I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13480

Does the COVID-19 Pandemic Improve Global Air Quality? New Cross-National Evidence on Its Unintended Consequences

Hai-Anh H. Dang
Trong-Anh Trinh

JULY 2020

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13480

Does the COVID-19 Pandemic Improve Global Air Quality? New Cross-National Evidence on Its Unintended Consequences

Hai-Anh H. Dang
World Bank, IZA, Indiana University and Vietnam Academy of Social Sciences

Trong-Anh Trinh
World Bank

JULY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Does the COVID-19 Pandemic Improve Global Air Quality? New Cross-National Evidence on Its Unintended Consequences*

Despite a growing literature on the impacts of the COVID-19 pandemic, scant evidence currently exists on its impacts on air quality. We offer the first study that provides cross-national evidence on the causal impacts of COVID-19 on air pollution. We assemble a rich database consisting of daily, sub-national level data of air quality for 178 countries before and after the COVID-19 lockdowns, and investigate their impacts on air quality using a Regression Discontinuity Design approach. We find the lockdowns to result in significant decreases in global air pollution. These results are consistent across measures of air quality and data sources and robust to various model specifications. Some limited evidence also emerges that countries with a higher share of manufacturing in the economy or with an initial lower level of air pollution witness more reduced air pollution after the lockdowns; but the opposite result holds for countries near the equator. We also find that mobility restrictions following the lockdowns is a possible explanation for improved air quality.

JEL Classification: D00, H00, O13, Q50

Keywords: COVID-19, air pollution, mobility restriction, regression discontinuity design

Corresponding author:
Hai-Anh H. Dang
Data Analytics & Tools Unit
Development Data Group
World Bank
1818 H St. N.W.
Washington, D.C. 20433
USA
E-mail: hdang@worldbank.org

* We would like to thank Paolo Verme for helpful discussions on earlier versions. Dang would also like to thank the UK Department of International Development for additional funding assistance through a Knowledge for Change (KCP) grant for the World Development Report 2021 "Data for Better Lives". Trinh acknowledges support from the World Bank Young Fellows Program in Forced Displacement.

1. Introduction

It has by now become clear that the COVID-19 pandemic is not only a global health emergency but has also led to a major global economic downturn. An emerging body of economic literature has examined impacts of COVID-19 on a wide range of outcomes including unemployment (Fairlie et al., 2020), household consumption (Baker et al., 2020), and individual income (loss) and behaviour changes for the whole population or for different income groups (Akesson et al., 2020; Dang et al., 2020). Most studies generally confirm the adverse effects of the pandemic on these various outcomes in both richer and poorer countries.

Yet, scant evidence currently exists on the impacts of the COVID-19 crisis on air quality, and there appears no conclusive evidence yet among the existing few studies on the impacts of the pandemic on air quality. Employing difference-in-differences models that compare cities with and without the pandemic-induced lockdown policies, He et al. (2020) find that city lockdowns led to considerable improvement in air quality as measured by Air Quality Index (AQI) and $PM_{2.5}$. This result is consistent with the findings for the United States, where Brodeur et al. (2020) find 'safer-at-home' policies to decrease PM2.5 emissions. Research in other disciplines such as environment studies also suggest a considerable decline in pollutant parameters during and after the lockdown.[1] Using a similar econometric approach to examine the linkage between COVID-19 and air pollution in Hubei, the province at the center of the outbreak in China, Almond et al. (2020) find that COVID-19 had ambiguous impacts on China's pollution, such as even some relative deterioration in air quality near the pandemic's epicenter. Furthermore, to our knowledge, the emerging literature on COVID-19 focuses on

[1] For example, Ma et al. (2020) show a decrease in concentration of nitrogen dioxide (NO_2) by 14 percent in Wuhan, China. Similarly, Tobías et al. (2020) find that NO_2 concentration was reduced by half during the lockdown in Spain, another hot spot of COVID-19.

country-specific case studies rather than investigates the impacts of the pandemic on the global scale.[2]

We fill in this gap in the literature and offer the first assessment of the pandemic impacts on air pollution in a multi-country setting. Given that air pollution has been linked to heart and lung damage and many other health diseases, understanding how air quality is affected during the COVID-19 pandemic will provide important empirical evidence for health and environmental policies.

Specifically, we make several new contributions in this study. First, we offer global estimates for the causal impacts of COVID-19 on air quality, using a Regression Discontinuity Design (RDD) approach in a short period of time before and after each country implemented its lockdown policies. Since the lockdown—as most society-wide regulations or policies—cannot be randomized across countries, the RDD offers us the most rigorous evaluation model that is available. Second, we provide estimates using several different measures of air quality. While most existing studies restrict analysis to one or two indicators of air quality, we employ two indicators NO_2 and $PM_{2.5}$ for our main analysis and several other indicators for robustness check including O_3, PM_{10}, and SO_2. These various indicators help strengthen the estimation results.

Finally, we combine a variety of real-time data sources for richer analysis. We obtain daily data on air pollution, at the sub-national level, from two sources: satellite data (from the European Union's Copernicus programme) and station-based data (from the World Air Quality Index). We then combine these air quality data with the Oxford COVID-19 Government Response Tracker (OxCGRT), which provides a unique measure of government

[2] Other studies examine instead a related outcome, the impacts on health outcomes caused by the pandemic-induced changes in air quality. For example, Cicala et al. (2020) use a sample of more than 3,100 counties in the US and show that reductions in emissions from travel and electricity usage reduced deaths by over 360 deaths per month. On the other hand, Cole et al. (2020) indicate that an increase in $PM_{2.5}$ concentrations of $1\mu/m^3$ is associated with an increase in COVID-19 cases of between 9.4 and 15.1. This study is based on a sample of 355 municipalities in the Netherlands. Notably, these studies focus on one specific country only.

responsiveness to COVID-19. We also supplement our analysis with data from several other reliable sources including the National Oceanic and Atmospheric Administration, Google Community Mobility Reports, World Bank World Development Indicators, WHO Global Ambient Air Quality Database, and Economist Intelligence Unit.

The rich database that we assemble allows us to address a key issue in cross-country analysis, which is to construct lockdown dates for different countries. Indeed, identifying comparable cut-off dates across different countries is challenging. The term 'lockdown' can refer to anything from mandatory quarantines to bans on events and gatherings, closures of certain types of businesses or non-mandatory recommendations to stay at home. Some governments immediately respond to the outbreak by implementing a (regional or national) complete lockdown (e.g., China, Italy), while some implement gradual lockdowns in a staggering manner for different locations (e.g., the United States). We also present a number of robustness tests regarding our selected lockdown dates. Once we establish the causal relationship of COVID-19-induced lockdowns on air pollution, we explore the role of movement and travel restrictions as potential mechanisms.

We find strong evidence for reduction of air pollution after the lockdowns, with the reduction becoming stronger as the lockdowns go into effect for a longer period. In particular, the global decreases in NO_2 and $PM_{2.5}$ hover around 9 percent and 4 percent, respectively, 90 days after the lockdowns. Our estimation results are qualitatively similar for different indicators of air quality and government policy indexes, and remain robust to different model specifications regarding bandwidths, functional forms, and the inclusion of different covariates. We also find some limited evidence that countries with a higher share of manufacturing in the economy have more reduced air pollution after the lockdown, as do countries with an initially lower level of air pollution. But the opposite result holds for countries near the equator. Our findings suggest that mobility restrictions following the lockdown can be a channel that explains the improvement of air quality.

The remainder of the paper is organized as follows. We describe the database we construct for analysis in Section 2 before discussing the empirical models in Section 3. We present the estimation results in Section 4 and provide further discussion and conclude in Section 5.

2. Data

To examine the relationship between COVID-19 and air quality, we use two measures of air pollution, namely fine particulate matter $PM_{2.5}$ (mass concentration of particles with diameters $\leq$2.5 um) and nitrogen dioxide NO_2. While other pollutants are available in our dataset, we select the $PM_{2.5}$ and NO_2 given their direct link to human health. $PM_{2.5}$ is a common cause for adverse health outcomes such as chronic obstructive pulmonary disease (COPD) and lower respiratory infection (LRI) causing death of nearly three million people globally (Gakidou et al., 2017). At the same time, NO_2 is the leading source of childhood asthma in urban areas globally (Achakulwisut et al., 2019). In this study, we collect these measures from 1st October 2019 to 1st June 2020. We also use other pollutants, such as NO_2, SO_2 and O_3, for robustness checks.

