Supplementary Information

Stringency of COVID-19 Containment Response Policies and Air Quality Changes: A Global Analysis across 1,851 Cities

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Table S1 – A selection of studies on the impact of COVID-19 lockdowns on air quality.

Note: AQI/API: Air quality(pollutant) index; PM10 (PM2.5): particulate matter with a diameter of <10 μm (2.5 μm); BC: black carbon; C6H6: benzene; CO: carbon monoxide; SO2: sulfur dioxide; NO2: nitrogen dioxide, NOx: total nitrogen oxides, O3: ozone; NH3: ammonia, BTEX: benzene, toluene, ethylbenzene, and o-xylene; VOC: volatile organic compound; WRF-CAMx: Weather Research and Forecasting model coupled with Comprehensive Air Quality Model; CAMQ: Community Multi-scale Air Quality model; WRF-Chem: Weather Research and Forecasting model coupled to Chemistry; LNY: Lunar New Year; OxCGRT: Oxford University's COVID-19 Government Response Tracker; ADM1: first-order administrative division

Table S2 - Summary statistics of daily air pollutants and CRPs implementation. Note that the population in each city is the total population in 2020, estimated by the Population division, Department of Economic and Social Affairs, United Nations. Further, the change in NO² was estimated by subtracting the mean difference in satellite observed $NO₂$ pre-CRPs and post-CRPs. Finally, the relative change (RC) and 95% confidence interval (CI) associated with 10 units increase for CRPs scores are presented. The RC was estimated by city-specific log-linear model, after adjusting the non-linear effect of time trend, meteorology, and the day of week. For the overall RC in last row, the estimates were pooled from each city using multilevel mixed effect meta-analytic model. Note that the RC here is for CRP score as a continuous variable (See Table S4 for results of CRPs as a categorical variable). Statistically significant (with P-value < 0.05) changes in NO₂ levels are indicated in bold.

Table S3 - Region-specific percent changes of Sentinel 5P satellite observed NO2 associated with stringent CRPs compared to the pre-CRP from January 1st 2019, to July 31st 2020, across 1,768 world locations. The regions are based on World Bank definition. Statistically significant (with P-value < 0.05) changes in NO2 levels are indicated in bold.

World Bank Region	Urban Agglomeration	Country or area	Population*	Relative Change (95% CI)**
East Asia and Pacific	Shanghai	China	27058479	-63.4% $(-42.7\%, -76.6\%)$
East Asia and Pacific	Beijing	China	20462610	-55.0% $(-34.3\%, -69.1\%)$
East Asia and Pacific	Chongqing	China	15872179	-67.0% $(-50.7\%, -77.9\%)$
East Asia and Pacific	Manila	Philippines	13923452	-42.4% $(-2.4\%, -66.0\%)$
East Asia and Pacific	Tianjin	China	13589078	-51.9% $(-31.7\%, -66.1\%)$
East Asia and Pacific	Guangzhou, Guangdong	China	13301532	-48.9% $(-23.7\%, -65.8\%)$
Europe and Central Asia	Istanbul	Turkey	15190336	78.4% (170.0%, 17.9%)
Europe and Central Asia	Paris	France	11017230	-42.5% (1.9%, -67.6%)
Europe and Central Asia	London	United Kingdom	9304016	-2.0% (47.2%, -34.8%)
Europe and Central Asia	Madrid	Spain	6617513	17.3% (71.2%, -19.6%)
Europe and Central Asia	Rome	Italy	4257056	-2.1% (42.2%, -32.6%)
Europe and Central Asia	Milan	Italy	3140181	-34.2% $(3.3\%, -58.0\%)$
Latin America and Caribbean	São Paulo	Brazil	22043028	-16.0% (10.6%, -36.2%)
Latin America and Caribbean	Mexico City	Mexico	21782378	-20.1% (31.4%, -51.4%)
Latin America and Caribbean	Buenos Aires	Argentina	15153729	-27.4% (-10.2% , -41.4%)
Latin America and Caribbean	Rio de Janeiro	Brazil	13458075	-26.4% $(-8.4\%, -41.0\%)$
Middle East and North Africa	Cairo	Egypt	20900604	-15.2% (6.1%, -32.2%)
Middle East and North Africa	Tehran	Iran (Islamic Republic of)	9134708	9.1% (119.8%, -45.8%)
Middle East and North Africa	Riyadh	Saudi Arabia	7231447	-23.3% $(0.2\%$, $-41.3\%)$
Middle East and North Africa	Baghdad	Iraq	7144260	-62.8% $(-38.5\%, -77.5\%)$
Middle East and North Africa	Alexandria	Egypt	5280664	-10.7% (5.4%, -24.3%)
North America	New York-Newark	United States of America	18803552	15.1% (111.0%, -37.2%)

