IDB WORKING PAPER SERIES Nº IDB-WP-1270

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November 2021

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Inter-American Development Bank
Climate and Sustainable Development Sector

November 2021

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Blackman, Allen.
Quantifying Covid's silver lining: avoided deaths from air quality improvements in Bogotá / Allen Blackman, Jorge A. Bonilla, Laura Villalobos.
p. cm. — (IDB Working Paper Series ; 1270)
Includes bibliographic references.
1. Air quality-Colombia. 2. Air-Pollution-Colombia. 3. Quarantine-Environmental aspects-Colombia. 4. Coronavirus infections-Environmental aspects-Colombia. I. Bonilla, Jorge A. II. Villalobos, Laura. III. Inter-American Development Bank. Climate Change and Sustainable Development Sector. IV. Title. V. Series.
IDB-WP-1270

http://www.iadb.org

QUANTIFYING COVID-19'S SILVER LINING: AVOIDED DEATHS FROM AIR QUALITY IMPROVEMENTS IN BOGOTÁ

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Acknowledgments: This research was funded by the Inter-American Development Bank via Economic Sector Work RG-E1543. We are grateful to Sally Atwater for editorial help and to Bjorn Larsen, José Ingacio Huertas, Neal Fann, Oscar Mitnik and seminar participants at the Environmental Defense Fund, Jönköping University, Cambridge University, Salisbury University and the University of Costa Rica for helpful comments and suggestions. The information and opinions presented herein are entirely those of the authors, and no endorsement by the Inter-American Development Bank, its Board of Executive Directors, or the countries they represent is expressed or implied.

QUANTIFYING COVID-19'S SILVER LINING: AVOIDED DEATHS FROM AIR QUALITY IMPROVEMENTS IN BOGOTÁ

Abstract. In cities around the world, COVID-19 lockdowns have improved outdoor air quality, in some cases dramatically. Even if only temporary, these improvements could have longer-lasting effects on policy 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 COVID-19 lockdowns and the benefits these improvements generate. We use panel data econometric models to estimate the effect of Bogotá's lockdown on fine particulate pollution, epidemiological models to simulate the effect of reductions in that pollution on long-term and short-term mortality, and benefit transfer methods to estimate the monetary value of the avoided mortality. We find that in its first year of implementation, on average, Bogotá's lockdown cut fine particulate pollution by more than one-fifth. However, the magnitude of that effect varied considerably over the course of the year and across the city's neighborhoods. Equivalent permanent reductions in fine particulate pollution would reduce long-term premature deaths by more than one-quarter each year, a benefit valued at $670 million per year. Finally, we estimate that in 2020-2021, the lockdown reduced short-term deaths by 31 percent, a benefit valued at $180 million.

Keywords. Pollution; COVID-19; lockdown; Colombia; panel data; integrated exposure-response model; benefit transfer

JEL codes. Q51, Q52, Q53, Q56, Q58, I15

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 (PM2.5), particulate matter smaller than 10 μm (PM10), 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 PM2.5 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 PM2.5 and a 60 percent reduction in NO_2. 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 were initiated: long-obscured vistas were suddenly reliably clear and respiratory symptoms associated with air pollution were 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 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 began March 20, 2020, on air quality and avoided mortality over the next 12 months, and we also estimate the monetary value of that avoided mortality. Our analysis has three stages. First, we use fixed effects panel-data models along with 11 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, controlling for the potentially confounding effects of weather and forest fires. 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 concentrations on long-term and short-term human mortality. We simulate the effects of the lockdown on mortality rather than econometrically estimating them because these effects are confounded by the pandemic itself, both directly (because it caused an enormous spike in mortality) and indirectly (because it likely affected patients' incentives to seek health care, the provision of health care, and the reporting of mortality data). Finally, we use benefit transfer methods to estimate the monetary value of avoided mortality.

We find that over the course of its first year, Bogotá's lockdown caused a 22 percent reduction in ambient PM2.5. 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 six months as lockdown restrictions were relaxed, and were relatively large again in the first two months 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, where baseline levels of PM2.5 were the highest. In general, our epidemiological models suggest that the effects of the lockdown on long-term and short-term mortality roughly scaled with the effects on PM2.5. We find that reductions in PM2.5 concentrations due to the lockdown avoided 115 short-term premature deaths during the first year of the lockdown, a 31 percent reduction from counterfactual levels. Permanent reductions in ambient PM2.5 of the same magnitude as those generated by Bogotá's lockdown would save 427 lives per year, a 26 percent reduction from counterfactual rates. Finally, we find that the monetary value of avoided short-term mortality was

$180 million per year, which represents 0.2 percent of Bogotá's 2019 GDP, and the value avoided long-term mortality was $670 million per year, which represents 0.8 percent of the city's 2019 GDP.