The NO_2 data are derived from images of pollution-monitoring satellites released by the National Aeronautics and Space Administration (NASA) and European Space Agency (ESA). In particular, we use data from the Sentinel-5P/TROPOMI (S5P) instrument of the European Union's Copernicus programme. The Copernicus S5P provides daily global coverage of atmospheric parameters at high resolution (i.e., a pixel size of about 5.5 km x 3.5 km after 6th

August 2019).[3] We then use Google Earth Engine to process and average air quality data at the sub-national level using administrative areas taken from Database of Global Administrative Areas (GADM).[4] While the Copernicus S5P records a wide range of pollutants including NO_2 and others (O_3, SO_2, CO, CH_4, and aerosols), we focus on NO_2 because this is a noxious gas emitted by motor vehicles, power plants, and industrial facilities (Dutheil et al., 2020; Ogen, 2020). Among other pollutants, NO_2 is also a particularly well-suited data to analysis of emission because it has a short lifetime; this implies that molecules of NO_2 stay fairly close to their sources and thus offer an appropriate measure of changes in emissions.

A potential concern of using satellite air quality, however, is cloud cover. This can bias results by obscuring the sensor's view of the lower atmosphere. For example, concentrations of NO_2 in the atmosphere are highly variable in space and time (for example the impacts of commuter traffic, weekdays and weekend days) as well as changes in weather conditions. Therefore, we follow suggestions from the Copernicus program and perform a cloud masking which excludes results from pixels with > 10 percent cloud fraction.[5] We also averaged data over weekly periods as a robustness test. Finally, we include data on daily rainfall and temperature to control for weather conditions, which are derived from the National Center for Environmental Prediction (NCEP) at the National Oceanic and Atmospheric Administration (NOAA). The global dataset provides four 6-hour daily records of temperature and precipitation at the resolution of approximately 25 km. We extract the weather data at the sub-national level using a similar process as with the air pollution data.

As an alternative measure of air quality, we use daily station-based air quality index (AQI) from the World Air Quality Index (WAQI) project. The AQI provides accurate and

---

[3] The data has been used recently to study changes in air quality caused by COVID-19 (e.g. Chen et al., 2020; Ogen, 2020; Zambrano-Monserrate et al., 2020).
[4] The data is available at https://gadm.org/about.html.
[5] For more details, see: https://atmosphere.copernicus.eu/flawed-estimates-effects-lockdown-measures-air-quality-derived-satellite-observations?q=flawed-estimates-effects-lockdown-measures-air-quality-satellite-observations

reliable information on different air pollutant species from more than 12,000 ground-based air quality monitoring stations (primarily located at/near the US embassies and consulates) situated in 1,000 major cities in more than 100 countries from 2014 to present. However, there are certain limitations with station-based data. One is that station-based data are likely reported more slowly, and not in a 'real-time' fashion as satellite data. Another limitation is the locations of air quality monitoring stations are likely not random, so they may not provide representative data on an area's air quality. Consequently, the satellite data are our preferred data for analysis.

We subsequently match the air pollution data with the country-level pandemic data from the Oxford COVID-19 Government Response Tracker (OxCGRT). The OxCGRT is a novel country-level dataset published by the Blavatnik School of Government at the University of Oxford, which contains information on various lockdown measures, such as school and workplace closings, travel restrictions, bans on public gatherings, and stay-at-home requirements (Hale et al., 2020).

As discussed earlier, lockdown dates vary from country to country, and countries may implement lockdowns with different degrees of strictness (i.e., business activities and travels can continue to varying extents for different countries). In fact, lockdown dates may differ even within the same country. For example, in quite a few countries, while all schools are shut down, universities operate on a different schedule, or different regions (states) impose different lockdown dates. To address this issue, the OxCGRT provides a unique composite measure which combines indicators on different aspects of lockdown policies into a general index.[6] By using a range of different indicators, this stringency index accounts for any indicator that may be over- or mis-interpreted and thus allows for a systematic comparison across countries (Hale et al., 2020).

[6] For the index components, see Table A1 (Appendix 1).

For each country, we define the official lockdown date as the first day on which the stringency index becomes positive. Using our constructed measure, Figure A1 (Appendix 1) shows that most countries introduced lockdown policies in the last week of January and first week of February. Notably, the start date of lockdown does not correspond to the intensity of policy index as countries that implemented lockdown policies later tend to be more stringent in their response.

To explore a potential channel of COVID-19 on air quality, we collect data on mobility from Google Community Mobility Reports. The Google Community Mobility Reports provide daily data on Google Maps users who have opted-in to the 'location history' in their Google accounts settings across 132 countries. The reports calculate changes in movement compared to a baseline, which is the median value for the corresponding day of the week from January to present. The purpose of travel has been assigned to one of the following categories: retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. In our analysis, we expect that the lockdown will lead to a reduction in mobility of all categories, except for the residential category. We also examine data from several additional sources for robustness checks.

3. Empirical Model

We first employ a panel data model with country fixed effects and time fixed effects to examine whether air quality improves in response to government COVID-19 lockdown policies

$$A_{i,t} = \beta S_{i,t} + \gamma X_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t} \qquad (1)$$

The coefficient of interest in Equation (1) is β, which measures how the air quality ($A_{i,t}$) in country *i* and date *t* changes in response to the stringency of government COVID-19 policies ($S_{i,t}$). Because $A_{i,t}$ varies by country and date, this fixed-effects model allows for the inclusion of country fixed effects (α_i) and time fixed effects (τ_t) to absorb the effects of unobservable time-invariant country or time characteristics. $X_{i,t}$ is a vector of time-varying control variables such as daily temperature and rainfall (or humidity). We estimate Equation (1) using global data at the sub-national level, and we also replicate our analysis at the country level as a robustness test.

Yet, Equation (1) will yield an inconsistent estimate of β if there are omitted factors that affect air quality and simultaneously correlate with the government responses to COVID-19. Since the model is based on a sample after the lockdown date (i.e., the stringency index being positive), it does not take into account the fact that different countries can differ in terms of pre-COVID-19 characteristics such as governance quality and public preferences for protecting the environment. For example, countries with strong institutions likely implement stringent policies during the pandemic, and at the same time, may have had better programs in place that ensures better air quality. Another potential threat to Equation (1) is reverse causality. If air pollution is positively associated with the number of COVID-19 cases (see, e.g., Cole et al. (2020) and Yongjian et al. (2020)), this can lead to governments implementing more stringent policies on air quality.

In order to identify the causal effect of COVID-19 on air quality, we take advantage of the timing of lockdown as an exogenous policy shock and apply a sharp Regression Discontinuity Design (RDD) approach to estimate its impact on air pollution. In this approach, the observations immediately before the lockdown provide the counterfactual outcomes for those observations immediately after the lockdown because the lockdown (treatment) status will be randomized in a small neighborhood of the lockdown date (Hahn et al., 2001). Consequently, once we can identify the lockdown date for each country based on its stringency index as discussed earlier (i.e., when $S_{it} > 0$), we can compare the average outcomes for the observations in a window of time (bandwidth) around this date to estimate the causal impacts of COVID-19-induced lockdowns on air quality.

More formally, the treatment effect can be estimated as the change in air quality (A) in the neighbourhood of lockdown dates

$$\tau_{RD} = \lim_{\varepsilon \downarrow 0} E[\mathrm{A}|d = 0 + \varepsilon] - \lim_{\varepsilon \uparrow 0} E[\mathrm{A}|d = 0 + \varepsilon] \quad (2)$$

where d is the number of days before and after the official date of lockdown. We thus estimate the following reduced form

$$A_{it} = \delta L_{it} + f(d_{it}) + \theta X_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (3)$$

where L_{it} (treatment variable) is a dummy variable that equals 1 after the lockdown and 0 otherwise, and δ is the parameter of interest. As we discussed earlier, the construction of lockdown date is measured on the first day when stringency index is positive. $f(d_{it})$ denotes a function of the running variable d_{it} (number of days from the lockdown date). Similar to Equation (1), μ_i and π_t respectively denote the country fixed effects and the time fixed effects, and ε_{it} denotes the error term. We cluster the standard errors at the sub-national level in all models.

