were implemented by governments and local authorities to control the pandemic. Previous studies mostly took the implementation of one certain policy as the characteristic node of COVID-19 lockdown.[8,15] Although such an approach could be informative, it did not consider the implementation quality of CRPs over time on AQ, as sometimes multiple policies are implemented simultaneously.[1] Moreover, it is still unclear whether AQ changes occurred across all cities worldwide or if they were modified by other factors, such as population, pollution level, and so on.

This study aimed to address these gaps by estimating the associations between AQ and COVID-19 CRPs, using data from the Sentinel-5 Precursor (Sentinel-5P) satellite across 1851 cities within 149 countries. This dataset allowed a comprehensive analytical approach to estimate the impact of COVID-19 CRPs on AQ. First, we examine the city-specific association between AQ and COVID-19 CRPs scores as a continuous covariate, which measured the stringency of the CRPs in each country on a scale ranging from 0 to 100. Then, we categorize CRPs into mild, moderate, and stringent policies and estimate the city-specific AQ changes associated with different CRP categories after adjusting for the nonlinear influences of time trends and meteorological factors. Finally, we conduct a meta-analysis to obtain global, regional, and national estimates. Effect modification by population and baseline NO_2 concentrations is also explored.

2. MATERIALS AND METHODS

2.1. National Daily COVID-19 CRPs Data. We obtained national time-series COVID-19 CRPs implementation data from January 01, 2019, to July 31, 2020, from Oxford's COVID-19 Government Response Tracker (OxCGRT).[1,16] The OxCGRT is a database that systematically collected and tracked 19 policy indicators and actions, such as health-, economic-, and closure-related policies, adopted by >180 countries around the world to respond to the COVID-19 pandemic since January 01, 2020.[17−20] Daily "containment and closure policies" were selected for the study, which consisted of the following eight types of policies and their implementation: school closures, workplace closures, public event cancellations, gathering restrictions, public transportation closures, stay-at-home requirements, internal movement restrictions, and international travel control.

Due to the spatial and temporal heterogeneity of COVID-19 CRPs implementation, we considered the policy implementation situation in each country and on each day as an individual observation in this analysis and clustered the country-days with similar policy implementations together. In brief, following the instructions of OxCGRT, we calculated the response score (0−100) for each country-day through additive unweighted indices and using the K-means algorithm with gap statistics clustered them into three categories (Table 1 and see Supplementary Text 1 for more details).

Table 1. Description of COVID-19 Containment Response Policies (CRPs) Categories

CRP	related policies
no intervention	
mild CRPs	recommend closing school
	recommend work from home
	recommend canceling public events for certain areas
	restriction on very large gatherings (>1000) in certain areas
	recommend not to travel between regions/cities
	quarantine arrivals from some or all regions and screening arrivals
moderate CRPs	require closing of certain levels of school
	require closing for some sectors
	require canceling public events for most areas
	gathering limit to 1000 or less
	recommend self-protection when using public transport
	recommend not leaving home
	recommend not travel to certain cities/regions
	ban arrivals from some regions, quarantine arrivals from all regions, and screening arrivals
stringent CRPs	require all school closure
	require closing for all-but-essential workplace
	require canceling all public events
	gathering limit to 10 people or less
	recommend closing public transportation in certain areas
	require not leaving the house with exceptions for daily exercise, grocery shopping, and "essential" trips
	recommend not travel between cities/regions, and internal movement restrictions in place
	ban on all regions or total border closure

2.2. Daily Ambient NO_2 Data. We retrieved tropospheric NO_2 concentration from the TROPOspheric Monitoring Instrument (TROPOMI) installed on the Sentinel-5P satellite. Following Ozone Monitoring Instrument (OMI) and Global Ozone Monitoring Experiment-2 (GEOM-2) instruments, TROPOMI measures the tropospheric NO_2 from the ultraviolet−visible backscatter satellite instruments, which is a well-established and matured approach developed over the past two decades.[21] The TROPOMI NO_2 processor adapted the progress in advanced Dutch OMI NO_2 product of the Royal Netherlands Meteorological Institute for OMI (DOMINO) chemistry modeling-retrieval-assimilation approach, differential optical absorption spectroscopy (DOAS) optimizations, and air-mass factor lookup table to provide the tropospheric NO_2 data daily. We used version 1.04.00 TROPOMI level 3 Near Real-Time NO_2 data products and aggregated their resolution to 10 km × 10 km in Google Earth Engine. We only included urban agglomerations (cities) with a population larger than 300 000 people as defined by the United Nation's World Urbanization Prospects (WUP2018-F22), resulting in 1851 cities across 149 countries.[22,23]

2.3. Daily Meteorological Conditions Data. Daily meteorological covariates, including temperature, humidity, wind speed, and surface pressure, were collected from the Climate Forecast System, National Oceanic and Atmospheric Administration, at a spatial resolution of 10 km × 10 km.[25]

2.4. Statistical Analysis. Log-transformed NO_2 was used to have a better model fitting and a normal distribution of residuals.[24] We applied a location-specific multiple regression model to each city, including data from January 1st, 2019, to July 31st, 2020, to quantify the impact of different CRPs on daily air quality.

$$\log(y_{u,t}) = \beta_{0,u} + \beta_{1,u}[P]_{u,t} + \sum_{c} \beta_{c,u} Z_{c,u,t} + \in_{u,t}$$

$$;\ \in_{u,t} \sim N(0, \sigma_u);\ u \in (1, 2, 3, \ldots\ldots, 1851)$$

where $y_{u,t}$ is the NO_2 level in location u on date t; $[P]_{u,t}$ represents the different CRPs (mild, moderate, or stringent intervention—categorical) or the CRPs scores—continuous—

