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Impact of COVID-19 containment and closure policies on tropospheric nitrogen dioxide: A global perspective

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**A B S T R A C T**

The containment and closure policies adopted in attempts to contain the spread of the 2019 coronavirus disease (COVID-19) have impacted nearly every aspect of our lives including the environment we live in. These influences may be observed when evaluating changes in pollutants such as nitrogen dioxide (NO\textsubscript{2}), which is an important indicator for economic, industrial, and other anthropogenic activities. We utilized a data-driven approach to analyze the relationship between tropospheric NO\textsubscript{2} and COVID-19 mitigation measures by clustering regions based on pollution levels rather than constraining the study units by predetermined administrative boundaries as pollution knows no borders. Specifically, three clusters were discovered signifying mild, moderate, and poor pollution levels. The most severely polluted cluster saw significant reductions in tropospheric NO\textsubscript{2}, coinciding with lockdown periods. Based on the clustering results, qualitative and quantitative analyses were conducted at global and regional levels to investigate the spatiotemporal changes. In addition, panel regression analysis was utilized to quantify the impact of policy measures on the NO\textsubscript{2} reduction. This study found that a 23.58 score increase in the stringency index (ranging from 0 to 100) can significantly reduce the NO\textsubscript{2} TVCD by 3.2\% (p < 0.05) in the poor cluster in 2020, which corresponds to a 13.1\% maximum reduction with the most stringent containment and closure policies implemented. In addition, the policy measures of workplace closures and public transport closures can significantly decrease the tropospheric NO\textsubscript{2} in the poor cluster by 6.7\% (p < 0.1) and 4.5\% (p < 0.1), respectively. An additional heterogeneity analysis found that areas with higher incomes, CO\textsubscript{2} emissions, and fossil fuel consumption have larger NO\textsubscript{2} TVCD reductions regarding workplace closures and public transport closures.

1. Introduction

In December 2019, cases of a respiratory illness were reported in Wuhan, China. This was the first occurrence of a novel coronavirus which came to be known as COVID-19 (Kantis et al., 2020). This virus has a notably fast transmission rate, as was seen with its quick spread throughout Wuhan and to countries all over the world (Bravo and Haseman, 2021). By March, the World Health Organization (WHO) declared COVID-19 to be a pandemic as it had spread to over 100 countries (Kantis et al., 2020). In response to the fast spread, many governments imposed mitigation measures (Hale et al., 2020; Li et al., 2021). Partial and total lockdowns in most affected countries ranged from a few weeks to months (Chakraborty and Maity, 2020). These policies were intended to reduce transmission, and in many cases they were successful in regard to this goal (Kharroubi and Saleh, 2020). However, these policies also had detrimental economic consequences. Many countries have witnessed low levels of production, high inflation, increasing unemployment, and declines in GDP during the pandemic (Chakraborty and Maity, 2020).

Despite the negative economic consequences, COVID-19 mitigation measures have had some positive outcomes in respect to the environment. Take air quality as an example, many pollutants (e.g., NO\textsubscript{2}, CO\textsubscript{2}, NO) and other measures such as PM2.5 have seen reductions coinciding with the worldwide lockdowns due to restricted industrial activity and decreased emissions from transportation systems (Venter et al., 2020; Wang et al., 2020b; Guevara et al., 2021; Cárcel-Carrasco et al., 2021).
Among these pollutants, NO\textsubscript{2} is notable as increased levels have been seen to affect the distribution of ozone (Villena et al., 2012) and give rise to secondary inorganic aerosol pollutants (Behera and Sharma, 2011; Gkatziulis et al., 2021). Furthermore, NO\textsubscript{2} and its associated secondary pollutants (Sokan-Adeaga et al., 2019) are respiratory irritants, thus metrics centered around NO\textsubscript{2} have frequently been used as robust indicators of health risks (Moshammer et al., 2020). In fact, many studies have found that air pollutants could increase COVID-19 cases (Zhu et al., 2020) and mortality (Wu et al., 2020). Additionally, NO\textsubscript{2} emission mainly comes from fossil fuel consumption in transportation and industrial processes (EPA, 2016; Dutheil et al., 2020). This makes it a valuable indicator of pollution over urban sites which have been greatly affected by COVID-19 restrictions. Overall, NO\textsubscript{2} is important to analyze in respect to COVID-19 mitigation policies as changes in NO\textsubscript{2} emissions can highlight economic and health consequences of the pandemic as well as possible environmental changes. In particular, the tropospheric NO\textsubscript{2} vertical column density (TVCD) is the focus of our study because the emission of NO\textsubscript{2} into the troposphere is strongly influenced by human activities (Lauer et al., 2002).