Our study makes two main contributions to the literature. First, it is one of a small number of studies to use both (i) fixed effect panel-data econometric models (that control for observed time-varying and unobserved time-invariant confounding factors) to identify the effect of a lockdown on air quality; and (ii) epidemiological models to simulate the impacts of these estimated effects on human health. 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. And 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] Second, ours is one of a small set of studies that estimate the monetary value of avoided mortality due to a COVID-19 lockdown (e.g., Kumar et al. 2020) and, to our knowledge, the first to do so using econometrically estimated effects of the lockdown on air quality.

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

Air quality in Bogotá regularly fails to meet World Health Organization standards by a considerable margin (Figure 1). Episodes of severe air pollution occur most frequently in February and March and to a lesser extent in January, April, November, and December, when thermal

[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.

inversions trap air pollution at ground level (Figure A1). Vehicles are the source of 81 percent of combustion emissions of PM2.5 in Bogotá, the pollutant on which we focus in this study, and trucks are the main source of the PM2.5 emitted by vehicles, accounting for 60 percent (SDA 2020). Air quality is markedly worse than average in the southwestern part of the city. The air quality monitoring network in Bogotá (Red de Monitoreo de Calidad del Aire de Bogotá, RMCAB) consists of 13 stations that provide hourly data on six air pollutants and seven weather variables (Figure 2).

[Insert Figures 1 and 2 here]

2.2. Bogotá's COVID-19 lockdown

During our year-long study period, March 1, 2020 through February 28, 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 (Figure 3). The lockdown's first year 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.

[Insert Figure 3 here]

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.[2] 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

[2] This policy was terminated May 11.

across the city's *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's first year began in the last month of 2020 and continued through mid-February 2021. It entailed reimposition 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's first year, which began in mid-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.

3. ANALYSIS

3.1. Scope

Our study area comprises all 20 of Bogotá's *localidades* (Figure 2).[3] We focus on the effects of Bogotá's lockdown during its first year, from March 1, 2020, through February 28, 2021. However, we use data for the previous 10 years to econometrically identify those effects. Finally, we focus on a single air pollutant, PM2.5, for several reasons. PM2.5 has significant effects on human health because small particles penetrate deeply into the lungs and can even pass into the bloodstream. At the global level, PM2.5 contributes to more than 9 million premature mortalities each year, mostly in severely polluted urban areas in developing countries (Vorha et al. 2021;

[3] The *localidades* are Antonio Nariño, Barrios Unidos, Bosa, Chapinero, Ciudad Bolívar, Engativá, Fontibón, Kennedy, La Candelaria, Los Mártires, Puente Aranda, Rafael Uribe, San Cristóbal, Santa Fe, Suba, Sumapaz, Teusaquillo, Tunjuelito, Usaquén, and Usme.

Burnett et al. 2018). Moreover, the links between ambient PM2.5 and human health are relatively well understood (Manisalidis et al. 2020; Anderson et al. 2012). Finally, in Bogotá, as noted above, the large majority of PM2.5 is generated by motor vehicles and therefore, in principle, can be controlled (SDA 2020). Because we examine a single pollutant, our estimates of the effect of air pollution on human health can be interpreted as lower bounds.

3.2. Effect of COVID-19 lockdown on ambient PM2.5

3.2.1. Methods

To measure the effect of Bogotá's lockdown on ambient PM2.5, 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 11 years of data: January 1, 2010–February 28, 2021.

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. Results from this model are used as inputs into the health effects models discussed in the next section. We estimate

$$Y_{ts} = \alpha + \beta POST_t + X'_{ts}\gamma + D'_t\sigma + \rho_s + \varepsilon_{ts} \qquad (1)$$

where t indexes days, s indexes monitoring stations, Y is the natural logarithm of PM2.5, $POST$ is a binary indicator variable equal to one on the first day of the city-level lockdown (March 20, 2021) and all days afterward, X is a vector of time-varying variables (discussed below), D is a vector of four sets of temporal fixed effects (month, year, week, and day of week), $\alpha, \beta, \gamma, \sigma, \rho$ are parameters or vectors of parameters, and ε is an error term. We cluster standard errors at the monitoring station level.

Station-day observations are population weighted—that is, observations from stations in or near densely populated *localidades* are given more weight than those in or near sparsely populated ones. Population weights for each monitoring station (Table A1, second column) are calculated as follows. First, each *localidad* is matched to the monitoring station nearest the *localidad*'s centroid (Table A1 note). Each station is assigned a weight equal to the fraction of the Bogotá's total population in the *localidad(es)* to which the station is matched. For example, the *localidad* Puente Aranda alone is matched to monitoring station Carvajal, so station-day observations from Carvajal are assigned a weight of 0.03—the percentage of Bogotá's population living in Puente Aranda. As discussed below, all observations from four of Bogotá's 13 monitoring stations are dropped from the analysis because of missing data or proximity to a major road. In each of these four cases, localidades are therefore matched monitoring stations farther from the localidad's centroids. One of the remaining nine monitoring stations (Guaymaral) is not matched to a *localidad* because it is not the closest station to any *localidad* centroid, and as a result, observations from this station are effectively excluded from the citywide econometric analysis (Equations 1 and 2).

