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Quantifying COVID-19’s silver lining: Avoided deaths from air quality improvements in Bogotá☆

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ABSTRACT

In cities around the world, COVID-19 lockdowns have significantly improved outdoor air quality. Even if only temporary, these improvements could have longer-lasting effects by making chronic air pollution more salient and boosting political pressure for change. To that end, it is important to develop objective estimates of both the air quality improvements associated with lockdowns and the benefits they generate. We use panel data econometric models to estimate the effect of Bogotá’s 16-month lockdown on PM 2.5 and NO 2 pollution, epidemiological models to simulate the effect of reductions in these pollutants on long- and short-term mortality, and benefit transfer methods to value the avoided mortality. We find that on average, Bogotá’s lockdown cut PM 2.5 pollution by 15% and NO 2 pollution by 21%. However, the magnitude of these effects varied considerably over time and across the city’s neighborhoods. Equivalent permanent reductions in these pollutants would reduce long-term premature deaths from air pollution by 23% each year, a benefit valued at $1 billion annually. Finally, we estimate that if they occurred ceteris paribus, the temporary reductions in pollutant concentrations in 2020–2021 due to Bogotá’s lockdown would have cut short-term deaths from air pollution by 19%, a benefit valued at $244 million.

1. Introduction

In cities around the world, lockdowns aimed at slowing the spread of COVID-19 have had an unintended co-benefit: by restricting mobility and economic activity, they have improved outdoor air quality, in some cases dramatically. For example, Sharma et al. (2020) find that in 22 cities in India, levels of particulate matter smaller than 2.5 μm (PM 2.5 ), particulate matter smaller than 10 μm (PM 10 ), carbon monoxide (CO), and nitrogen dioxide (NO 2 ) fell by 43, 31, 10, and 18 percent, respectively. Represa et al. (2020) find that in Buenos Aires, concentrations of PM 2.5 and NO 2 fell by 44 and 33 percent, respectively. And Venter et al. (2020) find that in 34 countries around the world, on average, lockdowns led to a 31 percent reduction in PM 2.5 and a 60 percent reduction in NO 2 (see also Dang and Trinh 2021). News media accounts suggest that in cities with chronic severe air pollution, these improvements were palpable and plain for all to see, particularly in the weeks just after lockdowns began: long-obscured vistas were suddenly reliably clear, and respiratory symptoms associated with air pollution noticeably diminished (Ellis-Petersen et al., 2020; Newberger and Jeffery 2020).

Even if only temporary, such conspicuous improvements in air quality could, in principle, have longer-lasting effects on policy by

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making pollution problems more salient and by boosting political pressure for change, in much the same way that extreme weather events appear to enhance political pressure for climate action (Konisky et al., 2016; Herrnstadt and Muehlegger 2014). In cities with chronic severe air pollution, both citizens and policymakers have arguably become inured to the problem. The air quality improvements associated with the COVID-19 pandemic have the potential to change that by demonstrating that a cleaner alternative is both possible and attainable in a relatively short timeframe, albeit by using extreme measures.

To that end, it is important to develop credible objective estimates of both the air quality improvements associated with COVID-19 lockdowns and the benefits these improvements generate. Such estimates, in turn, can inform efforts to “build back better”—that is, to include in economic recovery packages investments in clean energy, electromobility, public transportation, and other types of infrastructure that would help avoid a return to prepandemic levels of environmental quality.

Here, we study the effect of the COVID-19 lockdown in Bogotá, a megacity that for decades has suffered from severe air pollution (Gómez Peláez et al., 2020). We estimate the effect of the city’s lockdown, which lasted from March 2020 to June 2021, on air quality and avoided mortality and we also estimate the monetary value of the avoided mortality. Our analysis has three stages. First, we use fixed effects panel-data models along with 12 years of daily data from Bogotá’s air quality monitoring network (among other sources) to econometrically estimate the effect of the lockdown on ambient concentrations of PM2.5 and NO2, pollutants for which Bogotá does not comply with World Health Organization (WHO) air quality guidelines. We control for the potentially confounding effects of weather and forest fires, and we assess both temporal and spatial variation in these effects. Next, we use estimated treatment effects from our first-stage models along with epidemiological models to simulate effects of changes in PM2.5 and NO2 concentrations on long-term and short-term human mortality. Finally, we use benefit transfer methods to estimate the monetary value of this avoided mortality.

We find that on average, Bogotá’s lockdown caused a 15 percent reduction in ambient PM2.5 and a 21 percent reduction in ambient NO2. However, these effects varied over time. They were largest in the two months after the lockdown was initiated in March 2020, attenuated over the next 6 months as lockdown restrictions were relaxed, and were relatively large again in the first quarter of 2021, when restrictions were tightened in response to a holiday surge in infections. The effects of the lockdown also varied spatially: they were largest in the central and southwestern parts of the city, which had the highest average pre-lockdown levels of PM2.5 and NO2. In general, our epidemiological models suggest that the effects of the lockdown on long- and short-term mortality roughly scaled with the effects on PM2.5 and NO2. We find that permanent reductions in ambient PM2.5 and NO2 of the same magnitude as those generated by Bogotá’s lockdown would save 640 lives per year, a 23 percent reduction from counterfactual rates, and that temporary ceteris paribus reductions in pollutant concentrations in 2020–2021 due to Bogotá’s lockdown would have cut short-term deaths from air pollution by 19 percent. Finally, we find that the monetary value of avoided long-term mortality would be $1 billion per year, which represents 1.2 percent of the city’s 2019 GDP, and that the value of avoided short-term mortality would be $244 million, which represents 0.3 percent of Bogotá’s 2019 GDP.

Broadly speaking, our study’s main contribution is to provide a rigorous, comprehensive analysis of the effects of a COVID-19 lockdown in a single city. More specifically, our study makes four contributions. First, and most important, to our knowledge, it is the only analysis of the effect of a COVID-19 lockdown on air quality that does all three of the following: (a) uses econometric models that control for confounding factors to measure the effect of the lockdown on air quality; (b) uses epidemiological models to simulate the effect of the estimated improvement in air quality on premature mortality; and (c) uses a benefit-transfer method to calculate the monetary value of the avoided mortality. Regarding (a), most studies of the effect of lockdowns on air quality simply compare before-and-after levels of pollutant concentrations (Sharma et al., 2020; Represa et al., 2020), an approach subject to substantial bias because of the confounding effects of, among other things, weather during the lockdown year. For example, Shi et al. (2021) find that after controlling for weather, estimated effects of lockdowns on air quality in 11 cities around the world were significantly smaller than what simple before-and-after comparisons suggest. Regarding (b), few studies use econometrically estimated effects of lockdowns on air quality to simulate impacts on human health. Exceptions include Liu et al. (2021) and Venter et al. (2020).1 Regarding (c), only a small set of studies estimate the monetary value of avoided mortality due to a COVID-19 lockdown (e.g., Kumar et al., 2020).

Second, we examine both temporal and spatial variation in the effects of a COVID-19 lockdown on air quality within an urban area. We are not aware of any other studies that do that. Third, we directly control for the effect on air quality of wildfires, an important source of air pollution in cities in the Global South (Reddington et al., 2015; Johnston et al., 2012). Again, we are not aware of any other studies that do that. Finally, whereas most studies of the effect of COVID-19 lockdowns on air quality measure relatively short-term effects during the first several months of the lockdown, we examine effects over the entire 16-month course of a lockdown.

The remainder of this paper is organized as follows. The next section briefly presents background on Bogotá’s air pollution and its COVID-19 lockdown. The third section summarizes the methods, data, and results from each of the three stages of our analysis. And the last section sums up and discusses policy implications.

2. Background

2.1. Air quality

The air quality monitoring network in Bogotá (Red de Monitoreo de Calidad del Aire de Bogotá, RMCAB) consists of 13 stations that

1 Cole et al. (2020) estimate the effect of a lockdown on air quality using machine learning to control for confounding factors, and then use the estimated treated effects along with epidemiological models to simulate avoided mortality.
provide hourly data on six air pollutants and seven weather variables (Fig. 1). Of the five air pollutants for which the WHO has established ambient standards—CO, ozone (O₃), PM₂.₅, PM₁₀, NOₓ, and sulfur dioxide (SO₂) (WHO 2021)—Bogotá regularly fails to meet standards for three—PM₂.₅, PM₁₀, and NO₂ (Figures A1 and A2). Episodes of severe air pollution occur most frequently in the first and last quarters of the year, when thermal inversions trap air pollution at ground level (Figures A3 and A4). Vehicles are the source of 81 and 98 percent of combustion emissions of PM₂.₅ and nitrogen oxides (NOₓ), the pollutants on which we focus in this study. Trucks and buses are the main sources of PM₂.₅ and NO₂ emitted by vehicles (SDA 2020). Air quality is markedly worse than average in the central and southwestern part of the city (Fig. 2).

2.2. Bogotá’s COVID-19 lockdown

During Bogotá’s lockdown, which lasted from March 2020 to June 2021, city, national, and private sector actors instituted a series of lockdown policies that restricted mobility and economic activity and that varied over time in response to changes in rates of infection and hospitalization (Fig. 3). The lockdown can be divided into four phases. The first phase, which began just after the start of the pandemic and lasted about a month, entailed stringent restrictions. On March 12, 2020, a week after Bogotá’s first reported COVID-19 case, city authorities declared a state of emergency and prohibited gatherings larger than 500 people. By March 16, most schools and universities had closed. On March 20, local authorities initiated a citywide lockdown, requiring virtually all citizens to stay at home. Five days later, on March 25, national authorities declared a mandatory countrywide lockdown and halted air traffic.

The second phase, which began in mid-April 2020, entailed a slow easing of restrictions. On April 13, an even-odd day policy was implemented allowing men to conduct certain activities on odd-numbered days, and women on even-numbered days. The “secondary” economic sector (manufacturing, utilities, and construction) was allowed to reopen April 27, the “tertiary” sector (retail, information technology, and furniture) on May 11, and shopping centers, hairdressing services, and taxis on June 1. On July 13, city authorities initiated a policy of shifting lockdowns across the city’s 20 localidades (first-level municipal administrative units). In late August, restaurants were allowed to reopen, and in early September, airlines resumed operations.

Although easing of lockdown restrictions continued in the next several months, one policy measure during this period may have helped to depress traffic and mobility: on September 29, the city reactivated its longstanding driving restrictions program (prohibiting the driving of vehicles one day a week based on the last digit of their license plates), which had been suspended in the early days of the pandemic.

The third phase of the lockdown began in the last month of 2020 and continued through mid-February 2021. It entailed repositioning of restrictions on mobility and economic activity in response to a surge in infections associated with the holiday season. In late December, the city reactivated even-odd day mobility restrictions based on citizen identification numbers that had been in effect for a few months in the third quarter of the year. On January 5, localidades with the most COVID-19 cases were locked down. And starting in mid-January, a citywide lockdown was intermittently imposed for several days at a time, along with nighttime general curfews.

The fourth and final phase of the lockdown, which began in late-February 2021, entailed another easing of restrictions. On February 22, manufacturers, construction sites, restaurants, and hairdressing services were allowed to reopen and students began to return to in-person classes in some schools.

Bogotá’s lockdown effectively ended in June 2021. Under mounting public pressure to improve the economic situation, the Colombian government began lifting COVID-19 restrictions in May 2021, a process that was completed by the end of June except for prohibitions on massive events such as soccer games and concerts (Shultz et al., 2021).

3. Scope of analysis

Our study area comprises all 116 of Bogotá’s unidades de planeamiento zonal (UPZs), administrative units used for planning and regulation (Fig. 1). We examine on the effects of Bogotá’s lockdown on air quality and mortality from March 20, 2020 when city authorities promulgated it through June 30, 2021 when it effectively ended. However, we use more than 12 years of daily data spanning January 1, 2010 through February 28, 2022 to econometrically identify those effects.