Much research has discovered that air quality improved due to the implementation of COVID-19 mitigation measures. Many early-pandemic studies highlighted the notably stringent mitigation measures in China and found that air quality dramatically improved soon after these policies were enacted (Dutheil et al., 2020; He et al., 2020; Liu et al., 2020a; Wang et al., 2020a). These studies reasoned that mitigation efforts generally restricted mobility and economic activities, which are often major culprits of pollutant emissions. Similar analyses found declines in NO\textsubscript{2} emissions in other countries (Otmani et al., 2020; Baldasano, 2020; Bauwens et al., 2020; Liu et al., 2021a; Liu et al., 2021b). Furthermore, research has found that countries with more stringent policies saw greater reductions in pollution (Chakraborty and Maity, 2020). These studies largely rely on comparing NO\textsubscript{2} concentrations for selected locations at the start of the pandemic to those from previous years through surface observations (Otmani et al., 2020; Baldasano, 2020; Liu et al., 2021a; He et al., 2020), satellite observations (Dutheil et al., 2020; Liu et al., 2020a; Bauwens et al., 2020; Liu et al., 2021a; Liu et al., 2021b), model simulation results (Wang et al., 2020a; Liu et al., 2020a), etc. As exact lockdown dates are usually required, these studies are mostly restricted to a few months representing the early pandemic period. From a long-horizon perspective, this type of comparison cannot assess the impact of policies thoroughly. In addition, it is often hard to account for the re-implementation of policies as the severity of the disease often oscillates.

By mid-April in 2020, many countries started lifting lockdowns in attempts to revive the struggling economy (Edwards, 2020). This allowed further studies to evaluate air quality later on in the pandemic as restrictions were eased, and compare these results to the air quality during the lockdown phase. These analyses agreed that the air quality improvements achieved during the lockdown period were only temporary as pollutant levels slowly increased again as lockdowns were lifted (Kumari and Toshniwal, 2020; Liu et al., 2020a; Sulaymon et al., 2021, Hu et al., 2021). Most previous studies compared trends before, during, and after policy implementation to investigate possible changes associated with mitigation measures, and focused on the short-term impacts of these policies. Limited studies can be found which investigate the long-horizon impacts of COVID-19 mitigation policies on air pollution, especially for quantifying the effects of containment and closure measures (Hale et al., 2020) at the global level. In addition, most analyses selected the study units based on administrative divisions, either by countries or by states, provinces, and municipalities within a country. However, pollution knows no borders. To respect this intrinsic nature, our strategy is to classify regions according to pollution levels rather than constraining them by artificial administrative borders. To briefly summarize, we proposed an analytical framework using machine learning methods to detect pollution regions. Based on the clustering results, comprehensive statistical analyses were conducted within clusters to quantify the impact of containment and closure policies on NO\textsubscript{2} TVCD changes during the COVID-19 pandemic.

2. Study area and data

2.1. Satellite NO\textsubscript{2} observations

Global coverage of NO\textsubscript{2} products was collected to support this investigation. OMNO2d, the Nitrogen Dioxide Product of the Ozone Monitoring Instrument (OMI) aboard NASA’s Earth Observing System’s (EOS) Aura satellite, provides long-term, daily global-coverage NO\textsubscript{2} data. The OMNO2d is a level-3 daily global gridded product with a 0.25°×0.25 degree spatial resolution (Krotkov et al., 2019). The product contains total column NO\textsubscript{2} density and total tropospheric NO\textsubscript{2} vertical column density (TVCD). Specifically, OMNO2d data ranging from January 1, 2010 to December 31, 2020 were collected. Data from 2010 to 2019 provided a profile of the global-level NO\textsubscript{2} TVCD distribution before the pandemic, and data in 2020 enabled the tracking of NO\textsubscript{2} TVCD changes during the pandemic.

2.2. Policy tracking data

Since early 2020, governments worldwide have adopted a series of containment and closure policies in attempts to contain the spread of COVID-19. Implementing these policies, such as closures of non-essential industries, seemed to click a pause button on Earth. These measures have affected nearly every aspect of society, including economic, environmental, and educational sectors (Yang et al., 2020). Throughout the pandemic, the University of Oxford has maintained a policy tracker to record the daily stringency of different types of policies.
for 184 countries since January 1, 2020 (Hale et al., 2020, Fig. 1). The data repository contains 23 indicators and a miscellaneous notes field grouped into five major categories: (C) containment and closure policies, (E) economic policies, (H) health system policies, (V) vaccination policies, and (M) miscellaneous policies. In particular, the category of containment and closure policies includes C1_School closing, C2_Workplace closing, C3_Cancel public events, C4_Restrictions on gatherings, C5_Close public transport, C6_Stay at home requirements, C7_Restrictions on internal movement, and C8_International travel controls. A stringency index is constructed by the data maintenance team at the University of Oxford and is calculated from the aforementioned containment and closure policies and the public information campaign policies under category (H). The stringency index indicates the strictness of these measures on a scale ranging from 0 to 100. In this study, the global-level policy data in 2020 were collected from the policy tracker repository (Oxford Covid-19 Government Response Tracker).