Our treatment effect estimate is β, the coefficient on *POST*. Given our semi-log specification, a transformation of this coefficient, $\left(exp(\hat{\beta}) - 1\right) \times 100$, can be interpreted as the average percentage effect of the lockdown on PM2.5 during its entire first year.

To examine temporal variation in the effect of the lockdown on ambient PM2.5, we estimate a second city-level model that is identical to the first model except that instead of a single treatment indicator, *POST*, we include 12 indicators, one for each month of the lockdown period, March 2020–February 2021. We estimate

$$Y_{ts} = \alpha + \theta POST\_MONTH_t + X'_{ts}\gamma + D'_t\sigma + \rho_s + \varepsilon_{ts} \qquad (2)$$

where *POST_MONTH* is a vector of 12 month indicator variables and θ is 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 θ, the coefficients on $POST\_MONTH$. Transformations of these coefficients can be interpreted as the average percentage effects of the lockdown on ambient PM2.5 during each month in the first year of the lockdown (March 2020, April 2020, …).

Finally, to examine spatial variation in the effect of the lockdown on ambient PM2.5, we fit a set of nine monitoring station-level models that are identical to the first model (Equation 1) except that each uses observations from only a single monitoring station and therefore excludes station fixed effects and does not use population weighting (below, we explain the reason for using data from only nine of Bogotá's 13 monitoring stations). That is, we estimate

$$Y_{ts} = \alpha_s + \beta_s POST_t + X'_{ts}\gamma_s + D'_t\sigma_s + \varepsilon_{ts} \qquad \text{(s = 1,2,...9)} \qquad (3)$$

Our treatment effect estimates are the elements of β_s, the coefficients on *POST*. Transformations of these coefficients can be interpreted as the average percentage effect of the lockdown on ambient PM2.5 during the entire first year of the lockdown at a single monitoring station.

3.2.2. Data

Table 1 describes the variables used in our econometric models. The dependent variable is the natural logarithm of *pm2.5*, and the time-varying covariates that constitute the vector X are *wind speed, windspeed squared, wind direction1–wind direction8, temperature, temperature squared, rainfall, rainfall squared, thermal inversion*, and *upwind fires*. With the exception of *upwind fires*, all of these variables are derived from monitoring stations' hourly data (RMCAB 2020). From these hourly data, we obtain daily values by taking the daily mean of hourly PM2.5, 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, *temperature20m,* which is the temperature 20 meters above ground level, exceeds *temperature*, which is the temperature at ground level.[4] The *wind direction1–wind direction8* variables are binary indicators of whether the mode of hourly wind direction, measured in degrees, falls into eight bins.[5] 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. Such fires are often a significant source of ambient PM2.5 in the city (even when located many kilometers away because winds transport particulate matter over considerable distances). This variable is derived from satellite data on the location of fires (NASA 2020) and

[4] A thermal inversion occurs when air temperature at higher altitude exceeds that at lower altitudes and the warm air layer traps pollutants close to the ground. This phenomenon helps to explain high PM2.5 concentrations 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 *temperature20m* is available only for this station. Because Bogotá is located on a plateau, thermal inversion generally occurs throughout the city.
[5] 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.

wind direction data from 141 airport weather stations surrounding Bogotá (NOAA 2021).[6] To take into account that PM2.5 from fires is transported over time, we include in our models three variables: the count of upwind fires lagged one day, two days, and three days.

[Insert Table 1 here]

We drop all data from four of Bogotá's 13 monitoring stations. We drop data from the 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. In addition, we drop all data from the three stations with the most missing observations: for Fontibón, at least 80 percent of observations for all six pollution and weather variables are missing; for MinAmbiente, 100 percent of observations for *temperature* are missing; and for Puente Aranda, 65 percent of observations for *pm2.5* are missing (Table A1).[7]

Having dropped data from those four monitoring station, our regression sample includes data from nine monitoring stations and 4,077 days (January 1, 2010 to February 28, 2021) and comprises 36,693 station-days.

3.2.3. Results

Results from our main specification, a city-level model that pools station-days from all of the monitoring station in our sample (Equation 1), indicate that on average, the lockdown reduced ambient PM2.5 average annual concentrations in Bogotá by 22 percent, from a counterfactual (pre-lockdown average) level of 20.98 μg/m^3 to a post-lockdown level of 16.27 μg/m^3 (Table 2). For each day in our sample, the counterfactual is the average level of PM2.5 for the 10 years preceding the COVID-19 lockdown.

[6] We calculate upwind fires as follows. First we map out a rectangle 845 km to the north of Bogotá, 820 km to the south, 1,212 km to the west and 1,563 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, 2021. 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 January 1 was NE.

[7] Purent Aranda is the name of both a localidad and of a monitoring station in that localidad.