In summary, we offer a multiple-layered approach to ensure that estimation results are robust. First, the estimates using Equation (1) above provide the first set of evidence over whether air quality responds to the different levels of the government stringency policies. Second, we employ a parametric approach and use different functional forms of the running variable d_{it} to estimate Equation (3). These include (i) the linear model, (ii) the linear model with the interaction term of the running variable and the treatment variable (L_{it}*d_{it}), (iii) the quadratic model, and (iv) the quadratic model with the interaction term of the running variable and the treatment variable (L_{it}*d_{it}^2). Third, we present results for a broad range of bandwidths including 30, 60, and 90 days before and after the official lockdown dates. As suggested by Figure 1, the impacts of lockdowns become stronger over time, so these different bandwidths help capture the impacts of lockdowns over different time windows. Finally, we also offer results using a non-parametric approach as well as a battery of robustness checks regarding the bandwidths and different versions of the stringency index and other additional robustness tests in Section 4.2.[7]

An advantage of the RDD design is that the identification assumptions offer testable predictions. To validate our design, we present two types of tests. First, we investigate the distribution of observations (ADM1 level for satellite data and city level for station-based data) around the cut-off date.[8] Figure A2 (Appendix 1) provides results of the manipulation test suggested by McCrary (2008) and Cattaneo et al. (2018) based on the nonparametric local polynomial density estimator. The confidence intervals on the two sides of the discontinuity overlap, which confirms there is no evidence of systematic manipulation of the running variable. Second, we test for discontinuity in the other covariates around the date of lockdown. The results, shown in Figure A3 (Appendix 1), rule out this concern. We further offer a number of other robustness tests in Section 4.2.

4. Results

4.1. Main findings

We present in Table 1 the estimation results for Equation (1) using two data samples at the sub-national level (columns 1 and 2) and at the country level (columns 3 and 4). Our preferred estimates are shown in columns (2) and (4), which control for daily temperature and precipitation (humidity for station-based data)[9]. But we also show the estimates without control

[7] Although the OxCGRT data provides a systematic comparison across different countries as discussed earlier, it is still possible that not all business activities and travel cease exactly by the time of our proposed lockdown dates. In that case, a better approach is to employ the fuzzy RDD model than the sharp RDD model where the treatment variable L_{it} can assume the value of 0 for $S_{it} > 0$ for some countries. However, we do not have such additional information for L_{it} in our case, since we uniformly define this treatment variable as 1 after the lockdown date for each country. But the various robustness checks that we present can help address this concern. In particular, the different time bandwidths of 30, 60, and 90 days can average out the outcomes where lockdown policies may not be strictly applied after the lockdown date.

[8] For satellite data, we measure air pollution at the first-order administrative division (ADM1). In some countries, the ADM1 refers to province level while for others, it refers to state/region level.

[9] We do not use precipitation from the station-based data due to its low frequency (a large number of stations do not record rainfall level).

variables in columns (1) and (3) for comparison and robustness checks. The estimation results are strongly statistically significant in our preferred models (columns 2 and 4) and point to reduced air pollution where government policies are more stringent. Overall, our findings suggest that global air quality improved in response to COVID-19-induced lockdown policies.

In particular, column (2) indicates that a one-point increase in the stringency index is associated with a 0.046 (mol/km^2) decrease in NO_2 (Panel A). When using station-based data, the corresponding figure is a 0.132 (μg/m^3) decrease in $PM_{2.5}$ (Panel B). Estimates are rather similar when we analyse the data at the country level (column 4). However, as discussed earlier, these estimates are likely biased since employing Equation (1) does not allow us to properly account for the unobservables that may be correlated with both the stringency index and air quality.

We subsequently present our main analysis which examines the change in air quality before and after the lockdown using the RDD model. For illustrative purpose, Figure 1 provides prima facie evidence of the impact of lockdown on air quality. The figure shows the results from a local regression of air pollution, measured by NO_2 (Panel A) and $PM_{2.5}$ (Panel B), using the optimal bandwidth proposed by Imbens and Kalyanaraman (2012). We observe a negative jump at the threshold of cut-off date, which suggests a reduction of air pollution after the lockdown. The downward sloping trend for air pollution in Figure 1 also suggests that the reduction in air pollution becomes stronger as the lockdown went into effect for a longer period. This is understandable, since a short period of time may not be sufficient to detect the changes in air quality.

We report the results of the RDD model in Table 2, which shows estimates using two data samples: the satellite data (panel A) and the station-based data (panel B). We consider three different bandwidths, 30 days, 60 days, and 90 days before and after the lockdown. As suggested by Figure 1, a wider time window from the lockdown date can capture a stronger impact of the lockdown on air quality. Our preferred models are, again, those that control for weather conditions (columns 2, 4, and 6). In each panel of Table 2, we estimate four models using four different functional forms of the running variable as discussed earlier. Overall, Table 2 shows that air quality improves after the lockdown, and the results are rather qualitative similar regardless of whether we include control variables, except for the shortest time window of 30 days around the lockdown date. Estimation results are also statistically stronger with the satellite data, our main data for analysis.

Specifically, the coefficient on the lockdown variable is negative and statistically significant at the 1 percent level using the linear model (panel A, column 2). This indicates that a switch to lockdown leads to a 2.013 (mol/km^2) decrease in the global concentration of NO_2 after 90 days. This translates into an 8.8 percent decrease compared to an average value of NO_2 of 22.914 mol/km^2 before the lockdowns. We also find that using different functional forms (models 2 to 4) results in similar estimates. Finally, the negative impacts of lockdowns on NO_2 are rather consistent across bandwidths, but have a smaller magnitude with narrower bandwidths (as also seen with Figure 1). The decreases in concentration of NO_2 are roughly 4 percent for 60 days (panel A, column 4) and 2 percent for 30 days (panel A, column 6) after the lockdowns, respectively.

We turn next to the alternative station-based data and find a strong impact of the lockdown on $PM_{2.5}$ using the bandwidth of 90 days (panel B, column 2). The global decrease in $PM_{2.5}$ for 90 days after the lockdowns hovers around 3 to 4 percent depending on the functional form that we employ. But estimates become mostly statistically insignificant for the shorter bandwidths of 60 days and 30 days once we control for weather conditions. We then use different measures of air pollution available from the station-based data and reach a similar conclusion. Specifically, the results presented in Table A2 (Appendix 1) confirm the beneficial effects of lockdowns on air quality, as measured by NO_2 and PM_{10}, 90 days before and after the lockdown. While there is no evidence of the lockdown effect on SO_2, the indicator O_3 is found to be positively associated with the lockdowns at the windows of 90 days and 60 days. A possible explanation for the increase in concentration of O_3 is warmer weather during this period (Tobías et al., 2020).

4.2. Robustness tests

In this section, we conduct a battery of robustness tests on the estimation results. These include employing a nonparametric RDD method, adding different covariates to the regressions, using wider time bandwidths and different thresholds and versions of the stringency index, controlling for potentially differential time trends across countries, and converting the air quality variables into logarithmic form.

First, since employing specific functional forms can affect the parametric RDD estimation results, we adopt a nonparametric RDD method for robustness checks. An important feature of the nonparametric method is that the bandwidth is not selected arbitrarily; instead, it is calculated on a data-driven basis. In Table A3 (Appendix 1), we report the results of non-parametric specifications using two optimal bandwidths: the mean squared error (MSE) bandwidth and the coverage error rate (CER) bandwidth. We find consistent impacts of the lockdown on NO_2 using the satellite data, while there is little evidence of the impacts on $PM_{2.5}$ using the alternative station-based data.

Second, our main RDD specification assumes that the observations just below the cut-off (i.e., lockdown date) form good comparisons to those just above the cut-off not only in terms of outcomes but also in terms of covariates. To check on the latter assumption, we have already included weather conditions in the set of covariates in our RDD regression. For further checks, we include other covariates to control for the pre-pandemic country characteristics, namely country's log of GDP per capita (in constant 2010 USD), population density, log of energy consumption per capita, the number of motor vehicles per 1,000 inhabitants, and the share of electricity generated by coal power. The country characteristics come from the World Development Indicators (WDI) database in the latest year when data is available. We present the results in Table A4 (Appendix 1) using both the parametric and non-parametric approaches (using the covariate-adjust RDD method proposed by Calonico et al. (2019)). The results are consistent with our main findings, which further confirm the validity of the RDD design.

Third, a potential issue of using daily air pollution data is that these data substantially vary from one day to another because of variations in emission and changes in weather conditions. Therefore, we replicate our parametric RDD approach using a weekly indicator. We employ different bandwidths of 5, 10 and 15 weeks before and after the lockdown date. The results are presented in Table A5 (Appendix 1), which are generally consistent with the main findings in Table 2.

Fourth, the lockdown dates are identified based on the stringency index becoming positive. As a robustness check, we also consider other thresholds of the stringency index that range from 0 to 50% (on a scale of 0-100%). Estimates, shown in Figure A4 (Appendix 1), change somewhat in magnitude but are still strongly statistically significant. Fifth, we use alternative measures of stringency index taken from the OxCGRT dataset. There are two versions of the stringency index: (i) a "regular" version which returns null values if there are not enough data to calculate the index, and (ii) a "display" version which extrapolates to smooth over the last seven days of the index based on the most recent complete data. We use the latter indicator for our main analysis, but we also find consistent results using the "regular" version (Appendix 1, Table A6), except for $PM_{2.5}$ at the bandwidth of 60 days and 30 days.