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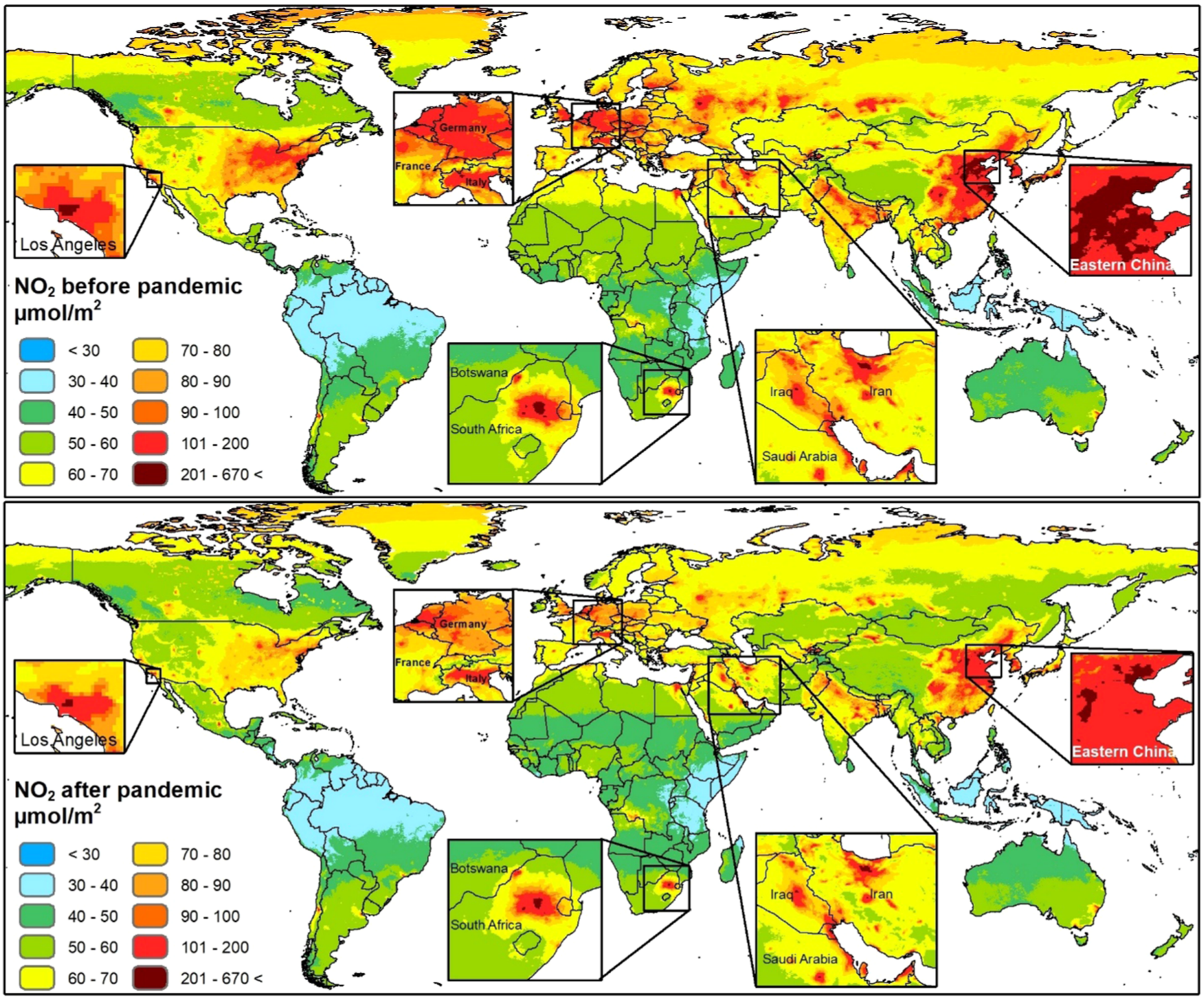

Figure 1. Mean satellite observed NO_2 concentrations before (January 1st to July 31st, 2019) and after (January 1st to July 31st, 2020) COVID-19 pandemic. Although NO_2 was reduced across many countries after the pandemic, these could not be totally attributable per se to CRPs as meteorology and time trends among other factors may have a role. The reader is referred to Table S2 for the exact start date of the CRPs in each city and detailed summary statistics on observed NO_2 before and after implementation of CRPs across 1851 cities.

ranging from 0−100; $Z_{c,u,t}$ represents the covariate c controlled in our studies, including temperature, humidity, wind speed, surface-level air pressure, time trend, and day of the week; $\beta_{c,u}$ represents the covariates' influence on the NO_2 level in each urban agglomeration; $\beta_{0,u}$ is the intercept of location u, indicating location's fixed emission effect characteristics, and $\epsilon_{u,t}$ is the error term. In this estimation, the relative change in air quality can be presented as: AQ = $e^{\beta_{1,u}} - 1$ (for the categorical CRP variable) and $AQ = e^{\beta 1,u*10} - 1$ (for the continuous CRP variable).