[Insert Table 2 here]

As for the temporal variation in the treatment effect, results from the model that includes month-specific treatment variables (Equation 2) show that the lockdown had statistically significant effects in eight of the 12 months of our study period (Table 2; Figure 4). These effects were largest in April 2020 (–36 percent), May 2020 (–45 percent), January 2021 (–42 percent), and February 2021 (–43 percent).

[Insert Figure 4 here]

The temporal variation in the estimated effects of the lockdown 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 untreated years in our sample) relatively poor—January through April, November, and December. 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 large negative estimated monthly treatment effects in April and May 2020 are likely due to the fact that air quality in April is typically relatively poor, and lockdown restrictions in both April and May of our treatment year were relatively stringent. The lack of significant treatment effects in June through August 2020 likely reflects the fact that during these months, air quality is generally relatively good, and in our treated year, lockdown restrictions were relatively lax. The relatively large negative estimated treatment effect in October may be due to the fact that during that month, air quality is generally relatively poor (Figure A1). It also may reflect the reimposition of Bogotá's license plate-based driving restrictions program in October 2020. Finally, the large negative estimated treatment effects in January and February of 2021 probably stem from the fact that air quality in those months is generally poor and in our treated year, strict lockdown measures were reimposed to address a postholiday surge in COVID-19 cases.

Because, as noted in the previous section, motor vehicles are the source of more than 80 percent of PM2.5 in Bogotá, the causal mechanism for our estimated negative treatment effects is presumably that the lockdown reduced trips and therefore vehicular emissions. Although formally testing that hypothesis is beyond the scope of this study, visual inspection of data on traffic congestion supports it. The temporal pattern of our treatment effects estimate corresponds roughly with that of a measure of traffic congestion intensity generated by the WAZE cell phone application (Figure 5).[8]

[Insert Figure 5 here]

Finally, results from the monitoring station-level models suggest some spatial variation in the effect of the lockdown on PM2.5 concentrations (Equation 3). Treatment effects were highest for Centro Alto Rendimiento in the northwest (–25 percent) and Kennedy in the southwest (–25 percent) and lowest (and statistically insignificant) at San Cristobal in the southeast (–1 percent) and Las Ferias in the northwest (–9 percent) (Table 2 and Figure 2). A variety of factors might explain this spatial variation. One is the average levels of PM2.5 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 PM2.5 were relatively high. That may help explain the relatively large estimated treatment effect for Kennedy, where average pretreatment daily levels of PM2.5 were second highest among all monitoring stations in Bogotá (29 $\mu g/m^3$), the relatively small effect in San Cristobal, where pretreatment levels were lowest in the city (11 $\mu g/m^3$), and the relatively small effect in Las Ferias, where pretreatment levels were third lowest in the city (16 $\mu g/m^3$) (Table 2). 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 PM2.5 in areas with higher baseline levels of congestion due specifically to commuting. Unfortunately, to our knowledge, the data to test that hypothesis are not available.

Placebo tests provide some assurance that our city-level treatment effect estimate is robust. We fit three models with annual average placebo treatments (Equation 1) corresponding to the same months as the actual lockdown (March through February) but for three previous years. In all three models, the placebo treatment is not significant (Table A2; Figure A2).

[8] WAZE traffic congestion intensity measures whether traffic at a given geographic point is slower than “free-flow”—the expected speed under no-jam conditions (IDB/IDB Invest 2020).

3.3. Effect of reductions in ambient PM2.5 on human mortality

As noted above, in an econometric analysis of human mortality, it would be exceptionally challenging to disentangle the effect of the reduction in PM2.5 associated with Bogotá's lockdown from the effect of the COVID-19 pandemic. Therefore, we use epidemiological models to simulate the effect of reductions in ambient PM2.5 on both long-term and short-term human mortality. The simulation of long-term effects models the effect of a permanent reduction in PM2.5. The first question we address is this: if the average annual treatment effects estimated in the previous section became permanent—that is, if PM2.5 concentrations permanently fell by 23 percent below historical averages—how many fewer residents of Bogotá would die each year from exposure to PM2.5? The simulation of short-term effects models the effect of a temporary reduction in PM2.5 and addresses this question: from March 2020 through February 2021, how many fewer people in Bogotá died because PM2.5 levels were lower than they otherwise would have been? Long-term effects will be larger than short-term effects because the former model the annual effect of reduced exposure over residents' entire lifetimes whereas the latter model the contemporaneous effect of reduced exposure over a single year.

A caveat about our analysis of short-term health effects is in order: we are not able to control for possible bias in our estimates due confounding effects of the pandemic. As noted above, several factors that affect short-term mortality were likely different during the pandemic versus the "normal" times to which our model's parameters are calibrated. These include patients' incentives to seek medical care, their access to medical care, the reporting of mortality causes, and co-morbidity between COVID-19 and various death causes. The net effect of these confounding factors on our short-term mortality estimates is uncertain. On one hand, some of these factors likely bias our estimates downwards. Patients 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 short-duration spikes in PM2.5 on which our short-term model focuses would have caused more deaths than during the pandemic than during "normal" times and that reductions in the frequency of those spikes due to the lockdown would therefor have avoided more deaths. The implication is that our estimates of avoided short-term deaths are likely biased downwards. But the effect of other potentially confounding factors is uncertain, specifically changes in the reporting of mortality along with possible co-morbidity between COVID-19 and death causes. Hence, our the results of our analysis of short-term effect must be interpreted with caution.