2.3. Meteorological variables

Although NO$_2$ concentration is highly affected by human activities, it is also affected by meteorological factors such as temperature, wind, and humidity (Jayamurugan et al., 2013; Richmond-Bryant et al., 2018; Zhang et al., 2015). Thus, three meteorological variables were collected for analysis alongside NO$_2$ TVCD and COVID-19 policies. Daily temperature, wind, and humidity values were extracted from Modern-Era Retrospective analyses for Research and Applications Version 2 (MERRA-2). MERRA-2 enables the assimilation of a broad range of satellite observations such as surface wind speed, temperature, ozone profiles, and atmospheric motion vectors. The reanalysis process ensures consistency in the reprocessing of meteorological observations, which is especially important for infrequent data or unobserved data (Gelaro et al., 2017). The reanalysis product provides daily gridded data with a 0.5°*0.625 spatial resolution.

3. Methodology

3.1. Outline

Fig. 2 shows the analytical workflow consisting of four main steps. First, NO$_2$ TVCD, policy measures, meteorological variables, and other auxiliary data were collected from different sources, and collocated with each other spatiotemporally (Liu et al., 2020b). Detrending and 7-day moving-average operations were applied to the collected data in the

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**Fig. 2.** The analytical workflow for investigating the impact of COVID-19 mitigation policies on NO$_2$ TVCD.
3.3. Global and regional spatiotemporal analysis

The global and regional spatiotemporal analyses were conducted on the clusters by comparing NO$_2$ TVCD in 2020 to the previous three years. In the global analysis, daily NO$_2$ TVCD of each cluster was aggregated from cells to form three time series. To investigate how NO$_2$ TVCD changed in each cluster during the pandemic, 7-day moving averages of NO$_2$ TVCD in 2020 were compared to the corresponding values from 2017 to 2019 month by month. Additionally, seasonal trends were removed by subtracting 10-year daily mean values from the original time series to investigate changes in terms of NO$_2$ TVCD anomaly in 2020.

We retrieved NO$_2$ TVCD for each cluster in a country to conduct spatiotemporal analyses at the regional level. Each country has at least one cluster and the country’s approximate lockdown and reopening dates were gathered from government announcements. Although some countries instituted lockdowns and reopened on multiple occasions, we only selected the first lockdown time period to demonstrate the impact of COVID-19 mitigation policies in the regional analysis. Specifically, three countries (China, the United States, and Italy) were selected to estimate the regional changes. These three countries were selected...
because the first infection was reported in China, the United States had the largest number of confirmed cases at the time of this study, and Italy was a typical epicenter in Europe. For each cluster in a country, we calculated the relative difference (Bauwens et al., 2020) and the peak reduction (Weir et al., 2020) to measure the changes of NO₂ TVCD in 2020 during a selected lockdown period. The relative difference is measured by the percentage change between the average NO₂ TVCD over the selected lockdown period in 2020 and the average column value in the same period in 2019. The peak reduction (Eq. (1)) defines the largest magnitude of NO₂ TVCD anomaly during the lockdown period in 2020 (with the convention that if the anomaly is negative, it is referred to as a reduction). The 2σ uncertainty (Eq. (2)) is computed as half of the min-to-max ranges of NO₂ TVCD anomaly from 2017 to 2019.

For a specified lockdown period \( L \) in 2020, \( A_{cd}^{(i)} \) denotes the NO₂ TVCD anomaly in 2020 using 10-year (2010 to 2019) daily mean NO₂ TVCD as the reference for cluster \( i \) in country \( c \) on day \( d \), where \( d \in L \). For

\[
\begin{align*}
R_{cd}^{(i),2020}(L) &= \max_{d \in L} |A_{cd}^{(i),2020}|, \text{if } A_{cd}^{(i),2020} < 0 \\
\delta_{cd}^{(i),2020}(L) &= \frac{1}{4} \left\{ \max_{d \in L} A_{cd}^{(i),2017-2019} - \min_{d \in L} A_{cd}^{(i),2017-2019} \right\}
\end{align*}
\]
the uncertainty estimate $\sigma$, $\max_{i \in A_{cd}, 2017}^{2019}$ and $\min_{i \in A_{cd}, 2017}^{2019}$ denote, respectively, the maximum and minimum values of the NO$_2$ TVCD anomaly over the interval $I$ during 2017 to 2019 for country $c$ in cluster $i$.

3.4. Panel regression analysis

3.4.1. The impact of stringency index on NO$_2$ emissions

The global and regional analyses investigate whether the NO$_2$ TVCD changed during the pandemic, however, they cannot quantify how COVID-19 mitigation measures affect the NO$_2$ TVCD. Therefore, comprehensive statistical analyses were utilized to address this scientific question quantitatively. First, daily NO$_2$ TVCD and meteorological measurements (wind, humidity, and temperature) were extracted for each cluster per country. The stringency index scores and other covariates are standardized because their scales differ substantially. Thus, the estimated regression coefficients (for policy) quantify the change in the response variable according to one standard deviation change in the stringency index. Since grid cells in a country belong to at least one cluster, there is at least one record for a country each day. Collocated with the daily policy stringency index, we formed a panel dataset for each of the three clusters. Since the policy data repository provides the daily country-level stringency index, for a country containing more than
one cluster, each panel shares the same policy stringency. In addition, daily mean TVCD were computed for each country per cluster based on 5-year historical data from 2010 to 2014.

