

DISCUSSION PAPER SERIES

IZA DP No. 13651

**The Beneficial Impacts of COVID-19
Lockdowns on Air Pollution:
Evidence from Vietnam**

Hai-Anh H. Dang
Trong-Anh Trinh

SEPTEMBER 2020

DISCUSSION PAPER SERIES

IZA DP No. 13651

The Beneficial Impacts of COVID-19 Lockdowns on Air Pollution: Evidence from Vietnam

Hai-Anh H. Dang

World Bank, IZA, Indiana University and Vietnam Academy of Social Sciences

Trong-Anh Trinh

World Bank

SEPTEMBER 2020

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

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

The Beneficial Impacts of COVID-19 Lockdowns on Air Pollution: Evidence from Vietnam*

Little evidence currently exists on the effects of COVID-19 on air quality in poorer countries, where most air pollution-linked deaths occur. We offer the first study that examines the pandemic's impacts on improving air quality in Vietnam, a lower-middle income country with worsening air pollution. Employing the Regression Discontinuity Design method to analyze a rich database that we compile from satellite air pollution data and data from various other sources, we find the concentration of NO₂ to decrease by 24 to 32 percent two weeks after the COVID-19 lockdown. While this finding is robust to different measures of air quality and model specifications, the positive effects of the lockdown appear to dissipate after ten weeks. We also find that mobility restrictions are a potential channel for improved air quality. Finally, our back-of-the-envelope calculations suggest that two weeks after the lockdown, the economic gains from better air quality are roughly \$0.6 billion US dollars.

JEL Classification: D00, H00, O13, Q50

Keywords: COVID-19, air pollution, mobility restriction, RDD, Vietnam

Corresponding author:

Hai-Anh H. Dang
Data Production & Methods 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 feedback on an earlier version. 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

The COVID-19 pandemic has now been recognized as a global health catastrophe that resulted in more than 800,000 deaths worldwide between late 2019 and August 2020. During the pandemic, countries all over the world have implemented lockdowns to slow down its infection. A wide range of policy responses such as stay-at-home orders, social distancing, and closure of retail establishments and non-essential businesses were used to limit movements. Against a considerable and growing body of literature on the negative economic consequences of the pandemic (e.g. Akesson *et al.*, 2020; Baker *et al.*, 2020; Dang *et al.*, 2020; Fairlie *et al.*, 2020),¹ a handful of studies emerged that point to the unexpected beneficial impacts of COVID-19 on global air quality (e.g. Dang and Trinh, 2020; Venter *et al.*, 2020).

Air pollution poses major challenges to human health such as heart and lung damage and other diseases (Liu *et al.*, 2019; WHO, 2006) and it is estimated to cause more than 4.6 million annual deaths worldwide (Cohen *et al.*, 2017). Human industrial and traffic activities represent a significant contribution to reduced air quality (World Bank, 2016). Most recorded air pollution-linked deaths occur in developing countries, where environment protection laws regarding these activities are weak or do not even exist.² But few studies currently exist that can quantify the impacts of these activities on air quality in a low-income country context. Furthermore, little evidence is available on key policy issues. In particular, does the COVID-19-induced lockdown (and resulting cessation of activities) also have positive impacts on the air quality of low-income countries as it does globally? If it does, how long do these impacts last after the lockdown? What are the major channels of air pollution reduction? Could we

¹ See also Bloom *et al.* (2020) and Brodeur *et al.* (2020a) for recent reviews of the economics literature on COVID-19.

² Recent estimates by WHO (2016, 2018) indicate that more than 90 percent of pollution-linked deaths occur in low- and middle-income countries. Mannucci and Franchini (2017) observe that low- and middle-income countries have experienced an intense process of urbanization and industrial development in a much shorter period of time than high-income countries, which has resulted in the former group of countries having the largest air pollution-related burdens in recent years.

compare the costs and benefits on air quality of the complete cessation of activities induced by the lockdown?

We makes several new contributions to the literature in this study. We provide an investigation into the key policy issues discussed above, some of which were examined separately, but not together, in previous studies. Vietnam—a lower-middle income country—offers an interesting case study to examine these questions. The country has been struggling with alarming air pollution that has been steadily rising with economic growth. Economic losses associated with ambient air pollution are estimated to cost Vietnam more than \$25 billion USD, which equals 5.5 percent of the country’s Gross Domestic Product (GDP) (World Bank, 2016). Figure 1 shows that Vietnam’s concentration of PM_{2.5} (fine particulate matter) is above the global average for the past 20 years. It is comparable to that of China—a country with a widely recognized high record of air pollution—and below countries currently with the most polluted air levels such as Bangladesh and India. Indeed, the capital city Hanoi experienced only eight days in 2019 during which air quality would be considered healthy by the national standards (Do, 2020).³

At the same time, Vietnam achieved early success against the COVID-19 pandemic with few cases of infection and death.⁴ The government imposed a nationwide lockdown between April 1 and April 14, 2020, which entailed tough controls on mobility and cessation of economic activities. This setting provides a natural experiment to investigate whether the lockdown helps reduce the existing air pollution levels. To our knowledge, we offer the first study to examine the impacts of the COVID-19 lockdown on air quality for Vietnam.⁵

³ The country’s national standard is 50 micrograms per cubic meter ($\mu\text{g}/\text{m}^3$). The number of days with unhealthy air quality would be even smaller if the World Health Organization’s annual safety threshold of $10 \mu\text{g}/\text{m}^3$ is applied. Another estimate suggests that Vietnam’s concentration of PM_{2.5} increases by 33 percent between 1990 and 2013 (World Bank, 2016).

⁴ From January 1 to July 1, 2020, the country reported more than 500 infection cases and zero death.

⁵ In fact, hardly any academic study currently exists on the economic impacts of COVID-19 in Vietnam. For example, an exception is a recent study by Dang and Giang (2020) that conduct a web-based assessment survey and examine household finance and economic expectations during the pandemic.

Finally, we obtain estimation results by applying a rigorous econometric technique on a rich database that we compile from various reliable sources; this framework of analysis can also be extended to other countries (as illustrated later in Section 5.2). In terms of econometric modelling, a major challenge to estimating the causal impacts of COVID-19 on air quality is endogeneity issues. There can be unobserved factors that simultaneously affect lockdown policies and air quality. For example, low-income countries likely have implemented less stringent policies during the pandemic and may also have weaker environment protection programs in place that ensure better air quality. Furthermore, air pollution may be positively associated with the number of infection cases (Cicala *et al.*, 2020; Cole *et al.*, 2020; Isphording and Prestel, 2020). We overcome these issues by using the Regression Discontinuity Design (RDD) approach, a quasi-experimental econometric technique that allows us to rigorously compare the impacts of the lockdown on air quality in a time window around the lockdown date.⁶ We also undertake a number of robustness exercises that further support our finding such as employing different time bandwidths, functional forms, and estimation methods.

We obtain daily data on air pollution at the district level from the satellite data provided by the European Union's Copernicus programme. We use nitrogen dioxide (NO₂) as the main indicator of air pollution, and other parameters such as Carbon Monoxide (CO), Sulphur Dioxide (SO₂), and Ozone (O₃) as alternative measures. Our paper departs from the station-based data used in a number of previous studies, which are likely not random and do not provide representative data on an area's air quality. We combine these satellite air quality data with a variety of real-time data sources for richer analysis including daily weather data, real-time human mobility data, government responses to COVID-19, and other sub-national

⁶ Some previous studies carefully compare the level of air pollution over different time periods, for example in previous years and the current year (e.g., Venter *et al.*, 2020). However, this approach does not allow more detailed within-year analysis of the duration of the impacts as we do in this study.

characteristics. Incidentally, we also provide a new dataset on the official lockdown dates for 67 countries around the world.

Our findings suggest that the lockdown imposed to combat COVID-19 improves air quality in Vietnam. Specifically, the average concentration of NO₂ drop by approximately 24-32 percent two weeks after the lockdown date. While this result is consistent across measures of air pollution and model specifications, we find that the effects tend to fade away ten weeks after the lockdown. When further exploring the heterogeneous effects of lockdown policies, our results show that the positive impacts of the lockdown on air quality are more pronounced in areas without coal-fired stations and cement plants. We also find the lockdown to be associated with less mobility in different categories except for residential mobility. Lastly, our back-of-the-envelope calculations show that two weeks after the lockdown, the economic gains from better air quality are roughly \$0.6 billion US dollars.

The remainder of the paper is organized as follows. We review recent studies on COVID-19 and air pollution and present an overview of air pollution in Vietnam in the next section. We subsequently describe the database that we construct for analysis in Section 3 before discussing the empirical model in Section 4. In Section 5, we present the main findings together with robustness checks and further extensions (Sections 5.1 and 5.2), discuss the potential channels for improving air quality (Section 5.3), and offer some back-of-the-envelope cost-benefit analysis (Section 5.4). We finally conclude in Section 6.

2. Literature Review and Air Pollution in Vietnam

2.1. Literature Review

Several studies investigate changes in air quality during the pandemic at the global scale. Using an input-output model for 38 regions around the world, Lenzen *et al.* (2020) find the pandemic to reduce greenhouse gas, PM_{2.5}, and air pollutants by 4.6 percent, 3.8 percent and 2.9 percent

of the global annual totals, respectively. Comparing air quality during the pandemic with that in previous years, Venter *et al.* (2020) analyze station-based air quality data in 34 countries and find concentration of NO₂ and PM_{2.5} to decrease by approximately 60 percent and 31 percent, respectively. Most recently, using a sample of 174 countries, Dang and Trinh (2020) find a 9.1 percent decrease in concentration of NO₂ 90 days after the lockdown. Given the difficulty of identifying comparable lockdown dates across country, this study employs the Oxford COVID-19 Government Response Tracker (OxCGRT) data and defines the lockdown date as the first day on which the government response index becomes positive.

Studies focusing on specific countries reach a similar finding of the unintended consequence of COVID-19. Early studies investigate this relationship in Hubei, the province at the center of the outbreak, and other regions in China (Almond *et al.*, 2020; Chen *et al.*, 2020; He *et al.*, 2020). For example, He *et al.* (2020) show that city lockdowns led to considerable improvement in air quality as measured by Air Quality Index (AQI) and PM_{2.5}. Similarly, Almond *et al.* (2020) show a significant decrease in concentration of NO₂, but the finding does not hold for other parameters of pollution such as SO₂ and O₃. Outside China, Brodeur *et al.* (2020b) find the lockdown to result in reduced PM_{2.5} emissions in the United States. Tobías *et al.* (2020) find that NO₂ concentration decreased by half during the lockdown in Spain, an early COVID-19 hotspot. Related research in environment studies also suggests considerable declines in pollutant parameters during and after the lockdown (e.g. Berman and Ebisu, 2020; Sharma *et al.*, 2020).⁷

In terms of identification strategy, a simple comparison of air quality before and after the lockdown date can be problematic since it fails to account for unobservable factors and might

⁷ Some studies investigate the related issue of how the outbreak-induced changes in air quality affect health outcomes. For example, Cicala *et al.* (2020) use a sample of more than 3,100 counties in the United States and show that reductions in emissions from travel and electricity usage reduce deaths by over 360 deaths per month. Cole *et al.* (2020) indicate that an increase in PM_{2.5} concentrations of 1 μ /m³ is associated with an increase in COVID-19 cases of between 9.4 and 15.1 in the Netherlands. These findings further point to the challenges of identifying the causal effects of COVID-19 on air pollution.

only capture the increasing (or decreasing) trend in air pollution over time. A number of studies thus have employed a difference-in-differences model in order to infer causal relationships (Almond *et al.*, 2020; Brodeur *et al.*, 2020b; Chang *et al.*, 2020; He *et al.*, 2020). In this paper, we follow Dang and Trinh (2020) and employ a more rigorous RDD approach to estimate the impact of lockdown on air pollution.⁸ We use the number of days from the lockdown date as the running variable. As a robustness check, we also obtain the government response indexes from OxCGRT data and conduct an alternative fuzzy RDD model (Section 4).

2.2. Air Pollution in Vietnam

Air pollution is one of the major environmental concerns in Vietnam, which has worsened alongside the country's steady economic growth in the recent decades. The country is ranked as the fifth highest emitter of black carbon in the world during the period 2000 – 2008 (Kurokawa *et al.*, 2013). Among Southeast Asian countries, Vietnam is expected to be most affected by pollution due to coal plant emissions by 2030 (Koplitz *et al.*, 2017). The country is also exposed to a rising high concentration of PM_{2.5} as earlier discussed with Figure 1.

Several key factors that can contribute to high air pollution levels in Vietnam include power generation, industry, residential buildings, and transportation. Among those, coal-fired power is the main source of air pollution which contributes to 4,300 premature deaths in 2011 (Koplitz *et al.*, 2017). Still, coal consumption has increased remarkably over the past decade and coal-fired power currently takes the lion's share of power generation, accounting for more than 40 percent of the country's total generated power (Baker, 2018). The country expects to build 26 additional coal power stations after 2020, despite its plans to generate more electricity from renewable sources (Bich Ngoc, 2018). For illustrative purpose, Figure 2 shows

⁸ The RDD approach has also been used to study the impacts of COVID-19 on well-being, employment, mobility and traffic accidents (Barnes *et al.*, 2020; Brodeur *et al.*, 2020c; Chetty *et al.*, 2020).

concentration of NO₂ across districts in Vietnam in 2019, as well as the distribution of coal-fired power stations and cements plants. Most of these plants are located in the north of the country, which may possibly contribute to higher levels of air pollution in this region compared to the south of the country (Popovich *et al.* 2019; Nguyen Quy, 2020).