3.3.1. Long-term effects

3.3.1.1. Methods

The foundation of our approach to simulating the effect of a reduction in ambient PM2.5 in Bogotá on long-term premature mortality is a set of relative risks (RRs)—estimates from epidemiological studies of the effect of long-term exposure to PM2.5 on the annual risk of death from specific health endpoints (death causes), such as stroke and cancer—which we use in combination with data specific to Bogotá (on population, the incidence of diseases, PM2.5 concentrations, and reductions in those concentrations). We use RR functions drawn from the integrated exposure-response (IER) models in GBD (2019), which have become the state-of-the-science tool for simulating the effects of air pollution on human health.[9] They are used by, among others, the World Health Organization, the World Bank, and the annual Global Burden of Disease studies (Burnett and Cohen 2020).[10] We calculate

$$AD = \sum_{e=1}^{6} \sum_{a=1}^{n} \left(population_a \times incidence_{ae} \times PIF[c1, c2]_{ae} \right) \qquad (5)$$

where *e* indexes health endpoints, *a* indexes age cohorts, *AD* is total attributable deaths from all health endpoints, *incidence* is the annual risk of death, *PIF* is the potential impact fraction, *c1* is

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[9] Produced by the Institute for Health Metrics and Evaluation (IHME) at the University of Washington and oiriginally 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 IER models in GBD (2019) so that our results are consistent with and comparable to the state-of-the-science method for simulating the effects of air pollution on human health.

[10] Early efforts to simulate the effect of PM2.5 on mortality used RRs drawn from single epidemiological studies. For example, US EPA (2012) and WHO (2004) used RRs from Pope et al. (2002), a study of a large population of adults in the United States. A limitation was that these epidemiological studies were typically conducted in high-income countries with relatively low levels of ambient PM2.5. As a result, applying their findings in low- and middle-income country settings with much higher levels of ambient PM2.5 entailed strong, often untenable, assumptions. About a decade ago, Pope et al. (2009, 2011) addressed this limitation by developing a model that integrated findings from epidemiological studies focused on a variety of emissions sources (including active smoking, secondhand smoking, and household burning of solid fuels as well as outdoor ambient sources) to estimate RRs as functions of a wide range of PM2.5 levels, including the relatively high levels found in many low- and middle-income countries. Estimated RR functions from IER models are concave—that is, the *marginal* effect of exposure to PM2.5 is larger at low levels of PM2.5 than at high levels. The IER functions reported in GBD (2019) improve on previous versions by, among other things, removing studies of active smoking and using more flexible spline models to fit RR curves.

the baseline (counterfactual) ambient PM2.5 concentration, and *c2* is the endline (postreduction) concentration. Following GBD (2019), we calculate *PIF* for each age group as one minus the ratio of the RR if a person is exposed to concentration *c1* divided by the RR if exposed to concentration *c2*.[11] That is,

$$PIF[c1, c2]_{ae} = \left(1 - \frac{RR_{ae,c2}}{RR_{ae,c1}}\right). \tag{6}$$

We estimate attributable deaths for the six health endpoints included in GBD (2019): stroke, including ischemic stroke; chronic obstructive pulmonary disease (COPD); ischemic heart disease; cancer of the trachea, bronchus, or lung; lower respiratory infections; and type 2 diabetes mellitus.

3.3.1.2. Data

We obtain $RR_{e,c1}$ and $RR_{e,c2}$ from the Global Burden of Disease Study 2019 (GBD 2019) (Table 3). This study presents PM2.5 risk curves (RR as a function of PM2.5 levels) specific to health endpoints and age groups. In the case of ischemic heart disease 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 health endpoints, GBD (2019) provides a single curve for all ages (0–99 for lower respiratory infections, which are common among people of all ages, and 25–99 for all other health endpoints, which are less common among younger people), and we use that curve.

[Insert Table 3 here]

Drawn from DANE (2018), our data on the incidence of our six modeled health endpoints are specific to Bogotá (Table 3). These data classify death causes according to the 10th revision of

[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, $RR_x = RR_{int(x)} + \left(RR_{int(x)+1} - RR_{int(x)}\right) \times frac(x)$ where, *x* is the concentration level, *int* is the integer part of the concentration level, and *frac* is the decimal part of the concentration level. For example, for a value of PM2.5 = 11.15, we calculate $RR_{11.15} = RR_{11} + (RR_{12}\text{-}RR_{11})\times 0.15$. For PM2.5 values smaller than 10, we rounded to two significant digits to match the GDB (2019) RR format. The two significant digits follow the pattern (0, 0.01, 0.02, … , 1.1, 1.2 ,… , 11, 12,… , 110, 120, … , 1100, 1200, … 2500).