We focus on two air pollutants, PM₂.₅ and NO₂, for several related reasons. Most important, as noted above, PM₂.₅, PM₁₀, and NO₂ are the three pollutants for which Bogotá fails to meet WHO air quality standards (Figures A1 and A2). Of the two types of particulate pollution, we limit our attention to PM₂.₅ because concentrations of PM₂.₅ and PM₁₀ are highly correlated and disentangling their effects on human health is challenging (Janssen et al., 2013). To avoid double counting, most recent analyses of the effect of particulate matter on human health focus only on PM₂.₅, which is particularly dangerous (e.g., WB/IHME, 2016; Vohra et al., 2021; Liu et al., 2021). Second, both PM₂.₅ and NO₂ have significant effects on human health. For example, at the global level, PM₂.₅ contributes to more than 9 million premature deaths each year, mostly in severely polluted urban areas in developing countries (Vohra et al., 2021; Burnett et al., 2018). In addition, the links between ambient PM₂.₅ and NO₂ on one hand and human health on the other are relatively well understood (Manisalidis et al., 2020; Anderson et al., 2012). Finally, in Bogotá, as noted above, the large majority of PM₂.₅ and NO₂ combustion emissions are generated by motor vehicles and therefore, in principle, can be controlled (SDA 2020).

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2 This policy was terminated on May 11.
4. Effect of COVID-19 lockdown on ambient PM$_{2.5}$ and NO$_2$

4.1. Methods

To measure the effect of Bogotá’s lockdown on ambient PM$_{2.5}$ and NO$_2$, we use two-way fixed effects panel-data models that control for both observable time-varying confounding factors (weather and upwind forest fires) and time-invariant unobserved factors. As noted above, recent research demonstrates that accurately measuring the effect of COVID-19 lockdowns on air quality requires controlling for meteorological and other confounders (Shi et al., 2021). The temporal scale of our data is a day and the spatial scale is a monitoring station. Hence, our observations are station-days. As discussed below, we fit our models using just over 12 years of data: January 1, 2010 to February 28, 2022.

We use three variants of a two-way fixed effects panel-data model. Our main model is at the city level—that is, it pools observations from multiple monitoring stations—and estimates the aggregate effect of the 16-month lockdown. Results from this model are used as inputs into the health effects models discussed in the next section. For each pollutant, PM$_{2.5}$ and NO$_2$, we estimate

$$Y_{ts} = \alpha + \beta \text{POST}_t + X'_{ts} \gamma + D' \sigma + \rho_s + \epsilon_{ts}$$  \hspace{1cm} (1)$$

where $t$ indexes days, $s$ indexes monitoring stations, $Y$ is the natural logarithm of either PM$_{2.5}$ or NO$_2$, POST is a binary indicator variable equal to one over the course of the city-level lockdown (March 20, 2021 through June 30, 2021) and equal to zero otherwise, $X$ is a vector of time-varying variables (discussed below), $D$ is a vector of four sets of temporal fixed effects (year, month, week of year, week of month, day of week).
Fig. 2. Population-weighted average monthly ambient PM$_{2.5}$ (Panel A) and NO$_2$ (Panel B) concentrations in Bogotá.

Fig. 3. Timeline of Bogotá’s COVID-19 lockdown.
and NO

Table 1 describes the variables used in our econometric models. The dependent variables, pm2.5 and no2, are the natural logarithms of pollutant levels, and the time-varying covariates that constitute the vector X are rainfall, rainfall squared, temperature, temperature squared, wind speed, wind direction, upwind fires, thermal inversion, wind direction 1-8, and NO.

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4.2. Data

Table 1 Variables used in econometric analysis of effect of lockdown on air pollution.

| Variable       | Notes                                             | Units   | Source                        | Scale |
|----------------|---------------------------------------------------|---------|-------------------------------|-------|
| POST           | Treated⁴                                          | 0/1     | N/A                           | Day   |
| pm2.5          | Fine particulate matter, natural logarithm⁷        | μg/m³   | RMCAB (2022)                  | Station-day |
| no2            | Nitrogen dioxide, natural logarithm               | μg/m³   | RMCAB (2022)                  | Station-day |
| Rainfall       |                                                   | mm      | RMCAB (2022)                  | Station-day |
| Temperature    | At ground level                                   | °C      | RMCAB (2022)                  | Station-day |
| temperature20m | Temperature at 20 m                               | °C      | RMCAB (2022)                  | Station-day |
| thermal inversion | Temp. at 20 m > temp. Ground level             | 0/1     | RMCAB (2022)                  | Station-day |
| upwind fires   | Upwind forest fires                               | no.     | NASA (2022)/NOAA (2022)      | Bogotá |
| wind direction 1-8 | Eight indicator variables⁴                       | 0/1     | RMCAB (2022)                  | Station-day |
| wind speed     |                                                   | m/s     | RMCAB (2022)                  | Station-day |

⁴ The temporal scale for all variables is January 1, 2010 to February 28, 2022.
⁷ Equal to one March 20, 2020 through June 30, 2021.
⁸ Smaller than 2.5 μm.
⁹ Criteria for indicator variables 1–8 are whether wind direction measured in degrees falls in the following ranges: (1) 337–360 and 0–22.5, (2) 22.5–67.5, (3) 67.5–112.5, (4) 112.5–167.5, (5) 167.5–202.5, (6) 202.5–247.5, (7) 247.5–292.5, and (8) 292.5–337.

and day of week), ρ are monitoring station fixed effects, α, β, γ, and σ are parameters to be estimated, and ε is an error term. We cluster standard errors at the monitoring station level.

We weight station-day observations from air quality monitoring stations in relatively densely populated areas of the city more heavily than those in less densely populated areas so that our treatment effect estimates more accurately reflect how Bogotá’s COVID-19 lockdown affected human exposure to pollution. Our population weights are created using 2010 demographic data at the level of Bogotá’s 116 UPZs, the finest spatial scale data available (Fig. 1 and Table A1), using a three-step process. First, we match each UPZ to the single monitoring station closest to its centroid (i.e., its nearest neighbor). Next, we assign to each monitoring station the population of all UPZs to which it is matched. Finally, we calculate the population weight for each station by dividing the population assigned to it by the total population of Bogotá.

Our treatment effect estimate is β, the coefficient on POST. Given our semi-log specification, a transformation of this coefficient, \( \exp(\beta) - 1 \) × 100, can be interpreted as the average percentage effect of the lockdown on PM2.5 and NO2.

To examine temporal variation in the effect of the lockdown on ambient PM2.5 and NO2, we estimate a second city-level model that is identical to Equation (1) except that instead of a single treatment indicator, POST, we include 16 indicators, one for each month of the lockdown, March 2020–June 2021. We estimate

\[
Y_n = \alpha + \theta_{POST\_MONTH} + \beta_{POST\_MONTH} X + D' \sigma + \rho + \epsilon_n
\]

where POST\_MONTH is a vector of 16 month indicator variables and \( \theta \) is a vector of parameters. Again, station-day observations are population weighted, and standard errors are clustered at the monitoring station level. Our treatment effect estimates are the elements of \( \theta \), the coefficients on POST\_MONTH. Transformations of these coefficients can be interpreted as the average percentage effects of the lockdown on ambient PM2.5 and NO2 during each month of the lockdown (March 2020, April 2020, etc.).

Finally, to examine spatial variation in the effect of the lockdown on ambient PM2.5 and NO2, we fit a set of monitoring station-level models that are identical to Equation (1) except that each uses observations from only a single monitoring station and therefore excludes station fixed effects. In addition, these models do not use population weighting. That is, for each pollutant (PM2.5 and NO2), we estimate

\[
Y_n = \alpha_s + \beta_{POST\_MONTH} + \beta_{POST\_MONTH} X + D' \sigma_s + \epsilon_n \quad (s = 1, 2, \ldots n)
\]

where n is the number of monitoring stations used in the analysis. Our treatment effect estimates are the elements of \( \beta_s \), the coefficients on POST. Transformations of these coefficients can be interpreted as the average percentage effect of the lockdown on ambient PM2.5 and NO2 at a single monitoring station.
Table 2
Effect of Bogotá’s lockdown on ambient PM$_{2.5}$ concentrations; two-way fixed effects regression results [s.e](%Δ).

| Station(s) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|
| All POST   | −0.16*** | −0.12*** | −0.26*** | −0.05* | −0.10*** | −0.19*** | −0.16*** | −0.11*** | −0.19*** | −0.26*** | −0.34*** |
|            | [0.02] | [0.02] | [0.03] | [0.03] | [0.02] | [0.03] | [0.03] | [0.04] | [0.03] | [0.06] | [0.04] |      |
|            | (−15.18) | (−11.70) | (−23.08) | (−4.70) | (−9.59) | (−17.00) | (−14.61) | (−10.36) | (−17.21) | (−22.89) | (−28.91) |      |
| POST, MAR20| −0.13*** | −0.60*** | [0.04] |      |      |      |      |      |      |      |      |      |
|            | [0.03] | [0.06] | (−44.90) |      |      |      |      |      |      |      |      |      |
| POST, APR20| −0.36*** | −0.12* | [0.07] |      |      |      |      |      |      |      |      |      |
|            | [0.06] | (−11.55) |      |      |      |      |      |      |      |      |      |      |
| POST, MAY20| −0.13*** | −0.14** | [0.03] |      |      |      |      |      |      |      |      |      |
|            | [0.05] | (−12.75) |      |      |      |      |      |      |      |      |      |      |
| POST, JUN20| −0.14** | −0.16*** | [0.04] |      |      |      |      |      |      |      |      |      |
|            | [0.04] | (−14.43) |      |      |      |      |      |      |      |      |      |      |
| POST, JUL20| −0.21*** | −0.19* | [0.07] |      |      |      |      |      |      |      |      |      |
|            | [0.07] | (−1.44) |      |      |      |      |      |      |      |      |      |      |
| POST, AUG20| −0.01 |      |      |      |      |      |      |      |      |      |      |      |
|            | [0.08] | (1.03) |      |      |      |      |      |      |      |      |      |      |
| POST, SEP20| −0.01 |      |      |      |      |      |      |      |      |      |      |      |
| POST, OCT20| −0.01 |      |      |      |      |      |      |      |      |      |      |      |
| POST, NOV20| −0.01 |      |      |      |      |      |      |      |      |      |      |      |
| POST, DEC20| −0.01 |      |      |      |      |      |      |      |      |      |      |      |
| POST, JAN21| −0.01 |      |      |      |      |      |      |      |      |      |      |      |

(continued on next page)
Table 2 (continued)

| Station(s) | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   | (7)   | (8)   | (9)   | (10)  | (11)  | (12)  |
|------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| All        | 0.10* | 0.10* | -0.12** | -0.16** | -0.42*** | -0.04 | 0.06  | 0.04  | 0.05  | 21.23 | 21.23 | 31.3  |
| Carvajal   | 0.05  | 0.05  | 0.04  | 0.06  | 0.11  | 0.05  | 0.502 | 0.51  | 0.501 | 29.270| 29.270| 2697  |
| Centro Alto Rend | -9.15 | -9.13 | -11.14 | -15.20 | -34.18 | -4.40 | 31.3  | 3740  | 2697  | 29.270| 29.270| 2697  |
| Guaymaral  | 9.15  | 9.13  | -11.14 | -15.20 | -34.18 | -4.40 | 18.52 | 3740  | 2697  | 29.270| 29.270| 2697  |
| Kennedy    | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 | 14.37 |
| Las Ferias | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 | 28.88 |
| MinAmbiente| 15.98 | 15.98 | 15.98 | 15.98 | 15.98 | 15.98 | 15.98 | 15.98 | 15.98 | 15.98 | 15.98 | 15.98 |
| San Cristóbal | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 | 15.31 |
| Suba       | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 | 10.76 |
| Tunal      | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 | 18.98 |
| Usaquén    | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 | 20.47 |