We employed a fixed effects panel regression model to examine the effects of containment and closure policies on the NO\textsubscript{2} TVCD in the three clusters separately. Let TVCD\textsubscript{cdy}\textsubscript{i} denote the NO\textsubscript{2} TVCD in cluster \textit{i} for country \textit{c} on day \textit{d} in year \textit{y} (from 2015 to 2019); other variables are defined similarly. In the first regression specification, we aimed to remove the potential influence of seasonality and inter-annual trends. To achieve this, month fixed effects and a yearly trend from 2015 to 2019 were estimated using the model specified in Eq. (3), where daily mean NO\textsubscript{2} TVCD based on the historical data from 2010 to 2014, denoted by meanTVCD\textsubscript{cdy}\textsubscript{i}\textsubscript{2010-2014}, is included as a control variable, and \(\alpha\textsubscript{i}, \gamma, \lambda\textsubscript{cy}\) denote the country fixed effects, month fixed effects, and country-specific quadratic yearly trend, respectively. In addition, constant and \(\varepsilon\) denote intercept and error term, respectively, in all the regression equations. The country fixed effects, month fixed effects, and yearly trend are intended to account for unobserved heterogeneity on the country level, the seasonality attributed to months, and inter-annual fluctuations, respectively. We find that quadratic yearly trend and linear yearly trend generally yield similar parameter estimates, but the former one has a slightly better model fit than the latter one. We also noticed that this specification is robust against the different number of years included (e.g., trending for 4 years and 5 years yield very similar results). The predicted pre-policy NO\textsubscript{2} TVCD trend for cluster \textit{i} in country \textit{c} on day \textit{d} in 2020 is denoted by \(\hat{\text{TVCD}}\textsubscript{cd}\textsubscript{i}\textsubscript{2020}\), and is included in the second regression (Eq. (4)) as a covariate to control for the effects of both

![Fig. 8. Time series of cluster-level regional NO\textsubscript{2} anomalies in China, the United States, and Italy.](image-url)

### Table 1

Cluster-level NO\textsubscript{2} regional reductions and associated uncertainties in the United States, China, and Italy.

| Country | Cluster | NO\textsubscript{2} TVCD | NO\textsubscript{2} TVCD anomaly | Start Date | End Date |
|---------|---------|-----------------|-------------------------------|------------|----------|
| United States | mild | Relative Difference: -3(±3)% | Peak Reduction*: -2.58(±2.35) \times 10^13 | March 21 | May 16 |
|           | moderate | 0(±1)% | -9.18(±9.26) \times 10^13 |           |          |
|           | poor | -7(±1)% | -4.85(±1.97) \times 10^14 |           |          |
| China    | mild | 18(±4)% | -5.09(±3.33) \times 10^12 | January 25 | March 25 |
|           | moderate | -7(±2)% | -4.48(±4.94) \times 10^13 |           |          |
|           | poor | -24(±2)% | -1.91(±0.62) \times 10^15 |           |          |
| Italy    | mild | -14(±2)% | -4.47(±1.88) \times 10^14 | March 18 | May 18 |
|           | moderate | -14(±2)% | -4.47(±1.88) \times 10^14 |           |          |
|           | poor | -21(±1)% | -9.91(±3.88) \times 10^14 |           |          |

*To be consistent with the relative difference, a negative sign is added to the peak reduction, which is defined in Eq. (1) as the maximum magnitude of the anomalies.
Fig. 9. NO$_2$ TVCD over China for successive time periods in 2020 and 2019.

Fig. 10. NO$_2$ TVCD over the US for successive time periods in 2020 and 2019.

Fig. 11. NO$_2$ TVCD over Italy for successive time periods in 2020 and 2019.
TVCD is affected by COVID-19 mitigation policies with a combined seasonal and inter-annual trends. Specifically, effects of the selected containment and closure measures on NO

| Stringency index | Mild cluster | Moderate cluster | Poor cluster |
|------------------|-------------|----------------|-------------|
| Predicted NO2 trend | -0.006*** | -0.008*** | -0.033*** |
| Constant | 0.027*** | 0.107*** | 0.548*** |
| Number of observations | 21588 | 49,427 | 35,464 |
| R² | 0.694 | 0.795 | 0.711 |

**p < 0.05, ***p < 0.01

Table 2

Effects of one standard deviation (23.58) increase in the policy stringency index on NO2 TVCD in the three clusters.

**p < 0.05, ***p < 0.01

Table 3

Effects of the selected containment and closure measures on NO2 TVCD in the three clusters.

| Workplace closing | Mild cluster | Moderate cluster | Poor cluster |
|--------------------|-------------|----------------|-------------|
| Close public transport | 0.025* | -0.020 | -0.046* |
| Stay-at-home requirements | 0.019 | 0.018 | 0.024 |
| International travel controls | 0.018 | -0.023 | 0.021 |
| Predicted NO2 trend | 0.028*** | 0.109*** | 0.610*** |
| Constant | 2.415*** | 1.063*** | 0.687*** |
| Number of observations | 21,744 | 49,427 | 35,464 |
| R² | 0.692 | 0.793 | 0.694 |