Although air pollution has become an alarming issue in Vietnam, only a handful of health studies have been conducted to examine its negative effects on human health. In particular, Luong *et al.* (2017) find a strong relationship between air pollution and respiratory illnesses, where an increase of 10 µg/m³ in PM_{2.5} is associated with a 2.2-percent higher risk of hospital admission. Analyzing 57,851 hospital admissions over eight years in Hanoi, Nhung *et al.* (2018) show that more concentration of NO₂ is associated with pneumonia-related hospitalizations. Examining a sample of the two largest hospitals in Ho Chi Minh City, Phung *et al.* (2016) observe an increase in respiratory admissions of between 0.7% to 8% for a 10-µg/m³ increase of each of the pollutants PM₁₀, NO₂, and SO₂.

3. Data

We obtain air pollution measurements in Vietnam from January 1 to July 1, 2020, provided by the Sentinel-5P/TROPOMI (S5P) instrument of the European Union's Copernicus programme. The S5P satellite uses spatial resolution of 5.5 km and provides a (near-)global coverage of air pollution caused by NO₂ and other pollutants such as O₃, SO₂, and CO. We use Google Earth Engine to process and average air quality parameters at the district level and perform a cloud masking exercise to address the issue of cloud cover. We use NO₂ as the main measure of air pollution for two reasons. First, NO₂ is a highly reactive pollutant and considered highly lethal to human health (Faustini *et al.*, 2014). It is also the leading source of childhood asthma in urban areas globally (Achakulwisut *et al.*, 2019). Second, NO₂ has a short lifetime which

implies that its molecules stay fairly close to their sources and thus offer an appropriate measure of changes in emissions.⁹

Since concentrations of NO₂ in the atmosphere are highly variable and sensitive to changes in weather conditions, we collect global daily data on temperature and precipitation from the National Center for Environmental Prediction (NCEP) at the National Oceanic and Atmospheric Administration (NOAA) as control variables. We extract the weather data at the district level using a similar process as with the air pollution data.

To investigate the channels of impacts and heterogenous impacts, we further collect data on various indicators. These variables are mostly available at the province level (except for the nightlight data at the district level) and include i) the locations of coal-fired stations and cement plants, ii) industrial production (including foreign direct investment and monthly nightlight data), iii) public perceptions about environment, and iv) human mobility patterns. These data come from different sources including the Statistical Yearbook published by the General Statistical Office of Vietnam, the NOAA, the Provincial Governance and Public Administration Performance Index provided by the Centre for Community Support Development Studies (CECODES), the Fatherland Front, and the United Nations Development Programmes (UNDP), the Google COVID-19 Community Mobility Reports, and the Apple COVID-19 Mobility Trends Reports.

To further check on the robustness of our findings, we obtain information on government response indexes from the Oxford COVID-19 Government Response Tracker (OxCGRT). This tracker implemented by the University of Oxford's Blavatnik School of Government systematically collects information on policy stringency taken by governments to tackle the

⁹ NO₂ is recommended by the European Union's Copernicus programme as the most appropriate indicator of air pollution. 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>. We analyze the S5P satellite data since they are available around the lockdown date of April 2020 for Vietnam. We plot Figure 1 based on the historical data on PM_{2.5} that are available up to 2016.

pandemic since February 2020 (Hale *et al.*, 2020). We provide a more detailed discussion of the various datasets and their sources in Appendix B.

4. Empirical Model

A naïve approach to estimate the effects of the COVID-19-induced lockdown on air pollution is to perform Ordinary Least Squares (OLS) regressions with changes in air quality as the dependent variable and the lockdown as the independent variable. However, this approach is likely biased because there are often observable and unobservable characteristics correlated with both variables, such as governance quality and public preferences for protecting the environment. Furthermore, establishing causality is difficult in this context because air pollution is positively associated with the number of COVID-19 cases (Cicala *et al.*, 2020; Cole *et al.*, 2020; Isphording and Prestel, 2020), which can lead to governments implementing more stringent lockdown. Failure to control for possible reverse causality would result in biased estimates of the effects of the lockdown.

To address these econometric concerns, our empirical strategy is to leverage the sharp discontinuities of economic activities when the lockdown goes into effect and employ the (sharp) Regression Discontinuity Design (RDD) model. The motivation of the RDD approach is that within a relatively narrow window of time around the lockdown date, the unobserved factors influencing air quality are likely similar so that observations before the lockdown provide a counterfactual group that can be compared with observations after the lockdown.¹⁰ More formally, the treatment effect can be estimated as the changes in air quality (A) in the neighborhood of the lockdown date

$$\tau_{RD} = \lim_{\varepsilon \downarrow 0} E[A|d = 0 + \varepsilon] - \lim_{\varepsilon \uparrow 0} E[A|d = 0 + \varepsilon] \quad (1)$$

¹⁰ See, for example, Cattaneo *et al.* (2020) for a textbook introduction to RDD methods.

where d is the number of days before and after the official lockdown dates. We subsequently estimate the following reduced form equation

$$A_{it} = \delta L_{it} + f(d_{it}) + \theta X_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (2)$$

In Equation (2), the outcome of interest (A_{it}) is changes in air quality on day t in district i . The parameter of our interest is δ , the (local average treatment) impacts of the lockdown on air pollution. The treatment variable (L_{it}) is a dummy variable that equals 1 after the lockdown and 0 otherwise. d_{it} is the running variable which represents the number of days before and after the official lockdown date. To provide robust analysis and for comparison purposes, we let the function $f(d_{it})$ take different functional forms to flexibly control for variations in air quality that would have occurred in the absence of the lockdown. They include (i) the linear model (d_{it}), (ii) the linear model with the interaction term of the running variable and the treatment variable ($L_{it} * d_{it}$), (iii) the quadratic model (d_{it}^2), and (iv) the quadratic model with the interaction term of the running variable and the treatment variable ($L_{it} * d_{it}^2$). As the lockdown in Vietnam was implemented between April 1 and April 14, 2020, we use a bandwidth of two weeks before and after the lockdown date (April 1) as our preferred time bandwidth. But we also present results for different bandwidths to investigate the duration of the lockdown impacts.

We include in Equation (2) X_{it} , a vector of control variables that may affect air quality such as daily temperature and daily precipitation. Finally, province fixed effects (μ_i) and time fixed effects (π_t) are also included to absorb the effects of unobservable time-invariant province or time characteristics, and ε_{it} denotes the error term. We cluster the standard errors at the district level.

Equation (2) assumes a sharp RDD model where the lockdown is strictly implemented in Vietnam. This model is consistent with the widely accepted views in both the academic literature and the media about the country's strict and successful implementation of the

lockdown (Huynh, 2020; La *et al.*, 2020; Mandhana and Le, 2020; Trevisan *et al.*, 2020).¹¹ But as a robustness check for the (unlikely) case that not all business activities and travel cease exactly by the time of the lockdown, we employ a fuzzy RDD model where the running variable measures the degrees of strictness of the lockdown implementation. We obtain these running variables (indexes) from the OxCGRT data, which range from 0 to 100, with higher scores indicating more stringent policies. As illustrated in Figure A1 (Appendix A), the stringency index increases significantly over time and reaches the highest value during the two weeks of the lockdown. We create an instrument E_{it} for the lockdown variable, which equals one when the stringency (or response) index of government policies S_{it} is positive ($S_{it} > 0$). We then apply the Two-Stage Least Squares (2SLS) method to estimate the following equations

$$L_{it} = \gamma E_{it} + g(S_{it}) + \gamma X_{it} + \varphi_i + \omega_t + \epsilon_{it} \quad (3)$$

$$A_{it} = \beta L_{it} + h(S_{it}) + \lambda X_{it} + \alpha_i + \vartheta_t + \nu_{it} \quad (4)$$

We employ different indexes from the OxCGRT data including (i) the stringency index, (ii) the government response index, and (iii) the containment and health index.¹² Similar to Equation (2), we control for weather conditions as well as the province and time fixed effects.

We now discuss some potential threats to the validity of our RDD approach. First, we implement the formal test proposed by McCrary (2008) to investigate whether there is any discontinuity in the density of the running variable (i.e., the number of days from the lockdown date) around the cut-off point. We follow the procedure implemented by Cattaneo *et al.* (2018) and provide the estimation results in Table A1 (Appendix A), which suggest that the difference

¹¹ Vietnam has won praise for its early success in controlling the COVID-19 pandemic. For example, the spirit of the country's fight against the pandemic can perhaps be best epitomized in the words of the Prime Minister of Vietnam Nguyen Xuan Phuc "Every business, every citizen, every residential area must be a fortress to prevent the epidemic" (Pham, 2020). Protection measures such as social distancing, washing one's hands, and staying at home were portrayed as actions of patriotism, and these message were well received by the public (Le Thu, 2020; M.Giao, 2020).

¹² The OxCGRT data also calculates economic support index. Our analysis does not use this measure as it only includes income support programs and debt relief programs and does not fully capture the overall responsiveness of the government to COVID-19.

between the frequency to the right and to the left of the threshold is not statistically significant. As such, we fail to reject the null hypothesis that the jump in the density of the running variable at the cut-off is zero.

Another concern is that the covariates should not jump around the cut-off (i.e., the official lockdown date). In our analysis the key control variables are temperature and precipitation. Following Lee and Lemieux (2010), we replace the dependent variable in Equation (2) by each of the weather variables and estimate the coefficient on the treatment variable, while controlling for province and time fixed effects. Figure A2 (Appendix A) shows that there is no discontinuity at the cut-off point, which rules out this concern.

5. Estimation Results

5.1. Main Findings

As a first look at the impacts of the COVID-19-induced lockdown on air quality, we run a data-driven RDD regression of the concentration of NO₂ against the number of days around the lockdown date, using the optimal (time) bandwidth proposed by Imbens and Kalyanaraman (2012). We plot in Figure 3 the results, which show that air pollution sharply decreases two weeks after the lockdown date. We also observe that the reduction of air pollution diminishes over a larger bandwidth. This suggests that the impacts of the lockdown on air quality may exist only in the short-term.

We turn next to estimate the effects of the lockdown on air pollution using the sharp RDD model presented in Equation (2). We report the estimation results in Table 1. Each of the 24 cells in this table represents the impacts of the lockdown estimated from a separate regression, with the bandwidth shown in the column headings and the functional form of the running variable shown in the row headings. We control for the province and time fixed effects and cluster the standard errors at the district level in all the regressions. Our preferred models

are presented in Columns (2), (4), and (6) which control for weather conditions (i.e., temperature and precipitation). But we also present the results without these control variables in Columns (1), (3), and (5) for comparison and robustness checks.

Overall, Table 1 suggests that the COVID-19-induced lockdown has strongly statistically significant impacts on improving air quality at the 1 percent level. This result remains qualitatively similar, regardless of inclusion of control variables, different functional forms of the running variable, or time bandwidths around the lockdown date. We are particularly interested in the bandwidth of two weeks as this is the duration of the official lockdown in Vietnam. The estimation result suggests that the lockdown leads to a 5.808 (mol/km^2) decrease in the concentration of NO_2 (Panel A, column 2), which equals a 24-percent reduction (compared to an average value of NO_2 of 24.441 mol/km^2 before the lockdown). Using different functional forms of the running variable (Panels B to D) results in similar estimates, although the magnitude of impact is more pronounced when we account for non-linearity. For example, the estimated impacts are larger at 32 percent for the model with the quadratic interaction term (Panel D, column 2).

These estimated impacts are stronger than that of Dang and Trinh (2020) who find a 9.1 percent decrease in air pollution using global data, but are more or less comparable to those in country-specific studies. For example, Almond *et al.* (2020) show a decrease in concentration of NO_2 in Hubei and all regions in China by 43.6 percent and 31.4 percent, respectively. Berman and Ebisu (2020) find a decline of 25.5 percent of NO_2 in the United States, while Sharma *et al.* (2020) find a smaller impact of 18 percent in India. It should be noted that most of these studies use a larger window of time when comparing changes in air pollution during the lockdown with those based on historical data (e.g., previous years).

Table 1 also suggests that the negative impacts of the lockdown on NO_2 diminish over time, or when larger bandwidths are considered. Specifically, the reduction of NO_2 hovers

around 18 percent for four and eight weeks after the lockdown (Panel A, columns 4, 6). This suggests that the reduction in air pollution may be short-lived once lockdown policies are eased and economic activities return to normal. We further estimate the short-term impacts of the lockdown on air pollution by using different bandwidths and applying the parametric RDD model that includes the interactions of the running variable (linear and quadratic terms) with the lockdown variable. We plot in Figure 4 the estimated coefficient and its 95 percent confidence interval, which confirms that the impacts of the lockdown disappear 10 to 15 weeks after the lockdown date.¹³

Table 2 further illuminates the effect of lockdown on air pollution using alternative measures of air quality. We use three parameters that are available for the country, including CO, SO₂, and O₃.¹⁴ We find some evidence of reduced levels of SO₂ (two or four weeks after the lockdown) and CO (eight weeks after the lockdown). But the estimation results are mixed for O₃, which increases over two and four weeks after the lockdown, but decreases eight weeks after the lockdown. Several studies also find ambiguous effects of lockdown policies on O₃ (Tobías *et al.*, 2020; Venter *et al.*, 2020). A possible explanation for the increase in concentration of O₃ for the two week or four week periods after the lockdown is warmer weather during these periods.