The dependent variable is the natural logarithm of PM$_{2.5}$. The independent variable of interest, POST, is an indicator equal to one for all station-days from March 20, 2020 to June 30, 2021. Covariates are four sets of temporal fixed effects (year, month, week, day-of-week), and 16 time-varying covariates: rainfall, rainfall squared, temperature, temperature squared, temperature20m, thermal inversion, upwind fires, wind direction1–wind direction8, wind speed, and wind speed squared. Models 1 and 2 include monitoring station fixed effects and weight station-day observations by population. Standard errors are clustered at the monitoring station level. The counterfactual is the population-weighted average of the natural logarithm of PM$_{2.5}$ for all station-days in years preceding the lockdown. %Δ = (exp (β) − 1) * 100. ***p < 0.01, **p < 0.05, *p < 0.1.
Fig. 4. Estimated effects of COVID-19 lockdown on PM$_{2.5}$ and NO$_2$ concentrations, point estimates, and 95% confidence intervals (Panels A and B) and traffic congestion using Waze data, means, and standard deviation (Panel C). Note: Traffic congestion intensity is the monthly average of daily percentage change, the baseline is the average value for the corresponding day of the week during the 2-week period February 11, 2020 to February 25, 2020 (IDB/IDB Invest, 2022).
Table 3
Effect of Bogotá’s lockdown on ambient NO$_2$ concentrations; two-way fixed effects regression results [s.e](%Δ).

| Station(s)    | (1) | (2) | (3)         | (4)         | (5) | (6) | (7)         | (8)         | (9)         |
|---------------|-----|-----|-------------|-------------|-----|-----|-------------|-------------|-------------|
| POST          | −0.23***<br>(−20.46) | −0.54***<br>(−41.69) | −0.17***<br>(−15.65) | −0.34***<br>(−29.06) | −0.07***<br>(−6.78) | −0.16***<br>(−15.11) | −0.14***<br>(−13.40) | −0.18***<br>(−16.21) |
| POST_MAR20    | −0.72***<br>[0.08] | −0.16***<br>[0.04] | −0.51.35<br>(−15.72) | −0.15.20<br>(−0.02) | −0.5.79<br>(−0.02) | −0.0.05<br>[0.04] | −0.0.05<br>[0.02] | −0.0.05<br>[0.02] |
| POST_APR20    | −0.63***<br>[0.09] | −0.06**<br>[0.02] | −0.46.54<br>(−5.17) | −0.25.53<br>(−5.17) | −0.25.20<br>(−0.02) | −0.25.05<br>[0.05] | −0.25.05<br>[0.05] | −0.25.05<br>[0.05] |
| POST_MAY20    | −0.29**<br>[0.12] | −0.17<br>[0.09] | −0.25.53<br>(−25.53) | −0.15.26<br>(−25.53) | −0.15.26<br>(−25.53) | −0.15.26<br>(−25.53) | −0.15.26<br>(−25.53) | −0.15.26<br>(−25.53) |
| POST_JUN20    | −0.17<br>[0.09] | 0.03<br>[0.04] | −0.323<br>(3.23) | −0.323<br>(3.23) | −0.323<br>(3.23) | −0.323<br>(3.23) | −0.323<br>(3.23) | −0.323<br>(3.23) |
| POST_JUL20    | −0.05<br>[0.05] | −0.06**<br>[0.02] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_AUG20    | −0.16***<br>[0.04] | −0.16***<br>[0.04] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_SEP20    | −0.05<br>[0.05] | −0.06**<br>[0.02] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_OCT20    | −0.06**<br>[0.02] | −0.06**<br>[0.02] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_NOV20    | −0.00<br>[0.09] | −0.00<br>[0.09] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_DEC20    | −0.02<br>[0.07] | −0.02<br>[0.07] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_JAN21    | −0.23**<br>[0.09] | −0.23**<br>[0.09] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_FEB21    | −0.25<br>[0.16] | −0.25<br>[0.16] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_MAR21    | −0.25<br>[0.16] | −0.25<br>[0.16] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_APR21    | −0.34***<br>[0.05] | −0.34***<br>[0.05] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_MAY21    | −0.34***<br>[0.08] | −0.34***<br>[0.08] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| POST_JUN21    | −0.17**<br>[0.06] | −0.17**<br>[0.06] | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) | −0.51.35<br>(−5.17) |
| Counterfactual| 33.58 | 33.58 | 48.82 | 30.09 | 23.29 | 31.77 | 38.8 | 36.68 | 30.47 |
| Observations  | 22,192 | 22,192 | 2779 | 3632 | 3192 | 3196 | 2957 | 3231 | 3205 |
| R-squared     | 0.316 | 0.331 | 0.446 | 0.652 | 0.557 | 0.686 | 0.605 | 0.583 | 0.520 |

The dependent variable is the natural logarithm of NO$_2$. The independent variable of interest, POST, is an indicator equal to one for all station-days from March 20, 2020 to June 30, 2021. Covariates are four sets of temporal fixed effects (year, month, week, day-of-week), and 16 time-varying covariates: rainfall, rainfall squared, temperature, temperature squared, temperature20m, thermal inversion, upwind fires, wind direction1–wind direction8, wind speed, and wind speed squared. Models 1 and 2 include monitoring station fixed effects and weight station-day observations by population. Standard errors are clustered at the monitoring station level. The counterfactual is the population-weighted average of the natural logarithm of NO$_2$ for all station-days in years preceding the lockdown. %Δ = (exp (β) − 1) * 100. ***p < 0.01, **p < 0.05, *p < 0.1.
### Table 4
Parameters used in analysis of effect of ambient PM$_{2.5}$ and NO$_2$ on mortality.

| Parameter | Notes | Source | Year |
|-----------|-------|--------|------|
| **Panel A: Long-term effects** | | | |
| Population | By age cohort | DANE (2018) | 2018 |
| annual incidence | By death cause and age cohort | DANE (2018) | 2018 |
| relative risk for PM$_{2.5}$ ($RR_{ae}$) | By death cause and age cohort | GBD (2019) | Various |
| annual excess mortality from NO$_2$ ($g_e$) | By death cause | Atkinson et al. (2018) | Various |
| baseline PM$_{2.5}$ and NO$_2$ (C1) | Annual average | RMCAB (2022) | 2010-2019 |
| endline PM$_{2.5}$ and NO$_2$ (C2) | Annual average | Own calculations | 2020-2021 |
| **Panel B: Short-term effects** | | | |
| Population | By age cohort | DANE (2018) | 2018 |
| daily incidence | By death cause | DANE (2018) | 2018 |
| daily excess mortality from PM$_{2.5}$ ($g_e$) | By death cause | Orellano et al. (2020) | Various |
| daily excess mortality from NO$_2$ ($g_e$) | By death cause | Mills et al. (2016) | Various |
| baseline PM$_{2.5}$ and NO$_2$ (c1) | Daily average | Own calculations | 2020-2021 |
| endline PM$_{2.5}$ and NO$_2$ (c2) | Daily average | Own calculations | 2020-2021 |

### Table 5
Simulated changes in avoided mortality due to PM$_{2.5}$ and NO$_2$.

| Pollutant | Death cause | Counterfactual (deaths) | Simulation (attributable deaths) | Change (percentage) | Value of change (millions US$) |
|-----------|-------------|-------------------------|---------------------------------|---------------------|-------------------------------|
| **Panel A: Long-term effects** | | | | | |
| PM$_{2.5}$ | ALRI | 142.26 | 27.23 | 19.14 | 42.75 |
| Cancer | 108.22 | 18.56 | 17.15 | 29.14 |
| COPD | 338.78 | 64.37 | 19.00 | 101.04 |
| Diabetes | 39.59 | 5.25 | 13.25 | 8.24 |
| IHD | 743.33 | 123.93 | 16.67 | 194.54 |
| Stroke | 352.46 | 63.86 | 18.12 | 100.25 |
| **Subtotal** | | | | | | 1724.64 | 303.20 | 17.58 | 475.96 |
| NO$_2$ | Cardiovascular | 764.75 | 228.69 | 29.90 | 358.99 |
| Respiratory | 300.37 | 89.82 | 29.90 | 141.00 |
| Lung cancer | 79.90 | 24.27 | 30.38 | 38.10 |
| **Subtotal** | | | | | | 1145.01 | 342.78 | 29.94 | 538.09 |
| Combined$^b$ | Cardiovascular | 1787.15 | 412.72 | 23.09 | 617.88 |
| Respiratory$^c$ | 749.19 | 179.59 | 23.97 | 281.91 |
| Cancer$^c$ | 176.42 | 42.22 | 23.93 | 66.28 |
| Diabetes | 39.59 | 5.25 | 13.25 | 8.24 |
| **Subtotal** | | | | | | 2752.35 | 659.78 | 23.24 | 1004.30 |
| **Panel B: Short-term effects** | | | | | |
| PM$_{2.5}$ | Cardiovascular | 217.45 | 41.80 | 19.22 | 65.62 |
| Respiratory | 67.94 | 13.05 | 19.20 | 20.48 |
| **Subtotal** | | | | | | 285.39 | 54.85 | 19.22 | 86.10 |
| NO$_2$ | Cardiovascular | 379.34 | 67.89 | 17.90 | 106.58 |
| Respiratory | 183.79 | 32.95 | 17.93 | 51.73 |
| **Subtotal** | | | | | | 563.13 | 100.85 | 17.91 | 158.31 |
| Combined$^b$ | Cardiovascular | 591.11 | 109.42 | 18.51 | 171.76 |
| Respiratory | 249.54 | 45.89 | 18.39 | 72.04 |
| **Subtotal** | | | | | | 840.65 | 155.31 | 18.47 | 243.80 |

Citywide model with population-weighted average effects. ALRI = acute lower respiratory infection; COP = chronic obstructive pulmonary disease; IHD = ischemic heart disease.

$^a$ Cancer of the lung, trachea and bronchus.

$^b$ Adjusted for multiple risk factors: see explanation in Section 5.4.

$^c$ Includes PM$_{2.5}$ long-term IHD and stroke deaths.

$^d$ Includes PM$_{2.5}$ long-term ALRI and COPD deaths.
squared, temperature\textsuperscript{20m}, thermal inversion, upwind fires, wind direction\textsuperscript{1}–wind direction\textsuperscript{8}, wind speed, and windspeed squared. With the exception of upwind fires, all of these variables are derived from hourly monitoring station data (RMCA\textsuperscript{B} 2022). From these hourly data, we obtain daily values by taking the daily mean of hourly PM\textsubscript{2.5}, NO\textsubscript{2}, wind speed, and temperature, and the daily sum of hourly rainfall. The variable thermal inversion is a binary indicator equal to one if at any hour of the day, temperature\textsuperscript{20m}, which is the temperature 20 m above ground level, exceeds temperature, which is the temperature at ground level.\textsuperscript{3} The wind direction\textsuperscript{1}–wind direction\textsuperscript{8} variables are binary indicators of whether the median of hourly wind direction, measured in degrees, falls into eight bins.\textsuperscript{4} Finally, the variable upwind fires is the number of fires—the large majority of which are forest fires—that are upwind of Bogotá each day. Because winds transport pollutants over considerable distances, such fires are often a significant source of ambient PM\textsubscript{2.5} and NO\textsubscript{2} in the city even when located many kilometers away. This variable is derived from satellite data on the location of fires (NASA 2022) and wind direction data from 141 airport weather stations surrounding Bogotá (NOAA 2022).\textsuperscript{5} To take into account that PM\textsubscript{2.5} and NO\textsubscript{2} from fires are transported over time, we include in our models three variables: the count of upwind fires lagged one day, two days, and three days.