Seasonal and inter-annual trends. Specifically, TVCD \(_{i,j}\) was obtained by using the covariate values in 2020 and the estimated regression coefficients based on Eq. (3). Standard errors were obtained using the robust standard error estimator clustered at the country level.

\[
TVCD_{i,j}^{(0)} = constant + \alpha_{i1}^{(0)} + \delta_{i0}^{(0)} + \beta_{i1}^{(0)} \text{humidity}_{i,j}^{(0)} + \beta_{i2}^{(0)} \text{temperature}_{i,j}^{(0)} + \gamma_{i1}^{(0)} \text{wind}_{i,j}^{(0)} + \gamma_{i2}^{(0)} \text{meanTVCD}_{i,2010-2014}^{(0)} + \epsilon_{i,j}^{(0)}
\]  

\[
\log\left(TVCD_{i,j}^{(0)}\right) = constant + \alpha_{i1}^{(0)} + \delta_{i0}^{(0)} + \beta_{i1}^{(0)} \text{stringencyIndex}_{i,j}^{(0)} + \gamma_{i2}^{(0)} TVCD_{i,j}^{(0)} + \epsilon_{i,j}^{(0)}
\]  

3.4.3. The heterogeneous effect of individual policies on NO2 TVCD

The above statistical analysis focused on the overall average effect of COVID-19 mitigation policies on NO2 TVCD across 184 countries in 2020. It is also critical to examine their individual effects in different types of countries. We collected several country-level socioeconomic and industrial indicators from the World Bank WDI database and the United Nations Human Development Reports to classify countries into different subgroups. These indicators fall into three major categories: (1) development related indicators, including the gross domestic product (GDP), the per capita GDP, and the gross national income (GNI); (2) population related indicators, including the population size, the urban population percentage, and the human development index (HDI); and (3) CO2 emissions and fossil fuel consumption for the energy related indicators. Countries were divided into high/low subgroups according to different policies; 2) the stringency index contains policies that may not have a direct impact on NO2 emission changes, e.g., school closure, restrictions on gatherings, etc. compared to other containment and closure policies. Thus, we conducted a further analysis consisting of four individual containment and closure policies: workplace closing, close public transport, stay-at-home requirement, and international travel controls. These industrial and transportation-related policies were chosen because ground-level emissions related to the burning of fossil fuels from vehicles, power plants, etc. are the principal outdoor sources of NO2 (Blaszczak, 1999; World Health Organization, 2010).

For each policy, we adopted the containment and closure policy measure record from the Oxford policy tracker (Hale et al., 2020; Hale et al., 2021). Each policy measure has a coding value \(C_{id}\) which represents the stringency on an ordinal scale ranging from 0 (no measures) to a maximum value (most stringent), and the maximum value varies from policy to policy (Oxford Covid-19 Government Response Tracker).

Based on the ordinal variable \(C_{id}\), we generated a binary variable \(I_{id}\) for a given policy \(j\) on a specific day \(d\) to indicate whether a policy was implemented. Specifically, for the first three individual policies (workplace closing, close public transport, and stay-at-home requirement), \(I_{id} = 0\) indicates no measures for such policy. For international travel controls, \(I_{id}\) is set to 0 if \(C_{id} \leq 2\) because strict bans take place for \(C_{id} \geq 3\) (0, no restrictions; 1, screening arrivals; 2, quarantine arrivals). With this transformation, policy values on the ordinal scale were converted to a binary indicator. In Eq. (5), the converted individual policy indicators were included, in conjunction with other control variables, as the main variables of interest replacing the stringency index in Eq. (4).

\[
\log\left(TVCD_{i,j}^{(0)}\right) = constant + \alpha_{i1}^{(0)} + \delta_{i0}^{(0)} + \beta_{i1}^{(0)} \text{workplace closing}_{i,j} + \beta_{i2}^{(0)} \text{close public transport}_{i,j}
\]  

\[
+ \beta_{i3}^{(0)} \text{stay-at-home}_{i,j} + \beta_{i4}^{(0)} \text{international travel controls}_{i,j} + \gamma_{i2}^{(0)} TVCD_{i,j}^{(0)} + \epsilon_{i,j}^{(0)}
\]

3.4.2. The impact of individual policies on NO2 TVCD

The previous regression specifications investigate how the NO2 TVCD is affected by COVID-19 mitigation policies with a combined index (the stringency index). Although analyses based on the stringency index can discover certain impacts on the environment, there are two main drawbacks: 1) these analyses cannot differentiate the effects of seasonal and inter-annual trends. Specifically, TVCD \(_{i,j}\) was obtained by using the covariate values in 2020 and the estimated regression coefficients based on Eq. (3). Standard errors were obtained using the robust standard error estimator clustered at the country level.