Sixth, the stringency index in the OxCGRT dataset is calculated using a simple additive unweighted approach. It is thus possible that some dimensions with higher weights will be underestimated in the index. To address this issue, we create a new index based on the Principal

Component Analysis (PCA) method for all the dimensions of stringency index. Table A7 in Appendix 1 shows similar estimation results for our own index. Seventh, we further explore other indexes that are available from the OxCGRT dataset. They include: (i) Government response index, (ii) Containment and health index, and (iii) Economic support index.[10] Compared to our main measure, the government response index and the containment and health index include two additional dimensions: testing policy and contact tracing. Still, we find a consistent impact of the lockdown on air pollution when using these indexes (Appendix 1, Table A8).

Finally, we also check whether our results are driven by differential time trends across countries. We include in the regressions the interaction terms of country dummies with linear time trends. The results, presented in Table A9 (Appendix 1), are consistent with our main findings. Our findings also remain consistent when we use the logarithmic form of the air quality variable (Appendix 1, Table A10).

4.3. Heterogeneity analysis

Having shown that changes in air quality are driven by COVID-19, it is useful to understand whether the impact of lockdown differs by certain country characteristics. In particular, the impacts of lockdown can vary according to a country's geographic location. For example, cities near the deserts are often affected by sand and dust storms, which can strongly impact air quality. We simply divide our sample into two subsamples based on whether they are near the equator and we interact this variable with the treatment variable (lockdown). The results presented in panel A of Table 3 show that countries near the equator have a higher concentration of NO_2 after the lockdown.

[10] Another index is Legacy stringency index; however, it is not recommended by the OxCGRT team (Hale et al., 2020). Also the economic support index only includes income support programs and debt relief programs, which do not capture the overall responsiveness of the government.

A country's institution may also affect the impacts of lockdown. A large body of economic literature has shown the important role of institutions and culture in shaping economic development (e.g. Gorodnichenko and Roland, 2017; Acemoglu et al., 2019). Consequently, we use the democracy index from the 2019 report of the Economist Intelligence Unit.[11] We expect that countries with strong institutions are more able to take stringent policies during the time of COVID-19, and therefore have a better performance in terms of air quality. The results in panel B of Table 3, however, provide little support for this argument. In contrast, partial democratic countries and countries with hybrid regime appear to have a lower reduction in air pollution after the lockdown than authoritarian countries.

Another useful heterogeneity analysis is whether countries with high level of openness have a large reduction of air pollution after the lockdown. Whether trade is good or bad for the environmental outcomes has been a topic of debate in the literature. While there is evidence of the beneficial effect of trade on the environment (e.g. Antweiler et al., 2001; Frankel and Rose, 2005), other studies show that trade openness could in fact lead to higher emissions (Managi et al., 2009, Li et al., 2015). To answer this question, we add a country's share of manufacturing and share of trade in its GDP from the 2019 World Development Indicators (WDI) database. Our results are presented in panels C and D of Table 3. We find that countries with a larger share of manufacturing have a higher reduction of air pollution after the lockdown, while there are mixed results for the share of trade.

Finally, we examine whether countries with existing lower levels of air pollution may reduce air pollution more. We use the WHO Global Ambient Air Quality Database that summarises concentration of $PM_{2.5}$ at the country level in 2018.[12] We then split our sample into five quintiles and interact each with our treatment variable in the model specification. The

[11] The report is available at: https://www.eiu.com/topic/democracy-index
[12] The data is available at: https://www.who.int/airpollution/data/en/

results in panel E indicate that countries with an initial lower level of air pollution (i.e., the 1st quintile) have a higher reduction of air pollution compared to those with higher levels of air pollution.

4.4. Stringency index and mobility restriction

Once we established the relationship between government response to COVID-19 and air pollution, we shift our attention to the role of mobility restriction as the potential mechanism. Due to COVID-19, human mobility and relevant production and consumption activities have since decreased significantly. Given that one main source of air pollution comes from traffic mobility (Viard and Fu, 2015), it is reasonable to argue that more stringent policies will result in less mobility, thereby improving air quality.

We directly test this hypothesis by using data from the Google Community Mobility Reports. Since mobility data was not available before the lockdown date, we are unable to apply the more rigorous the RDD approach. Consequently, we estimate the panel data model with the country and time fixed effects in Equation (1). The estimation results obtained by this model discussed in the preceding sections are in fact qualitatively very similar to those obtained by the RDD approach.[13] As such, applying the panel data can provide some qualitative evidence on the mechanism of impacts.

We present the estimation results in Table 4, which show that geographic mobility has declined significantly where government policies are more stringent. In particular, a higher stringency index is associated with less mobility in both 'essential services' (e.g., grocery and pharma, workplace) and 'non-essential services' (retail and recreation, parks), but more mobility in the 'residential' category.

[13] In addition, the heterogeneity analysis in Table 3, panel B suggests that unobservables such as institutions may not bias the estimation results in the panel data model.

5. Conclusions

We contribute to the emerging literature on COVID-19 by offering the first study that provides cross-national evidence on the causal impacts of COVID-19 on air pollution. We assemble a rich database consisting of data from a number of different reliable sources, which we analyze with panel data and RDD econometric models.

Our findings provide a better understanding of the unexpected positive impacts of the pandemic on air quality. We find heterogeneous impacts for different country characteristics such as shares of manufacturing in the economy, initial levels of air pollution or proximity to the equator. We identify reduced mobility as a potential channel that can help reduce air pollution. Our findings suggest that while mobility restrictions appear not to be a long-term solution to address air pollution, reducing nonessential individual movements can help improve air quality on a global scale. A promising direction for future research can be more in-depth country studies on the impacts of the pandemic on air quality.

References

Acemoglu, D., Naidu, S., Restrepo, P., & Robinson, J. A. (2019). Democracy does cause growth. *Journal of Political Economy, 127*(1), 47-100.

Achakulwisut, P., Brauer, M., Hystad, P., & Anenberg, S. C. (2019). Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO2 pollution: estimates from global datasets. *The Lancet Planetary Health, 3*(4), e166-e178.

Akesson, J., Ashworth-Hayes, S., Hahn, R., Metcalfe, R. D., & Rasooly, I. (2020). Fatalism, Beliefs, and Behaviors During the COVID-19 Pandemic (No. w27245). National Bureau of Economic Research.

Almond, D., Du, X., & Zhang, S. (2020). Did COVID-19 Improve Air Quality Near Hubei? (No. w27086). National Bureau of Economic Research.

Antweiler, W., Copeland, B. R., & Taylor, M. S. (2001). Is free trade good for the environment? *American Economic Review, 91*(4), 877-908.

Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic (No. w26949). National Bureau of Economic Research.

Brodeur, A., Cook, N., & Wright, T. (2020). On the Effects of COVID-19 Safer-At-Home Policies on Social Distancing, Car Crashes and Pollution. (No. 132\55). IZA Discussion Paper.

Calonico, S., Cattaneo, M. D., Farrell, M. H., & Titiunik, R. (2019). Regression discontinuity designs using covariates. *Review of Economics and Statistics, 101*(3), 442-451.

Cattaneo, M. D., Jansson, M., & Ma, X. (2018). Manipulation testing based on density discontinuity. *The Stata Journal, 18*(1), 234-261.

Chen, K., Wang, M., Huang, C., Kinney, P. L., & Anastas, P. T. (2020). Air pollution reduction and mortality benefit during the COVID-19 outbreak in China. *The Lancet Planetary Health, 4*(6), e210-e212.

Cicala, S., Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2020). Expected Health Effects of Reduced Air Pollution from COVID-19 Social Distancing (No. w27135). National Bureau of Economic Research.

Cole, M., Ozgen, C., & Strobl, E. (2020). Air Pollution Exposure and COVID-19 (No. 13367). IZA Discussion Paper.

Dang, Hai-Anh, Toan Huynh, and Manh-Hung Nguyen. (2020). Does the COVID-19 Pandemic Disproportionately Affect the Poor? Evidence from a Six-Country Survey (No. 13352). IZA Discussion Paper.

Dutheil, F., Baker, J. S., & Navel, V. (2020). COVID-19 as a factor influencing air pollution? *Environmental Pollution, 263*, 114466.

Fairlie, R. W., Couch, K., & Xu, H. (2020). The impacts of covid-19 on minority unemployment: First evidence from April 2020 cps microdata (No. w27246). National Bureau of Economic Research.