5.2. Robustness Checks and Further Extensions

Our results are robust to a number of sensitivity checks which we discuss next. First, our main analysis employs the parametric RDD model to estimate Equation (2) and our main window of time is two weeks before and after the lockdown. Alternatively, we supplement these estimates by estimating a nonparametric RDD model using the local linear regressions (LLR) suggested

¹³ To date, the satellite data on air pollution is only available for 15 weeks after the lockdown date. But we expect these findings to remain consistent for a longer period of time.

¹⁴ Our analysis does not use station-based data due to small number of stations recorded in the database.

by Hahn *et al.* (2001). This method helps reduce the estimation bias that can result from analyzing observations that are further away from the threshold (Calonico *et al.*, 2019; Lee and Lemieux, 2010). We use the optimal bandwidth suggested by Imbens and Kalyanaraman (2009), which minimizes the sum of the squared bias and the variance of the estimates (MSE). We report the estimation results in Table A2 (Appendix A), which are consistent across different optimal bandwidths. The magnitudes of the estimated impacts are comparable to those in our main specifications.

Second, to account for (the remote) possibility that the economy may not completely shutdown by the time of the lockdown, we employ a fuzzy RDD model to provide robustness checks. As discussed earlier in section 4, the strictness of the implementation of the lockdown can be measured by government responses indexes from the OxCGRT database.¹⁵ We estimate the IV model in Equations (3) and (4), with our instrument being a dummy variable equal to one for the response indexes being positive and the government responses indexes being the running variable. We analyze the period of January 1 and July 1, 2020, when OxCGRT provides these indexes. The estimation results of the fuzzy RDD model, shown in Table A3 (Appendix A), are consistent with our main findings in Table 1.

Third, as an alternative to the changes in air pollution levels, we convert these changes to the logarithmic form. The estimation results, shown in Table A4 (Appendix A), remain qualitatively similar. Finally, one possible concern is that differences in province-specific resources and policies may result in differential provincial time trends in air pollution. To account for this, we include the interaction terms for the dummy variables for 63 provinces in Vietnam with the linear time trends. The results, presented in Table A5 (Appendix A), are generally consistent with our main findings.

¹⁵ Table B2 (Appendix B) provides further details regarding components of OxCGRT indexes.

We turn next to extend our analysis to examine heterogeneity of impacts. As discussed earlier, the effects of COVID-19 lockdown on air pollution may vary according to province and district characteristics. To shed more light on this issue, we first explore the question whether the lockdown has differential effects on locations with and without coal-fired power stations. Since coal-fired power generation is considered a major source of air pollution in Vietnam as discussed earlier, it is plausible to assume that locations without coal stations would record more reduced air pollution after the lockdown. The estimation results, shown in Table 3, Panel A, confirm our expectation.

Similarly, we would expect that locations without cement plants would likely have more decreased air pollution, which is supported by the estimation results in Table 3, Panel B. Furthermore, locations with neither coal-powered stations nor cement stations have a stronger reduced air pollution in the two-week period after the lockdown; but this result does not hold for longer periods (Table 3, Panel C). Yet, one may argue that it is the capacity of these stations—rather than their numbers—that determines the levels of pollution. Therefore, we provide estimates using the capacities of coal-powered and cement stations instead in Table A6 (Appendix A), which offers a qualitatively similar conclusion. But as a note of caveat, the magnitudes of the estimated impacts in Table 3 should be interpreted with caution since we do not have information on the extent that operations of these stations were affected by the lockdown.

We next examine a related question on whether the less industrialized locations have a more reduced air pollution after the lockdown. To answer this question, we interact the lockdown variable with indicators of industrial production. We start with an industrial production index, followed by two alternative measures, FDI investment, and nightlight intensity. Findings from previous studies on the relationship between FDI and air pollution are inconclusive with some evidence of the deleterious consequences for the environment (e.g.

Shahbaz *et al.*, 2015). On one hand, pollution-intensive industries likely move from richer to poorer economies because the environmental rules and regulations in the latter are relatively weaker. On the other hand, other studies indicate that FDI can contribute to a cleaner environment, especially if it comes with green technologies (e.g. Demena and Afesorgbor, 2020). We also use nightlight intensity at the district level as a proxy for economic development. The results presented in Table 4 show that locations with lower levels of industrial production record more reduced air pollution after the lockdown.

Lastly, we examine whether citizen perceptions about the environment in Vietnam affect the impacts of the COVID-19-induced lockdown and air pollution. We obtain data from the PAPI database which provides indicators of quality of local economic governance. We are interested in two dimensions—that is, seriousness in environmental protection and quality of air—both of which are available at the province level. The estimation results, shown in Table 5, provide evidence that locations where citizens have higher awareness about the environment do not witness more improved air quality within up to four weeks after the lockdown date. The improvements in air quality in these locations appear to occur only eight weeks after the lockdown date.

Does our analytical framework allow us to use a similar RRD model to estimate the impacts of the lockdowns on air quality in other countries beyond Vietnam? One challenge with cross-country analysis is that not all countries have a single official lockdown date, and if they do, not all countries cleanly implement the lockdowns for the whole country (Dang and Trinh, 2020). As such, we compile a list of 67 countries which we are able to identify the national lockdown date from reliable sources (such as reputable media sources or local government websites). These lockdown dates range from March 9, 2020 (Italy) to April 7, 2020 (Singapore) and are shown in Figure B1 and Table B3 (Appendix B) together with their sources. We also put together a database on concentration of NO₂ for these 67 countries for

analysis as with Vietnam. The estimation results, shown in Table 6, point to similar negative impacts of the lockdowns on reduced air pollution. While these global estimates are somewhat stronger for wider time bandwidths, they are relatively smaller compared to those of Vietnam.

5.3. Potential Mechanisms for Improving Air Quality

We provide next some insights on the potential mechanisms that the COVID-19-induced lockdown could result in improved air quality. Some previous studies have examined the relationship between COVID-19 and mobility restrictions, in particular the role of traffic activities in increasing air pollution. For example, analyzing global data from Google mobility reports (GCMR), Dang and Trinh (2020) find significant reductions of traffic mobility during the pandemic. Coibion *et al.* (2020) use the same database and show that lockdowns substantially deterred social mobility in the United States.

Our estimation results, shown in Table 7, reaffirm these findings for Vietnam. Table 7 shows that mobility activities have declined significantly after the lockdown, and the results are consistent across bandwidths (shown in Panels A, B, and C). In particular, the lockdown resulted in less mobility in categories such as “essential services” (e.g., grocery and pharma, workplace) and “non-essential services” (retail and recreation, parks), but more mobility in the “residential” category.

For further comparison, we examine another source of mobility data that are provided by Apple. Unlike the Google mobility data, the Apple dataset provides statistics of daily changes in driving and walking direction requests from its users. The data for Vietnam are, however, only available for the two largest cities in the country (i.e., Hanoi and Ho Chi Minh City) and the number of data points significantly decreases to just more than 300. Therefore, we are unable to apply the RDD model to analyze this dataset, but we employ instead a standard panel data econometric model with fixed effects. The estimation results, shown in Table A7

(Appendix A), suggest a qualitatively similar result that the lockdown has negative impacts on driving and walking activities.

5.4. Back-of-the-envelope Cost-Benefit Analysis

While it is generally accepted that the economic costs of enforcing lockdown policies during the pandemic are undoubtedly prohibitive, these measures could unintentionally result in certain benefits coming from improved air quality. Put differently, since lockdown policies significantly improve air quality, this would partially offset the costs of these counter-COVID-19 measures. In this section, we perform some back-of-the-envelope calculations to examine the extent of the benefits of higher air quality in Vietnam.

Recall that our main finding shows a decrease in concentration of NO₂ of between 24-32 percent in our main specification (Table 2, column 2). To estimate the health benefits of reduced air pollution, we rely on two experimental studies in Vietnam which investigate how changes in concentration of NO₂ affect prevalence of hospital respiratory admissions, cardiovascular admissions, and pneumonia hospitalization (Nhung *et al.*, 2018; Phung *et al.*, 2016). For better interpretation, we convert the amount of NO₂ concentration into percentage changes using the mean values provided in those studies. Specifically, we find that a one-percent decrease in concentration of NO₂ will lead to 0.15 percent, 0.07 percent, and 0.14 percent decreases in hospital admissions of respiratory, cardiovascular, and pneumonia diseases, respectively. Table 8 provides estimates of health benefits resulting from the COVID-19 lockdown, which range from decreases of between 3.6 and 4.8 percent for respiratory admissions to decreases of between 3.4 and 4.5 percent for pneumonia admissions for the two-week to eight-week periods after the lockdown (Panel A).

We provide next some cost-benefit analysis of reduced air pollution from the lockdown. We use the World Bank's pre-COVID-19 projection of economic growth rate of 6.5 percent in

2020 (World Bank, 2020) and the 2019 GDP (\$262 billion US dollars) for Vietnam to estimate the hypothetical projected GDP in 2020 in the absence of the pandemic. As a rough approximation, the economic losses during the two weeks of lockdown is estimated as its proportionate share of the GDP for the whole year (i.e., 52 weeks). In terms of economic benefits, we use estimates that the economic losses, represented by total welfare losses and forgone labour output, caused by air pollution could be roughly 5.5 percent of the GDP (World Bank, 2016) to calculate the proportion of GDP saved by reduced air pollution.

Our estimates show that the losses of GDP during a two-week lockdown period is roughly \$10.7 billion US dollars (Table 8, Panel C). This is roughly 20 times larger than the economic gains of approximately \$0.6 billion US dollars coming from improved air quality (Table 8, Panel B). Yet, the economic gains from improved air quality discussed above only consider hospital admissions and do not take into account the general non-monetary health benefits of a cleaner environment and better quality of life that all individuals can enjoy.

6. Discussion and Conclusion

Together with economic growth, Vietnam has witnessed rising high levels of air pollution, which can lead to public health challenges. This underscores the importance of evaluating policies that have the potential to improve air quality. The COVID-19 pandemic provides an unprecedented opportunity for us to do just that, which is to investigate how air quality changes in response to lockdown policies. In particular, in order to curb COVID-19 infection, the government has put in place containment measures which have ranged from school closures and cancellations of public gatherings to restrictions on mobility.

Our empirical analysis reveals that the COVID-19-induced lockdown significantly reduces air pollution in Vietnam. However, the impacts are short-lived and dissipate ten weeks after the lockdown date. But we find that the lockdown effects are greater in districts without

coal power stations and cement plants. This indicates that reduced reliance on coal power generation and continued transition to renewable energy can help the country improve its air quality and achieve a sustainable growth trajectory.

We also investigate the mediating role of human mobility on the relationship between lockdown policies and air pollution. A meaningful finding is that sharp reductions in human mobility are strongly associated with the lockdown, which implies that these activities are indeed important sources of air pollution. This also highlights the importance of better control over the emissions from these sources when the economy returns to normal. As such, our estimates can provide useful input parameters for the country's future environmental regulations. Finally, our back-of-the-envelope calculations suggest that while the economic gains from improvements in air quality are just a small fraction compared to the economic losses caused by the lockdown, these do not take into account non-monetary health benefits.

References

- 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.
- Baker, J. (2018, May 21). "This Clean Energy Champion Is Out To Break Vietnam's Coal Habit". *Forbes*. Retrieved from <https://www.forbes.com/sites/jillbaker/2018/05/21/this-clean-energy-champion-is-out-to-break-vietnams-coal-habit/#6e10ed0476b2>
- 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.
- Barnes, S. R., Beland, L. P., Huh, J., & Kim, D. (2020). The Effect of COVID-19 Lockdown on Mobility and Traffic Accidents: Evidence from Louisiana (No. 616). GLO Discussion Paper.
- Berman, J. D., & Ebisu, K. (2020). Changes in US air pollution during the COVID-19 pandemic. *Science of the Total Environment*, 139864.
- Bich Ngoc. (2018, June 7). "Vietnam needs just one, not 26 coal power plants". *VnExpress*. Retrieved from <https://e.vnexpress.net/news/business/vietnam-needs-just-one-not-26-coal-power-plants-3759808.html>
- Bloom, D. E., Kuhn, M., & Prettnner, K. (2020). Modern Infectious Diseases: Macroeconomic Impacts and Policy Responses. *Journal of Economic Literature*.
- Brodeur, A., Gray, D., Islam, A., & Bhuiyan, S. J. (2020a). A Literature Review of the Economics of COVID-19 (No. 601). Global Labor Organization (GLO).
- Brodeur, A., Cook, N., & Wright, T. (2020b). On the Effects of COVID-19 Safer-At-Home Policies on Social Distancing, Car Crashes and Pollution. (No. 13255). IZA Discussion Paper.
- Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2020c). COVID-19, Lockdowns and Well-Being: Evidence from Google Trends (No. 552). GLO 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.