Considering the important influence of time trends and meteorological variables (temperature, humidity, wind speed, surface-level air pressure), we built five different models to adjust for the time trend and meteorological variables and chose the final model based on the lowest average Akaike information criterion[26] across all 1851 cities. The models included:

- Model 1 (final model): Used natural cubic splines with city-specific degrees of freedom for both time trend and meteorological variables (temperature, humidity, wind speed, and surface-level air pressure).
- Model 2: Used a time-stratified approach to control for the time trend and natural cubic splines with city-specific degrees of freedom for meteorological variables.
- Model 3: Used a periodic function for the time trend and natural cubic splines with city-specific degrees of freedom for meteorological variables.
- Model 4: Used natural cubic splines with city-specific degrees of freedom for time trend and linear terms for meteorological variables.
- Model 5: Used a natural cubic spline with city-specific degrees of freedom for time trend and natural cubic splines with 2 degrees of freedom for meteorological variables.

The above-mentioned city-specific optimal degrees of freedom for time trend or meteorological variables were estimated using the penalized spline terms in the generalized additive models.

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After obtaining city-specific results, in the pooled analysis, we applied multilevel meta-analytical models as a priori considering the variations in the associations across two nested groups (cities and countries) and pooled city-specific estimations to calculate the overall (global) association. We assessed heterogeneity using I^2 statistic and Cochran's Q test and calculated the heterogeneity in each level[27] (see Supplementary Text 2 for more details). Further, city-specific random effect was also applied to synthesize the associations, and the likelihood ratio test was used to examine the necessity to consider two nested variations. The high heterogeneity (I^2 = 80.7% in city-specific random-effect models, I^2 = 78.1% in the city- and country-specific random-effect models) in the pooled estimates and the likelihood ratio test between city-specific random-effects model and city- and country-specific random-effect models ($P < 0.001$) further confirmed the need to consider the nested variation across the city and country level.

We examined whether the associations persisted in the early months of the pandemic by restricting our study endpoints to different months, across 5 months of the changing pandemic timeline. For each endpoint, the number of cities was reduced as CRPs were time-varying across countries. We also calculated country-specific and region-specific (defined by World Bank) estimates of the CRPs−AQ association to examine the geographic distribution of the association.

To further explore the potential effect modifications by population, baseline pollution, and climate characteristics, we conducted subgroup analyses first to observe their patterns and fitted separate meta-regression models with the baseline pollution level and the logarithm of the population (see Supplementary Text 2 for more details). We also fitted multivariate meta-regression models to separate the modification effect of population size and baseline pollution level.

We performed several sensitivity analyses. First, we restricted our analysis to cities in the UK and US, where we have finer policy data from 1st administrative areas. Second, we compared the effect estimates and model performance (assessed by the Akaike Information Criteria) with an alternative time-series model, with an autocorrelation structure of order one into the final model.

We used R for cluster and statistical analysis and in particular, the following packages: cluster, factoextra, mgcv, splines, and metaphor; ESRI's ArcGIS for geo-visualization; and Google Earth Engine for satellite and meteorological data retrieval.[5,21,23] See Supplementary Text 3 for a sample R code used for the analyses.

3. RESULTS

3.1. COVID-19 CRPs. This analysis included a total of 324 092 implemented CRP days (from the beginning of implementation at each location up to July 31st, 2020) across 1851 cities in 149 countries. The population living in these cities comprised 33.4% of the world's population. During the study period, China and its provinces had the longest implemented CRPs starting from January 2020, whereas several countries in Africa implemented CRPs from March 2020 (Figure S1). Mild CRPs were implemented in 1699 cities, with the earliest start on January 1st, 2020, in Hong Kong and Taiwan, while moderate CRPs were implemented in 1792 cities. Stringent CRPs were implemented on an average of 113 days (about 3 and a half months) in 1768 cities: minimum in Turkmenistan with 1 day, and maximum in China with 156 days (about 5 months).

3.2. Description of NO_2. The mean concentration of NO_2 pre-CRPs was 106.4 μmol/m^2 across 1851 cities (Table S2), while it was 93.3 μmol/m^2 post-CRPs (Figure 1 and Table S2). The maximum mean NO_2 concentrations (>300 μmol/m^2) pre-CRPs were observed in cities across Iran, China, and South Korea, while the lowest (<40 μmol/m^2) were in cities across Indonesia, Colombia, and Somalia. Tehran (Iran) had the highest NO_2 value of 908.4 μmol/m^2 out of 1851 cities pre-CRPs and also post-CRPs with 508.4 μmol/m^2. The NO_2 values in some populated cities pre-CRPs and post-CRPs in μmol/m^2 units were: Moscow (339 vs 218), Seoul (328 vs 270), Beijing (305 vs 199), Los Angeles (246 vs 203), Milan (237 vs 167), New York (230 vs 192), New Deli (200 vs 141), London (163 vs 136), and Paris (163 vs 123). Across all cities, 83.2% had a decrease in the mean concentration of NO_2 post-CRPs vs pre-CRPs but note that these decreases could not be totally attributable to CRPs per se as meteorology and time trends among other factors may have a role (see Table S2 for detailed summary statistics across 1851 cities). All in all, tropospheric NO_2 was negatively correlated with temperature (Pearson correlation: −0.35), humidity (Pearson correlation: −0.41), and positively correlated with surface pressure (Pearson correlation: 0.14) (Figure S2).

3.3. Association between NO_2 and CRP Scores. Overall, when we evaluated the impact of CRP score (0−100) as a continuous variable on NO_2, a larger CRP score was associated with lower NO_2 concentrations, and an increase of 10 units in CRP score was associated with a 1.1% (95% confidence interval [CI]: 0.8, 1.3%) decrease in NO_2 concentration on lag 3 days of CRP score across 1851 cities. We found evidence of delayed effect from the implementation of policies to AQ changes. As shown in Figure S3, the magnitude of associations increased from lag 0 to lag 3 days and then decreased. Besides, we observed high and significant heterogeneity across country- and location-specific associations (I^2 = 77.5%; Cochran's Q-test $P < 0.0001$). Country-level variances explained 28.6% and location-specific variances explained 48.9% of the heterogeneity.