We drop all data from three of Bogotá’s 13 air quality monitoring stations to fit our model of PM\textsubscript{2.5}, and from six monitoring stations to fit our model of NO\textsubscript{2} (Table A1). For both the PM\textsubscript{2.5} and NO\textsubscript{2} models, we drop all data from Fontibon station because at least 74 percent of observations for PM\textsubscript{2.5}, NO\textsubscript{2} and all weather variables are missing, and we drop all data from Móvil 7ma station because it is located next to a main transportation artery, and as a result, its measurements are not representative of the surrounding area.\textsuperscript{6,7,8} For the PM\textsubscript{2.5} model, we also drop all data from Puente Aranda station because 61 percent of PM\textsubscript{2.5} data are missing. And for the NO\textsubscript{2} model, we also drop all data from four stations—MinAmbiente, San Cristóbal, Suba, and Usaquén—because each is missing at least 89 percent of NO\textsubscript{2} data.\textsuperscript{9} Having dropped data from those monitoring station, the regression sample for our city-wide PM\textsubscript{2.5} models comprises 29,270 station-days, and the sample for our city-wide NO\textsubscript{2} models comprise 22,192 station-days.

4.3. Results

4.3.1. PM\textsubscript{2.5}

Results from our main specification, a city-level model that pools station-days from all the monitoring station in our sample (Equation (1)), indicate that on average, between March 2020 and June 2022, the lockdown reduced ambient PM\textsubscript{2.5} daily concentrations in Bogotá by 15 percent from a counterfactual level of 21.23 μg/m\textsuperscript{3} to a lockdown level of 18.01 μg/m\textsuperscript{3} (Tables 2 and A2). The

\textsuperscript{3} A thermal inversion occurs when air temperature at higher altitude exceeds that at lower altitude and the warm air layer traps pollutants close to the ground. This phenomenon helps to explain high concentrations of pollution during early morning and late evening hours in some months of the year. Following Bonilla (2019), we use thermal inversion data from the Guaymaral monitoring station for all of Bogotá because the variable temperature\textsuperscript{20m} is available only for this station. Because Bogotá is located on a plateau, thermal inversion generally occurs throughout the city.

\textsuperscript{4} The bins are defined by the following ranges expressed in degrees: (1) 337–360 and 0–22.5, (2) 22.5–67.5, (3) 67.5–112.5, (4) 112.5–167.5, (5) 167.5–202.5, (6) 202.5–247.5, (7) 247.5–292.5, and (8) 292.5–337.

\textsuperscript{5} We calculate upwind fires as follows. First we map out a rectangle 845 km to the north of Bogotá, 820 km to the south, 1212 km to the west, and 1563 km to the east. Next, we divide this rectangle into four quadrants, NE, SE, SW, and NW. We define the prevailing wind direction for each quadrant on each day of our study period as the mode of hourly wind direction (NE, SE, SW, and NW) at all airports in that quadrant on that day using data from January 1, 2015, to February 28, 2022. Finally, we count the number of fires upwind of Bogotá on each day as the number of fires for which the quadrant where the fire was located and prevailing wind direction match. For example, a fire on January 1, 2015 in the NE quadrant would be counted as an upwind fire if the prevailing wind direction on that day was NE.

\textsuperscript{6} In all cases of monitoring stations that lack a significant percentage of data, the temporal pattern of missing data is decidedly nonrandom: the major percentage of problematic observations occur in the early years of our panel. As a result, including data from these stations has the potential to bias our treatment effect estimates by systematically putting more weight on observations from more recent years. The reason for missing data from the early years of our panel is that at many monitoring stations, capacity to measure certain pollutants was only developed fairly recently. At five stations—Fontibon, MinAmbiente, Móvil 7ma, San Cristóbal, and Suba—capacity to monitor PM\textsubscript{2.5} was added between 2014 and 2018 and capacity to monitor NO\textsubscript{2} was added between 2019 and 2021. Finally, at Usaquén station, capacity to monitor NO\textsubscript{2} was only added in 2021.

\textsuperscript{7} Data from roadside monitors are typically dropped from analyses of the impact of air pollution on human health (Ostro 2004, 36). Although major roads like Carrera 7ma in Bogotá generate high ambient concentrations of pollutants in the immediate surrounding area, these concentrations fall precipitously within a few hundred meters (e.g., Cao et al., 2020). As a result, including observations from Móvil 7ma monitoring station could bias our econometrically estimated treatment effect estimates downward (larger negative effect). The reason is that the estimated effect of the COVID lockdown on PM\textsubscript{2.5} and NO\textsubscript{2} at Móvil 7ma monitoring station is large relative to the effect at other stations included in the analysis mostly because the baseline prelockdown level of PM\textsubscript{2.5} at Móvil 7ma (the 2010–2019 average) is higher than for other monitoring stations.

\textsuperscript{8} For MinAmbiente station, we impute missing temperature observations using values from its closest neighboring station (MinAmbiente, Móvil 7ma). Spatial variation in temperature across Bogotá’s monitoring stations is not large. For average annual temperature (2010–2020), the coefficient of variation across monitoring stations is 8 percent.

\textsuperscript{9} In principle, stakeholders in Bogotá could have strategically avoided pollution hotspots when siting air quality monitors (e.g., Grainger and Schreiber 2019). However, the location of the Móvil 7ma monitoring station next to a major transportation artery where levels of pollution are significantly higher than the surrounding area indicates that not all of the city’s air quality monitoring stations were strategically sited. The systematic siting of air quality monitoring stations in places with relatively low levels of pollution would likely bias our treatment effect estimates upward (smaller negative effect). As discussed in Section 4.3.3, the magnitude and statistical significance of our station-level treatment effect estimates is positively correlated with the counterfactual (2010–2019 average) level of pollution. Hence, strategic siting would imply our treatment effect estimates are too conservative. We are grateful to an anonymous reviewer for raising this issue.
counterfactual is the population-weighted average level of PM$_{2.5}$ for the 10 years preceding the COVID-19 lockdown.

Results from the model that includes month-specific treatment variables (Equation (2)) show that the lockdown had heterogeneous temporal effects. Thirteen of the 16 monthly treatment effects estimates are statistically significant (Table 2; Fig. 4). These effects were largest in April 2020 (−30 percent), May 2020 (−45 percent), October 2020 (−19 percent), and May 2021 (−34 percent).

Finally, results from the monitoring station-level models suggest some spatial variation in the effect of the lockdown on PM$_{2.5}$ concentrations (Equation (3)). Station-specific treatment effects were highest for Usaquén in the northeast (−29 percent), Centro Alto Rendimiento in the center (−23 percent) and Tunal in the southwest (−23 percent) (Table 2 and Figure A7).

4.3.2. NO$_{2}$

Results from our aggregate city-level model (Equation (1)), indicate that on average, between March 2020 and June 2021, the lockdown reduced ambient daily NO$_{2}$ average concentrations by 21 percent from a counterfactual (prelockdown average for 2010–2019) level of 33.58 μg/m$^3$ to a lockdown level of 26.71 μg/m$^3$ (Tables 3 and A3).

As for the temporal variation in the treatment effect (Equation (2)), the lockdown had statistically significant effects in nine of the 16 months of the lockdown (Table 3 and Fig. 4). These effects were largest in March 2020 (−51 percent), April 2020 (−47 percent), May 2020 (−26 percent), April 2021 (−29 percent), and May 2021 (−29 percent).

Finally, results from the monitoring station-level models suggest some spatial variation in the effect of the lockdown on NO$_{2}$ concentrations (Equation (3)). Treatment effects were largest for Carvajal in the southwest (−42 percent) and Guaymaral in north (−29 percent) (Table 3 and Figure A7).

4.3.3. Discussion

The temporal variation in the estimated effects of the lockdown for both PM$_{2.5}$ and NO$_{2}$ is likely explained by two moderating factors: the historical temporal pattern of air quality (described in Section 2.1) and the temporal variation in the lockdown’s stringency (described in Section 2.2). Regarding the former, any policy intervention, including the COVID-19 lockdown, is more likely to have a discernible effect on air quality in months when air quality is typically (i.e., in the prelockdown years in our sample) relatively poor—the first and last quarters of the year (Figures A3 and A4). Regarding the latter, the lockdown is more likely to have discernible effects when it entails strict measures that substantially limit mobility and economic activity.

Hence, the highly significant, large negative estimated monthly treatment effects for PM$_{2.5}$ and NO$_{2}$ in March, April and May 2020 and April and May of 2021 are likely due to the fact that air quality in March and April is typically relatively poor and lockdown restrictions in March and April of 2020 were relatively stringent. The lack of large, highly significant treatment effects in June through August 2020 likely reflects the fact that during these months, air quality is generally relatively good and lockdown restrictions were relatively lax. The highly significant, relatively large negative estimated treatment effect for PM$_{2.5}$ in October 2020 may reflect the reimposition of Bogotá’s license plate-based driving restrictions program on September 29 and/or the launch of a fleet of new low-emissions buses on October 13.

Because, as noted in the previous section, motor vehicles are the main sources of PM$_{2.5}$ and NO$_{2}$ in Bogotá, the causal mechanism for our estimated negative treatment effects is presumably that the lockdown reduced trips and therefore vehicular emissions. Visual inspection suggests that our monthly treatment effect estimates are correlated with monthly averages of Waze smart phone application data on the percentage change in traffic congestion intensity relative to the prelockdown week of March 2–8 (Fig. 4 Panel C). To further explore this hypothesis, we regress the log of pollutant concentration onto the percentage change in traffic congestion using day-level city-wide data. The results indicate that traffic congestion is positively correlated with pollutant concentrations (Table A4).

For PM$_{2.5}$ (NO$_{2}$), on average, a percentage point reduction in traffic congestion intensity leads to a 0.5 (0.6) percent reduction in pollution concentration.

A variety of factors might explain the spatial variation in our treatment effects. One is the average levels of ambient pollution in untreated years. As in the case of temporal variation in treatment effects, we are more likely to be able to discern an effect when and where average pretreatment levels of pollution were relatively high. For PM$_{2.5}$, that may help explain the relatively large estimated treatment effect for Tunal and Centro Alto Rendimiento monitoring stations where average pretreatment daily levels of PM$_{2.5}$ (20 μg/m$^3$ and 19 μg/m$^3$) were third and fourth highest among all monitoring stations in Bogotá (Table 2). And it may help explain the relatively small effects for Guaymaral and San Cristóbal stations where pretreatment levels (14 μg/m$^3$ and 11 μg/m$^3$) were among the lowest in the city (Table 2). For NO$_{2}$, pretreatment levels of pollution may help explain the relatively large estimated treatment effect for Carvajal station, where average pretreatment daily levels of NO$_{2}$ were highest among all stations included in our NO$_{2}$ model (49 μg/m$^3$) (Table 3). Another potential spatial moderator is congestion from commuter traffic, the type of congestion most likely to have been affected by the lockdown. The lockdown likely had larger effects on PM$_{2.5}$ and NO$_{2}$ in areas with higher baseline levels of congestion due specifically to commuting. Unfortunately, to our knowledge, the commuter traffic data needed to explore that hypothesis are not available.

Placebo tests provide some assurance that our aggregate city-level treatment effect estimate is robust. For each pollutant (PM$_{2.5}$ and NO$_{2}$), we fit three models with placebo treatments (Equation (1)) corresponding to the same 16 months as the actual lockdown (March through June of the following year) but for three previous years. In four of these six models, the placebo treatment is not statistically significant (Table A5 and Figure A5). In both models where it is significant, the sign is positive, not negative.