Frankel, J. A., & Rose, A. K. (2005). Is trade good or bad for the environment? Sorting out the causality. *Review of Economics and Statistics, 87*(1), 85-91.

Gakidou, E., Afshin, A., Abajobir, A. A., Abate, K. H., Abbafati, C., Abbas, K. M., ... & Abu-Raddad, L. J. (2017). Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. *The Lancet*, *390*(10100), 1345-1422.

Gorodnichenko, Y., & Roland, G. (2017). Culture, institutions, and the wealth of nations. *Review of Economics and Statistics, 99*(3), 402-416.

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica, 69*(1), 201-209.

Hale, T., Petherick, A., Phillips, T., & Webster, S. (2020). Variation in government responses to COVID-19. Blavatnik school of government working paper, 31.

He, G., Pan, Y. & Tanaka, T. (2020). The short-term impacts of COVID-19 lockdown on urban air pollution in China. *Nature Sustainability*. https://doi.org/10.1038/s41893-020-0581-y

Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies, 79*(3), 933-959.

Li, Z., Xu, N., & Yuan, J. (2015). New evidence on trade-environment linkage via air visibility. *Economics Letters*, *128*, 72-74.

Ma, Y., Zhao, Y., Liu, J., He, X., Wang, B., Fu, S., Yan, J., Niu, J., Zhou, J. & Luo, B. (2020). Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. *Science of the Total Environment*, 138226.

Managi, S., Hibiki, A., & Tsurumi, T. (2009). Does trade openness improve environmental quality? *Journal of Environmental Economics and Management, 58*(3), 346-363.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics, 142*(2), 698-714.

Ogen, Y. (2020). Assessing nitrogen dioxide (NO2) levels as a contributing factor to the coronavirus (COVID-19) fatality rate. *Science of the Total Environment*, 138605.

Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Minguillón, M. C., ... & Querol, X. (2020). Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. *Science of the Total Environment*, 138540.

Viard, V. B., & Fu, S. (2015). The effect of Beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics, 125*, 98-115.

Yongjian, Z., Jingu, X., Fengming, H., & Liqing, C. (2020). Association between short-term exposure to air pollution and COVID-19 infection: Evidence from China. *Science of the Total Environment*, 138704.

Zambrano-Monserrate, M. A., Ruano, M. A., & Sanchez-Alcalde, L. (2020). Indirect effects of COVID-19 on the environment. *Science of the Total Environment*, 138813.

Figure 1: COVID-19 lockdown and air pollution

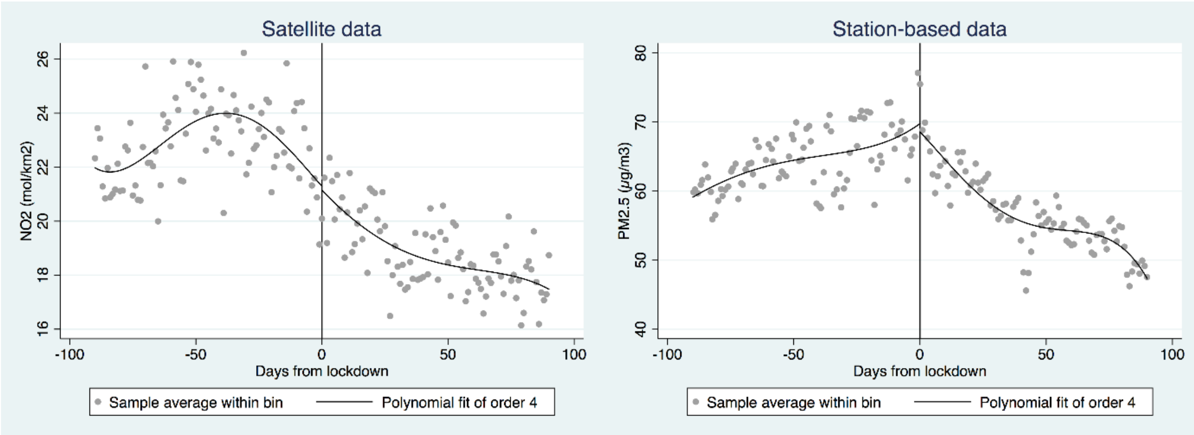


Table 1: Government response to COVID-19 and air pollution

	ADM1/City level		Country level	
	(1)	(2)	(3)	(4)
Panel A: Air quality is measured by NO_2 (satellite data)				
Stringency index	-0.032***	-0.046***	-0.040***	-0.040***
	(0.003)	(0.003)	(0.012)	(0.012)
Controls	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	250,838	216,170	14,850	12,756
R-squared	0.381	0.353	0.657	0.644
Panel B: Air quality is measured by $PM_{2.5}$ (station-based data)				
Stringency index	-0.167***	-0.132***	-0.181***	-0.154***
	(0.018)	(0.017)	(0.050)	(0.040)
Controls	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	79,464	73,041	12,457	11,659
R-squared	0.452	0.458	0.592	0.613

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of panel model. Robust standard errors in parentheses. Standard errors are clustered at ADM1/city level in columns (1) and (2), and country level in columns (3) and (4). Regressions in columns (2) and (4) include country dummies and week dummies. Control variables are daily temperature and rainfall (humidity for station-based data).

Table 2: COVID-19 lockdown and air pollution

Panel A: Satellite air pollution

Air quality:	+/-90 days		+/-60 days		+/-30 days	
NO_2	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: No running variable						
Lockdown=1	-2.037***	-2.013***	-1.209***	-0.880***	-0.568**	-0.433*
	(0.231)	(0.231)	(0.220)	(0.207)	(0.223)	(0.234)
Model 2: With running variable						
Lockdown=1	-1.973***	-1.968***	-1.182***	-0.843***	-0.540**	-0.391*
	(0.229)	(0.230)	(0.219)	(0.206)	(0.221)	(0.232)
Model 3: Quadratic term of running variable						
Lockdown=1	-1.987***	-1.991***	-1.197***	-0.868***	-0.551**	-0.408*
	(0.229)	(0.231)	(0.220)	(0.207)	(0.222)	(0.233)
Model 4: Cubic term of running variable						
Lockdown=1	-1.986***	-1.986***	-1.184***	-0.835***	-0.613***	-0.476**
	(0.229)	(0.230)	(0.220)	(0.205)	(0.224)	(0.236)
Means before lockdown	22.914	22.914	23.316	23.316	22.719	22.719
Controls	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	381,872	329,735	255,628	221,174	128,041	110,864

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results of parametric RDD. Robust standard errors in parentheses. Standard errors are clustered at ADM1 level. Air pollution is measured by NO_2 from satellite data. Model 1 does not include running variable, Model 2 includes running variable, Model 3 includes quadratic term of running variable, Model 4 includes cubic term of running variable. All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall.

Panel B: Station-based air pollution

Air quality:	+/-90 days		+/-60 days		+/-30 days	
$PM_{2.5}$	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: No running variable						
Lockdown=1	-4.539***	-2.665***	-1.952*	-0.288	0.903	-0.669
	(0.925)	(0.912)	(1.007)	(0.914)	(1.008)	(1.047)
Model 2: With running variable						
Lockdown=1	-3.905***	-2.182**	-1.386	0.127	1.195	-0.493
	(0.917)	(0.900)	(0.996)	(0.905)	(1.002)	(1.049)
Model 3: Quadratic term of running variable						
Lockdown=1	-4.057***	-2.271**	-1.520	0.063	1.104	-0.570
	(0.919)	(0.901)	(0.999)	(0.905)	(1.001)	(1.049)
Model 4: Cubic term of running variable						
Lockdown=1	-3.886***	-2.159**	-1.331	0.081	1.295	-0.367
	(0.918)	(0.900)	(0.996)	(0.903)	(1.007)	(1.048)
Means before lockdown	64.599	64.599	66.015	66.015	67.544	67.544
Controls	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,941	82,193	63,779	52,502	33,151	24,910

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results of parametric RDD. Robust standard errors in parentheses. Standard errors are clustered at city level. Air pollution is measured by $PM_{2.5}$ from station-based data. Model 1 does not include running variable, Model 2 includes running variable, Model 3 includes quadratic term of running variable, Model 4 includes cubic term of running variable. All regressions include country dummies and week dummies. Control variables are daily temperature and humidity.