the International Statistical Classification of Diseases and Related Health Problems (ICD-10), the medical classification list used by the World Health Organization. We map the ICD-10 codes to our six health endpoints using the correspondence published by the Institute for Health Metrics and Evaluation (Table A3). The incidence for each cause is the number of deaths for that cause divided by the total population (ages 0–99 for lower respiratory infections and ages 25–99 for all other causes). For each health endpoint, we use age-specific population, incidence, and (where available) relative risks to calculate changes in avoided deaths. For lower respiratory infections, we use population and incidence for cohorts spanning ages 0–99. For our other five health endpoints, we use population and incidence for age cohorts spanning ages 25–99.

Our data on population are from the 2018 national population census (DANE 2018) (Table 3). They are disaggregated at the level of *localidades* and five-year age cohorts.

As for ambient PM2.5 concentrations, for *c1*, we use the 10-year (2010–2019) population-weighted historical annual average values of PM2.5 concentrations (Table 3).[12] For *c2*, we rely on our econometrically estimated average population-weighted percentage treatment effects. That is, *c2* is calculated as *c1* times one plus the estimated treatment effect generated by Equation 1.

3.3.1.3. Results

Our city-level simulation suggests that a permanent reduction in ambient PM2.5 of the same magnitude as that generated by Bogotá's lockdown would save 427 lives per year (from the death causes included in our study), a 26 percent reduction from the 1631 long-term deaths that would have occurred absent the lockdown (Table 4). More than 40 percent of these avoided deaths are from ischemic heart disease, a fifth are from stroke, and another fifth are from COPD.

[Insert Table 4 here]

3.3.2. Short-term effects

3.3.2.1. Methods

To simulate the short-term effects on mortality of the reduction in PM2.5 levels caused by the lockdown, we follow Atkinson et al. (2014) as applied by Giani et al. (2020). Here, too, the

[12] To get an annual average from our raw hourly data, we first average over hours of the day, then over days of the year, and finally over the 10 years of our baseline period.

foundation is a set of RRs. But in this case, RRs are estimates from epidemiological studies of the effect of short-term spikes in ambient PM2.5 on the daily risk of death from all causes for people of all ages.

We use RRs drawn from metanalyses of epidemiological studies along with data specific to Bogotá (on population, the incidence of death from all causes, PM2.5 concentrations, and reductions in those concentrations). We calculate

$$AD = \sum_{d=1}^{365}(population \times incidence \times PIF[c1, c2]_d) \qquad (7)$$

where *d* indexes calendar days and *incidence* is the daily baseline risk of death from all causes,

$$PIF[c1, c2]_d = \left(1 - \frac{RR_{d,c2}}{RR_{d,c1}}\right). \qquad (8)$$

and

$$RR_{d,ck} = exp\ (\gamma \times ck) \qquad \text{(k = 1,2)} \qquad (9)$$

where γ is daily excess mortality due to PM2.5, *c1* is the baseline (counterfactual) ambient PM2.5 concentration for each day of the year, and *c2* is the endline (postreduction) concentration for each day.[13]

3.3.2.2. Data

Our data on population are from the 2018 national population census (DANE 2018) (Table 3). For daily incidence, we use the annual rate of deaths from all causes in 2018 for Bogotá divided by 365 days (DANE 2018). For γ, we use the mean value from a systematic metanalysis of epidemiological studies of the effect of daily variations in PM2.5 on deaths from all causes—1.04 percent per 10μg/m^3 (Atkinson et al. 2014).[14] For *c1*, we use the 10-year historical citywide

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[13] Note that our model implicitly assumes that during the lockdown, Bogotá's citizens spent the same amount of time outdoors exposed to ambient pollution as before the lockdown. That is a strong assumption, since they likely spent less time outdoors. Therefore, our estimates of short-term effects may be biased upward.

[14] Note that Atkinson et al. (2014) report another value for the Region of the Americas, AMR B, which includes Colombia: 2.08 percent per 10μg/m^3. However, this value is based on only two studies. Moreover, it is twice as high

average (2010–2019) values of PM2.5 for every calendar day. Finally, *c2* is calculated as *c1* times one plus the estimated monthly treatment effect.

3.3.2.3. Results

Our city-level simulation suggests that from March 2020 through February 2021, reductions in PM2.5 concentrations due to the lockdown avoided 115 premature deaths, a 31 percent reduction from the 371 short-term deaths that would have occurred absent the lockdown (Table 4).

3.4. Valuation of avoided mortality

3.4.1. Methods

We use benefit transfer methods to estimate the monetary value of avoided mortality. Following World Bank/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 Organisation 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 metanalysis 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):

$$VSL_{c,2019} = VSL_{OECD,2011} \times \left(\frac{Y_{c,2011}}{Y_{OECD,2011}}\right)^{\varepsilon} \times (1 + \%\Delta P + \%\Delta Y)^{\varepsilon} \qquad (9)$$

where c is the country (Colombia), VSL is value of statistical life, Y is per capita gross domestic product, ε 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).

as the average value based on dozens of studies and almost twice as high as the second-highest value for a single region (Europe A). Therefore, to ensure that our estimates are conservative, we use the average value based on dozens of studies.