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10 Waze traffic congestion intensity measures whether traffic at a given geographic point is slower than “free-flow”—the expected speed under no-jam conditions (IADB and IADB-Invest 2020).
5. Effect of reductions in ambient PM\(_{2.5}\) and NO\(_2\) on human mortality

We simulate both long-term and short-term effects of the reductions in ambient PM\(_{2.5}\) and NO\(_2\) due to the lockdown estimated in the previous section. The long-term effects concern hypothetical permanent reductions. The first question we address is this: if the average annual treatment effects estimated in the previous section became permanent—that is, if PM\(_{2.5}\) and NO\(_2\) concentrations permanently fell by 15 and 21 percent below historical annual averages so that Bogotá’s residents enjoyed them from cradle to grave—how many fewer residents would die each year from exposure to PM\(_{2.5}\) and NO\(_2\)? By contrast, short-term effects concern a hypothetical temporary reduction in PM\(_{2.5}\) and NO\(_2\) and address this question: how many fewer people in Bogotá would have died from March 2020 through June 2021 if the monthly treatment effects estimated in the previous section occurred ceteris paribus—that is, if each month PM\(_{2.5}\) and NO\(_2\) concentrations fell by the amounts listed in the columns of Tables 2 and 3 but nothing else changed compared with prepandemic times. Although estimating the long-term effects of Bogotá’s COVID-19 lockdown avoided deaths is by definition a hypothetical exercise and therefore necessarily relies on simulation modeling, in principle we could estimate actual avoided short-term mortality due to improvements in air quality associated with Bogotá’s COVID-19 lockdown. Appendix 1 discusses the challenges of using econometric and epidemiological models to do that. Note that simulated long-term effects will always be larger than short-term effects because the former model the annual effects of reduced exposure over residents’ lifetimes whereas the latter model the contemporaneous effects of reduced exposure over a 16-month period. Given the motivation for our analysis—to develop credible objective estimates of the benefits of permanent reductions in PM\(_{2.5}\) and NO\(_2\) in Bogotá—our estimates of long-term effects are more important for our purposes than our short-term estimates.

5.1. Modeling framework

The foundation of our approach to simulating the effect of reductions in ambient PM\(_{2.5}\) and NO\(_2\) in Bogotá on both long-term and short-term premature mortality is relative risk (RR)—an estimate derived from epidemiological studies of the effect of exposure to these pollutants on the risk of death from specific causes, such as cancer and stroke. To estimate long-term mortality, we use RRs derived from studies of the effects of long-term exposure on the annual risk of death from specific causes. And to estimate short-term mortality, we use RRs derived from studies of the effect of short-term spikes in pollution on the daily risk of death from specific causes.

In general, we have designed and parameterized our modeling framework so as to generate conservative estimates of avoided mortality. For example, we simulate the effects of reductions in pollution on specific death causes rather than on death from all natural causes because the former approach generally yields lower estimates of mortality (Burnett and Cohen 2020).

5.1.1. Long-term effects

To estimate the effects of PM\(_{2.5}\) and NO\(_2\) on long-term mortality, we calculate

$$AD = \sum_{c=1}^{C} \sum_{t=1}^{T} \left( population_{ct} \times annual\ incidence_{ct} \times PIF[C1, C2]_{ct} \right)$$

(4)

### Table 6
Parameters used to calculate value of statistical life (VSL).

| ID | Description | Units | Value | Source |
|----|-------------|-------|-------|--------|
| A  | VSL OECD    | 2011 IS (PPP) | 3,830,000 | WB/IHME (2016) |
| B  | Average OECD GDP per capita | 2011 IS (PPP) | 37,000 | WB/IHME (2016) |
| C  | Colombia GDP per capita 2011 | 2011 COP | 13,556,411 | WB/OECD (2021a) |
| D  | Exchange rate COP to $I | N/A | 1180 | OECD (2021) |
| E  | Colombia GDP per capita 2011 | 2011 IS (PPP) | 11,489 | Formula: C/D |
| F  | Income elasticity of VSL | N/A | 1.2 | WB/IHME (2016) p. 49 |
| G  | Colombia VSL 2011 | 2011 IS (PPP) | 941,180 | Formula: A*(E/B)^F |
| H  | Colombia CPI 2011 | N/A | 103 | WB/OECD (2021b) |
| I  | Colombia CPI 2019 | N/A | 141 | WB/OECD (2021b) |
| J  | %ΔP | % | 0.4 | Formula: (I-H)/H |
| K  | Colombia GDP per capita 2011 | 2017 IS (PPP) | 12,481 | WB/OECD (2021c) |
| L  | Colombia GDP per capita 2019 | 2017 IS (PPP) | 14,585 | WB/OECD (2021c) |
| M  | %ΔY | % | 0.2 | Formula: (L-K)/K |
| N  | Colombia VSL 2019 | 2019 IS (PPP) | 1,569,770 | Formula: G*((1 + J + M)/F) |

\%Δ P = percentage change in price level; \% Δ Y = percentage change in per capita GDP; COP = Colombian pesos; GDP = gross domestic product; IS = international United States dollars; PPP = purchasing power parity.
where \( e \) indexes death causes, \( a \) indexes age cohorts, \( AD \) is total attributable deaths from all causes, \( annual \ incidence \) is the annual risk of death, \( PIF \) is the potential impact fraction, \( C1 \) is the average annual baseline ambient PM\(_{2.5}\) or NO\(_2\) concentration, and \( C2 \) is the average annual endline concentration. We calculate the \( PIF \) for each death cause and age group as \(^{11}\)

\[
PIF[C1, C2]_{ae} = \left(1 - \frac{RR_{ae,c2}}{RR_{ae,c1}}\right)
\]

(5)

We use this modeling framework to estimate two type of effects. First we estimate the effect on long-term mortality of the reduction in pollution associated with the COVID-19 lockdown. For this simulation, \( C1 \) is the prelockdown 2010–2019 average annual level of pollution, and \( C2 \) is the lockdown level. Second, we estimate the average annual effect of prelockdown levels of pollution (i.e., the counterfactual). For this simulation, \( C1 \) remains the 2010–2019 average annual level of pollution and \( C2 \) is the theoretical minimum risk level (TMRL) below which pollution has negligible effects on human health.

5.1.2. Short-term effects
To estimate the effects of PM\(_{2.5}\) and NO\(_2\) on short-term mortality, we calculate

\[
AD = \sum_{d=1}^{467} \sum_{a=1}^{n} \left( population \times daily \ incidence, \times PIF[c1, c2]_{ae}\right)
\]

(6)

where \( d \) indexes calendar days from March 20 through June 30 of the following year and \( daily \ incidence \) is the daily baseline risk of death from cause \( e \). Furthermore,

\[
PIF[c1, c2]_{ae} = \left(1 - \frac{RR_{de,c2}}{RR_{de,c1}}\right)
\]

(7)

where \( c1 \) is the baseline ambient PM\(_{2.5}\) or NO\(_2\) concentration for each day of the year, and \( c2 \) is the endline concentration for each day.

Here, too, we estimate two types of effects: the effect on short-term mortality of the reduction in pollution associated with the COVID-19 lockdown, and the average daily effect of prelockdown levels of pollution (i.e., the counterfactual). For the former analysis, \( c1 \) is pre-lockdown 2010–2019 average daily level of pollution and \( c2 \) is the lockdown level. And for the latter, \( c1 \) remains the 2010–2019 average daily level of pollution and \( c2 \) is the TMRL.

5.2. PM\(_{2.5}\)

5.2.1. Long-term effects
To estimate effects of PM\(_{2.5}\) on long-term mortality, we use RR functions drawn from the integrated exposure-response models in GBD (2019), which have become the state-of-the-science tools for simulating the effects of PM\(_{2.5}\) on human health (Table 4).\(^ {12}\) They are used by, among others, the WHO, the World Bank, and the annual Global Burden of Disease (GBD) studies (Burnett and Cohen 2020). We estimate attributable deaths for the six death causes included in GBD (2019): acute lower respiratory infection (ALRI); cancer of the lung, trachea, and bronchus; chronic obstructive pulmonary disease (COPD); ischemic heart disease (IHD); type 2 diabetes mellitus; and stroke. GBD (2019) presents PM\(_{2.5}\) risk curves (RR as a function of PM\(_{2.5}\) levels) specific to death causes and age groups. In the case of IHD and stroke, GBD (2019) provides curves for five-year cohorts spanning ages 25–99, and we use the appropriate curve for each age cohort. For all other death causes, GBD (2019) provides a single curve for all ages and we use that curve.\(^ {13}\)

For each death cause, we use age-specific population, \( annual \ incidence \), and (where available) RRs to calculate changes in avoided deaths. For ALRI, we use population and \( annual \ incidence \) for cohorts spanning ages 0–99. For our other five death causes, we use population and \( annual \ incidence \) for age cohorts spanning ages 25–99. Our data on \( annual \ incidence \) for our six modeled death causes are from Colombia’s 2018 national population census (DANE 2018) (Table 4). These data classify death causes according to the 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD-10), the medical classification list used by the WHO. We map the ICD-10 codes to our six death causes using the correspondence published by the Institute for Health Metrics and Evaluation (Table A6). The \( annual \ incidence \) for each cause is the number of deaths per year divided by the total population (ages 0–99 for ALRI and ages 25–99 for the other five causes). Our data on population are from the 2018 national population census (DANE 2018). They are disaggregated at the level of five-year age cohorts.

\(^{11}\) Because changes in concentration levels are often small, we improve precision when matching pollution levels with the corresponding RR by prorating RR. That is, \( RR_{x} = RR_{int(x)} + (RR_{int(x)} - 1) - RR_{int(x)} \times frac(x) \) where \( x \) is the concentration level, \( int(x) \) is the integer part of the concentration level, and \( frac(x) \) is the decimal part of the concentration level. For example, for a value of PM\(_{2.5}\) = 11.15, we calculate \( RR_{11.15} = RR_{11} + (RR_{12} - RR_{11}) \times 0.15 \). For PM\(_{2.5}\) Values smaller than 10, we rounded to two significant digits to match the GBD (2019) RR format. The two significant digits follow the pattern (0, 0.01, 0.02, ..., 1, 1.1, 1.2, ..., 11, 12, ..., 110, 120, ..., 1100, 1200, ..., 2500).

\(^{12}\) Produced by the Institute for Health Metrics and Evaluation at the University of Washington and originally commissioned by the World Bank, the Global Burden of Disease (GBD) is a global research program that assesses mortality and morbidity from major diseases, injuries, and risk factors. We follow the implementation of the integrated exposure-response models in GBD (2019).

\(^{13}\) GBD (2019) defines “all ages” as 0–99 for ALRI, which is common among people of all ages and 25–99 for the other five death causes, which are less common among younger people.
...eventually, which is probable albeit not certain, avoided COVID-19 deaths will not be a benefit of such future policies and programs. In addition, reasons. First, the broad aim of our study is to generate objective estimates of the benefits of air quality improvements associated with Bogotá’s lockdown would save 303 lives per year, an 18 percent reduction from the 1725 annual counterfactual deaths from PM$_{2.5}$ exposure (Table 5).

5.3. NO$_2$

5.3.1. Long-term effects

We simulate the effects on long-term mortality of the reduction in NO$_2$ levels caused by the COVID-19 lockdown using a log-linear RR model along with estimated effects drawn from a systematic meta-analysis of epidemiological studies. Specifically, we estimate RRs as

$$RR_{s,c,k} = \exp(\gamma_s \times C_k) (k = 1, 2)$$

(8)

where $\gamma_s$ are derived from the effect estimates reported by Orellano et al. (2020): a 0.9 and 0.7 percent increase in cardiovascular and respiratory mortality per 10 $\mu g/m^3$ increment in PM$_{2.5}$ (Table 4). Once again, our data on population are from the 2018 national population census (DANE 2018). For daily incidence, we use the annual rate of cardiovascular, respiratory, and cerebrovascular death in 2018 for Bogotá divided by 365 days (DANE 2018). To simulate the effect on short-term mortality of the reduction in PM$_{2.5}$ levels caused by the lockdown, $c_1$ is the 10-year historical citywide average (2010–2019) values of PM$_{2.5}$ for every calendar day, and $c_2$ is calculated as $c_1$ times one plus the estimated monthly treatment effect. To simulate the counterfactual short-term mortality due to PM$_{2.5}$, $c_2$ is the TMRL (5 $\mu g/m^3$).