Table S4 - Percentage change of tropospheric NO2 concentration associated with stringent CRPs in some populated cities. Statistically significant (with P-value < 0.05) changes in NO₂ levels are indicated in bold.

* Population in each city is the total population in 2020, estimated by the Population division, Department of Economic and Social Affairs, United Nations

** Results are present as relative change (RC) and 95% confidence interval (CI). This is estimated in linking categorical CPRs with satellite observation NO2 using city-specific log-linear regression model, after adjusted for time trend, meteorology and the day of week.

Only cities that experienced stringent CPRs were presented above.

Table S5 - The effect modification of COVID-19 stringent CRPs on tropospheric NO₂ concentration by population size and baseline NO₂ pollution

The estimations presented here are the relative changes of nitrogen dioxide associated with 10 unites increase in CRPs score, which were the pooled estimations from 1851 cities using the two-stage framework (obtaining city-specific estimates, and then meta-analysis).

City-specific natural spline: natural cubic spline with city-specific degrees of freedom to control the time-dependent or meteorology-dependent change in tropospheric nitrogen dioxide;

Time-stratified: the day of the week, the day of the month, the month of the year, and year as factors to control the fixed effects of the long-term and short-term trend. Periodic function: the time trend was decomposed into a combination of cosine and sine functions with 365.25 days as a period, to control the seasonal and short-term change for tropospheric nitrogen dioxide.

Linear: a linear association between meteorological covariates and nitrogen dioxide was assumed and adjusted in the model.

Universal nonlinear: natural spline with two degrees of freedom was applied for all cities to control the non-linear association between meteorology and nitrogen dioxide.

Table S7: Percentage change of tropospheric NO2 concentration associated with 10 unit increase in CRPs scores (sample size was 1851 cities). The AIC values are for the average values across 1851 models.

The estimations presented here are the relative changes of nitrogen dioxide associated with 10 unites increase in CRPs score, which were the pooled estimations from 1851 cities using the two-stage framework (obtaining city-specific estimates, and then meta-analysis).

Final model used natural cubic spline with city-specific degrees of freedom to control the time-dependent or meteorology-dependent change in tropospheric nitrogen dioxide;

Supplementary Text 1: COVID-19 containment response policies data and clustering

To compare the global "containment and closure" related COVID-19 response policies, we obtained eight policy indicators data (Table S8) from Oxford's COVID-19 Government Response Tracker (OxCGRT) (29, 30). Each policy indicator at each country was recorded as time series.

We collected each policy indicator since firstly implemented in each country until July 31, 2020. The observations used in this analysis constituted 40,163 COVID-19 response policies dates across 229 countries and areas (note that the eight policies of Table S3 were implemented at different days across 229 countries).

$$
I_{j,t} = 100 \times \frac{v_{j,t} - 0.5 \times (F_j - f_{j,t})}{N_j}
$$

Following the equation above proposed by OxCGRT, we converted the ordinal scale of each implemented policy in Table S4 to a numerical score from 0 to 100 (29) (Table S9). Where, N_j is the maximum value of each indicator; F_j and $f_{j,t}$ are the indicator of scope record and the recorded binary number in certain time, and $v_{j,t}$ is the recorded policy value on the ordinal scale.

After summarizing the CRPs, we observed that "International Travel Control" and "Restriction on Gathering" were the earliest COVID-19 response policies, initially issued on January 01, 2020. With the COVID-19 gradually formulating the epidemic, other COVID-19 response policies were introduced step by step. Besides, the 1st quarter value of "School Closure", "Cancel Public events", and "International Travel Control" were quite higher than other COVID-19 response policies meaning that these policies were widely implemented across countries compared to others (Table S10).