3.4.2. Data

Table 5 summarizes the parameters used in this calculation. They result in a value of $1,569,770 per avoided mortality.

[Insert Table 5 here]

3.4.3. Results

The total value of the simulated effect of the lockdown on avoided long-term mortality is $670 million per year, which represents 0.8 percent of Bogotá's 2019 GDP (Table 4). The total value of the simulated effect of the lockdown on avoided short-term mortality is $180 million per year, which represents 0.2 percent of Bogotá's 2019 GDP.

4. DISCUSSION

We have used panel-data econometric models to estimate the effect of Bogotá's COVID-19 lockdown on PM2.5 concentrations, IER 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, in its first year of implementation, the lockdown cut PM2.5 concentrations by more than one-fifth. However, the size of that reduction varied considerably over the course of the year and, to a lesser extent, across Bogotá's neighborhoods. We found that the greatest reductions occurred in in geographic 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 PM2.5 equivalent to those generated by the lockdown would reduce long-term premature deaths from PM2.5 by about a quarter each year, mostly as a result of reduced mortality from ischemic heart disease, stroke, and COPD, and that in 2020–2021, the lockdown reduced short-term deaths from PM2.5 by 31 percent. Finally, we find that the monetary value of avoided long-term mortality is $670 million per year and that from avoided short-term mortality is $180 million per year.

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 premature mortality. These simulations, in turn, have limitations. For example, because of a shortage of site- and source-specific epidemiological studies, the IER model we use to estimate long-term mortality effects is based on a metanalysis of findings from studies conducted in a range of developed and developing countries, not just Colombia. Moreover, these studies examine a range of types of fine particulate pollution, not just outdoor particulate pollution. Finally, because we lack site-specific studies valuing marginal changes in mortality risk, we use benefit transfer methods that rely on metanalyses 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 in early 2020 may influence their attitudes more, in principle, our estimates of the magnitude of the improvement and the number of lives it could save (about one-quarter of premature deaths due to air pollution each year) and the economic cost (in the hundreds of millions of dollars) 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 TransMillenio 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 PM2.5 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 these restrictions reduced particulate pollution the most in those neighborhoods of the city where geophysical and meteorological conditions exacerbate air quality—the southwest and northwest. 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.

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Tables

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

Variable	Notes	Units	Source	Scale	Years
pm2.5	Fine particulate matter [1]	μg/m3	RMCAB (2021)	Station-day	2010-2021 [4]
POST	Treated [2]	0/1	N/A	Day	2010-2021 [4]
wind speed		m/s	RMCAB (2021)	Station-day	2010-2021 [4]
wind direction 1-8	Eight indicator variables [3]	0/1	RMCAB (2021)	Station-day	2010-2021 [4]
temperature	At ground level	Celsius Degrees	RMCAB (2021)	Station-day	2010-2021 [4]
rainfall		mm	RMCAB (2021)	Station-day	2010-2021 [4]
temperature20m	Temperature at 20m	Celsius Degrees	RMCAB (2021)	Station-day	2010-2021 [4]
thermal inversion	Temp. at 20m>temp. ground level	0/1	RMCAB (2021)	Station-day	2010-2021 [4]
upwind fires	Upwind forest fires	no.	NOAA (2021)	Bogotá	2015-2021

[1] Smaller than 2.5 μm; [2] On or after March 20, 2020; [3] 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; [4] Until February 28, 2021.

Table 2: Effect of Bogotá's lockdown on ambient PM2.5 concentrations; two-way fixed effects regression results, [s.e](%Δ)

Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Monitoring station(s)	**All**	**All**	**Carvajal**	**Centro Alto Rend.**	**Guaymaral**	**Kennedy**	**Las Ferias**	**San Cristóbal**	**Suba**	**Tunal**	**Usaquén**
POST	-0.25***		-0.23***	-0.29***	-0.11**	-0.28***	-0.09	-0.01	-0.23***	-0.26***	-0.26***
	[0.03]		[0.03]	[0.06]	[0.04]	[0.04]	[0.07]	[0.06]	[0.04]	[0.07]	[0.05]
	(-22.46)		(-20.73)	(-24.82)	(-10.39)	(-24.54)	(-8.71)	(-0.51)	(-20.21)	(-22.82)	(-23.07)
POST_MAR20		-0.03									
		[0.04]									
		(-2.64)									
POST_APR20		-0.45***									
		[0.04]									
		(-36.21)									
POST_MAY20		-0.59***									
		[0.02]									
		(-44.60)									
POST_JUN20		-0.11									
		[0.08]									
		(-10.70)									
POST_JUL20		-0.19**									
		[0.06]									
		(-17.72)									
POST_AUG20		-0.17**									
		[0.06]									
		(-15.77)									
POST_SEP20		-0.16**									
		[0.07]									
		(-14.62)									
POST_OCT20		-0.26***									
		[0.06]									
		(-22.86)									
POST_NOV20		-0.11									
		[0.09]									
		(-10.44)									
POST_DEC20		-0.10									
		[0.10]									
		(-9.13)									
POST_JAN21		-0.55***									
		[0.10]									
		(-42.05)									
POST_FEB21		-0.56***									
		[0.08]									
		(-43.14)									
Counterfactual	20.98	20.98	31.36	18.26	14.28	28.73	15.94	11.08	19.16	20.67	12.81
Observations	9,371	9,371	2,439	3,442	2,244	3,631	3,266	2,062	2,379	2,985	2,222
R-squared	0.529	0.536	0.489	0.605	0.605	0.625	0.618	0.577	0.687	0.559	0.604