Our simulation suggests that if they occurred cetetis paribus, the reductions in PM$_{2.5}$ concentrations from March 2020 through June 2021 due to Bogotá’s lockdown would have avoided 55 premature deaths, a 19 percent reduction from the 285 short-term deaths from PM$_{2.5}$ exposure that would have occurred otherwise (Table 5).

5.3.2. Short-term effects

Once again, our data on daily incidence, we use the annual rate of cardiovascular, respiratory, and cerebrovascular death from March 2020 through June 2021 associated with the Bogotá’s lockdown Avoided 55 premature deaths, a 19 percent reduction from the 555 short-term deaths from PM$_{2.5}$ exposure (Table 5).

5.4. NO$_2$
\(\gamma_5\) are derived from the effect estimates reported in Mills et al. (2016): an 8.8 and 1.1 percent increase in cardiovascular and respiratory deaths per 10 \(\mu g/m^3\) increment in \(\text{NO}_2\) (Table 4). Pollutant concentrations \(c1\) and \(c2\) are analogous to those used in our simulation of \(\text{PM}_{2.5}\) short-term deaths. Here, too, we use a TMRL of 10 \(\mu g/m^3\). The remaining parameters are the same as those used to model the effects of \(\text{PM}_{2.5}\) on short-term deaths.

Our simulation suggests that if they occurred \textit{ceteris paribus}, the reductions in \(\text{NO}_2\) concentrations from March 2020 through June 2021 due to Bogotá’s lockdown would have avoided 101 premature deaths, an 18 percent reduction from the 563 short-term deaths from \(\text{NO}_2\) exposure that would have occurred otherwise (Table 5).

### 5.4. Combined effects of \(\text{PM}_{2.5}\) and \(\text{NO}_2\)

Here, we calculate total avoided mortality due to reductions in \(\text{PM}_{2.5}\) and \(\text{NO}_2\). We use the standard approach to avoid potential double counting of avoided deaths due to multiple risk factors (WB/IHME 2016; Ezzati et al., 2003). First, for each death cause included in our study, we calculate a single total PIF according to the formula

\[
PIF_{\text{total},e} = 1 - \prod_{i=1}^{n} (1 - PIF_{i,e})
\]

where \(e\) indexes death causes and \(i\) indexes \(\text{PM}_{2.5}\) and \(\text{NO}_2\). Next, we use this total PIF to calculate total attributable deaths (ADs) for each death cause. Finally, we sum total ADs for all death causes. A complication is that our simulation of long-term ADs for \(\text{PM}_{2.5}\) uses more disaggregated death causes than does our simulation for \(\text{NO}_2\), which reflects the epidemiological studies that underpin these simulations (BDI 2019; Atkinson et al., 2018). We map \(\text{PM}_{2.5}\) long-term death causes to \(\text{NO}_2\) long-term death causes as follows: IHD and stroke comprise cardiovascular death causes, and ALRI and COPD comprise respiratory death causes. For each of these aggregated \(\text{PM}_{2.5}\) death cause categories, we recover \(PIF_{\text{total},e}\) using Equation (6) by substituting values of total AD, population, and annual incidence from Tables 4 and 5, and then solving for \(PIF_{\text{total},e}\).

We find that a permanent reduction in ambient \(\text{PM}_{2.5}\) and \(\text{NO}_2\) of the same magnitude as that generated by Bogotá’s lockdown would save 640 lives per year, a 23 percent reduction from the 2752 annual long-term deaths from \(\text{PM}_{2.5}\) and \(\text{NO}_2\) exposure that would occur otherwise (Table 5). In addition, we find that if they occurred \textit{ceteris paribus}, the reductions in \(\text{PM}_{2.5}\) and \(\text{NO}_2\) concentrations from March 2020 through June 2021 due to Bogotá’s lockdown would have avoided 155 premature deaths, a 19 percent reduction from the 841 short-term deaths from \(\text{PM}_{2.5}\) and \(\text{NO}_2\) exposure that would have occurred otherwise (Table 5).

### 6. Valuation of avoided mortality

We use benefit transfer methods to estimate the monetary value of avoided mortality. Following WB/IHME (2016) and Narain and Sall (2016), we value avoided deaths using an off-the-shelf estimate of the value of statistical life (VSL) circa 2011 generated by the Organization for Economic Co-operation and Development (OECD), adjusted for the difference in per capita income in Colombia and for inflation and income growth in Colombia after 2011. The OECD VSL estimate is from a systematic meta-analysis of more than 1000 stated-preference studies of willingness to pay for marginal reductions in mortality risk in more than 30 industrialized and developing countries (Lindheim et al., 2011; OECD, 2012). We adjust it using the following formula (Narain and Sall 2016):

\[
VSL_{c,2019} = VSL_{OECD,2011} \times \left(\frac{\epsilon_{c,2011}}{\epsilon_{OECD,2011}}\right)^{\varepsilon} \times (1 + \%\Delta Y + \%\Delta P)^{\varepsilon}
\]

where \(c\) is the country (Colombia), VSL is value of statistical life, \(Y\) is per capita gross domestic product, \(\varepsilon\) is the income elasticity of the VSL, \(\%\Delta P\) is the percentage change in Colombia’s consumer price index from 2011 to 2019, and \(\%\Delta Y\) is percentage change in Colombia’s GDP during the same period. VSL is expressed in constant 2019 USD adjusted for purchasing power parity (PPP). Table 6 summarizes the parameters used in this calculation. They result in a value of US $1,569,770 per avoided mortality.

The total value of the simulated effect of the lockdown on avoided long-term mortality from both \(\text{PM}_{2.5}\) and \(\text{NO}_2\) is $1 billion per year, which represents 1.2 percent of Colombia’s 2019 GDP (Table 5). The total value of the simulated effect of the lockdown on avoided short-term mortality from both pollutants is $244 million, which represents 0.3 percent of Colombia’s 2019 GDP.

### 7. Conclusion

We have used panel-data econometric models to estimate the effect of Bogotá’s COVID-19 lockdown on \(\text{PM}_{2.5}\) and \(\text{NO}_2\) concentrations, epidemiological models to estimate the effect of reductions in those concentrations on both long-term and short-term mortality, and benefit transfer methods to estimate the monetary value of the avoided mortality. We find that on average, the lockdown cut daily \(\text{PM}_{2.5}\) concentrations by 15 percent and daily \(\text{NO}_2\) concentrations by 21 percent. However, the size of that reduction varied considerably over the course of the year and, to a lesser extent, across Bogotá’s neighborhoods. We find that the greatest reductions occurred in areas with the worst air quality and in months when (i) air quality was poor as a result of seasonal meteorological conditions and (ii) lockdown restrictions were most stringent. We find that permanent reductions in \(\text{PM}_{2.5}\) and \(\text{NO}_2\) equivalent to those generated by the lockdown would reduce long-term premature deaths from these pollutants by 23 percent each year, and that if they occurred \textit{ceteris paribus}, the reductions in \(\text{PM}_{2.5}\) and \(\text{NO}_2\) concentrations in 2020–2021 due to Bogotá’s lockdown would have reduced

short-term deaths from these pollutants by 19 percent. Finally, we find that the monetary value of avoided long-term mortality is $1 billion per year, and that from avoided short-term mortality is $244 million.

Our study has several limitations. Given the identification challenges created by the COVID-19 pandemic, we have relied on simulations rather than observational methods to estimate the effect of the lockdown on short-term premature mortality. These simulations, in turn, have limitations. For example, because of a shortage of site- and source-specific epidemiological studies, the models we use to estimate mortality effects are based on a meta-analysis of findings from studies conducted in a range of developed and developing countries, not just Colombia. Finally, because we lack site-specific studies valuing marginal changes in mortality risk, we use benefit transfer methods that rely on meta-analyses of valuation studies conducted in a range of countries. Despite these limitations, we believe we have generated credible estimates of the effects of the lockdown.

What are the policy implications of our findings? As noted in the Introduction, they could help enhance the salience of Bogotá’s chronic air pollution problems. Although local stakeholders’ first-hand experience of improved air quality during the lockdown may influence their attitudes more, in principle, our estimates of the magnitude of the improvement and the number of lives it could save (almost one-quarter of premature deaths due to air pollution each year) and the economic cost (more than $1 billion) can help buttress whatever policy momentum that experience has created. In particular, our estimates may help strengthen the case for long-debated investments in electromobility (the electrification of the TransMilenio system), public transportation (a subway system), and renewal of the truck fleet—all the focus of proposals to improve air quality in Bogotá.

Beyond helping to make the general case for improving air quality, our study has implications for how policies and programs could be targeted both temporally and spatially to enhance their efficiency. As for temporal targeting, we find that lockdown restrictions cut PM$_{2.5}$ and NO$_2$ concentrations the most in those months when seasonal meteorological conditions exacerbated air pollution—January, February, March, and April. As for spatial targeting, we find that the restrictions tended to reduce particulate pollution the most in those neighborhoods of the city where geophysical and meteorological conditions exacerbate air quality—the southwest and center. This treatment effect heterogeneity implies that it may be possible to enhance the efficiency of air pollution interventions by targeting them to certain seasons and geographic areas.

Conflict of interest and financial disclosure statements

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APPENDIX 1. ESTIMATING ACTUAL VERSUS HYPOTHETICAL AVOIDED SHORT-TERM MORTALITY

Econometric modeling. In principle, we could econometrically identify short-term effects of the reductions in ambient PM$_{2.5}$ and NO$_2$ associated with Bogotá’s lockdown by regressing observed deaths during our entire 12-year panel onto a lockdown indicator variable along with other time-varying covariates. In practice, however, identification would likely be confounded by the pandemic, both because it caused a significant contemporaneous spike in mortality and because it likely affected Bogotá residents’ incentives to seek health care, their behaviors and emotional states, the provision of health care, and the reporting of mortality data.

To explore this issue, we analyze 2015–2021 daily data on deaths by cause for the six death causes commonly associated with exposure to air pollution: acute lower respiratory infection (ALRI); cancer of the lung, trachea, and bronchus; chronic obstructive pulmonary disease (COPD); ischemic heart disease (IHD); type 2 diabetes mellitus; and stroke (GBD 2019). For two of these death causes—diabetes and stroke—we find a positive correlation between the COVID-19 lockdown and deaths despite the significant improvements in air quality during the lockdown described in the previous section (Figure A6). These two positive correlations persist even after controlling for COVID-19 cases and other potentially confounding factors (Table A7). The implication is that unobserved confounders likely bias upward (smaller negative effects) econometrically estimated short-term mortality effects of the reductions in air pollution associated with the lockdown.

Epidemiological modeling. Using epidemiological models to simulate deaths avoided as a result of reductions in air pollution associated with the lockdown also may not accurately reflect the true number of deaths avoided. The reason is that the epidemiological models used to generate these estimates are based on prepandemic empirical correlations between daily pollution levels and daily premature mortality. However, these correlations were likely different during the pandemic as a result of the same confounding factors listed above—patients’ incentives to seek medical care, their behavior and emotional states, their access to medical care, etc. These confounding factors likely have countervailing effects on simulated short-term mortality estimates, and the overall net effect is uncertain. On one hand, some likely bias these estimates upward (smaller negative effects). Bogotá residents presumably were more hesitant to visit hospitals during the pandemic for fear of contracting COVID-19, and access to all manner of health care was more restricted. That, in turn, implies that during the pandemic, spikes in PM$_{2.5}$ and NO$_2$ caused more deaths from exposure to air pollution.
than in prepandemic times, and as a result, reductions in the frequency of those spikes associated with the lockdown would have avoided more deaths. But other confounding factors could bias simulated estimates of actual avoided death downward (larger negative effects). For example, Bogotá residents presumably stayed indoors more during the pandemic and were therefore less exposed to air pollution. That, in turn, implies that spikes in PM$_{2.5}$ and NO$_2$ caused fewer deaths during the pandemic than in prepandemic times, and as a result, reductions in the frequency of those spikes associated with the lockdown would have avoided fewer deaths.