Table 3: Heterogeneity tests

Air quality: NO_2	+/-90 days	+/-60 days	+/-30 days
	(1)	(2)	(3)
Panel A: Location			
Lockdown*Countries near equator	4.016***	3.571***	1.710***
	(0.297)	(0.294)	(0.251)
Observations	329,735	221,174	110,864
Panel B: Democracy			
Reference: Authoritarian			
Lockdown*Hybrid regime	0.876	1.212*	0.735
	(0.680)	(0.719)	(0.599)
Lockdown*Partial democracy	1.229**	1.498**	0.737
	(0.621)	(0.679)	(0.525)
Lockdown*Full democracy	0.507	0.736	-0.377
	(0.727)	(0.775)	(0.640)
Observations	311,104	208,498	104,492
Panel C: Share of trade			
Lockdown*Trade	-0.012**	-0.006	0.010**
	(0.005)	(0.006)	(0.004)
Observations	268,704	179,788	89,929
Panel D: Share of manufacturing			
Lockdown*Manufacturing	-0.366***	-0.393***	-0.308***
	(0.048)	(0.060)	(0.060)
Observations	231,935	156,097	78,171
Panel E: Air pollution index			
Reference: 1st quintile			
Lockdown*2nd quintile	0.794*	0.741*	0.820**
	(0.441)	(0.424)	(0.379)
Lockdown*3rd quintile	1.212***	1.310***	2.177***
	(0.397)	(0.397)	(0.390)
Lockdown*4th quintile	-0.885	-0.575	0.718
	(0.672)	(0.647)	(0.558)
Lockdown*5th quintile	-0.216	-0.980	-0.289
	(0.663)	(0.750)	(0.671)
Observations	326,198	218,856	109,754
Means before lockdown	22.914	23.316	22.719
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic terms) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at ADM1 level. Air pollution is measured by NO_2 from satellite data. All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall.

Table 4: Stringency index and mobility restriction

Mobility changes	Retail and recreation	Grocery and pharmacy	Park	Transit	Workplaces	Residential
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sub-national level						
Stringency index	-0.825***	-0.484***	-0.611***	-0.820***	-0.595***	0.283***
	(0.007)	(0.007)	(0.012)	(0.008)	(0.006)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122,839	120,069	111,574	107,215	142,524	101,186
R-squared	0.742	0.489	0.534	0.669	0.633	0.732
Panel B: Country level						
Stringency index	-0.762***	-0.478***	-0.536***	-0.784***	-0.592***	0.281***
	(0.023)	(0.021)	(0.032)	(0.019)	(0.020)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,016	11,016	11,016	11,016	11,016	11,003
R-squared	0.801	0.605	0.663	0.839	0.704	0.783

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of panel model. Robust standard errors in parentheses. Standard errors are clustered at sub-region level in Panel A and country level in Panel B. Results of panel analysis. All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall.

Appendix 1: Additional Figures and Tables

Figure A1: Number of countries that introduced lockdown and policy stringency index, OxCGRT database

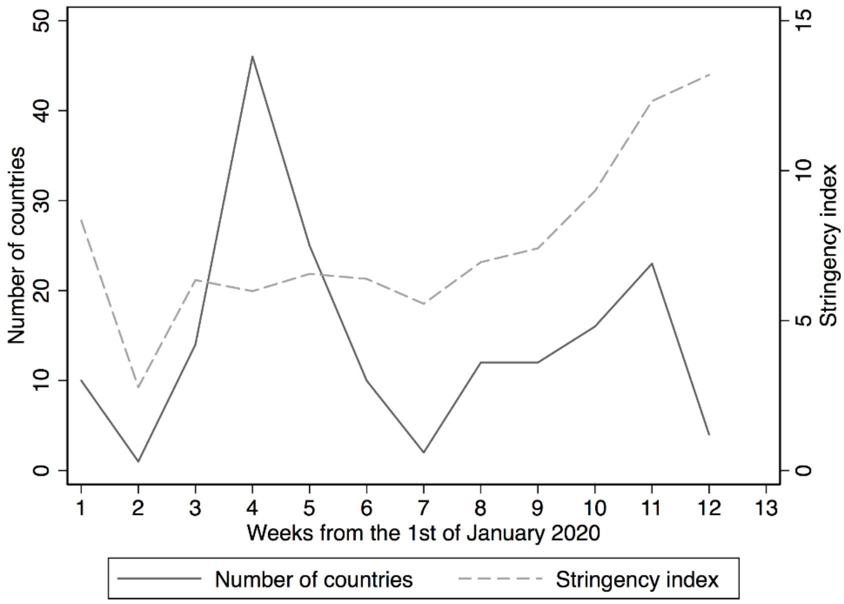


Figure A2: Manipulation test

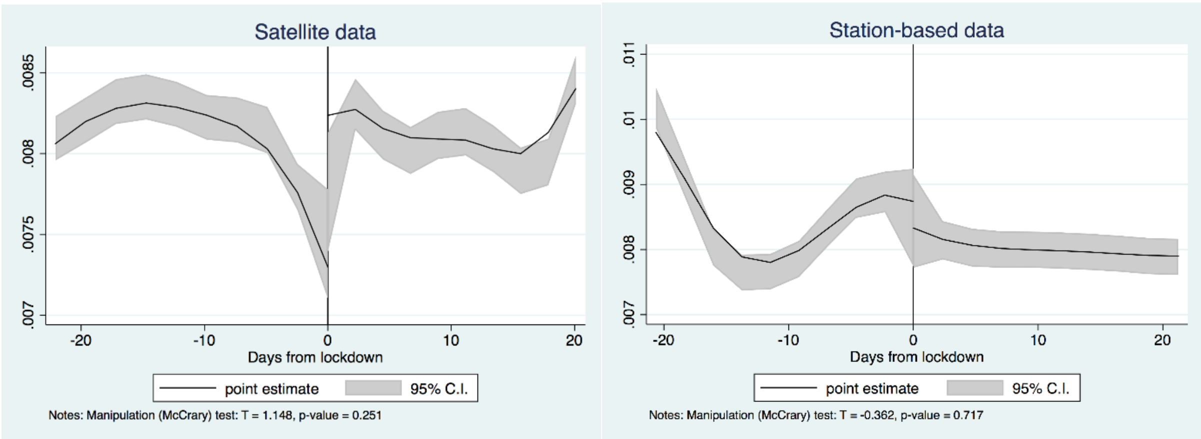


Figure A3: COVID-19 lockdown and temperature/precipitation

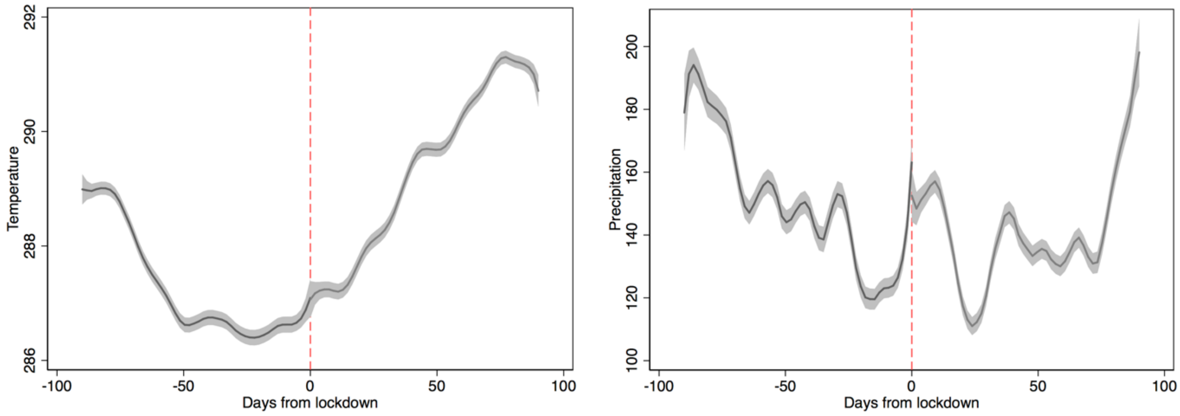
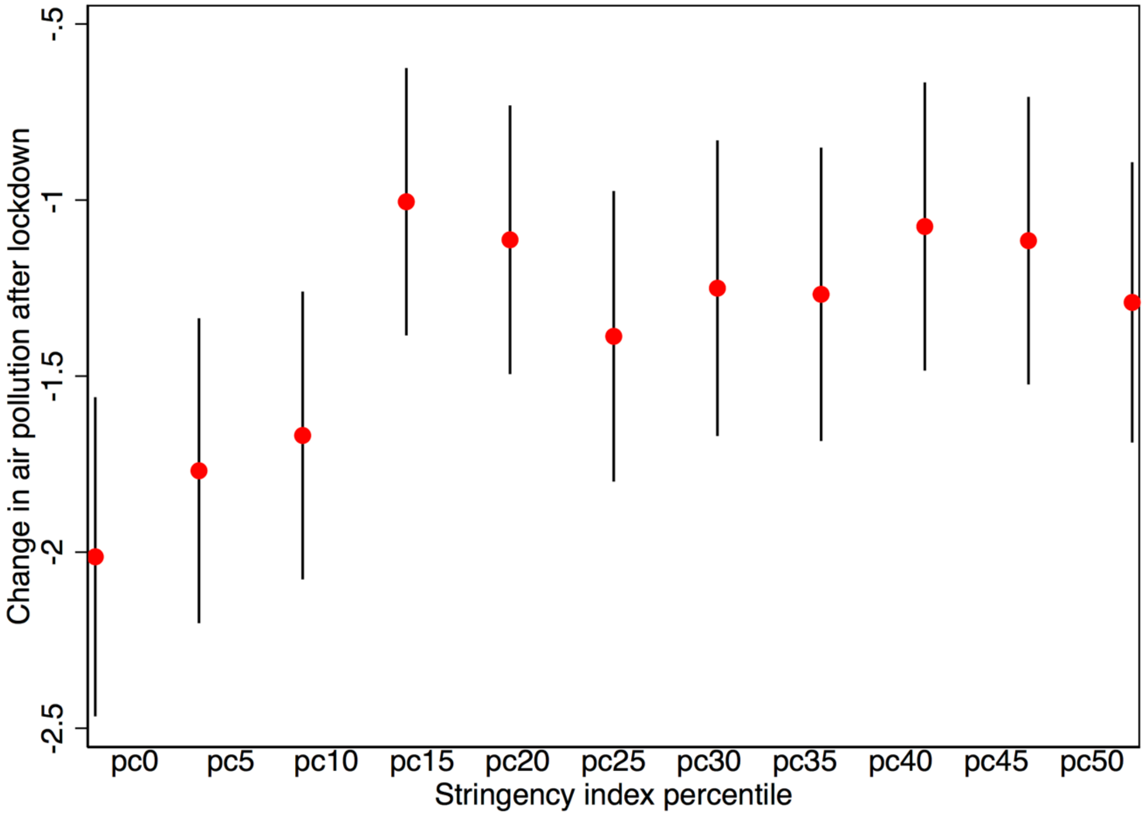