- Cattaneo, M. D., Idrobo, N., & Titiunik R. (2020). *A Practical Introduction to Regression Discontinuity Designs: Foundations*. Cambridge University Press.
- 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.
- Chang, H-H., Meyerhoefer, C., & Yang, F-A. (2020). COVID-19 Prevention and Air Pollution in the Absence of a Lockdown (No. 27604). National Bureau of Economic Research.
- 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.
- Chetty, R., Friedman, J. N., Hendren, N., & Stepner, M. (2020). How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data (No. w27431). National Bureau of Economic Research.
- Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., ... & Feigin, V. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *The Lancet*, 389(10082), 1907-1918.
- Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending (No. w27141). National Bureau of Economic Research.
- Cole, M., Ozgen, C., & Strobl, E. (2020). Air Pollution Exposure and COVID-19 (No. 13367). IZA Discussion Paper.
- Dang, H. A. H., & Giang, L. T. (2020). Turning Vietnam's COVID-19 Success into Economic Recovery: A Job-Focused Analysis of Individual Assessments on Their Finance and the Economy. (No. 13315). IZA Discussion Paper.
- Dang, H. A. H., Huynh, T. L. D., & Nguyen, M. H. (2020). Does the COVID-19 Pandemic Disproportionately Affect the Poor? Evidence from a Six-Country Survey (No. 13352). IZA Discussion Paper.
- Dang, H. A. H., & Trinh, T. A. (2020). Does the COVID-19 Pandemic Improve Global Air Quality? New Cross-national Evidence on Its Unintended Consequences (No. 13480). IZA Discussion Paper.
- Demena, B. A., & Afesorgbor, S. K. (2020). The effect of FDI on environmental emissions: Evidence from a meta-analysis. *Energy Policy*, 138, 111192.
- Do, Thang Nam. (2020, March 30). "Vietnam's Big Air Pollution Challenge: Bold action is needed to address the country's problem". *The Diplomat*. Retrieved from <https://thediplomat.com/2020/03/vietnams-big-air-pollution-challenge/#:~:text=Vietnam%20is%20struggling%20with%20alarming,Fine%20particu>

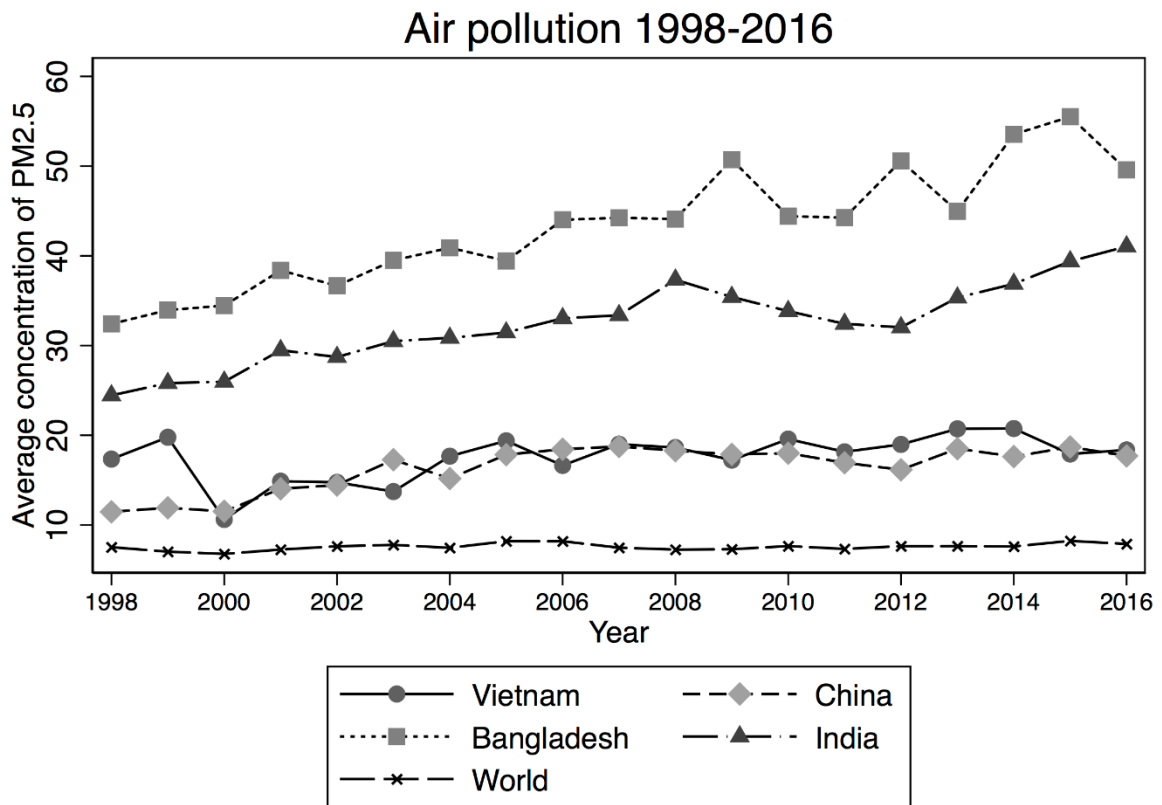
[late%20matter%20\(PM2.&text=In%202019%2C%20Hanoi%20had%20only%20eight%20days%20with%20PM2.](#)

- 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.
- Faustini, A., Rapp, R., & Forastiere, F. (2014). Nitrogen dioxide and mortality: review and meta-analysis of long-term studies. *European Respiratory Journal*, 44(3), 744-753.
- 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>
- Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2), 994-1028.
- Hodler, R., & Raschky, P. A. (2014). Regional favoritism. *The Quarterly Journal of Economics*, 129(2), 995-1033.
- Huynh, T. L. D. (2020). "The COVID-19 containment in Vietnam: What are we doing?" *Journal of Global Health*, 10(1).
- Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies*, 79(3), 933-959.
- Isphording, I. E., & Pestel, N. (2020). Pandemic Meets Pollution: Poor Air Quality Increases Deaths by COVID-19. (No. 13418). IZA Discussion Paper.
- Kopplitz, S. N., Jacob, D. J., Sulprizio, M. P., Myllyvirta, L., & Reid, C. (2017). Burden of disease from rising coal-fired power plant emissions in Southeast Asia. *Environmental Science & Technology*, 51(3), 1467-1476.
- Kurokawa, J., Ohara, T., Morikawa, T., Hanayama, S., Janssens-Maenhout, G., Fukui, T., ... & Akimoto, H. (2013). Emissions of air pollutants and greenhouse gases over Asian regions during 2000–2008: Regional Emission inventory in ASia (REAS) version 2. *Atmospheric Chemistry and Physics*, 13(21), 11019-11058.
- La, V. P., Pham, T. H., Ho, M. T., Nguyen, M. H., P Nguyen, K. L., Vuong, T. T., Tran, T. Khuc, Q., Ho, M.-T., & Vuong, Q. H. (2020). Policy response, social media and science journalism for the sustainability of the public health system amid the COVID-19 outbreak: The Vietnam lessons. *Sustainability*, 12(7), 2931.

- Lee, D. S., & Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2), 281-355.
- Lenzen, M., Li, M., Malik, A., Pomponi, F., Sun, Y. Y., Wiedmann, T., ... & Gómez-Paredes, J. (2020). Global socio-economic losses and environmental gains from the Coronavirus pandemic. *PloS one*, 15(7), e0235654.
- Le Thu, Huong. (2020, August 15). “Vietnam’s successful battle against Covid-19”. *Council of Foreign Relations*. Retrieved from <https://www.cfr.org/blog/vietnams-successful-battle-against-covid-19>
- Liu, C., Chen, R., Sera, F., Vicedo-Cabrera, A. M., Guo, Y., Tong, S., ... & Valdes Ortega, N. (2019). Ambient particulate air pollution and daily mortality in 652 cities. *New England Journal of Medicine*, 381(8), 705-715.
- Luong, L. M., Phung, D., Sly, P. D., Morawska, L., & Thai, P. K. (2017). The association between particulate air pollution and respiratory admissions among young children in Hanoi, Vietnam. *Science of the Total Environment*, 578, 249-255.
- Mandhana, N. & Le, L. (2020, April 27). “Some Countries Are Squashing the Coronavirus Curve. Vietnam Is One.” *Wall Street Journal*. Retrieved from <https://www.wsj.com/articles/some-countries-are-squashing-the-coronavirus-curve-vietnam-is-one-11587989361>
- Mannucci, P. M., & Franchini, M. (2017). Health effects of ambient air pollution in developing countries. *International Journal of Environmental Research and Public Health*, 14(9), 1048.
- McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2), 698-714.
- M.Giao. (2020, August 15). “Mỗi người dân là một chiến sĩ phòng chống dịch bệnh” (Every citizen is a soldier in the fight against the pandemic). *Thanh Nien*. Retrieved from <https://thanhnien.vn/thoi-su/moi-nguoi-dan-la-mot-chien-si-phong-chong-dich-benh-1200259.html>
- Nguyen Quy. (2020, August 15). Hanoi ranked world's seventh most polluted capital city in 2019. Retrieved from <https://e.vnexpress.net/news/news/hanoi-ranked-world-s-seventh-most-polluted-capital-city-in-2019-4061412.html>
- Nhung, N. T. T., Schindler, C., Dien, T. M., Probst-Hensch, N., Perez, L., & Künzli, N. (2018). Acute effects of ambient air pollution on lower respiratory infections in Hanoi children: an eight-year time series study. *Environment International*, 110, 139-148.
- Pham, Linh. (2020, April 10). Why does Vietnam gain international praise for fight against Covid-19? *Hanoi Times*. Retrieved from <http://hanoitimes.vn/why-does-vietnam-gain-international-praise-for-fight-against-covid-19-311680.html>

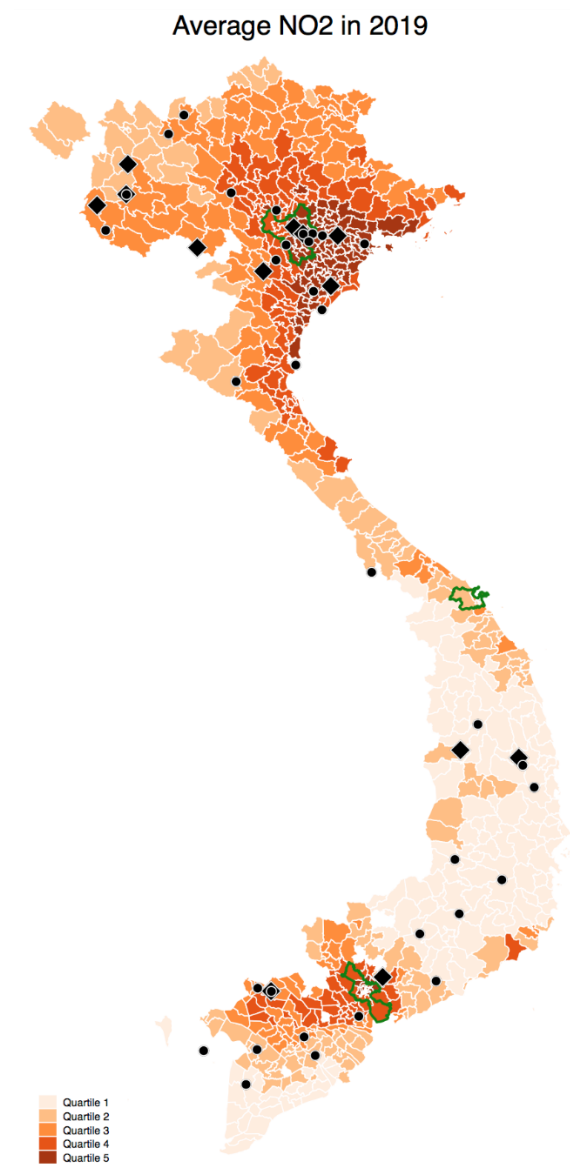
- Phung, D., Hien, T. T., Linh, H. N., Luong, L. M., Morawska, L., Chu, C., ... & Thai, P. K. (2016). Air pollution and risk of respiratory and cardiovascular hospitalizations in the most populous city in Vietnam. *Science of the Total Environment*, 557, 322-330.
- Popovich, N., Migliozzi, B., Patanjali, K., Singhvi, A., & Huang, J. (2019). See How the World's Most Polluted Air Compares With Your City's. <https://www.nytimes.com/interactive/2019/12/02/climate/air-pollution-compare-around.html>
- Shahbaz, M., Nasreen, S., Abbas, F., & Anis, O. (2015). Does foreign direct investment impede environmental quality in high-, middle-, and low-income countries?. *Energy Economics*, 51, 275-287.
- Sharma, S., Zhang, M., Gao, J., Zhang, H., & Kota, S. H. (2020). Effect of restricted emissions during COVID-19 on air quality in India. *Science of the Total Environment*, 728, 138878.
- Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Minguillón, M. C., Alastuey, A. & 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.
- Trevisan, M., Le, L. C., & Le, A. V. (2020). The COVID-19 Pandemic: A View from Vietnam. *American Journal of Public Health*, 110(8): 1152–1153.
- World Bank. (2016). *The cost of air pollution: strengthening the economic case for action*. Washington: World Bank Group.
- World Bank. (2020, April 27). Vietnam country overview. *The World Bank In Vietnam*. Retrieved from <https://www.worldbank.org/en/country/vietnam/overview#:~:text=Nevertheless%2C%20the%20economic%20growth%20is,6.5%20percent%20pre%2Dcrisis%20projections.>
- World Health Organization (WHO). (2006). *Air quality guidelines: global update 2005: particulate matter, ozone, nitrogen dioxide, and sulfur dioxide*. World Health Organization.
- World Health Organization (WHO). (2016). *Ambient air pollution: A global assessment of exposure and burden of disease*. World Health Organization.
- World Health Organization (WHO). (2018, May 2). 9 out of 10 people worldwide breathe polluted air, but more countries are taking action. *World Health Organization*. Retrieved from <https://www.who.int/news-room/detail/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-countries-are-taking-action>
- Venter, Z. S., Aunan, K., Chowdhury, S., & Lelieveld, J. (2020). COVID-19 lockdowns cause global air pollution declines. *Proceedings of the National Academy of Sciences*, 202006853.