Using such data, we conducted a K-mean algorithm with gap statistic method (31) to explore the potential cluster number within the whole observations. The principle of cluster analysis was to group the observations based on their similarity (32, 33). Within the clusters, the K-mean algorithm with Euclidean distance (34, 35) was used, which projected all the observations into a N-dimension Euclidean space and centroid calculation and observation grouping process was iterated to cluster the observations (35).

The result of the gap statistic is presented in Figure S13. As shown, we can see that although there was no peak in the gap statistic curve, the rising rate of the gap function sharply decreased after cluster number larger than 3, which was then chosen as the optimal number for clustering.

Applying the K-mean algorithm, all the COVID-19 CRPs dates were classified into three groups (mild, moderate, and stringent CRPs). To take a snapshot of what the three groups look like, we calculated the cluster centroids for each cluster (Table S11).

Comparing among different clusters, we can see that the centroids values for all COVID-19 CRPs were largest at stringent, and were smallest at mild CRPs. In other words, from mild to stringent, all COVID-19 CRPs got stricter. Looking at CRPs at

each cluster, "International Travel Control" stand out most. Even at the mild cluster, the centroid value of "International Travel Control" already surpassed half of the scale (>50). However, the centroid values of other COVID-19 CRPs just reached 15% of the scale at this cluster (for "School Closure"). This indicated that "International Travel Control" was a commonly used COVID-19 response policy and widely and strictly implemented during the pandemic. Across all the clusters, the centroid values of "Close Public Transportation" and "Stay at Home Requirement" were always the least two. This may show that these two CRPs were conservatively used during this pandemic.

In order to better interpret and understand the detailed COVID-19 CRPs, this study linked the policy feature in each cluster with the OxCGRT codebook, and presented the policies description of each COVID-19 response phase, which are presented in Table 1.

Table S8- Summary of the included containment and closure policies

Table S9 – The data structure of COVID-19 CRPs in OxCGRT.

	1st Quarte r	Media n	3rd Ouarte r	Mea n	First issued date	Issued country/area \star
School closure	50.00	100.00	100.00	71.08	Jan. 24th	229
Workplace closing	0.00	66.67	66.67	48.41	Jan. 26th	229
Cancel public events	50.00	100.00	100.00	71.13	Jan. 22nd	229
Restriction on gatherings	0.00	75.00	100.00	60.23	Jan. 1st	229
Close public transportation	0.00	0.00	50.00	29.51	Jan. 23rd	229
Stay home at requirement	0.00	33.33	66.67	33.13	Jan. 23rd	229
Restriction on internal movement	0.00	50.00	75.00	47.94	Jan. 23rd	229
International travel control	75.00	75.00	100.00	75.76	Jan. 1st	229

Table S10 – Summary of the converted daily COVID-19 CRPs data used for the analysis

Note: The areas/country here counted all sub-regions/states in UK and US separately. The table describes the data distribution of each policy. As an example, for policy "school closure," the table shows that 3/4 of the total countries-dates have the school closure level higher than score 50, and the mean implementation score across overall countries-dates was 71.08.

Policy Indicator	Mild	Moderate	Stringent
School closure	15.15036	68.49417	92.84664
Workplace closing	7.927928	44.22697	72.29106
Cancel public events	10.90788	77.8721	95.40996
Restriction on gatherings	10.98496	65.14231	86.41839
Close public transportation	1.821469	12.61517	55.39967
Stay at home requirement	3.366324	23.80726	55.56279
Restriction on internal movement	5.590027	32.95125	81.40778
International travel control	57.59041	72.46204	81.90763

Table S11 – The cluster centroids of each COVID-19 CRP based on K-mean algorithm results

Supplementary Text 2: Statistical analysis

Multilevel mixed effect model

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. Further, city-specific random-effect was also applied to synthesize the association, 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 city- and country-level.

Our model can be written as:

$$
\beta_{r,u,n} = \beta_r x_{r,u,n} + \xi_{r,u} + \xi_n + \varepsilon;
$$

What this study was interested in was β_r , which represented the certain COVID-19 CRPs' (r) average effects; and $\beta_{r,u,n}$ represented the urban-agglomeration-specific effects coming from urban u in country n first-stage analysis.