Appendix. Tables

Table A1
Monitoring stations: Population weights and percentages of observations missing for air quality and weather variables January 1, 2010 to February 28, 2022

| Monitoring station | Population weight for PM$_{2.5}$ | Population weight for NO$_2$ | PM$_{2.5}$ | NO$_2$ | Wind speed | Wind direction | Temperature | Precipitation | Temperature 20 m |
|--------------------|----------------------------------|-------------------------------|------------|-------|------------|---------------|-------------|--------------|-----------------|
| Carvajal           | 0.08                             | 0.07                          | 39         | 37    | 5          | 5             | 4           | 5             | 100             |
| Centro Alto        | 0.07                             | 0.07                          | 16         | 15    | 5          | 5             | 3           | 3             | 100             |
| Rendimiento        | n/a                             | n/a                           | 75         | 76    | 74         | 74            | 74          | 95            | 100             |
| Guaymaral          | 0.03                             | 0.08                          | 44         | 27    | 11         | 6             | 3           | 4             | 6               |
| Kennedy            | 0.23                             | 0.20                          | 8          | 25    | 5          | 7             | 4           | 20            | 100             |
| Las Ferias         | 0.12                             | 0.24                          | 24         | 30    | 4          | 5             | 3           | 4             | 100             |
| MinAmbiente        | 0.03                             | n/a                          | 39         | 95    | 20         | 20            | 100         | 16            | 100             |
| Móvil 7ma          | n/a                             | n/a                          | 51         | 90    | 28         | 32            | 30          | 30            | 100             |
| Puente Aranda      | n/a                             | 0.10                          | 61         | 20    | 10         | 12            | 3           | 9             | 100             |
| San Cristobal      | 0.11                             | n/a                          | 43         | 89    | 14         | 8             | 7           | 13            | 100             |
| Suba               | 0.11                             | n/a                          | 40         | 90    | 4          | 4             | 11          | 6             | 100             |
| Tunal              | 0.15                             | 0.24                          | 16         | 16    | 6          | 4             | 13          | 2             | 100             |
| Usaquén            | 0.06                             | n/a                          | 22         | 89    | 11         | 6             | 32          | 13            | 100             |

a Dropped from the analysis because of missing observations.
b Dropped from the analysis because located next to a main road.

Table A2
Effect of Bogotá’s lockdown on ambient PM$_{2.5}$ concentrations; two-way fixed effects regression results with covariate coefficients (s.e.)

| Station(s)         | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  | (10) |
|--------------------|------|------|------|------|------|------|------|------|------|------|
| POST               | -0.16*** | -0.12*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_MAR20         | -0.13*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_APR20         | -0.36*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_MAY20         | -0.60*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_JUN20         | -0.12* | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_JUL20         | -0.13*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_AUG20         | -0.14** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_SEP20         | -0.16*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_OCT20         | -0.21*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_NOV20         | -0.01 | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_DEC20         | -0.01 | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_JAN21         | -0.10* | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_FEB21         | -0.10* | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_MAR21         | -0.12** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |
| POST_APR21         | -0.12*** | -0.26*** | -0.05* | -0.10*** | -0.19*** | -0.16*** | -0.11** | -0.19*** | -0.26*** | -0.34*** |

(continued on next page)
Table A2 (continued)

| Station(s)        | (1) | (2) | (3)          | (4)          | (5)          | (6)          | (7)          | (8)          | (9)          | (10)         | (11)         | (12)         |
|-------------------|-----|-----|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| POST_MAY21        |     |     |              |              |              |              |              |              |              |              |              |              |
| POST_JUN21        |     |     |              |              |              |              |              |              |              |              |              |              |
| rainfall          | 0.01** | 0.01** | -0.01*** | 0.01*** | -0.01*** | -0.01*** | 0.01*** | 0.02*** | 0.02*** | -0.00 | 0.01*** | 0.01*** |
| rainfall²         |     |     |              |              |              |              |              |              |              |              |              |              |
| temperature       | 0.02 | 0.00 | 0.08        | -0.02       | -0.99*** | 0.01        | 0.24        | -0.36** | -0.74*** | -0.25* | 0.13*       | 0.25         |
| temperature²      | -0.00 | -0.00 | 0.00        | -0.00       | 0.00     | -0.00       | -0.00       | -0.00** | -0.00** | 0.00 | -0.00     | -0.00**     |
| thermal inversion | 0.05** | 0.05** | 0.04***     | -0.01       | 0.08*** | 0.08***    | 0.06***     | 0.01    | 0.03   | 0.00** | 0.04*** | 0.00         |
| upwind fires      | 0.00 | 0.00 | 0.00        | 0.00        | 0.00     | 0.00        | 0.00        | 0.00    | 0.00   | 0.00 | 0.00     | 0.00         |
| upwind fires (t-1)| 0.00 | 0.00 | 0.00        | 0.00        | 0.00     | 0.00        | 0.00        | 0.00    | 0.00   | 0.00 | 0.00     | 0.00         |
| upwind fires (t-2)| 0.00 | 0.00 | 0.00        | 0.00        | 0.00     | 0.00        | 0.00        | 0.00    | 0.00   | 0.00 | 0.00     | 0.00         |
| upwind fires (t-3)| 0.00 | 0.00 | 0.00        | 0.00        | 0.00     | 0.00        | 0.00        | 0.00    | 0.00   | 0.00 | 0.00     | 0.00         |
| wind speed        | 0.05 | 0.04 | -0.00       | 0.06        | 0.18***  | -0.02*      | 0.05        | 0.21*** | 0.02   | 0.04*** | -0.01      | 0.24***      |
| wind speed²       |     |     |              |              | 0.00     | 0.00        | 0.00        | 0.00    | 0.00   | 0.00 | 0.00     | 0.00         |
| Observations      | 29,270 | 29,270 | 2697       | 3740        | 2468     | 3861        | 3571        | 2198    | 2404   | 2713 | 3205      | 2413         |
| R-squared         | 0.502 | 0.511 | 0.501      | 0.663       | 0.633    | 0.662       | 0.664       | 0.667   | 0.589  | 0.693 | 0.650     | 0.614        |

The dependent variable is the natural logarithm of PM$_{2.5}$. The independent variable of interest, POST, is an indicator equal to one for all station-days from March 21, 2020 to June 30, 2021. Models 1 and 2 include monitoring station fixed effects and weight station-day observations by population. Standard errors are clustered at the monitoring station level. Other covariates are four sets of temporal fixed effects (year, month, week, day-of-week) and wind direction1–wind direction8. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A3

Effect of Bogota’s lockdown on ambient NO$_2$ concentrations; two-way fixed effects regression results with covariate coefficients (s.e.)

| Station(s) | (1) | (2) | (3)          | (4)          | (5)          | (6)          | (7)          | (8)          | (9)          | (10)         |
|------------|-----|-----|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| POST       | -0.23*** | -0.54*** | -0.17***     | -0.34***     | -0.07***     | -0.16***     | -0.14***     | -0.18***     |              |              |
| POST_MAR20 |     |     |              |              |              |              |              |              |              |              |
| POST_APR20 |     |     |              |              |              |              |              |              |              |              |
| POST_MAY20 |     |     |              |              |              |              |              |              |              |              |
| POST_JUN20 |     |     |              |              |              |              |              |              |              |              |
| POST_JUL20 |     |     |              |              |              |              |              |              |              |              |
| POST_AUG20 |     |     |              |              |              |              |              |              |              |              |
| POST_SEP20 |     |     |              |              |              |              |              |              |              |              |
| POST_OCT20 |     |     |              |              |              |              |              |              |              |              |
| POST_NOV20 |     |     |              |              |              |              |              |              |              |              |
| POST_DEC20 |     |     |              |              |              |              |              |              |              |              |

(continued on next page)
### Table A3 (continued)

| Station(s)   | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
|              | All | All | Carvajal | Centro Alto Rend. | Guaymaral | Kennedy | Las Ferias | Puente Aranda | Tunal |
| POST_JAN21   | −0.23*** | (0.09) | | | | | | | |
| POST_FEB21   | −0.25 | (0.16) | | | | | | | |
| POST_MAR21   | −0.25 | (0.16) | | | | | | | |
| POST_APR21   | −0.34*** | (0.05) | | | | | | | |
| POST_MAY21   | −0.34*** | (0.08) | | | | | | | |
| POST_JUN21   | −0.17** | (0.06) | | | | | | | |
| rainfall     | 0.01* | (0.00) | 0.00 | 0.01*** | 0.01*** | 0.00 | 0.01*** | 0.01*** | 0.01*** |
| temperature  | 0.09** | (0.05) | −0.05 | 0.00 | −0.00*** | 0.00 | −0.00*** | 0.00 | −0.00** |
| temperature  | 0.01** | (0.01) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| thermal      | 0.03** | (0.01) | −0.03** | 0.03** | 0.03* | −0.05*** | 0.04*** | 0.02 | 0.02 |
| inversion    | 0.00 | (0.00) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| upwind fires | 0.00 | (0.00) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| upwind fires | 0.00** | (0.00) | 0.00** | 0.00** | 0.00** | 0.00** | 0.00** | 0.00** | 0.00** |
| upwind fires | 0.00 | (0.00) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| wind speed   | −0.42** | (0.15) | −0.39*** | −0.49*** | −0.47*** | −0.11 | −0.19*** | −0.15 | −0.15 |
| wind speed   | 0.06* | (0.03) | 0.00 | −0.02 | 0.08*** | 0.05*** | −0.06** | −0.00 | −0.08 |
| Observations | 22,192 | 22,192 | 2779 | 3632 | 3192 | 3196 | 2957 | 3231 | 3205 |
| R-squared    | 0.316 | 0.331 | 0.446 | 0.652 | 0.557 | 0.686 | 0.605 | 0.583 | 0.520 |

The dependent variable is the natural logarithm of NO\textsubscript{2}. The independent variable of interest, POST\textsuperscript{a}, is an indicator equal to one for all station-days from March 20, 2020 to June 30, 2021. Models 1 and 2 include monitoring station fixed effects and weight station-day observations by population. Standard errors are clustered at the monitoring station level. Other covariates are four sets of temporal fixed effects (\textit{year, month, week, day-of-week}) and \textit{wind direction\textsuperscript{1–wind direction\textsuperscript{8}}}. ***p < 0.01, **p < 0.05, *p < 0.1.

### Table A4

Correlation between pollutant concentrations and traffic congestion intensity: ordinary least squares regression results [s.e.](\%Δ)

|                          | ln (pm2.5) | ln (no2) |
|--------------------------|------------|----------|
| traffic congestion intensity\textsuperscript{a} | 0.005*** | 0.006*** |
|                          | [0.001] | [0.000] |
|                          | (0.534) | (0.581) |
| Observations\textsuperscript{b} | 709 | 709 |
| R-squared | 0.074 | 0.222 |

\%Δ=\text{exp}(β) − 1) * 100. The dependent variables are daily city-wide levels of pollution, computed as the population-weighted daily average using only data from monitoring stations included in analysis of the effect of the lockdown on pollution concentrations. The temporal range of the panel for this regression is March 20, 2020 to June 30, 2021.

\textsuperscript{a}Percentage change relative to the prelockdown week of March 2–8. Derived from Waze smart phone application data on whether traffic at a given geographic point is slower than “free-flow”—the expected speed under no-jam conditions (DB/IDB Invest 2022).