Figure 1: Long-term air pollution



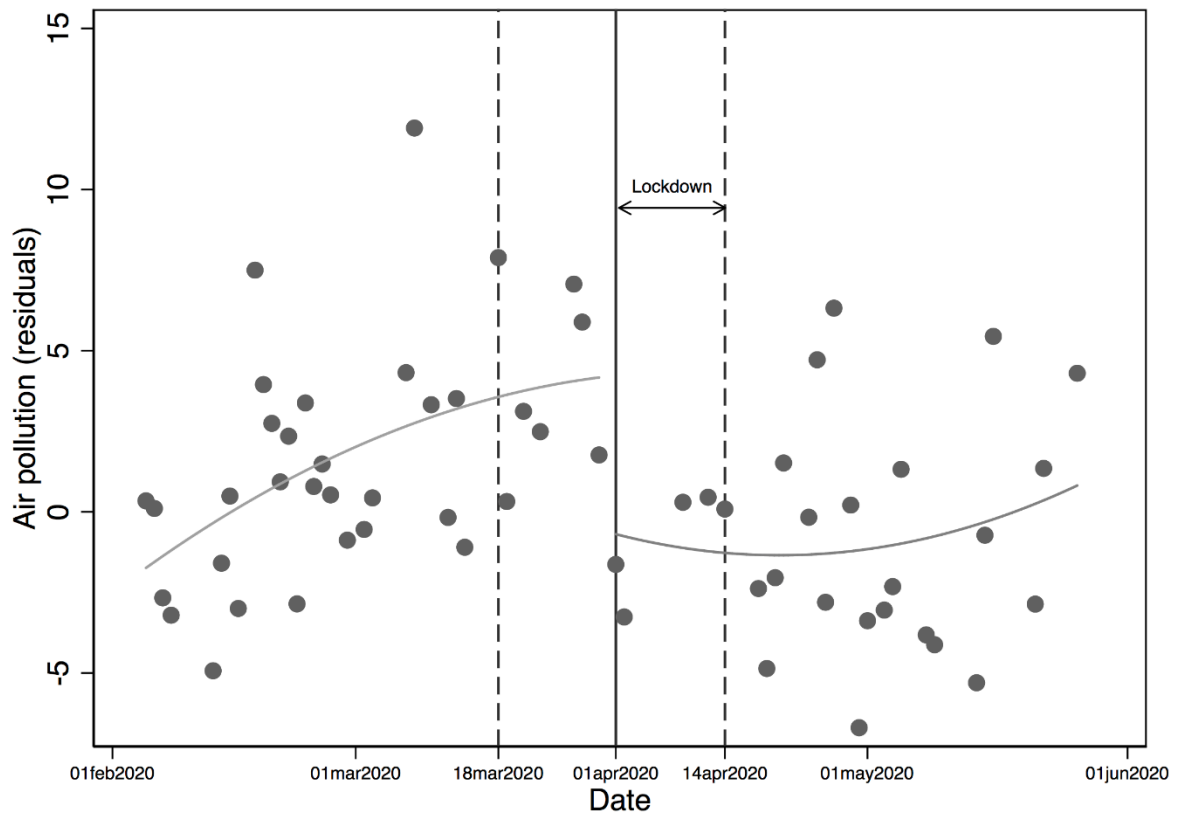
Notes: Air pollution is measured by mean annual PM_{2.5} exposure (micrograms per cubic meter). The data are derived from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS).

Figure 2: Air pollution in Vietnam in 2019



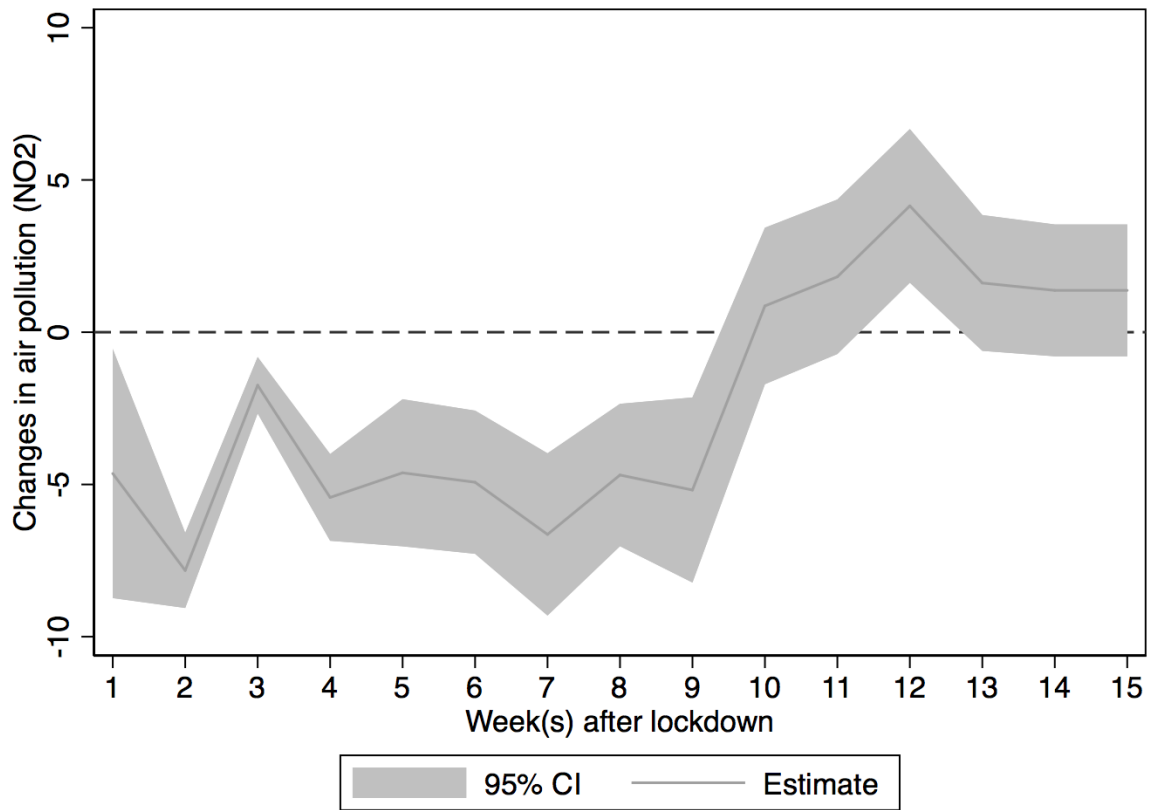
Notes: Average NO₂ is taken from satellite data. Darker values represent higher concentration of NO₂. Areas with green border represent three big cities in Vietnam (Hanoi, Da Nang, and Ho Chi Minh City). Two islands of Vietnam, Hoang Sa and Truong Sa, are not presented in this map. Locations of coal-fired power stations and cement plants are marked with black diamond and black dot, respectively.

Figure 3: Air pollution before, during, and after the lockdown



Notes: The plotted dots are predicted residuals from estimating air pollution (NO₂) with province and time fixed effects. The dash lines represent two weeks before and after the official lockdown date.

Figure 4: Changes in air pollution after lockdown



Notes: Air pollution is measured by NO₂ from satellite data. Each point in the figure shows point estimate and 95 percent confidence interval of treatment variable (lockdown) using different bandwidths after the lockdown. 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. All regressions include province dummies and month dummies. Control variables are daily temperature and precipitation.

Table 1: COVID-19 lockdowns and air pollution – Main results

Air quality:	+/-2 weeks		+/-4 weeks		+/-8 weeks	
NO ₂	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear model						
Lockdown=1	-6.126*** (0.378)	-5.808*** (0.373)	-4.807*** (0.636)	-4.977*** (0.621)	-4.289*** (1.175)	-4.724*** (1.192)
Panel B: Linear interaction model						
Lockdown=1	-5.670*** (0.402)	-5.059*** (0.389)	-4.900*** (0.647)	-5.052*** (0.629)	-4.218*** (1.168)	-4.716*** (1.190)
Panel C: Quadratic model						
Lockdown=1	-6.297*** (0.378)	-6.139*** (0.368)	-5.086*** (0.668)	-5.196*** (0.647)	-4.221*** (1.169)	-4.724*** (1.192)
Panel D: Quadratic interaction model						
Lockdown=1	-7.696*** (0.649)	-7.824*** (0.627)	-5.444*** (0.745)	-5.426*** (0.725)	-4.216*** (1.169)	-4.690*** (1.191)
Means before lockdowns	24.441	24.441	27.579	27.579	25.369	25.369
Controls	No	Yes	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,524	3,518	8,636	8,620	22,962	22,851

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution is measured by NO₂ from satellite data. Running variable is number of days from the lockdown date. 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 province dummies and month dummies. Control variables are daily temperature and precipitation.

Table 2: COVID-19 lockdowns and air pollution – Other parameters of pollution

Bandwidths	+/-2 weeks	+/-4 weeks	+/-8 weeks
	(1)	(2)	(3)
<i>Panel A: Air quality is measured by CO</i>			
Lockdown=1	-0.006*** (0.001)	-0.003*** (0.000)	-0.001 (0.001)
Means before lockdowns	0.059	0.057	0.052
Observations	13,376	25,988	53,857
<i>Panel B: Air quality is measured by SO₂</i>			
Lockdown=1	0.291* (0.161)	-0.343 (0.458)	-4.352*** (0.643)
Means before lockdowns	0.257	0.228	0.594
Observations	852	3,052	9,023
<i>Panel C: Air quality is measured by O₃</i>			
Lockdown=1	3.529*** (0.902)	0.096*** (0.024)	-0.138*** (0.028)
Means before lockdowns	11.854	11.632	11.513
Observations	1,339	5,569	16,320
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that includes interactions of running variable (linear and quadratic terms) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution parameters are taken from satellite data. All regressions include province dummies and month dummies. Control variables are daily temperature and precipitation.

Table 3: COVID-19 lockdowns and air pollution – Power stations and cement plants

Air pollution:	(1)	(2)	(3)
NO ₂	+/-2 weeks	+/-4 weeks	+/-8 weeks
<i>Panel A: Coal-fired stations</i>			
Lockdown*No coal-powered plants	-9.218*** (3.136)	-10.621*** (2.771)	-8.752*** (1.708)
<i>Panel B: Cement plants</i>			
Lockdown*No cement plants	-6.885*** (1.939)	-0.450 (1.527)	-2.368** (0.949)
<i>Panel C: Coal-fired and cement plants</i>			
Lockdown*No coal-powered and no cement plants	-10.454*** (1.731)	-2.948** (1.403)	-3.828*** (0.872)
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3,518	8,620	22,851

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that includes interactions of running variable (linear and quadratic terms) with treatment variable. All regressions include province dummies and month dummies. Control variables are daily temperature and precipitation.

Table 4: COVID-19 lockdowns and air pollution – Industrial production indicators

Air pollution:	(1)	(2)	(3)
NO ₂	+/-2 weeks	+/-4 weeks	+/-8 weeks
Panel A: Industrial production index			
Lockdown*Industrial index	-21.698** (9.204)	-4.196 (5.286)	0.288 (3.625)
Observations	3,518	8,620	22,851
Panel B: FDI capital			
Lockdown* FDI (in log)	-0.344 (0.217)	-0.198 (0.159)	-0.348*** (0.130)
Observations	3,518	8,620	22,851
Panel C: Nightlight			
Lockdown*Nightlight	-0.718** (0.335)	-0.512 (0.326)	-0.477** (0.220)
Observations	3,439	8,399	22,246
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. For ease of interpretation, industrial production indicators are reversed so that higher index is associated with less industrial activities. Results of parametric RDD that includes interactions of running variable (linear and quadratic terms) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution is measured by NO₂ from satellite data. All regressions include province and month dummies. Control variables are daily temperature and precipitation.