\[
TVCD_{i,j}^{(0)} = constant + \alpha_{i1}^{(0)} + \delta_{i0}^{(0)} + \beta_{i1}^{(0)} \text{humidity}_{i,j}^{(0)} + \beta_{i2}^{(0)} \text{temperature}_{i,j}^{(0)} + \gamma_{i1}^{(0)} \text{wind}_{i,j}^{(0)} + \gamma_{i2}^{(0)} \text{meanTVCD}_{i,2010-2014}^{(0)} + \epsilon_{i,j}^{(0)}
\]  

\[
\log\left(TVCD_{i,j}^{(0)}\right) = constant + \alpha_{i1}^{(0)} + \delta_{i0}^{(0)} + \beta_{i1}^{(0)} \text{stringencyIndex}_{i,j}^{(0)} + \gamma_{i2}^{(0)} TVCD_{i,j}^{(0)} + \epsilon_{i,j}^{(0)}
\]

Fig. 12. The heterogeneous impacts of specific policies on NO2 TVCD in the poor cluster.
one of these indicator values. For example, if a country’s GDP is larger than the median value among the corresponding indicator values, it will be assigned to the “high” subgroup, otherwise the “low” subgroup.

4. Results

4.1. NO₂ clusters

The k-median clustering algorithm identifies three NO₂ TVCD clusters, including the mild, moderate, and poor clusters. The mild cluster represents areas where NO₂ TVCD was relatively low in the past several years. In comparison, grid cells in the moderate cluster and poor cluster are characterized by higher values of NO₂ TVCD. Fig. 3 shows the spatial distributions of the three clusters.

The poor cluster consists of a total of 43,329 grid cells, occupying about 12.0% of the total grid cells. These cells represent regions including Eastern Canada, Europe, Western and Southern Russia, India, and the Eastern United States. These areas are also associated with high NO₂ TVCD (Fig. 4) ranging from 0.9 to 6.2 * 10¹⁵ molecules/cm². The median value is around 2.2 * 10¹⁵ molecules/cm² which is significantly higher than the medians of the other clusters. NO₂ emissions typically come from fuel burning such as from vehicles and powerplants (EPA, 2016; Dutheil et al., 2020). These regions may have high NO₂ TVCD due to their social and industrial nature.

There are 145,885 grid cells in the moderate cluster, corresponding to about 40.3% of the total grid cells. Moderate cluster regions are seen in Southern Canada, the Western United States, Australia, most of Africa, the Arabian Peninsula, Southern South America, and Western Asia. Some of these regions in mid-Africa may be subject to NO₂ emissions from biomass burning (Edwards et al., 2006). NO₂ emissions can also come from petroleum and metal refinement as well as manufacturing (New Zealand Ministry for the Environment, 2018). Pollution in Southern Canada and the Western United States could also be attributed to manufacturing industries. Furthermore, Africa and Australia are notable sources of precious metals and minerals which result in NO₂ emissions as they are processed (Myers, 2016; Desjardins, 2018). The moderate cluster regions have NO₂ TVCD between 0.4 and 0.8 * 10¹⁵ molecules/cm² with half of the cells between 0.6 and 0.7 * 10¹⁵ molecules/cm². The median NO₂ TVCD is around 0.65 * 10¹⁵ molecules/cm² which is significantly lower than that for the poor cluster. The mild cluster contains 172,799 grid cells which is 47.7% of the total global continent grid cells. Grid cells in the mild cluster were mainly found in high-latitude and sparsely-populated regions. Accordingly, the NO₂ TVCD values were low for these areas as seen in Fig. 4; their values range from 0 to 0.4 * 10¹⁵ molecules/cm², with 75% of them being between 0 and 0.2 * 10¹⁵ molecules/cm², and the median being around 0.1 * 10¹⁵ molecules/cm². Compared to the distribution of the 10-year mean NO₂ TVCD as shown in Fig. 5, the clustering results can capture the spatial distribution of global NO₂ TVCD.

4.2. Spatiotemporal analysis

4.2.1. Global analysis

Using violin plots, Fig. 6 and Fig. 7 display the distributions of NO₂ TVCD and anomaly derived from 10-year daily mean NO₂ TVCD, respectively, for each month in 2020 and the three previous years (2017 to 2019). The white dot in the middle of each violin indicates the median value for the NO₂ TVCD/anomaly for the labeled month. The mild and moderate clusters saw similarity in the overall temporal trends for the NO₂ TVCD (Fig. 6). Contrary to these two clusters, which displayed no explicit pattern in terms of changes in the median values, the poor cluster exhibited lower median NO₂ TVCD in 2020 starting around the spring and persisting through the remainder of the year. Spring 2020 correlated with the start of COVID-19 containment and closure policies in most places. In addition, we noticed that major anthropogenic activities take place in the poor cluster. Selecting the study area by using the Global Human Settlement Layer (GHSL) as a filter (Venter et al., 2020) or hard-thresholding the NO₂ level (Liu et al., 2021b) can be found in contemporary research. The former method excluded data from uninhabited areas to focus on pollution that is most relevant to human exposure, while the latter one disregarded pixels with NO₂ TVCD smaller than a certain value, below which the level of pollution was judged too small to be attributable to anthropogenic sources. Our clustering approach offers an alternative method to detect polluted areas that is consistent, in general, with the foregoing methods, but with the primary advantage that it is a data-driven approach—the data speak for themselves. It is also worth mentioning that the hard-thresholding method ignores the changes in NO₂ emissions over time and the GHSL has a drawback that it can hardly be up-to-date (the latest available GHSL data was produced in 2015). When the anomaly data was used, larger within-month variation in the NO₂ emissions can be observed. Fig. 7 displays the apparent reduction in 2020 NO₂ TVCD anomaly compared to the previous years in the poor cluster. Therefore, it is reasonable to conclude that the lower NO₂ concentrations seen in the 2020 poor clusters may be attributed to the COVID-19 containment and closure policies.