\textsuperscript{b}Observations are days.
Table A5
Placebo tests: Effect of Bogotá’s lockdown on ambient PM$_{2.5}$ and NO$_2$ concentrations; two-way fixed effects city-level regression models [s.e.]

|               | 2020-2021 | 2019-2020 | 2018-2019 | 2017-2018 |
|---------------|-----------|-----------|-----------|-----------|
| **Panel A: PM$_{2.5}$** |           |           |           |           |
| POST (actual) | $-0.16^{***}$ |           |           |           |
| POST (placebo)|           | $-0.03$   |           |           |
| POST (placebo)|           |           | $-0.06$   |           |
| Observations  | 29,270    | 23,940    | 20,592    | 14,519    |
| R-squared     | 0.504     | 0.498     | 0.500     | 0.502     |
| **Panel B: NO$_2$** |           |           |           |           |
| POST (actual) | $-0.23^{***}$ |           |           |           |
| POST (placebo)|           | $0.22^{**}$ |           |           |
| POST (placebo)|           |           | $0.34$    |           |
| Observations  | 22,192    | 18,705    | 16,602    | 12,548    |
| R-squared     | 0.316     | 0.314     | 0.312     | 0.357     |

Note: The dependent variable is the natural logarithm of PM$_{2.5}$/NO$_2$. The independent variable of interest, POST, is an indicator equal to one for all station-days on and after March 20, 2020, when Bogotá’s lockdown began, until June 30, 2021, or for the same time period in previous years. Covariates are monitoring station fixed effects, four sets of temporal fixed effects (year, month, week, day-of-week), and 16 time-varying covariates: rainfall, rainfall squared, temperature, temperature squared, temperature20m, thermal inversion, upwind fires, wind direction1–wind direction8, wind speed, and windspeed squared. Standard errors are clustered at the monitoring station level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A6
Correspondence between Global Burden of Disease (GBD, 2019) death causes, International Classification of Diseases-10 (ICD-10) codes, and death cause classification for Colombia (CEPAL/CELADE 2018)

| GBD (2019) cause | Short name | ICD-10 code | Codes available for Colombia (DANE, 2018) |
|------------------|------------|-------------|------------------------------------------|
| Chronic obstructive pulmonary disease | COPD | J41-J42.4, J43-J44.9 | J42-J44 |
| Ischemic heart disease | IHD | I20–I21.6, I21.9-I25.9, Z82.4-Z82.49 | I20, I21, I24, I25 |
| Acute lower respiratory infections | ALRI | A48.1, A70, B96.0-B96.1, B97.21, B97.4-B97.6, J09-J18.2, J18.8-J18.9, J19.6-J22.9, J85.1, J91.0, P23-P23.9, U04-U04.9, Z25.1 | J90, J11-J13, J15, J16, J18, J20-J22, J85, P23 |
| Trachea, bronchus, and lung cancer | LC | C33, C34, C34.9, Z12.2, Z80.1-Z80.2, Z85.1-Z85.20 | C33-C34 |
| Stroke | Stroke | G45-G46.8, I60–I62, I62.9-164, I64.1, I65-169.98, J22.3 | G45, I60–I64, I67,169 |
| Ischemic stroke | Stroke | G45-G46.8, I63-163.9, I65-166.9, I67.2-167.848, I69.3-169.4 | G45, I63, I67, 169 |
| Diabetes mellitus type 2 | Diabetes | E11-E11.1, E11.3-E11.9 | E11 |
| Cardiovascular diseases | Cardiovascular | I00-199 | I01, I05, I07-I13, I20, I21, I24-I27, I30, I31, I33-I36, I38, 140, 142, 144, 145, 147-151, I60-164, I67, I69-I74, I77, I78, I80, I82, I83, I85-I87, I89 |
| Cerebrovascular diseases | Cerebrovascular | I160-I169 | I60-164, I67, I69 |
| Respiratory diseases | Respiratory | J00-J99 | J04, J06, J09, J11-J13, J15, J16, J18, J20-J22, J32, J38-J40, J42-J47, J60-J69, J80, J81, J84-J86, J90, J93, J94, J96, J98 |

Table A7
Effect of COVID-19 lockdown on mortality due to specific causes (s.e.)

|               | 1        | 2        | 3        | 4        |
|---------------|----------|----------|----------|----------|
| **Panel A: Acute Lower Respiratory Infection (ALRI)** |           |           |           |           |
| POST          | $-0.294^{***}$ | $-0.312^{***}$ | $-0.260^{***}$ | $-0.344^{***}$ |
| Cases         | 1.09E-05 | (-0.0921) | (-0.0934) | (-0.0949) |
| cu_cases      | (-2.30E-05) |          |          |          | (continued on next page)
| Panel | Condition | Model no. | POST (SE) | Cases (SE) | cu_cases (SE) | ma_cases (SE) | Observations | R-squared |
|-------|-----------|-----------|-----------|------------|---------------|---------------|--------------|-----------|
| A.     | ALRI      |           | 2.11E-07  | 2.80E-05   | 7.85E-06      | 5.84E-08      | 2105         | 0.133     |
|        |           | 1          | -0.105 (-0.0823) | -0.141 (-0.0917) | -9.61E-06 (-1.75E-05) | -2.39E-05 (-2.29E-05) | 2105         | 0.133     |
|        |           | 2          | 0.105 (0.0636) | -0.296e-06 (-0.0697) | -9.61E-06 (-1.75E-05) | -5.84E-08 (-2.51E-07) | 2105         | 0.133     |
|        |           | 3          | 0.105 (0.0636) | -0.296e-06 (-0.0697) | -9.61E-06 (-1.75E-05) | -5.84E-08 (-2.51E-07) | 2105         | 0.133     |
|        |           | 4          | 0.105 (0.0636) | -0.296e-06 (-0.0697) | -9.61E-06 (-1.75E-05) | -5.84E-08 (-2.51E-07) | 2105         | 0.133     |
| B.     | Cancer    | 1          | 0.005 (0.003) | -0.266e-06 (-0.0707) | -9.61E-06 (-1.75E-05) | -5.84E-08 (-2.51E-07) | 1915         | 0.063     |
|        |           | 2          | 0.005 (0.003) | -0.266e-06 (-0.0707) | -9.61E-06 (-1.75E-05) | -5.84E-08 (-2.51E-07) | 1915         | 0.063     |
|        |           | 3          | 0.005 (0.003) | -0.266e-06 (-0.0707) | -9.61E-06 (-1.75E-05) | -5.84E-08 (-2.51E-07) | 1915         | 0.063     |
|        |           | 4          | 0.005 (0.003) | -0.266e-06 (-0.0707) | -9.61E-06 (-1.75E-05) | -5.84E-08 (-2.51E-07) | 1915         | 0.063     |
| C.     | COPD      | 1          | 0.312*** (0.0636) | -0.0949 (-0.0926) | -2.82E-07 (-1.98E-07) | -5.84E-08 (-2.51E-07) | 2214         | 0.165     |
|        |           | 2          | 0.312*** (0.0636) | -0.0949 (-0.0926) | -2.82E-07 (-1.98E-07) | -5.84E-08 (-2.51E-07) | 2214         | 0.165     |
|        |           | 3          | 0.312*** (0.0636) | -0.0949 (-0.0926) | -2.82E-07 (-1.98E-07) | -5.84E-08 (-2.51E-07) | 2214         | 0.165     |
|        |           | 4          | 0.312*** (0.0636) | -0.0949 (-0.0926) | -2.82E-07 (-1.98E-07) | -5.84E-08 (-2.51E-07) | 2214         | 0.165     |
| D.     | Diabetes  | 1          | 0.151** (0.0727) | -0.0358 (0.0816) | -4.58E-08 (-2.15E-07) | -5.84E-08 (-2.51E-07) | 1202         | 0.11      |
|        |           | 2          | 0.151** (0.0727) | -0.0358 (0.0816) | -4.58E-08 (-2.15E-07) | -5.84E-08 (-2.51E-07) | 1202         | 0.11      |
|        |           | 3          | 0.151** (0.0727) | -0.0358 (0.0816) | -4.58E-08 (-2.15E-07) | -5.84E-08 (-2.51E-07) | 1202         | 0.11      |
|        |           | 4          | 0.151** (0.0727) | -0.0358 (0.0816) | -4.58E-08 (-2.15E-07) | -5.84E-08 (-2.51E-07) | 1202         | 0.11      |
| E.     | Stroke    | 1          | 0.158*** (0.0387) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2221         | 0.106     |
|        |           | 2          | 0.158*** (0.0387) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2221         | 0.106     |
|        |           | 3          | 0.158*** (0.0387) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2221         | 0.106     |
|        |           | 4          | 0.158*** (0.0387) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2221         | 0.106     |
| F.     | IHD       | 1          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
|        |           | 2          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
|        |           | 3          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
|        |           | 4          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
| G.     | All Causes| 1          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
|        |           | 2          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
|        |           | 3          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
|        |           | 4          | 0.158*** (0.0632) | -0.0355 (0.0419) | -4.83E-08 (-1.15E-07) | -5.84E-08 (-2.51E-07) | 2219         | 0.057     |
### Table A7 (continued)

| POST          | -0.0261 (−0.0256) | -0.104*** (−0.0277) | -0.0505* (−0.0284) | -0.119*** (−0.0285) |
|---------------|-------------------|---------------------|-------------------|---------------------|
| Cases         | 4.79e-05*** (−6.96E-06) |                      | 1.49e-07* (−7.60E-08) |                      |
| cu_cases      |                   |                     |                   |                     |
| ma_cases      | 6.69e-05*** (−9.53E-06) |                      |                   |                     |
| Observations  | 2221              | 2221                | 2221              | 2207                |
| R-squared     | 0.118             | 0.137               | 0.119             | 0.138               |

Data are at the day level, not monitoring station-day level (i.e., all observations are city-wide). The dependent variable is the natural logarithm of the number of deaths due to a specific cause. The independent variable of interest, POST, is an indicator equal to one for all days from March 20, 2020, when Bogotá’s lockdown began, to February 28, 2021, cases is the number of new cases of COVID-19 per day, cu_cases is the cumulative number on each day, and ma_cases is the seven-day moving average of cases 14 days before the current day. Covariates are four sets of temporal fixed effects (year, month, week, day-of-week), and 16 time-varying covariates: rainfall, rainfall squared, temperature, temperature squared, temperature20m, thermal inversion, upwind fires, wind direction1–wind direction8, wind speed, and windspeed squared. ***p < 0.01, **p < 0.05, *p < 0.1.

### Appendix Figures

**Fig. A1.** Noncompliance with World Health Organization (WHO) air quality guidelines in Bogotá
Fig. A2. Compliance with World Health Organization (WHO) air quality guidelines in Bogotá
Fig. A3. Population-weighted average monthly ambient PM$_{2.5}$ concentration in Bogotá by month

Fig. A4. Population-weighted average monthly ambient NO$_2$ concentration in Bogotá by month
Panel A: Results for PM$_{2.5}$

Panel B: Results for NO$_2$
Fig. A5. Placebo tests: Effects of actual COVID-19 lockdown in 2020–2021 and effects of placebo treatments in 2017–2018, 2018–2019, and 2019–2020 for PM$_{2.5}$ (Panel A) and NO$_2$ (Panel B); two-way fixed effects city-level regression models, point estimates, and 95 percent confidence intervals.

Note: The dependent variable is the natural logarithm of PM$_{2.5}$ or NO$_2$. The independent variable of interest, POST, is an indicator equal to one for all station-days on and after March 2 until June 30, 2021, or for the same time period in previous years. Covariates are monitoring station fixed effects, four sets of temporal fixed effects (year, month, week, day-of-week), and 16 time-varying covariates: rainfall, rainfall squared, temperature, temperature squared, temperature20m, thermal inversion, upwind fires, wind direction1–wind direction8, wind, and windspeed squared. Standard errors are clustered at the monitoring station level.

Fig. A6. 14-day moving average of deaths in Bogotá by cause
Fig. A7. Treatment effects of COVID-19 lockdown on ambient PM$_{2.5}$ (Panel A) and NO$_2$ (Panel B) concentrations in Bogotá.

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