Table 5: COVID-19 lockdowns and air pollution – Citizens perception

Air pollution:	(1)	(2)	(3)
NO ₂	+/-2 weeks	+/-4 weeks	+/-8 weeks
<i>Panel A: Environmental protection</i>			
Lockdown*Environmental protection	-1.041 (1.669)	1.386 (1.178)	-4.033*** (0.751)
<i>Panel B: Quality of air</i>			
Lockdown*Quality of air	-9.535 (8.046)	3.545 (4.206)	-10.229*** (3.273)
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3,518	8,620	22,851

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that includes interactions of running variable (linear and quadratic terms) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution is measured by NO₂ from satellite data. All regressions include month dummies. Control variables are daily temperature and precipitation. A higher score on PAPI indexes is associated with better awareness of environmental protection and quality of air, respectively.

Table 6: COVID-19 lockdowns and air pollution – Cross-country sample

Air pollution:	(1)	(2)	(3)
NO ₂	+/-2 weeks	+/-4 weeks	+/-8 weeks
Lockdown=1	-0.799*	-1.045**	-1.292***
	(0.469)	(0.458)	(0.397)
Means before lockdowns	20.195	21.311	22.010
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	22,885	43,716	86,346

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that includes interactions of running variable (linear and quadratic terms) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution is measured by NO₂ from satellite data. All regressions include country dummies and month dummies. Control variables are daily temperature and precipitation. We present summary of country lockdown dates in Figure B1 (Appendix B).

Table 7: COVID-19 lockdowns and mobility restriction

Mobility changes	Retail and recreation	Grocery and pharmacy	Park	Transit	Workplaces	Residential
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: +/-2 weeks						
Lockdown=1	-13.758*** (0.629)	-17.141*** (0.668)	-9.999*** (0.793)	-16.014*** (0.781)	-18.438*** (0.587)	4.870*** (0.239)
Observations	1,763	1,705	1,758	1,663	1,763	1,697
Panel B: +/-4 weeks						
Lockdown=1	-26.676*** (0.769)	-19.955*** (0.952)	-13.609*** (0.935)	-22.759*** (1.087)	-23.877*** (0.784)	7.708*** (0.309)
Observations	3,527	3,406	3,512	3,304	3,527	3,410
Panel C: +/-8 weeks						
Lockdown=1	-29.215*** (0.831)	-23.369*** (1.028)	-13.855*** (1.286)	-29.339*** (1.330)	-33.502*** (0.792)	10.040*** (0.292)
Observations	6,419	6,209	6,384	5,956	6,420	6,247

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that includes interactions of running variable (linear and quadratic terms) with treatment variable. Robust standard errors in parentheses. Standard errors are clustered at province level. Control variables are daily temperature and precipitation.

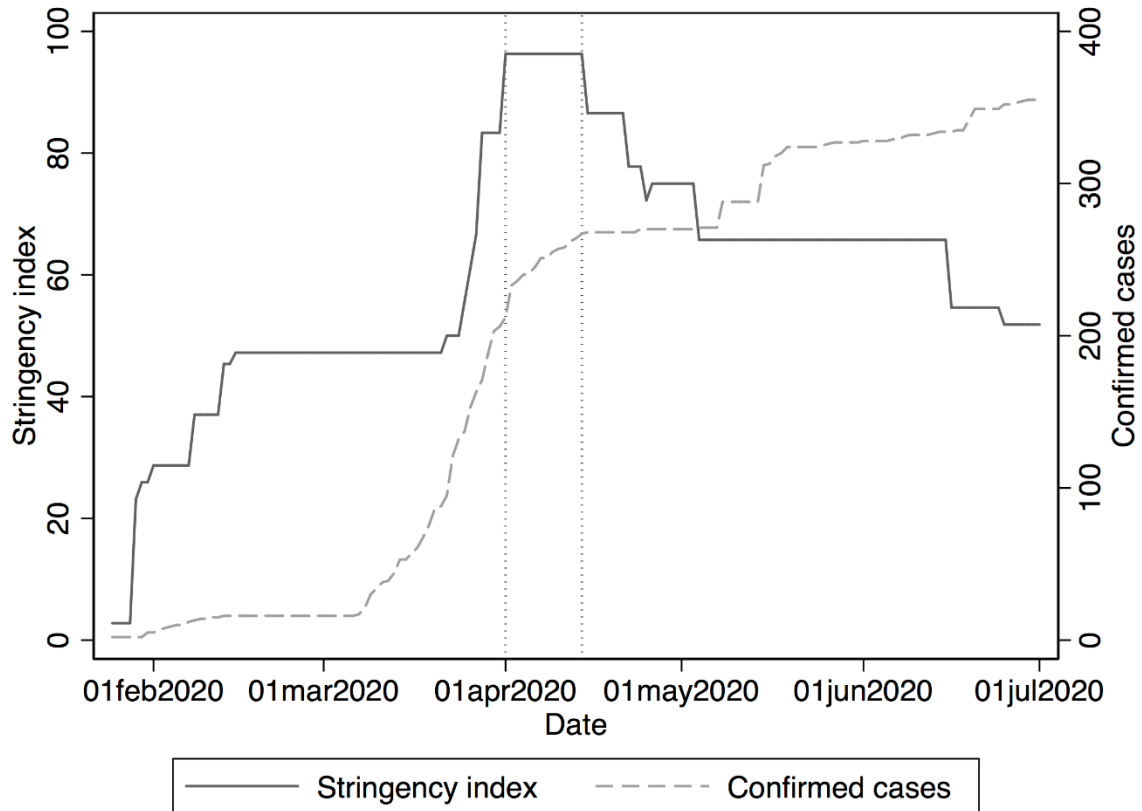
Table 8: COVID-19 lockdowns and air pollution – Cost-benefits analysis

	(1)	(2)	(3)
Bandwidths	+/-2 weeks	+/-4 weeks	+/-8 weeks
<i>Panel A: Health benefits</i>			
Decrease in respiratory admissions	3.6 percent – 4.8 percent		
Decrease in cardiovascular admissions	1.7 percent – 2.2 percent		
Decrease in pneumonia hospitalization	3.4 percent – 4.5 percent		
<i>Panel B: Economic benefits</i>			
Estimated benefit of higher air quality (in bil. USD)	0.6	1.2	2.4
<i>Panel C: Economic losses</i>			
Estimated losses (in bil. USD)	10.7	21.5	42.9

Notes: We use our estimated decrease in concentration of NO₂ of between 24-32 percent. Using findings from Nhung *et al.* (2018) and Phung *et al.* (2016), we find that one percent decrease in concentration of NO₂ will lead to 0.15 percent, 0.07 percent, and 0.14 percent decreases in hospital admissions of respiratory, cardiovascular, and pneumonia diseases, respectively. The gains and losses of GDP during the lockdown are calculated using 2019 GDP (\$262 billion US dollars) and projection of economic growth rate in 2020 (6.5 percent) in the absence of the pandemic.

Appendix A: Additional Figures and Tables

Figure A1: Stringency index and confirmed cases



Notes: The data is derived from Oxford COVID-19 Government Response Tracker (OxCGRT). The vertical dot lines represent lockdown period in Vietnam (April 1 – April 14).

Figure A2: COVID-19 lockdowns and temperature/precipitation

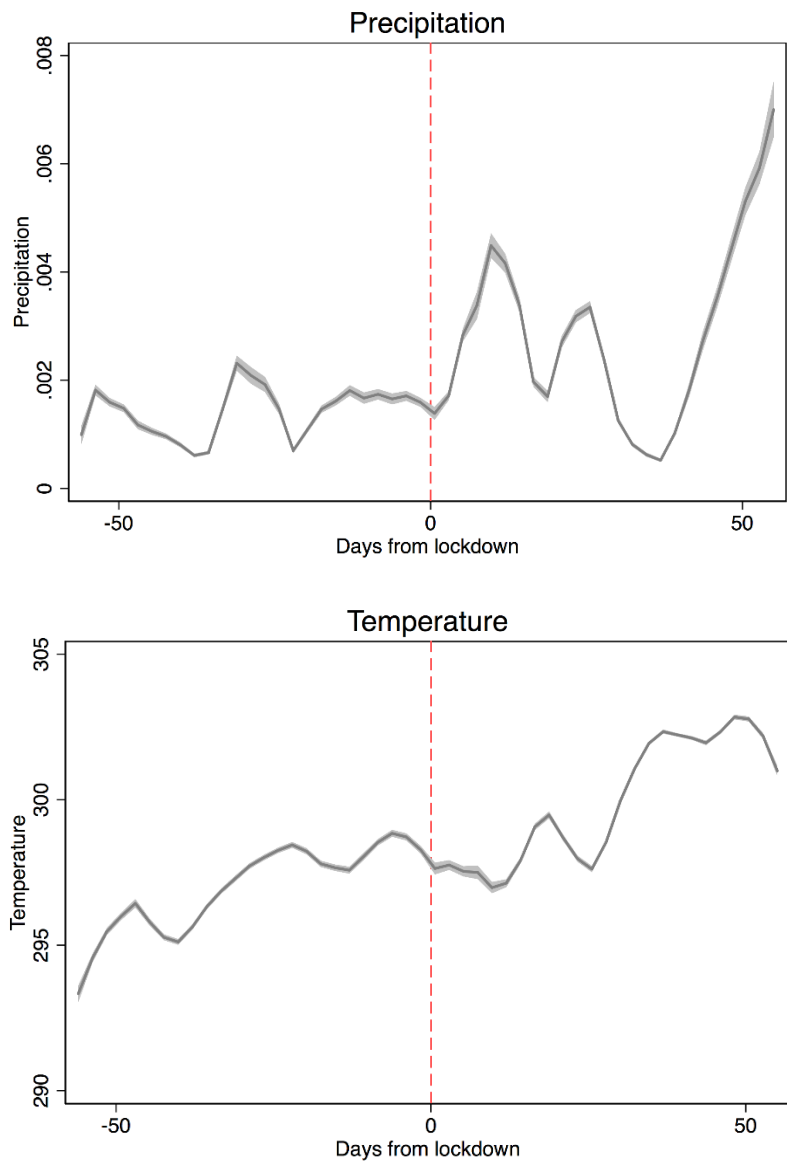


Table A1: Manipulation test

	Bandwidth		Observations		t-test	
	left	right	left	right	t-test	p-value
NO ₂	14.504	12.460	4,970	2,840	0.394	0.693

Notes: Results of manipulation test developed by McCrary (2008). We implement a regression discontinuity (RD) manipulation test using local polynomial density estimation following Cattaneo *et al.* (2018). T-tests and their corresponding p-values indicate there is no statistical evidence of systematic manipulation of the running variable.

Table A2: COVID-19 lockdowns and air pollution – Optimal bandwidth

Air pollution: NO ₂	Optimal bandwidth		
	Mserd	Msetwo	Msesum
Lockdown=1	-5.808*** (0.373)	-4.740*** (0.406)	-3.826*** (0.376)
Means before lockdowns	24.441	24.441	24.441
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3,518	6,280	6,417

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of RDD using the optimal bandwidths based on Calonico *et al.* (2019). Standard errors are in parentheses and are obtained by clustering at the district level. Mean of air quality before lockdowns is calculated two weeks before the official date of lockdown. All regressions include province dummies and month dummies. Control variables are daily temperature and precipitation.

Table A3: COVID-19 lockdowns and air pollution – OxCGRT data

Air pollution:	(1)	(2)	(3)
NO ₂	Stringency index	Government response index	Containment and health index
Lockdown=1	-3.256*** (0.782)	-3.959*** (0.666)	-3.359*** (0.707)
Means before lockdowns	24.441	24.441	24.441
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	39,888	39,888	39,888

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of fuzzy RDD. The running variable is response indexes taken from OxCGRT data. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution is measured by NO₂ from satellite data. Mean of air quality before lockdowns is calculated two weeks before the official date of lockdown. All regressions include province and day dummies. Control variables are daily temperature and precipitation.

Table A4: COVID-19 lockdowns and air pollution – Air pollution in log

Air quality:	+/-2 weeks		+/-4 weeks		+/-8 weeks	
NO ₂ (in log)	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear model						
Lockdown=1	-0.322*** (0.017)	-0.306*** (0.017)	-0.206*** (0.015)	-0.216*** (0.015)	-0.168*** (0.036)	-0.217*** (0.035)
Panel B: Linear interaction model						
Lockdown=1	-0.302*** (0.018)	-0.272*** (0.018)	-0.205*** (0.015)	-0.214*** (0.015)	-0.171*** (0.036)	-0.218*** (0.035)
Panel C: Quadratic model						
Lockdown=1	-0.330*** (0.018)	-0.321*** (0.018)	-0.204*** (0.015)	-0.211*** (0.015)	-0.168*** (0.036)	-0.217*** (0.035)
Panel D: Quadratic interaction model						
Lockdown=1	-0.394*** (0.026)	-0.406*** (0.025)	-0.202*** (0.016)	-0.205*** (0.016)	-0.170*** (0.036)	-0.219*** (0.035)
Means before lockdowns	3.099	3.099	3.159	3.159	3.047	3.047
Controls	No	Yes	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,524	3,518	8,636	8,620	22,962	22,851

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution is measured by NO₂ from satellite data. Running variable is number of days from the lockdown date. 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 province dummies and month dummies. Control variables are daily temperature and precipitation.