3.4. Association between NO_2 and CRP Categories. When we evaluated the impact of CRPs as a categorical variable (mild, moderate, stringent; see Section 2 for details) across all studied cities and compared with pre-CRPs, the NO_2 changes associated with CRPs were −.9% (95% CI: −7.6, −2.2%) for stringent, −0.9% (95% CI: −3.4, +1.7%) for moderate, and +2.3% (95% CI: +0.7, +4.0%) for mild CRPs (Figure 2). Stringent and moderate CRPs had similar associations with NO_2 across various months of the study. However, mild CRPs were significantly associated with an increased NO_2 only when including the last month of the study (July 2020) and were positive but not significant when restricted to previous months (Figure S4). The heterogeneity was larger for the stringent CRPs compared to mild CRPs (I^2 = 79.7% vs I^2 = 56.1%; Cochran's Q-test $P < 0.0001$ for both).

Across regions defined by the World Bank (East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa (MENA), North America, South Asia, and Sub-Saharan Africa), stringent CRPs were associated with significant NO_2 reductions in MENA by −14.7% (95% CI: −21.4, −7.5%), South Asia by −8.2% (95% CI: −14.7, −1.1%), and Latin America and the Caribbean by −6.1% (95% CI: −8.8, −3.4%). Under moderate CRPs, only MENA had significant reductions in NO_2 by −6.7% (95% CI: −11.4, −1.7%). Finally, under mild CRPs, Europe and Central

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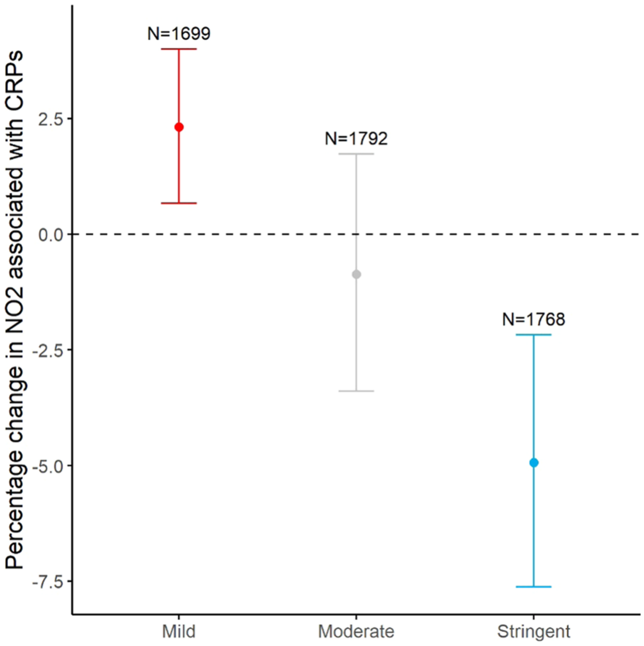

Figure 2. Overall percentage change of Sentinel 5P satellite observed NO_2 concentration associated with different CRP categories compared to the pre-CRP from January 1st, 2019, to July 31st, 2020. Across all studied cities, NO_2 significantly increased by 2.3% across 1699 world cities when mild policies were implemented, had no significant changes under moderate policies, and significantly decreased by about 5% when stringent CRPs were implemented across 1768 world cities.

Asia had significant increases in NO_2 by 6.8% (2.0, 12.0%) (Figure 3 and Table S3).

Among countries, 132 countries implemented stringent CRPs, and their NO_2 changes ranged from −45.9% in Qatar to +33.1% in Norway. Overall, 31 countries had significant reductions in NO_2 where Qatar, Kyrgyzstan, and China had the highest reductions by −45.9% (95% CI: −31.2, −57.5%), −45.7% (95% CI: −16.2, −64.8%), and −42.8% (95% CI: −40.9, −44.7%), respectively. However, 13 countries experienced significant increases in NO_2 even under stringent CRPs, such as Norway, Germany, the UK, and Romania (Figure S5). Overall, about 141 countries implemented moderate CRPs, and among them China with about −45% had the largest reduction in NO_2 while Norway with about 80% had largest increase (Figure S6). Additionally, 140 countries implemented mild CRPs, and their NO_2 changes ranged from −25.7% in Kyrgyzstan to +86.0% in Norway. Nine countries had significant reductions in NO_2, and 24 had significant increases under mild CRPs (half of these were located in Europe and Central Asia) (Figure S7).

Among 1768 cities that implemented stringent CRPs, 531 (30.0%) had a significant reduction, 111 (6.3%) had a significant increase, and there was no difference in NO_2 concentration at 1126 (63.7%) cities (Figure 4). These values across 1792 cities that implemented moderate CRPs were 432 cities (24.1%) with significant reductions, 139 cities (7.8%) with significant increases, and 1221 cities (68.1%) with no significant changes. Finally, for the 1699 cities that implemented mild CRPs, these were 126 cities (7.4%) with significant reductions, 159 cities (9.4%) with significant increases, and 1414 cities (83.2%) with no significant changes. As examples, during the stringent implementation of CRPs, Johannesburg (South Africa) had ∼75% reduction in NO_2 while Kinshasa (Congo) had 58% increase in total column NO_2 (Table S4). Across cities in the United States, we found that Boston in Massachusetts had the largest reductions in NO_2 during both moderate and stringent CRPs by about −50%, while Buffalo in New York had the largest increases in NO_2 during both mild and moderate CRPs by about 150% (Figures S8−S10).