4.2.2. Regional analysis

Regional analysis was conducted through investigating changes in NO₂ TVCD and anomaly over time for clusters in China, the United States, and Italy. The NO₂ TVCD anomaly data are plotted in Fig. 8, in which the ranges of NO₂ TVCD anomalies from 2017 to 2019 are represented by areas shaded in gray color, and the 2020 anomalies for the mild, moderate, and poor clusters are represented by blue, orange, and red curves, respectively. The dashed lines highlight the first lockdown period in each country; their corresponding start and end dates can be found in Table 1.

With respect to the lockdown dates, the poor clusters in each country saw a decrease in NO₂ TVCD, with peak reductions of 4.85(±1.97) * 10¹⁵, 1.91(±0.62) * 10¹⁵, and 9.91(±3.88) * 10¹⁴ molecules/cm² for the United States, China, and Italy, respectively (Table 1). Meanwhile, the average NO₂ percentage reduction calculated over the poor clusters during the selected lockdown period are 7(±1)%, 24(±2)%, and 21(±1)% in the three countries (Table 1). Because our analysis is on a per-cluster basis, in general, these results are not directly comparable to most of the current research, which are mainly city-based or country-based analyses, and the data source, study period, and reference years usually differ as well. However, by using percentage reduction as a metric in the poor cluster where most anthropogenic activities occur, our findings are in agreement, for example, with Metya et al. (2020), who reported an average decrease of 25% NO₂ emission due to the transport sector in China. Furthermore, Liu et al. (2021b) reported that the US did not demonstrate a significant decline in NO₂ TVCD, but using a clustered-based approach, we saw a 7% reduction in the poor cluster in the US. In addition, the mild and moderate clusters in each country often did not show a significant change in NO₂ TVCD during the lockdown period. Interestingly, our analysis revealed that certain mild clusters even saw an increase of the NO₂ TVCD, which is consistent with the findings reported by Gkatzelis et al. (2021) who discovered sporadic increase in NO₂ column densities in less densely populated regions. The decrease during the lockdown interval in China is notable and may be related to the country’s strict implementation of containment and closure policies. Comprehensive reviews have also noted that greater declines in NO₂ emissions have been observed in countries with more stringent policies (Gkatzelis et al., 2021).

The monthly averaged NO₂ TVCD for successive periods in 2020 (top) and 2019 (bottom) for the poor cluster in China (Fig. 9), the United States (Fig. 10), and Italy (Fig. 11) are displayed. The NO₂ TVCD in each country showed a gradual decline over time in 2019. With more abrupt changes, similar decrease patterns can be seen for the corresponding time periods in 2020. In all countries, there was a noticeable decline in NO₂ TVCD within the first month that the lockdowns started to be active. The connection between lockdowns and NO₂ trends is apparent
when looking at China in Fig. 9. China experienced one of the earlier outbreaks of COVID-19 and promptly implemented strict lockdown policies in early January. Accordingly, there was a drastic reduction in NO\(_2\) TVCD between January and February. As these lockdown measures were lifted, the NO\(_2\) values started to rise again as seen in the March and April months of 2020. However, these NO\(_2\) TVCD values were not as high as they were before the lockdowns. Within these three countries, we also notice that NO\(_2\) TVCD is high around clusters of cities and areas with large populations. This could be the case as many cities are industrial centers which consume large amounts of fossil fuels and produce great volumes of NO\(_2\) emissions. For these industrial centers, a considerable volume of NO\(_2\) may be associated with high transportation emissions. A recent study supports the claim that changes in air pollutant emissions can be largely attributed to the transportation sector (Guevara et al., 2021).

4.3. Statistical analysis

4.3.1. The impact of the stringency index on NO\(_2\) TVCD

Statistical analysis using the stringency index quantitatively studies the average impact of COVID-19 mitigation policies on different clusters. The regression results in Table 2 (based on Eq. (4)) indicate that the impact varies in the three clusters. COVID-19 containment and closure policies did not significantly decrease NO\(_2\) TVCD in the mild or moderate clusters, but they led to significant reductions in the poor cluster. Specifically, one standard deviation (23.58) increase in the stringency index corresponds to a decrease of 3.2% NO\(_2\) TVCD in the poor cluster (coefficient = -0.033, p < 0.05). In other words, these estimates indicate a maximum reduction of 13.1% NO\(_2\) TVCD when the stringent containment and closure policies (index score 100) were implemented.