Table A5: COVID-19 lockdowns and air pollution – Province linear time trend

Air quality: NO ₂	+/-2 weeks		+/-4 weeks		+/-8 weeks	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear model						
Lockdown=1	-19.626*** (1.918)	-10.112*** (2.144)	-14.946*** (1.777)	-11.861*** (1.746)	-8.586*** (1.334)	-12.301*** (1.569)
Panel B: Linear interaction model						
Lockdown=1	-21.418*** (1.933)	-16.481*** (2.036)	-14.985*** (1.762)	-11.899*** (1.731)	-8.500*** (1.327)	-12.309*** (1.572)
Panel C: Quadratic model						
Lockdown=1	-23.192*** (1.963)	-18.920*** (2.094)	-15.037*** (1.765)	-11.934*** (1.731)	-8.490*** (1.327)	-12.319*** (1.574)
Panel D: Quadratic interaction model						
Lockdown=1	-27.256*** (2.200)	-20.886*** (2.285)	-15.090*** (1.786)	-11.950*** (1.742)	-8.493*** (1.328)	-12.296*** (1.573)
Means before lockdowns	24.441	24.441	27.579	27.579	25.369	25.369
Controls	No	Yes	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Province linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,524	3,518	8,636	8,620	22,962	22,851

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD. Robust standard errors in parentheses. Standard errors are clustered at the district level. Air pollution is measured by NO₂ from satellite data. Running variable is number of days from the lockdown date. 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 province dummies and month dummies. Control variables are daily temperature and precipitation.

**Table A6: COVID-19 lockdowns and air pollution – Power-stations and cement plants
(capacity)**

Air pollution:	(1)	(2)	(3)
NO ₂	+/-2 weeks	+/-4 weeks	+/-8 weeks
<i>Panel A: Coal-fired plants</i>			
Lockdown* Non-coal plants	-1.228*** (0.432)	-1.359*** (0.380)	-1.242*** (0.240)
<i>Panel B: Cement plants</i>			
Lockdown* Non-cement plants	-1.367*** (0.272)	-0.177 (0.214)	-0.436*** (0.132)
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3,518	8,620	22,851

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of parametric RDD that includes interactions of running variable (linear and quadratic terms) with treatment variable. All regressions include region dummies and month dummies. Control variables are daily temperature and precipitation.

Table A7: COVID-19 lockdowns and mobility restriction – Apple mobility data

	(1)	(2)
Mobility changes	Driving	Walking
Lockdown=1	-11.875*** (3.013)	-15.179*** (3.187)
Controls	Yes	Yes
Time FE	Yes	Yes
Observations	338	338

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Results of panel analysis with fixed effects. Standard errors in parentheses. All regressions include date dummies. Control variables are daily temperature and precipitation. Apple mobility data are available at <https://www.apple.com/covid19/mobility/>

Appendix B: Data Appendix

We obtain air pollution measurements in Vietnam from January 1 to July 1, 2020, provided 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 S5P satellite uses spatial resolution of 5.5 km and provides a (near-)global coverage of air pollution caused by NO₂ and other pollutants such as O₃, SO₂, and CO. We use Google Earth Engine to process and average air quality parameters at the district level using administrative areas of Vietnam taken from Database of Global Administrative Areas (GADM). We use NO₂ as the main measure of air pollution for two reasons. First, NO₂ is a highly reactive pollutant and considered highly lethal to human health (Faustini *et al.*, 2014). It is also the leading source of childhood asthma in urban areas globally (Achakulwisut *et al.*, 2019). Second, NO₂ has a short lifetime which implies that its molecules stay fairly close to their sources and thus offer an appropriate measure of changes in emissions.¹⁷ We then perform a cloud masking which excludes results from pixels with > 10 percent cloud fraction. This addresses the issue of cloud cover which may obscure the sensor's view of the lower atmosphere.

Given that concentrations of NO₂ in the atmosphere are highly variable and sensitive to changes in weather conditions, we collect daily temperature and precipitation as control variables. The data are available 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 then extract the weather data at the district level using a similar process as with the air pollution data.

To investigate differential impacts of COVID-19 on air pollution, we obtain the list of coal-fired stations and cement plants from multiple sources. We focus on those that are operating by the time of 2019. For other heterogeneity tests, we collect information on industrial production from the Statistical Yearbook of Vietnam, published by the General Statistical Office of Vietnam (GSO). The GSO provides two measures of industrial production including industrial production index and foreign direct investment (FDI). The former indicator is calculated as the percentage of the quantity of industrial production generated in a given year compared to the base year, while the latter indicator measures accumulation of FDI projects having effect as of 2019. Both indicators are available at the province level.

We also use monthly nightlight data from NOAA as alternative measure for industrial production. Satellite nightlight have been widely used in the economic literature as a proxy for numerous economic, social and environmental indicators (e.g. Henderson *et al.*, 2012; Hodler and Raschky, 2014). We use data from the Suomi National Polar-Orbiting Partnership system (SNPP/VIIRS) system, which provides high resolution of nightlight (450m by 450m). We then calculate average nightlight in 2019 at the district level. Prior to averaging, the data are filtered to exclude data impacted by stray light, lightning, lunar illumination, and cloud-cover.

We also collect data on public perceptions about environment from the Provincial Governance and Public Administration Performance Index (PAPI). PAPI is calculated from surveys conducted annually by the Centre for Community Support Development Studies (CECODES), the Fatherland Front, and the United Nations Development Programmes (UNDP). The survey uses a clustered random sampling approach, starts from 2009 and covers all provinces of Vietnam from 2011. PAPI collects information from a sample of over 13,000

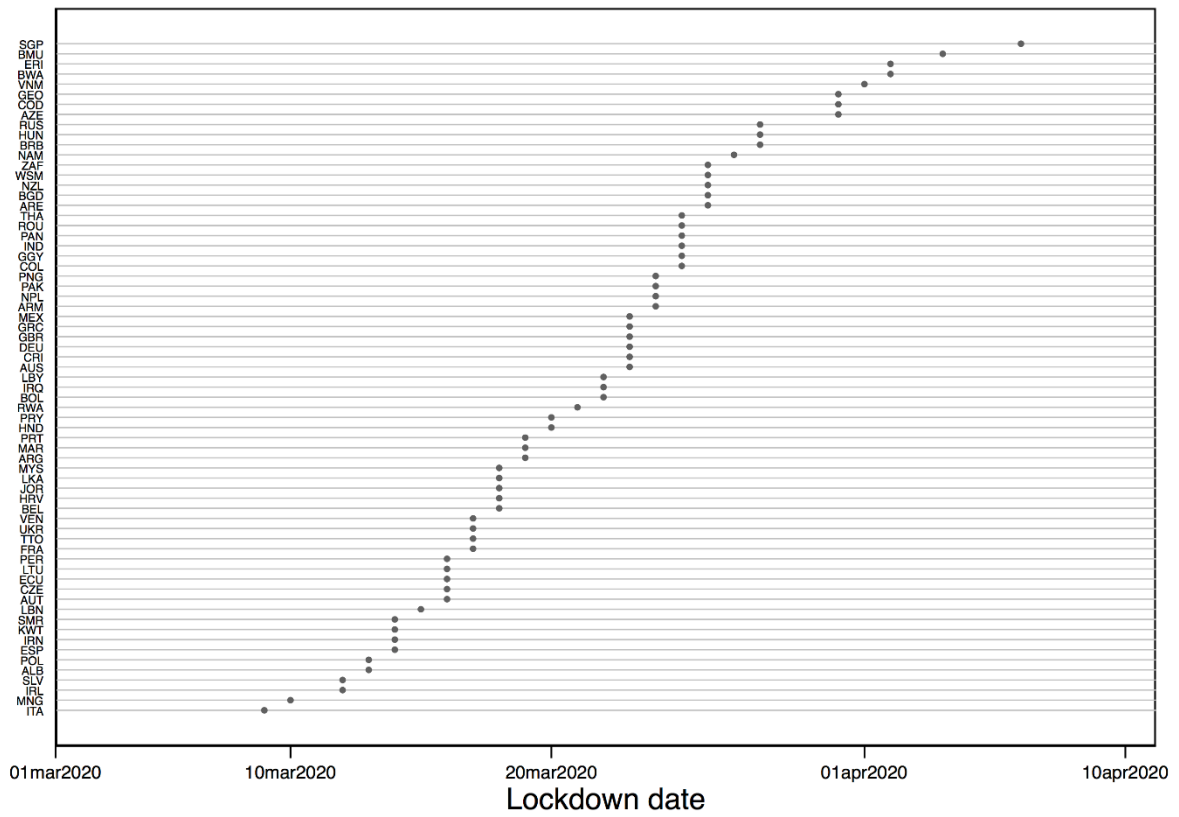
¹⁷ NO₂ is recommended by the European Union's Copernicus programme as the most appropriate indicator of air pollution. For more details, see: <https://atmosphere.copernicus.eu/flawed-estimates-effects-lockdown-measures-air-quality-derived-satellite-observations?q=flawed-estimates-effects-lockdown-measures-air-quality-satellite-observations>

individuals each year regarding their experiences with multiple dimensions of governance. In this paper, we are interested in indicators of individual experiences and perceptions on environmental governance, namely environmental protection and quality of air.

To check robustness of our findings, we obtain information on government response indexes from the Oxford COVID-19 Government Response Tracker (OxCGRT). This tracker implemented by the University of Oxford's Blavatnik School of Government systematically collects information on policy stringency taken by governments to tackle the pandemic since February 2020 (Hale *et al.*, 2020). OxCGRT collects information on government policy responses across eight dimensions, namely: (i) school closures; (ii) workplace closures; (iii) public event cancellations; (iv) gathering restrictions; (v) public transportation closures; (vi) stay-at-home orders; (vii) restrictions on internal movement; and (viii) international travel bans. These dimensions are then used to calculate response indexes to COVID-19. Each index is rescaled to get a score between 0 and 100 (100 representing the highest degree of strictness/restriction).

Finally, we collect data on human mobility from February 15 to July 1, 2020, using the freely available Google COVID-19 Community Mobility Reports (GCMR) dataset. The GCMR reports mobility as percentage changes relative to a baseline period (from January 3 to February 6, 2020). Absolute mobility values are not available to protect users' privacy. The data account for weekly seasonality of movement by estimating a set of seven baseline weekdays using the median value for each particular weekday during the 5-week baseline period. Daily relative change is estimated as the percentage change with respect to the corresponding baseline weekday for any given report date. In Vietnam, the GCMR data are aggregated at the province level, and by category of place (e.g. supermarket and pharmacy, workplaces, residential). We expect that the lockdown will lead to reduced mobility of all categories, except for the residential. We also use mobility reports released by Apple. The dataset provides statistics of daily changes in driving and walking direction requests from its users in two big cities in Vietnam (Hanoi and Ho Chi Minh City). The descriptions and summary statistics of variables used in our analysis are listed in Table B1 below.

Figure B1: Lockdown dates by country



Notes: We collect the underlying data on the lockdown dates from reliable sources including the media and local governments, which are provided in Table B3, Appendix B.

Table B1: Data sources and summary statistics

Variable	Descriptions	Mean	Standard deviation	Min	Max
Satellite air quality (daily)					
<i>Source: European Union's Copernicus programme (https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-5p)</i>					
NO ₂	Nitrogen dioxide	24.962	21.571	-12.100	427.000
CO	Carbon Monoxide	0.049	0.015	0.018	0.856
SO ₂	Sulphur Dioxide	-0.021	2.194	-9.480	33.600
O ₃	Ozone	11.976	0.530	10.832	13.421
Satellite weather data (daily)					
<i>Source: National Oceanic and Atmospheric Administration (NOAA) (https://www.ncep.noaa.gov)</i>					
Rainfall	Average rainfall (m)	0.002	0.004	0.000	0.030
Temperature	Average temperature (K)	298.069	4.363	281.834	308.665
Google Mobility data					
<i>Source: Google Community Mobility Reports (https://www.google.com/covid19/mobility/)</i>					
Retail & Recreation	Changes in people's mobility (%) in different categories	-25.690	18.445	-84.000	32.000
Grocery & pharmacy		-13.780	17.411	-66.000	53.000
Park		-21.801	18.728	-80.000	74.000
Transit		-25.034	22.910	-81.000	94.000
Workplaces		-1.450	18.493	-71.000	62.000
Residential		8.029	5.386	-8.000	35.000
Apple Mobility data					
<i>Source: Apple Mobility Reports (https://covid19.apple.com/mobility)</i>					
Driving	Volume of directions requests per city (Hanoi and Ho Chi Minh City) compared to a baseline volume on 13 January 2020.	81.291	21.579	23.420	120.990
Walking		84.442	23.280	28.220	134.310
Oxford COVID-19 Government Response Tracker (OxCGRT)					
<i>Source: Blavatnik School of Government at the University of Oxford (https://covidtracker.bsg.ox.ac.uk/)</i>					

Stringency index		60.913	18.356	28.700	96.300
Government response index	Government responses to COVID-19 (Score between 0 and 100)	56.084	16.718	22.440	85.900
Containment and health index		64.420	18.081	26.520	96.970
Economic support index		10.246	12.295	0.000	25.000
<i>Other control variables (Tables 4 and 5)</i>					
Industrial index	Province growth rate of industrial production (Statistical Yearbook 2019)	113.055	12.683	99.400	188.500
FDI	Foreign direct investment projects licensed by province (Statistical Yearbook 2019)	7,068.502	11,296.800	1.500	45,194.300
Nightlight	Average night-time light at the district level in 2019 (National Oceanic and Atmospheric Administration – NOAA)	3.362	9.922	0.103	148.763
Environmental protection	Viet Nam Provincial Governance and Public Administration	3.559	0.528	2.710	4.940
Quality of air	Performance Index (PAPI) in 2019	1.935	0.198	1.290	2.430

Notes: Summary statistics of real-time data are calculated using the bandwidth of eight weeks before and after the lockdown date.