The NO_2 changes associated with stringent CRPs were larger in more populated, more polluted, and less humid cities. In addition, there was a larger reduction in NO_2 in cities with moderate temperature and wind speed. Of note, the NO_2 change in the cleaner cities (cities from the 1st quarter range of 2019 annual mean NO_2) was +0.1% (95% CI: −3.0, +3.4%); however, in the most polluted cities (cities from the 4th quarter range), the change was −22.7% (95% CI: −25.8, −19.5%). Such results were still robust even considering the joint effects of population and baseline NO_2 in a linear analysis (Figure S11 and Table S5).

4. DISCUSSION

In this study, we analyzed the air quality from 1851 cities in 149 countries, covering the period from January 1st, 2019, to July 31st, 2020. We found that, after adjusting for the effect of meteorological covariates and time trend, AQ improved across studied cities when stringent COVID-19 CRPs were implemented, did not significantly change under moderate CRPs, and significantly increased under mild CRPs. We observed that NO_2 reduction was larger at the beginning of the COVID-19 pandemic and modified by the population size of the cities and their baseline NO_2 level in 2019, where more populated and polluted cities had larger improvements in AQ.

This is the first comprehensive study that considered in detail the association between the stringency of COVID-19 CRPs and AQ changes across 1851 world cities. As shown in Table S1, none of the studies, to date, have considered the temporal variability and intensity of CRPs when evaluating the AQ changes attributable to the COVID-19 pandemic. Lian et al. in Wuhan (China), Zangari et al. in New York City (USA), Dantas et al. in Rio de Janeiro (Brazil), and Berman et al. across continental US, among many others, have considered a specific period as lockdown but did not address the stringency of lockdown policies and their temporal variability daily.[2,3,28,29] Such an approach may not accurately identify the impact of a diverse set of policies on AQ that changed over time. Furthermore, numerous studies have not controlled the impact of weather conditions, such as temperature and humidity, and time trends in their analyses.[2,28,30−32]

Overall, both continuous and categorical CRP analyses showed that stringency and implementation of stricter measures improved AQ. To date, several studies have assessed associations between air pollution and COVID-19 lockdown.[8,18,19] Venter et al. reported a 60% population-weighted decline in ground-monitored NO_2 concentration in 34 countries, while a smaller reduction was reported in tropospheric NO_2 by Sentinel 5P, as observed in our analysis. Using data from the world air quality index project, Liu et al. found that ground-level NO_2 reduced between 23 and 37% due to different COVID-19 lockdown measures. Dang et al. used data from Sentinel 5P satellite to explore the subnational AQ changes across 164 countries associated with COVID-19 lockdowns and found a 5% decrease in global NO_2 concentration. However, none of these global studies have

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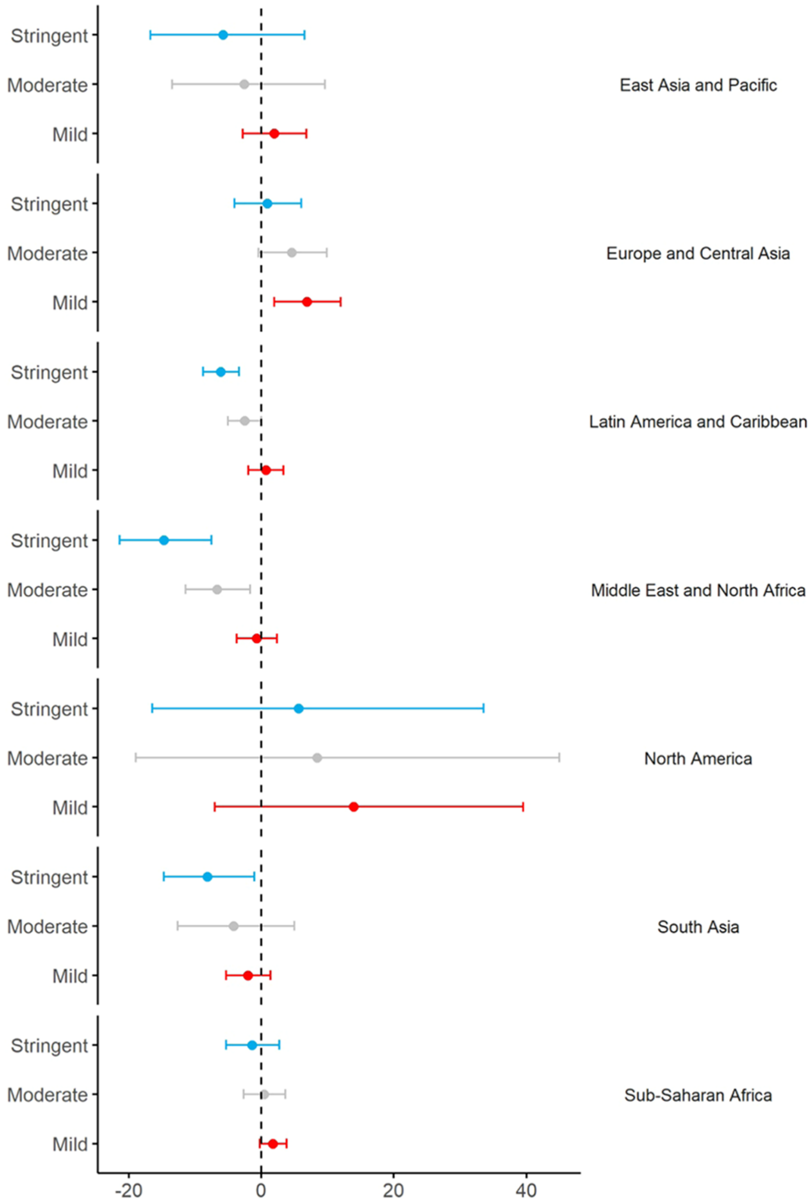