The random effects $\xi_{r,u}$ in the location level are induced first, which can minimize the bias when we introduce national lockdown policy situation to location level; another random effects ξ_n could capture the political and cultural related variance at the country level. Besides, an unstructured covariance matrix structure was adapted here, to estimate and capture heterogeneity for each CRP.

Our two-stage analytic framework controlled the influence from the meteorology and time trend at first and focused on the policy intervention effect in each urban agglomeration. Besides, it enabled us to pool our evidence into national and regional level.

• Effect modification by population of locations

We applied a mixed-effects meta-regression model to explore the effect modification by urban population.

$$
\beta_{r,u} = \beta_r x_{r,u} + \xi_u + \varepsilon;
$$

Where β_r with the categorical variable was the average policy intervention effects for cities with population r; β_r with the continual population size variable represented the population size's modification effect; ξ_u and ε represent the country- and locationspecific random effects unobserved by our data.

Figure S1 – Timeline of different COVID-19 CRPs for each country from Jan 1st to July 31st 2020. A) National or regional timeline (except US and UK); B) Regional or state-level timeline for US and UK; C) Counts for countries' first-issued dates.

Figure S2 – Pearson correlation coefficient between population sizes, baseline NO2 concentration (2019), and annual mean meteorological variables (2019).

Figure S3– Percentage change of tropospheric NO2 concentration associated with 10 increase in CRPs scores on different lag days for CRPs in 1,851 cities across 149 countries from January $1st$ 2019, to July $31st$ 2020. Lags indicate the time difference between the NO₂ concentration and the CRPs.

Figure S4 – The percentage change in satellite observed NO₂ concentration associated with COVID-19 CRPs compared to the pre-CRP from January 1st 2019, to different study periods.

Figure S5 – The percentage change in satellite observed NO₂ associated with stringent COVID-19 CRPs compared to the pre-CRP from January 1st 2019, to July 31st 2020, across 132 countries. Significant reductions are shown in blue while significant increases are shown in red.

Figure S6 – The percentage change in satellite observed NO₂ associated with moderate COVID-19 CRPs compared to the pre-CRP from January 1st, 2019, to July 31st, 2020, across 141 countries. Significant reductions are shown in blue while significant increases are shown in red.

Figure S7 – The percentage change in satellite observed NO₂ associated with mild COVID-19 CRPs compared to the pre-CRP from January $1st$, 2019, to July 31 st , 2020,</sup> across 140 countries. Significant reductions are shown in blue while significant increases are shown in red.

Figure S8 – The percentage change in satellite observed NO₂ associated with stringent COVID-19 CRPs compared to the pre-CRP from January $1st$ 2019, to July 31 st 2020,</sup> across 141 US cities (see SI, Figures S7, S8, or S10 for further US-specific results). Significant reductions are shown in blue while significant increases are shown in red.

Figure S9 – The percentage change in satellite observed NO₂ associated with mild COVID-19 CRPs compared to the pre-CRP from January 1st, 2019, to July 31st, 2020, across the US cities. Significant reductions are shown in blue while significant increases are shown in red.

Figure S10 – The percentage change in satellite observed NO₂ associated with moderate COVID-19 CRPs compared to the pre-CRP from January 1st, 2019, to July 31st, 2020, across the US cities. Significant reductions are shown in blue while significant increases are shown in red.

Figure S11 – The potential effect modification by weather covariates, population and baseline NO² level. The NO² change in the least populated locations (locations from the 1st quarter range of population) was $+0.3\%$ (95% CI: -3.0% , $+3.8\%$); however, in most populated locations (the locations from the $4th$ quarter range of population) the change was -9.7% (95% CI: -12.7%, -6.6%). The $NO₂$ change in the cleaner locations (locations from the 1st quarter range of 2019 annual mean $NO₂$) was +0.1% (95% CI: -3.0% , $+3.4\%$); however, in the most polluted locations (locations from the $4th$ quarter range), the change was -22.7% (95% CI: -25.8%, -19.5%).

Figure S12 – The air quality and corresponding change due to different CRPs in the United States. A) The time series of national average air quality in 2019 and 2020; B) The country-specific association between air quality and different CRPs in the USA (# of cities in this analysis was 141 where population of each city was $> 300,000$ inhabitants). The P-value is estimated using Cochran's Q-test; C) Effect modification by population and NO² level in the USA. The cities in the US were divided into three population and NO² level categories based on tertiles.