Table B2: Response indexes components

Number	Components	Description	Stringency index	Government response	Containment and health
1	School closing	Closings of schools and universities	x	x	x
2	Workplace closing	Closings of workplaces	x	x	x
3	Cancel public events	Cancelling public events	x	x	x
4	Restrictions on gatherings	Cut-off size for bans on private gatherings	x	x	x
5	Close public transport	Closing of public transport	x	x	x
6	Stay at home requirements	Orders to “shelter-in- place” and otherwise confine to home.	x	x	x
7	Restrictions on internal movement	Restrictions on internal movement	x	x	x
8	International travel controls	Restrictions on international travel	x	x	x
9	Income support	Salaries/cash payments to people who lose their jobs		x	
10	Debt relief	Government freezing financial obligations		x	
11	Public info campaigns	Presence of public info campaigns	x	x	x
12	Testing policy	Who can get tested?		x	x
13	Contact tracing	Governments doing contact tracing?		x	x

Notes: Each component is measured by an ordinal scale. The indexes are 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 response indexes.

Table B3: National lockdown date by country

Number	Country	Country code	Official lockdown date	Source
1	Albania	ALB	3/13/20	https://www.reuters.com/article/us-health-coronavirus-albania/albania-extends-lockdown-till-end-of-coronavirus-outbreak-idUSKBN21J6AZ
2	Argentina	ARG	3/19/20	https://www.bloomberg.com/news/articles/2020-03-20/argentina-orders-exceptional-lockdown-in-bid-to-contain-virus
3	Armenia	ARM	3/24/20	https://www.reuters.com/article/health-coronavirus-armenia/update-1-armenia-closes-down-enterprises-bans-outdoor-movements-without-passport-pm-idUSL8N2BH7AW
4	Australia	AUS	3/23/20	https://www.abc.net.au/news/2020-03-22/major-coronavirus-crackdown-to-close-churches-pubs-clubs/12079610
5	Austria	AUT	3/16/20	https://www.businessinsider.com/how-austria-reacted-quickly-and-firmly-to-tackle-coronavirus-crisis-2020-4?r=AU&IR=T
6	Azerbaijan	AZE	3/31/20	https://www.aa.com.tr/en/latest-on-coronavirus-outbreak/azerbaijan-to-impose-curfew-amid-coronavirus-outbreak/1785680
7	Bangladesh	BGD	3/26/20	https://thediplomat.com/2020/04/the-covid-19-catastrophe-in-bangladesh/
8	Barbados	BRB	3/28/20	https://www.voice-online.co.uk/news/coronavirus/2020/03/27/barbados-to-impose-nightly-curfews-as-covid-cases-jump-to-24/
9	Belgium	BEL	3/18/20	https://www.usnews.com/news/world/articles/2020-03-17/belgium-to-impose-coronavirus-lockdown-from-march-18-at-1100-gmt
10	Bermuda	BMU	4/4/20	https://www.garda.com/crisis24/news-alerts/328696/bermuda-government-announces-24-hour-curfew-from-april-4-update-1
11	Bolivia	BOL	3/22/20	https://www.reuters.com/article/us-health-coronavirus-bolivia/bolivia-announces-nationwide-14-day-quarantine-to-stem-spread-of-coronavirus-idUSKBN2180VG
12	Botswana	BWA	4/2/20	https://www.osac.gov/Content/Report/f5897d81-7dfa-42eb-a614-1854dd818775
13	Colombia	COL	3/25/20	https://www.reuters.com/article/us-health-coronavirus-colombia-quarantin/colombia-to-hold-19-day-quarantine-to-fight-coronavirus-idUSKBN218068
14	Republic of Congo	COD	3/31/20	https://www.msn.com/en-xl/news/other/covid-19-lagos-brazzaville-lockdown-begins/ar-BB11ZAhm
15	Costa Rica	CRI	3/23/20	https://www.ministeriodesalud.go.cr/index.php/centro-de-prensa/noticias/741-noticias-2020/1582-gobierno-endurece-medidas-sanitarias-para-impedir-contagio-de-covid-19
16	Croatia	HRV	3/18/20	https://www.total-croatia-news.com/news/42223-covid-19

17	Czech Republic	CZE	3/16/20	https://orf.at/stories/3158055/
18	Ecuador	ECU	3/16/20	https://www.garda.com/crisis24/news-alerts/322931/ecuador-government-to-close-all-borders-due-to-covid-19-march-15-16-update-1
19	El Salvador	SLV	3/12/20	https://www.theguardian.com/world/live/2020/mar/11/coronavirus-update-live-news-uk-health-minister-italy-lockdown-australia-us-china-stock-markets-outbreak-latest-updates?page=with:block-5e6971ab8f085f0b8d946d20#block-5e6971ab8f085f0b8d946d20
20	Eritrea	ERI	4/2/20	https://www.garda.com/crisis24/news-alerts/328486/eritrea-authorities-implement-21-day-lockdown-from-april-2-update-3
21	France	FRA	3/17/20	https://www.independent.co.uk/news/world/europe/coronavirus-france-lockdown-cases-update-covid-19-macron-a9405136.html
22	Georgia	GEO	3/31/20	https://www.nytimes.com/2020/04/04/us/coronavirus-georgia-beaches.html
23	Germany	DEU	3/23/20	https://www.cnbc.com/2020/04/16/germany-set-to-lift-lockdown-cautiously-while-uk-exit-strategy-remains-unknown.html
24	Greece	GRC	3/23/20	https://www.reuters.com/article/us-health-coronavirus-greece-curfew/greece-imposes-lockdown-after-coronavirus-infections-jump-idUSKBN2190Z1
25	Guernsey	GGY	3/25/20	https://guernseypress.com/news/2020/03/24/coronavirus-guernsey-in-lockdown-from-midnight-tonight/
26	Honduras	HND	3/20/20	https://covid19honduras.org/?q=toque-de-queda-absoluto-para-todo-el-pais
27	Hungary	HUN	3/28/20	https://www.usnews.com/news/world/articles/2020-03-27/hungary-to-restrict-people-leaving-their-homes-to-fight-coronavirus-pm
28	India	IND	3/25/20	https://www.nytimes.com/2020/03/24/world/asia/india-coronavirus-lockdown.html
29	Iran	IRN	3/14/20	https://www.garda.com/crisis24/news-alerts/322811/iran-natiowide-lockdown-implemented-as-over-11300-covid-19-cases-confirmed-march-13-update-12
30	Iraq	IRQ	3/22/20	https://www.garda.com/crisis24/news-alerts/325526/iraq-nationwide-lockdown-implemented-march-22-update-15
31	Ireland	IRL	3/12/20	https://www.theguardian.com/world/2020/mar/27/stay-home-varadkar-urges-irish-in-drastic-lockdown
32	Italy	ITA	3/9/20	https://www.bbc.com/news/world-europe-51810673
33	Jordan	JOR	3/18/20	https://www.abc.net.au/news/2020-05-07/how-jordan-is-tackling-coronavirus/12188520
34	Kuwait	KWT	3/14/20	https://www.algemeiner.com/2020/03/13/preparing-for-coronavirus-lockdown-kuwait-asks-muslims-to-pray-at-home/
35	Lebanon	LBN	3/15/20	https://www.france24.com/en/20200315-lebanon-announces-two-week-lockdown-over-coronavirus

36	Libya	LBY	3/22/20	https://www.libyanexpress.com/libya-on-lockdown-from-6-00-pm-to-6-00-am-amid-coronavirus-preventive-measures/
37	Lithuania	LTU	3/16/20	https://www.garda.com/crisis24/news-alerts/324497/lithuania-government-closes-borders-to-foreign-nationals-march-16-update-2
38	Malaysia	MYS	3/18/20	https://www.todayonline.com/world/covid-19-malaysia-goes-nationwide-pause-march-18-and-what-we-know-so-far
39	Mexico	MEX	3/23/20	https://medicalxpress.com/news/2020-06-mexico-reopening-two-month-lockdown.html
40	Mongolia	MNG	3/10/20	https://www.garda.com/crisis24/news-alerts/321181/mongolia-government-places-ulaanbaatar-and-other-cities-on-lockdown-due-to-covid-19-march-10-update-7
41	Morocco	MAR	3/20/20	https://www.reuters.com/article/us-health-coronavirus-morocco/morocco-to-ease-coronavirus-lockdown-measures-idUSKBN23G2ZH
42	Namibia	NAM	3/27/20	https://www.usnews.com/news/world/articles/2020-03-24/namibia-announces-travel-ban-partial-lockdown-after-seventh-coronavirus-case
43	Nepal	NPL	3/24/20	https://www.garda.com/crisis24/news-alerts/326601/nepal-government-announces-nationwide-lockdown-from-march-24-31-update-4
44	New Zealand	NZL	3/26/20	https://www.bbc.com/news/av/world-52001578
45	Pakistan	PAK	3/24/20	https://www.aa.com.tr/en/asia-pacific/pakistan-stays-under-lockdown-amid-coronavirus-outbreak/1777394
46	Panama	PAN	3/25/20	https://medicalxpress.com/news/2020-03-panama-lockdown-paraguay-borders.html
47	Papua New Guinea	PNG	3/24/20	https://www.businessadvantagepng.com/png-in-lockdown-what-it-means-for-you-and-your-business/
48	Paraguay	PRY	3/20/20	https://www.aa.com.tr/en/americas/paraguay-extends-lockdown-until-april-12-amid-virus/1783353
49	Peru	PER	3/16/20	https://www.bbc.com/news/world-latin-america-53150808
50	Poland	POL	3/13/20	https://www.bloomberg.com/news/articles/2020-03-13/poland-imposes-full-border-controls-quarantines-for-visitors
51	Portugal	PRT	3/19/20	https://www.usnews.com/news/world/articles/2020-03-19/portugal-restricts-movement-to-stem-coronavirus-rules-out-rationing
52	Romania	ROU	3/25/20	https://www.reuters.com/article/health-coronavirus-romania/romania-to-enforce-strict-lockdown-to-slow-coronavirus-idUSL8N2BH4LL
53	Russia	RUS	3/28/20	https://www.bbc.com/news/world-europe-52061381
54	Rwanda	RWA	3/21/20	https://www.dw.com/en/coronavirus-rwanda-imposes-africas-first-lockdown/a-52878787
55	Samoa	WSM	3/26/20	https://www.rnz.co.nz/international/pacific-news/412647/samoa-officially-on-lock-down

56	San Marino	SMR	3/14/20	https://www.sanmarinortv.sm/news/politica-c2/nuovo-decreto-legge-in-vigore-fino-al-6-aprile-a185082
57	Singapore	SGP	4/7/20	https://www.straitstimes.com/politics/ban-on-social-gatherings-of-any-size-in-homes-or-public-areas
58	South Africa	ZAF	3/26/20	https://www.washingtonpost.com/world/africa/south-africa-enters-lockdown-as-known-covid-19-cases-surpass-1000/2020/03/27/d6092194-6f7d-11ea-a156-0048b62cdb51_story.html
59	Spain	ESP	3/14/20	https://www.cNBC.com/2020/03/14/spain-declares-state-of-emergency-due-to-coronavirus.html
60	Sri Lanka	LKA	3/18/20	https://edition.cnn.com/world/live-news/coronavirus-outbreak-03-18-20-intl-hnk/h_865d45b4069a33a409d20daff4adee7b
61	Thailand	THA	3/25/20	https://www.straitstimes.com/asia/se-asia/thailand-declares-state-of-emergency-to-curb-spread
62	Trinidad and Tobago	TTO	3/17/20	https://www.nationnews.com/nationnews/news/244418/trinidad-lockdown
63	Ukraine	UKR	3/17/20	https://www.ukrinform.net/rubric-society/2899162-ten-facts-about-coronavirus-lockdown-in-ukraine.html
64	United Arab Emirates	ARE	3/26/20	https://www.forbes.com/sites/jamesasquith/2020/04/05/dubai-enters-24-hour-lockdown-as-travel-restrictions-extended-in-uae/#7a26ea44f312
65	United Kingdom	GBR	3/23/20	https://www.bbc.com/news/uk-53141763
66	Venezuela	VEN	3/17/20	https://www.reuters.com/article/us-health-coronavirus-venezuela-reopenin/some-venezuelans-welcome-relaxing-of-lockdown-after-14-weeks-inside-idUSKBN23O373
67	Vietnam	VNM	4/1/20	https://www.cNBC.com/2020/07/23/vietnam-zero-coronavirus-deaths.html