Figure 3. Region-specific percent changes of Sentinel 5P satellite-observed NO_2 associated with different CRPs across 1768 world cities compared to the pre-CRP from January 1st, 2019, to July 31st, 2020. The regions are based on the World Bank definition.

considered the time-varying feature of COVID-19 CRPs. Besides, in the study by Venter et al., they reported that the global AQ status returned to pre-COVID-19 time after about 2 months due to the relaxation of lockdowns in many countries. However, we found that lockdown intensity matters more and stringent CRPs improved AQ in all periods of the study while it gradually reduced over time (Figure S4). This might reflect reduced adherence to COVID-19-related mobility control regulations over time, as discovered by Anna Petherick and their colleagues in their recent study combining individual surveys from 14 countries as well as micro mobile and macro policy data.[33]

At the World Bank regions, we observed consistent AQ improvements in the MENA, followed by South Asia and Latin America, and the Caribbean. These were led by countries such as Qatar, Sri Lanka, China, Kyrgyzstan, and Ecuador. Such results agree with numerous studies conducted in individual countries. Liu et al. reported that when the government in each Chinese province announced the first confirmed COVID-19 case or declared a lockdown, tropospheric NO_2 abruptly declined by 48% from the 20 days averaged before the 2020 Lunar New Year to the 20 days averaged after.[34] Findings from Liu et al. and Naeger and Murphy[35,36] in California, USA, also reported significant AQ improvement during the COVID-19 pandemic. Many other studies have confirmed reductions in NO_2 over China, the USA, and Europe during the lockdowns.[6,9,32,37] Using the high-resolution global coverage Sentinel 5P satellite, our study adds new evidence for many data-deficient cities and countries and strengthens the evidence for the hypothesis that cleaner AQ was associated with the stringent COVID-19 CRPs.

Our findings of increased NO_2 associated with mild CRPs, especially in Europe and Central Asia regional designations of the World Bank, need to be cautiously interpreted. First, the association we found might not be causal. Second, Europe and Central Asia region includes many countries from Europe to

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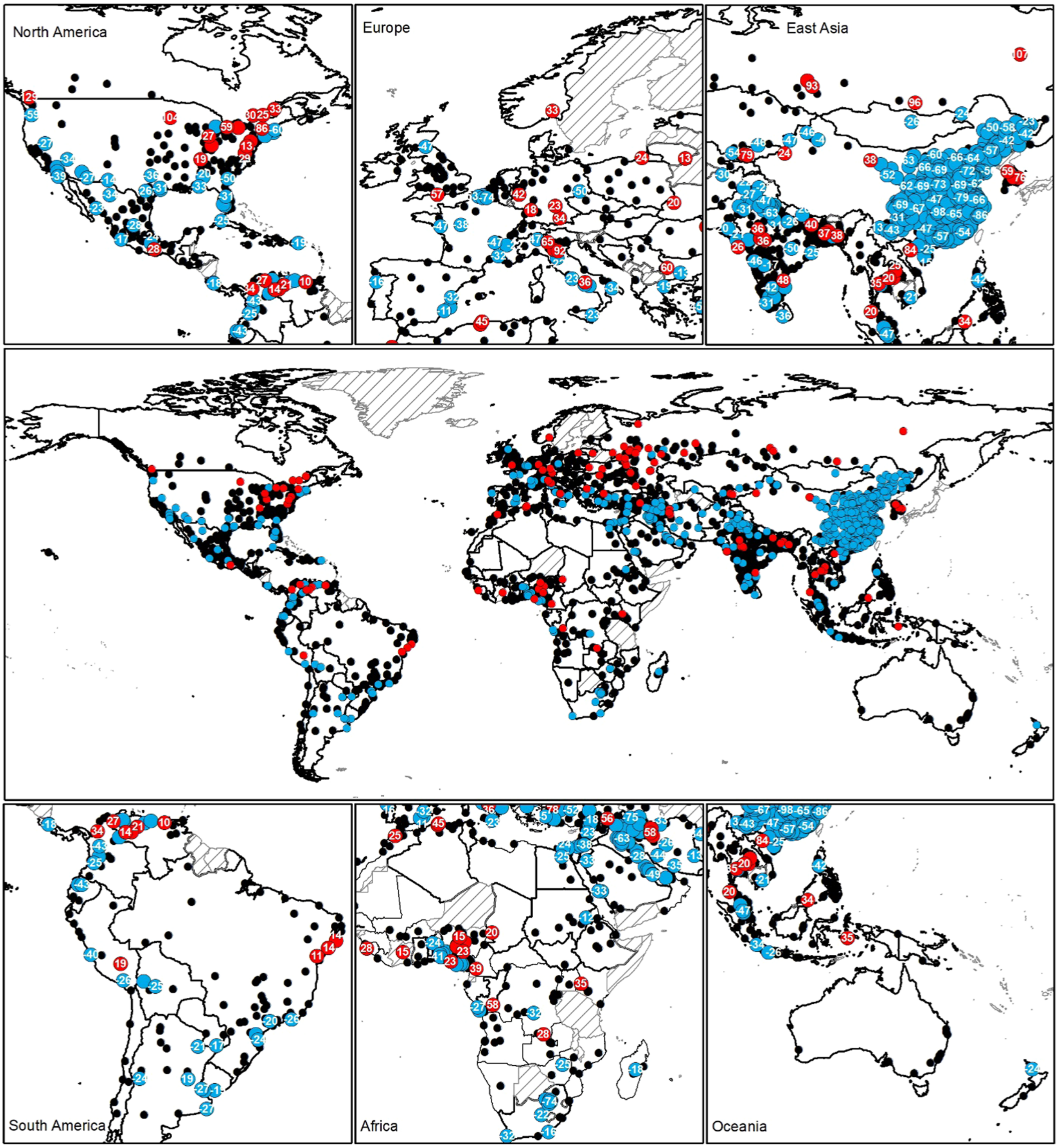