Figure S13 – The gap statistic curve for COVID-19 response date across countries

Figure S14 – The spatial distribution of 1,851 locations across 149 countries where daily Sentinel 5P NO2 was collected from January 01, 2019 up to July 31, 2020.

Supplementary Text 3: Sample R code for Analysis

##

Sample R code for the analysis in:

" Stringency of COVID-19 Containment Response Policies and Air Quality Changes: A

Global Analysis across 1,851 Cities"

##

library(readr); library(dplyr); library(metafor); library(mgcv); library(lubridate);

library(splines)

library(broom); library(splines)

CAMP <- readRDS("H:/Ana/workdata/CAMP.rds")

#Pre-process the data

CAMP\$timetrend <- as.numeric(CAMP\$date)

CAMP\$week <- as.numeric(wday(CAMP\$date))

 $CAMP$NO2_1 < log(CAMP$NO2)$

#Extract location specific data

Cov.ID <- subset.data.frame(CAMP, CAMP\$City.Code==S5City\$City.Code[1])

location-specific log-linear regression models for CRPs score gam 1 l <- gam(NO2 $\text{1-Score1} + \text{s}$ (timetrend, k=12) + as.factor(week) + $s(Temperature) + s(Humidity) + s(Wind_Speed) + s(Surface_Pressure),$

```
data=Cov.ID)
```
GAM df score \le - round(summary(gam_1l)\$edf)) names(GAM_df_score) < c("timetrend","Temperature","Humidity","Wind_Speed","Surface_Pressure")

glm_res <- glm(NO2_l~Score1 + ns(timetrend, df=GAM_df_score\$timetrend[1]) + as.factor(week) $+$

 ns(Temperature,df=GAM_df_score\$Temperature[1]) + $ns(Humidity, df = GAMdf \simeq 5$ score\$Humidity[1]) + ns(Wind_Speed,,df=GAM_df_score\$Wind_Speed[1]) + ns(Surface_Pressure,df=GAM_df_score\$Surface_Pressure[1]), data=Cov.ID)

```
summary(glm_res)
GLM. Res.score < -tdy(glm\_res)[c(2),]
```
##Calculating the relative reduction associated with per 10 increase in CRPs scores GLM.Res.score\$RR <- exp(GLM.Res.score\$estimate*10)-1 GLM.Res.score\$URR <- exp((GLM.Res.score\$estimate+qnorm(1- 0.05/2)*GLM.Res.score\$std.error) *10)-1 GLM.Res.score\$LRR <- exp((GLM.Res.score\$estimate-qnorm(1- 0.05/2)*GLM.Res.score\$std.error) *10)-1

```
# location-specific log-linear regression models for categorical CRPs
gam_df <- gam(NO2_l~RANK2 + s(timetrend, k=12) + as.factor(week) +
         s(Temperature) + s(Humidity) + s(Wind_Speed) + s(Surface_Pressure),data=Cov.ID)
```
GAM_ldf <- round(summary(gam_df)\$edf) names(GAM_ldf) \lt c("timetrend","Temperature","Humidity","Wind_Speed","Surface_Pressure")

```
glm_res <- glm(NO2_l-RANK2 + ns(timetrend, df=GAM_ldf$timetrend[1]) +
as.factor(week) +
```

```
 ns(Temperature,df=GAM_ldf$Temperature[1]) + 
ns(Humidity,df=GAM_ldf$Humidity[1]) + 
ns(Wind_Speed,,df=GAM_ldf$Wind_Speed[1]) + 
ns(Surface_Pressure,df=GAM_ldf$Surface_Pressure[1]), data=Cov.ID)
```
 $GLM.$ IRes <- tidy(glm_res)[c(2,3,4),]

#Calculating relative reduction

GLM.lRes\$RR <- exp(GLM.lRes\$estimate)-1

GLM.lRes\$URR <- exp(GLM.lRes\$estimate+qnorm(1-0.05/2)*GLM.lRes\$std.error)-1

GLM.lRes\$LRR <- exp(GLM.lRes\$estimate-qnorm(1-0.05/2)*GLM.lRes\$std.error)-1

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