Figure A4: Reduction of air pollution using alternative cut-offs of stringency index



Notes: Air pollution is measured by NO_2 from satellite data. Each point in the figure shows point estimate and 95 percent confidence interval of treatment variable (lockdown) using different percentiles of stringency index to construct lockdown date. The parametric RDD model includes interactions of running variable (linear and quadratic terms) with treatment variable. The running variable is number of days from the lockdown date. We use bandwidth of 90 days before and after the lockdown. All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall.

Table A1: Stringency index components

Number	Components	Description
1	School closing	Record closings of schools and universities
2	Workplace closing	Record closings of workplaces
3	Cancel public events	Record cancelling public events
4	Restrictions on gatherings	Record the cut-off size for bans on private gatherings
5	Close public transport	Record closing of public transport
6	Stay at home requirements	Record orders to "shelter-in- place" and otherwise confine to home.
7	Restrictions on internal movement	Record restrictions on internal movement
8	International travel controls	Record restrictions on international travel
9	Public info campaigns	Record presence of public info campaigns

Notes: Each component is measured by an ordinal scale. The stringency index is measured by the OxCGRT team as simple averages of the individual component indicators. Each component is measured by an ordinal scale (e.g. 0 – no measures, 1 – recommended closing, 2 – require partial closing, 3 – require closing all levels). It is then rescaled by maximum value to create a score between 0 and 100. These scores are then averaged to get the stringency index.

Table A2: COVID-19 lockdown and air pollution – Other parameters of pollution

	(1)	(2)	(3)
Bandwidths	+/-90 days	+/-60 days	+/-30 days
Panel A: Air quality is measured by PM_{10}			
Lockdown=1	-1.529***	-0.423	-0.694
	(0.552)	(0.546)	(0.582)
Means before lockdown	30.676	30.904	31.242
Observations	80,024	51,207	24,208
Panel B: Air quality is measured by NO_2			
Lockdown=1	-1.523***	-0.709***	0.180
	(0.233)	(0.214)	(0.200)
Means before lockdown	12.747	12.899	12.815
Observations	79,912	51,094	24,090
Panel C: Air quality is measured by O_3			
Lockdown=1	2.214***	1.132***	-0.608**
	(0.308)	(0.214)	(0.251)
Means before lockdown	14.982	14.493	14.464
Observations	74,209	47,295	22,372
Panel D: Air quality is measured by SO_2			
Lockdown=1	-0.457	-0.325	0.466
	(0.331)	(0.417)	(0.649)
Means before lockdown	4.535	4.697	4.866
Observations	67,689	43,341	20,628
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic terms) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at city level. Air pollution parameters are derived from station-based data. All regressions include country dummies and week dummies. Control variables are daily temperature and humidity.

Table A3: COVID-19 lockdown and air pollution – Non-parametric RDD

	Satellite NO_2		Station-based $PM_{2.5}$	
Optimal bandwidth:	MSE	CER	MSE	CER
Lockdown=1 (Conventional)	-1.587***	-1.836***	-5.436	-4.328
	(0.611)	(0.695)	(3.410)	(3.804)
Lockdown=1 (Bias-corrected)	-1.876***	-1.975***	-6.741**	-4.928
	(0.611)	(0.695)	(3.410)	(3.804)
Lockdown=1 (Robust)	-1.876***	-1.975***	-6.741*	-4.928
	(0.625)	(0.701)	(3.668)	(3.975)
Means before lockdown	22.914	22.914	64.599	64.599
Controls	Yes	Yes	Yes	Yes
Observations	329,735	329,735	82,193	82,193

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of non-parametric RDD. Standard errors in parentheses. Standard errors are clustered at ADM1 level (satellite data) and city level (station-based data). Mean of air quality before lockdown is calculated 90 days before the official date of lockdown. Control variables are daily temperature and rainfall (humidity for station-based data).

Table A4: COVID-19 lockdown and air pollution – RDD with additional covariates

Panel A: Parametric RDD

	Air pollution: NO_2			Air pollution: $PM_{2.5}$		
Bandwidth	+/-90 days	+/-60 days	+/-30 days	+/-90 days	+/-60 days	+/-30 days
Lockdown=1	-2.957***	-1.524***	-1.011***	-2.913***	-0.411	0.308
	(0.322)	(0.265)	(0.371)	(1.080)	(1.184)	(1.129)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Means before lockdown	22.914	23.316	22.719	64.599	66.015	67.544
Observations	252,827	169,261	84,589	78,705	50,297	23,818
R-squared	0.160	0.161	0.164	0.421	0.441	0.466

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at ADM1 level. Control variables are daily temperature and rainfall (humidity for station-based data), log of GDP per capita (constant 2010 USD), population density, log of energy consumption per capita, motor vehicles per 1,000 inhabitants, and share of electricity generated by coal power. All regressions include week dummies.

Panel B: Non-parametric RDD

	Satellite NO_2		Station-based $PM_{2.5}$	
Optimal bandwidth:	MSE	CER	MSE	CER
Lockdown=1 (Conventional)	-1.771**	-2.332***	-3.519	-6.295***
	(0.710)	(0.877)	(2.199)	(2.359)
Lockdown=1 (Bias-corrected)	-2.170***	-2.529***	-4.312**	-6.697***
	(0.710)	(0.877)	(2.199)	(2.359)
Lockdown=1 (Robust)	-2.170***	-2.529***	-4.312*	-6.697***
	(0.737)	(0.891)	(2.321)	(2.436)
Means before lockdown	22.914	22.914	64.599	64.599
Controls	Yes	Yes	Yes	Yes
Observations	252,827	252,827	78,705	78,705

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of non-parametric RDD following Calonico et al. (2019). Standard errors in parentheses. Standard errors are clustered at ADM1 level. Control variables are daily temperature and rainfall (humidity for station-based data), log of GDP per capita (constant 2010 USD), population density, log of energy consumption per capita, motor vehicles per 1,000 inhabitants, and share of electricity generated by coal power. Mean of air quality before lockdown is calculated 90 days before the official date of lockdown.