Figure 4. Percent change in Sentinel 5P satellite observed NO_2 across 1736 world cities under stringent CRPs compared to the pre-CRP from January 1st, 2019, to July 31st, 2020. The cities in blue color had a statistically significant reduction, while red-colored cities had statistically significant increases. The black-colored cities had no significant difference in NO_2 before or after the implementation of COVID-19 stringent CRPs. The crosshatched countries/territories had no data on stringent policy interventions in Oxford's COVID-19 Government Response Tracker.

Central Asia, which have had considerable differences in the implementation of COVID-19 CRPs. Third, such increases became insignificant and even null when we restricted the analysis to the early months of the pandemic (Figure S4). However, we have observed significant increases in NO_2 in July 2020 (the last month of our study), which can be attributed to the reopening of the society. On the other hand, Figure S4 highlights that stringent CRPs significantly decreased NO_2 concentrations but not mild CRPs. One speculation could be that mild CRPs might have resulted in population avoidance of public transportation in favor of private transportation, increasing the number of vehicles on the road and overall emissions of NO_2. This may not be true in all countries, and further studies are required to investigate this matter. Our findings may provide useful information for future cost-and-benefit and health impact assessment studies due to the

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COVID-19 pandemic. The European Environment Agency (EEA) using 2015–2019 data for about 2000 regulatory monitoring network stations trained generalized additive models (GAMs), which controlled for meteorological covariates and temporal metrics, and then predicted for the same cities in April–July 2020 in the absence of a lockdown. They calculated the difference between monitored data during the pandemic and the predicted concentrations and reported that difference as the impact of lockdown measures. The EEA reported that the largest NO_2 reductions were in Spain, France, Italy, Great Britain, and Portugal, and the smallest were in eastern EU countries, such as Poland and Hungary. The findings of the EEA are in line with our findings (Figure 4).[37] It is important to note that the EEA did not provide details on the effect of the stringency of CPRs on NO_2.

We also found some unexpected increases in air pollution in certain countries or places during the implementation of stringent CRPs. Although stringent CRPs had reduced emission from some major sources, such as the transportation and industrial sector,[8,38] its impact on other sectors, such as the residential, electricity, and agricultural sectors, have been reported to be limited.[39] Due to the closure of schools and workplaces, people spent more time at home, and the energy consumption in residential places has increased in some settings. Comparable results were also observed in California, USA, during the lockdown, where Liu et al.[40] found that an increase in NO_2 levels occurred in residential regions following the lockdown order by the government. Moreover, Zhu et al.[39] revealed that the global CO_2 levels changed during the COVID-19 pandemic. They further found that despite the sharp decrease in overall carbon dioxide emissions in China during the COVID-19 pandemic, the emission from China's steel industry had a significant increase. People's mobility patterns also changed during the COVID-19 pandemic, which could also account for the increases in NO_2 levels in certain countries. Coven and Gupta[41] pointed out that during the COVID-19 pandemic in New York, richer and younger residents were more willing to leave the city center and sheltered in second homes. In addition, using mobility data in China, researchers also found that during the pandemic, people tended to avoid public transportation and utilized private transportation to minimize human contact.[42] This may contribute to an increase in emissions from road transport, which is a major source of nitrogen dioxide.

The pandemic with its need for CRPs is of utmost public health relevance. The primary and secondary effects of CRPs must be elucidated carefully to fully evaluate the public health impact of the pandemic. Although our analysis cannot address the contribution of single causes and local conditions, regional authorities may well use our results to further investigate the likely local CRPs that caused increases or decreases in air pollution. This, in turn, may guide or endorse environmental policy decisions. For example, some increases may demonstrate the impact of policies that result in the more frequent use of private vehicles, especially in some specific regions of the world.

The results of this study have important implications for public and environmental health. We demonstrated here that not all COVID-19 lockdowns improved AQ. Air pollution has been linked with increased transmission of SARS-CoV-2.[43] Additionally, air pollution has been associated with increased mortality due to COVID-19.[44] Beyond COVID-19, air pollution has been linked with all-cause mortality and morbidities.[45,46] Thus, slight changes in air quality could result in substantial impacts on population health as billions of people are exposed. We highlight the recent calls 6to adopt WHO Air Quality Guidelines 2021 as national AQ standards to protect public health.[47−49] The health impacts of AQ under mild CRPs could present a different situation than moderate or stringent CRPs, which could be investigated in future studies. As a side remark, as a main source of NO_2 is combustion, our findings that during mild CRPs, NO_2 increased across the world underscores the high sensitivity of combustion emissions related to behavioral changes. In our case, those were due to CRPs, but other policy domains may result in similar adaptive behavior. Needless to say that combustion-related NO_2 emissions correlate with other pollutants and increased release of CO_2; hence, policies may have jeopardized attempts to abate climate change. Thus, assessments of the climate change impact of the pandemic will need to take our findings into account.