4.3.2. The impact of specific policies on NO\(_2\) TVCD

Compared to Table 2, Table 3 shows how the four individual containment and closure policies affected NO\(_2\) TVCD in the three clusters (based on Eq. (5)). Among these policies, workplace closing policies significantly decreased the NO\(_2\) TVCD by 6.7% (coefficient = -0.069, p < 0.1) in the poor cluster. The close public transportation policies also significantly decreased NO\(_2\) TVCD by 4.5% in the poor cluster (coefficient = -0.046, p < 0.1). Stay-at-home orders and international travel controls did not see significant changes in NO\(_2\) TVCD. It is also important to note the interplay between these policies and the possible connections among their impacts. For example, stay-at-home orders and workplace closings both likely limited transportation to work and, therefore, may have reduced vehicle NO\(_2\) emissions in a similar way. The connections between these policies and their effects should be further deconvoluted in future research.

4.3.3. Heterogeneous impacts of policies on NO\(_2\) TVCD in the poor cluster

Previous analyses found that workplace closing and close public transport policies are more effective in reducing NO\(_2\) TVCD in the poor cluster. Thus, additional heterogeneity analyses were conducted to investigate whether the effects vary across different types of countries. In Fig. 12, the blue diamonds and the dashed lines represent the estimated coefficients and their corresponding confidence intervals, respectively. Each row represents the result from a regression with subsamples from the corresponding subgroup, where H and L denote the “high” and “low” subgroups, respectively. The plots in Fig. 12 demonstrate that the estimated coefficients are not substantially different from the baselines. Meanwhile, significant heterogeneity in the policy effect was discovered. Regarding workplace closures, countries with a higher income level, a higher urban population percentage, a higher CO\(_2\) emission level, and a higher fossil fuel consumption level experienced a larger reduction in NO\(_2\) TVCD. Since countries rely more on industrial activities when these four indicators are high, these findings suggest that the industrial sector is an essential source of NO\(_2\) emissions. For the close public transport policy, countries with a higher income level, a higher population size, a higher CO\(_2\) emission level, and a higher fossil fuel consumption level were accompanied by a larger decrease in NO\(_2\) TVCD in the study period. A possible reason for this relation is that public transportation may play a vital role in these countries. Indeed, transportation-based emissions constitute a major source of NO\(_2\) pollution (Guevara et al., 2021).

5. Conclusion and discussion

This study evaluated the impact of various COVID-19 mitigation policies on tropospheric NO\(_2\) across clusters discovered by a machine learning method. First, three clusters were formed based on NO\(_2\) TVCD data using the k-median clustering algorithm. Then, we investigated the NO\(_2\) emission changes through qualitative and quantitative analyses over the clusters at the global and regional levels. To assess the impact of policies on NO\(_2\) TVCD reduction, panel regression analyses were conducted to quantify the effects of several containment and closure policies in each cluster separately. Further heterogeneity analysis provided more insight into how policy effects vary in different types of countries. In regard to workplace closures, areas with higher incomes, urban populations, CO\(_2\) emissions, and fossil fuel consumption were seen to have larger NO\(_2\) TVCD reductions. In regard to public transport closures, places with higher incomes, population size, CO\(_2\) emissions, and fossil fuel consumption had larger decreases. These findings emphasize the importance of looking at industrial and anthropogenic activities as sources of pollution. It is worth mentioning that since our regional and global analyses (Section 4.2.1 and Section 4.2.2) are on a per-cluster basis, these results may not be directly compared to most existing studies, we have interesting findings consistent with contemporary reports (Gkatzelis et al., 2021). Besides, our regression analyses (Section 4.3) estimate the average effect of the stringency index/specific policy on NO\(_2\) TVCD for the entire year 2020, which is different from those merely focusing on much shorter lockdown periods.

Despite the insight gained from this study, there are some areas that can be further investigated. First, the daily NO\(_2\) TVCD displays different patterns across the clusters. Specifically, the mild and moderate clusters exhibit inverted U-shape curves in contrast to the expected shape seen in the poor cluster. Future research may investigate the mechanism and possible driving factors for such diverging patterns. Second, since the burning of fossil fuels is one of the major sources of emission, the long-term impact on fuel demands (Ou et al., 2020) and climate change (Forster et al., 2020) may also be explored. In addition, a recent study (Guevara et al., 2021) identified the potential sources of reduction by constructing sector-based reduction factors and concluded that road transport led to the most significant amount of reduction for many pollutants. It would be interesting to apply this technique to study the long-term effects induced by the containment and closure policies, possibly at the global scale. As time progresses, it is more reasonable to incorporate the “wave” effect (Kim and Kwan, 2021) rather than treating the entire year uniformly, which has not been considered in the current study. Last but not least, this study only focused on the policy impacts on tropospheric NO\(_2\); the entire analysis can be applied and extended to different pollutants such as CO\(_2\) and O\(_3\). The complex separate and joint effects of these pollutants may be alleviated by necessary regulations through policy-making processes. The “side-effect” of the containment and closure policies experienced during this unprecedented global pandemic provides an effective way to visualize an explicit change in pollution. A better understanding of the mechanism and consequences induced by policies is critical and fundamental to all researchers and policy makers concerning the health and economic well-being of people across the whole world, as well as environmental sustainability. Therefore, future research along these directions is certainly warranted.
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.

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