Table A5: COVID-19 lockdown and air pollution - Weekly data

Panel A: Satellite air pollution

Air quality:	+/-15 weeks		+/-10 weeks		+/-5 weeks	
NO_2	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: Linear model						
Lockdown=1	-2.291***	-2.310***	-1.235***	-0.652	-0.231	-0.070
	(0.239)	(0.246)	(0.229)	(0.477)	(0.254)	(0.269)
Model 2: Linear interaction model						
Lockdown=1	-2.087***	-2.120***	-1.163***	-0.831***	-0.150	0.070
	(0.235)	(0.243)	(0.227)	(0.215)	(0.247)	(0.260)
Model 3: Quadratic model						
Lockdown=1	-2.110***	-2.154***	-1.196***	-0.882***	-0.172	0.029
	(0.236)	(0.244)	(0.227)	(0.216)	(0.249)	(0.262)
Model 4: Quadratic interaction model						
Lockdown=1	-2.098***	-2.135***	-1.191***	-0.840***	-0.257	-0.055
	(0.235)	(0.243)	(0.228)	(0.212)	(0.256)	(0.270)
Means before lockdown	22.756	22.756	23.225	23.225	22.955	22.955
Controls	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	435,571	375,728	296,819	256,627	146,864	127,216

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD. Robust standard errors in parentheses. Standard errors are clustered at ADM1 level. Air pollution is measured by NO_2 from satellite data. Model 1 uses running variable in linear form, Model 2 includes interaction of running variable and treatment variable, Model 3 includes quadratic term of running variable, Model 4 includes interactions of running variable (linear and quadratic terms) with treatment variable. All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall.

Panel B: Station-based air pollution

Air quality:	+/-15 weeks		+/-10 weeks		+/-5 weeks	
$PM_{2.5}$	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: Linear model						
Lockdown=1	-4.950***	-3.191***	-2.481**	-0.756	-0.115	-1.099
	(0.914)	(0.941)	(1.054)	(0.989)	(1.131)	(1.144)
Model 2: Linear interaction model						
Lockdown=1	-4.160***	-2.597***	-1.619	-0.203	0.732	-0.560
	(0.902)	(0.919)	(1.044)	(0.979)	(1.100)	(1.129)
Model 3: Quadratic model						
Lockdown=1	-4.466***	-2.797***	-1.852*	-0.358	0.595	-0.689
	(0.905)	(0.923)	(1.046)	(0.980)	(1.098)	(1.127)
Model 4: Quadratic interaction model						
Lockdown=1	-4.173***	-2.505***	-1.461	-0.050	0.436	-0.660
	(0.907)	(0.930)	(1.044)	(0.978)	(1.141)	(1.167)
Means before lockdown	63.477	63.477	65.666	65.666	66.682	66.682
Controls	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107,611	95,855	73,452	61,863	38,031	28,633

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD. Robust standard errors in parentheses. Standard errors are clustered at city level. Air pollution is measured by $PM_{2.5}$ from station-based data. Model 1 uses running variable in linear form, Model 2 includes interaction of running variable and treatment variable, Model 3 includes quadratic term of running variable, Model 4 includes interactions of running variable (linear and quadratic terms) with treatment variable. All regressions include country dummies and week dummies. Control variables are daily temperature and humidity.

Table A6: COVID-19 lockdown and air pollution – 'Regular' stringency index

	Air pollution: NO_2			Air pollution: $PM_{2.5}$		
Bandwidth	+/-90 days	+/-60 days	+/-30 days	+/-90 days	+/-60 days	+/-30 days
Lockdown=1	-2.013***	-0.880***	-0.433*	-2.665***	-0.288	-0.669
	(0.231)	(0.207)	(0.234)	(0.912)	(0.914)	(1.047)
Means before lockdown	22.914	23.316	22.719	64.599	66.015	67.544
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	329,735	221,174	110,864	82,193	52,502	24,910
R-squared	0.335	0.341	0.366	0.525	0.562	0.603

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at ADM1/city level. All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall (humidity for station-based data).

Table A7: Stringency index and air pollution – Principal Component Analysis

	Air pollution: NO_2			Air pollution: $PM_{2.5}$		
Bandwidth	+/-90 days	+/-60 days	+/-30 days	+/-90 days	+/-60 days	+/-30 days
Lockdown=1	-1.149***	-0.749***	0.375*	-1.758*	1.118	-2.563**
	(0.209)	(0.223)	(0.227)	(0.910)	(1.040)	(1.157)
Means before lockdown	22.914	23.316	22.719	64.599	66.015	67.544
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306,471	223,713	112,864	82,214	52,795	25,344
R-squared	0.319	0.324	0.323	0.503	0.546	0.570

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at ADM1/city level. Stringency index is constructed using Principal Component Analysis. For all dimensions of stringency index, see Table A1 (Appendix). All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall (humidity for station-based data).

Table A8: Stringency index and air pollution – Alternative stringency indexes

	Air pollution: NO_2		
Bandwidth	+/-90 days	+/-60 days	+/-30 days
Panel A: Government response index			
Lockdown=1	-2.230***	-1.134***	-0.539**
	(0.228)	(0.200)	(0.236)
Observations	329,705	220,239	110,067
R-squared	0.337	0.341	0.364
Panel B: Containment and health index			
Lockdown=1	-2.234***	-1.147***	-0.539**
	(0.228)	(0.200)	(0.235)
Observations	329,586	220,250	110,064
R-squared	0.337	0.341	0.364
Panel C: Economic support index			
Lockdown=1	-0.356**	0.131	0.170
	(0.181)	(0.178)	(0.226)
Observations	272,178	204,216	104,539
R-squared	0.339	0.342	0.361
Means before lockdown	22.914	23.316	22.719
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at ADM1 level. All indexed are taken from "display" version of OxCGRT which will extrapolate to smooth over the last seven days of the index based on the most recent complete data. All regressions include country dummies and week dummies. Control variables are daily temperature and rainfall (humidity for station-based data).

Table A9: COVID-19 lockdown and air pollution – Country linear time trend

	Air pollution: NO_2			Air pollution: $PM_{2.5}$		
Bandwidth	+/-90 days	+/-60 days	+/-30 days	+/-90 days	+/-60 days	+/-30 days
Model 1: Linear model						
Lockdown=1	-2.025***	-0.821***	-0.357	-2.979***	-0.347	-2.702**
	(0.233)	(0.210)	(0.251)	(0.923)	(0.916)	(1.099)
Model 2: Linear interaction model						
Lockdown=1	-1.984***	-0.772***	-0.283	-2.484***	0.104	-2.508**
	(0.232)	(0.209)	(0.248)	(0.909)	(0.903)	(1.089)
Model 3: Linear interaction model						
Lockdown=1	-2.011***	-0.800***	-0.312	-2.575***	0.043	-2.599**
	(0.233)	(0.210)	(0.249)	(0.910)	(0.904)	(1.092)
Model 4: Quadratic interaction model						
Lockdown=1	-2.004***	-0.762***	-0.454*	-2.460***	0.067	-2.655**
	(0.232)	(0.208)	(0.253)	(0.910)	(0.903)	(1.122)
Means before lockdown	22.914	23.316	22.719	64.599	66.015	67.544
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Country linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	329,735	221,174	110,864	82,193	52,502	24,910

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at ADM1/city level. All regressions include country dummies, week dummies, and interaction of country dummies with linear time trend. Control variables are daily temperature and rainfall (humidity for station-based data).

Table A10: COVID-19 lockdown and air pollution – Air pollution in log form

	Air pollution: NO_2			Air pollution: $PM_{2.5}$		
Bandwidth	+/-90 days	+/-60 days	+/-30 days	+/-90 days	+/-60 days	+/-30 days
Model 1: Linear model						
Lockdown=1	-0.069***	-0.032***	-0.001	-0.050***	-0.020	-0.013
	(0.006)	(0.006)	(0.007)	(0.014)	(0.013)	(0.017)
Model 2: Linear interaction model						
Lockdown=1	-0.067***	-0.030***	0.001	-0.045***	-0.015	-0.011
	(0.006)	(0.006)	(0.007)	(0.013)	(0.013)	(0.017)
Model 3: Linear interaction model						
Lockdown=1	-0.068***	-0.031***	-0.000	-0.046***	-0.017	-0.012
	(0.006)	(0.006)	(0.007)	(0.013)	(0.013)	(0.017)
Model 4: Quadratic interaction model						
Lockdown=1	-0.068***	-0.029***	-0.000	-0.045***	-0.016	-0.008
	(0.006)	(0.006)	(0.007)	(0.013)	(0.013)	(0.017)
Means before lockdown	22.914	23.316	22.719	64.599	66.015	67.544
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	326,647	218,821	109,580	82,193	52,502	24,910

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that include interactions of running variable (linear and quadratic) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at ADM1/city level. All regressions include country dummies and week dummies. Air pollutants are in log form. Control variables are daily temperature and rainfall (humidity for station-based data).