Several limitations should also be acknowledged in this study. First, our study directly used data of national-level CRPs for location-specific analyses. However, such policies may have been heterogeneously implemented across cities within the same countries. Although we collected and used available 1st level administrative division CRPs data for the UK and the US, we still lacked CRPs data in other countries and regions, especially in countries such as China, where previous research noted the varied implementation of CRPs in each administrative subdivision. We tried to address this using a multilevel meta-analytical model to consider the variation from both cities and countries. Compared to the city-specific random effect meta-model, our approach significantly improved the model fit ($P < 0.001$) and revealed a relatively small reduction in tropospheric NO_2 concentration, indicating the potential overestimation when only considering the variation of policy implementation at the city level. We believe the uncertainty from this would not challenge our main findings. Second, our results need to be carefully interpreted as we used CRPs as indicators instead of actual actions that happened in each city. Although the governments recommended the implementation of CRPs, the public may not have fully implemented such policies. Third, we were not able to examine the intra-urban variation of AQ using satellite data, which may not be uniform within cities.[50] Fourth, our results may not be interpreted as fully globally representative estimates because we only included cities with more than 300 000 inhabitants, accounting for about one-third of the global population. However, since NO_2 sources largely exist in more populated areas, our results could be valid and likely unchanged even with the inclusion of cities with smaller populations. Nevertheless, our results may not be generalizable to rural areas. Notably, our results should be interpreted as pooled estimates for all cities. On the other hand, after including such a large sample size, we found strong effect modification by population size and reduced to null decreases in air pollution in less populated areas even when stringent national CRPs were implemented.

As a sensitivity analysis, we also conducted subgroup analysis for more than 140 US cities, where we found consistent differences between the effects of mild, moderate, and stringent CRPs on AQ, and again AQ improved mostly in the more populated cities (Figure S12). However, we did not find that AQ improvement was mostly in more polluted cities in the US, which contradicts the global results. Possible reasons could be explained by the unabated heavy-duty trucking during the

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COVID-19 pandemic in the USA,[51] and possibly a high correlation between urban NO_2 disparities and social inequality.[52,53]

We finally highlight that the purpose of this work was not designing future CRP policies for COVID-19 restrictions. Such an important work requires considering not only the impacts of COVID-19 CRPs on air quality but also the impacts on numerous other sectors, such as impacts of adopting or not-adopting CRPs on the health care system, economy, and mental well-being of the population, among many others. However, if one focuses on improving air quality, our work provides a solid foundation that stringent policies could lead to significant improvements in air quality.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c04303.

> Supplementary Text 1: COVID-19 containment response policies data and clustering; Supplementary Text 2: statistical analysis; Supplementary Text 3: sample R code for analysis; Table S1: selection of studies on the impact of COVID-19 lockdown on air pollution; Table S2: summary of statistics in each city; Table S3: regional-specific percent changes of NO_2 associated with stringent CRPs; Table S4: percent change of tropospheric NO_2 concentration associated with stringent CRPs in some populated cities; Table S5: effect modification of AQ changes by population and baseline NO_2; Tables S6 and S7: model validation results; Figure S1: timeline for COVID-19 CRPs implementation in each country or region; Figure S2: correlation plot for AQ and covariates adjusted in the model; Figures S3 and S4: lag effect of the association and subset analysis for different ends; Figures S5−S10: heterogeneity of the association in each country and region; and Figure S11: potential effect modification by weather covariates, population, and baseline NO_2 level (PDF)

■ AUTHOR INFORMATION

Corresponding Author

Heresh Amini − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark; Department of Environmental Health, Harvard TH Chan School of Public Health, Boston, Massachusetts 02115, United States;* orcid.org/0000-0002-4825-1322; Email: heresh.amini@sund.ku.dk, heresh@hsph.harvard.edu

Authors

Jiawei Zhang − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Youn-Hee Lim − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Zorana Jovanovic Andersen − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

George Napolitano − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Seyed Mahmood Taghavi Shahri − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Rina So − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Maude Plucker − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Mahdieh Danesh-Yazdi − *Department of Environmental Health, Harvard TH Chan School of Public Health, Boston, Massachusetts 02115, United States; Program in Public Health, Department of Family, Population & Preventive Medicine, Stony Brook University School of Medicine, Stony Brook, New York 11794-8434, United States*

Thomas Cole-Hunter − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark;* orcid.org/0000-0002-6827-6084

Jeanette Therming Jørgensen − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Shuo Liu − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Marie Bergmann − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Amar Jayant Mehta − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Laust H. Mortensen − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark; Methods and Analysis, Statistics Denmark, 2100 Copenhagen, Denmark*

Weeberb Requia − *School of Public Policy and Government, Fundação Getúlio Vargas, Brasilia, Distrito Federal 72125590, Brazil*

Theis Lange − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Steffen Loft − *Department of Public Health, University of Copenhagen, 1014 Copenhagen, Denmark*

Nino Kuenzli − *Swiss Tropical and Public Health Institute (Swiss TPH), Basel 4051, Switzerland; University of Basel, Basel 4001, Switzerland*

Joel Schwartz − *Department of Environmental Health, Harvard TH Chan School of Public Health, Boston, Massachusetts 02115, United States*

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.2c04303

Notes

The authors declare no competing financial interest.

The data used to perform the present analysis are available in GitHub at https://github.com/StevenZhangJW/CRPs_And_Air_Pollution. The sample code used in the analysis is available in the Supporting Information.

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