The dependent variable is the natural logarithm of *pm2.5*. 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. Covariates are four sets of temporal fixed effects (*month, year, week, day-of-week*), and 16 time-varying covariates: *wind speed, windspeed squared, wind direction2–wind direction8, temperature, temperature squared, rainfall, rainfall squared, thermal inversion,* and *upwind fires.* Models 1 and 2 include monitoring station fixed effects (n = 9) 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 *PM2.5* for all station-days in years preceding the lockdown. $\%\Delta = (exp(\hat{\beta}) - 1) * 100$. ***p<0.01, **p<0.05, *p<0.1.

Table 3: Parameters used in analysis of effect of ambient PM2.5 on mortality

Parameter	**Notes**	**Source**	**Year**
Panel A: Long-term effects			
population	By age cohort and *localidad*	DANE (2018)	2018
incidence	By health endpoint and age cohort	DANE (2018)	2018
relative risk (RR)	By health endpoint	GBD (2019)	various
baseline PM2.5 (c1)		RMCAB (2020)	2010-2019
endline PM2.5 (c2)		Own calculations	2020-2021
Panel B: Short-term effects			
population	By *localidad*	DANE (2018)	2018
incidence	All death causes	DANE (2018)	2018
daily excess mortality (γ)	Per unit PM2.5	Atkinson et al. (2014)	various
baseline PM2.5 (c1)		RMCAB (2020)	2010-2019
endline PM2.5 (c2)		Own calculations	2020-2021

Table 4: Simulated changes in avoided mortality

Health endpoint	Counterfactual (deaths)	Simulation (attributable deaths)	Change (%)	Value of change (millions 2019 US$)
Panel A: Long-term effects, by health endpoint				
ALRI	131.46	36.87	28.04	57.87
COPD	315.14	87.80	27.86	137.82
Diabetes	39.36	8.33	21.17	13.08
IHD	709.54	178.38	25.14	280.02
LC	102.79	26.44	25.72	41.50
Stroke	332.51	89.02	26.77	139.74
Total	*1630.79*	*426.84*	*26.17*	*670.04*
Panel B: Short-term effects				
Total	370.57	114.65	30.94	179.97

Citywide model with population-weighted average effects. ALRI = Acute Lower Respiratory Infections; COPD = Chronic Obstructive Pulmonary Disease; IHD = Ischemic Heart Disease; LC= Lung Cancer.

Table 5: Parameters used to calculate value of statistical life (VSL)

ID	Description	Units	Value	Source
A	VSL OECD	2011 I$ (PPP)	3,830,000	WB (2016). p. 48
B	Average OECD GDP per capita	2011 I$ (PPP)	37,000	WB (2016). p. 48
C	Colombia GDP per capita 2011	2011 COP	13,556,411	WB/OECD (2021a)
D	Exchange rate COP to $I	N/A	1180	OECD (2021)
E	Colombia GDP per capita 2011	2011 I$ (PPP)	11,489	Formula: C/D
F	Income elasticity of VSL	N/A	1.2	WB (2016) p. 49
G	Colombia VSL 2011	2011 I$ (PPP)	941,180	Formula: A*(E/B)ˆF
H	Colombia CPI 2011	N/A	103	WB/OECD (2021b)
I	Colombia CPI 2019	N/A	141	WB/OECD (2021b)
J	$\%\Delta P$	%	0.4	Formula: (I-H)/H
K	Colombia GDP per capita 2011	2017 I$ (PPP)	12,481	WB/OECD (2021c)
L	Colombia GDP per capita 2019	2017 I$ (PPP)	14,585	WB/OECD (2021c)
M	$\%\Delta Y$	%	0.2	Formula: (L-K)/K
N	Colombia VSL 2019	2019 I$ (PPP)	1,569,770	Formula: G*((1+J+M)ˆF)

%Δ P = percentage change in price level; % Δ Y = percentage change in per capita GDP; COP = Colombian Pesos; GDP = gross domestic product; I$ = international United States Dollars; PPP = purchasing power parity.

Figures

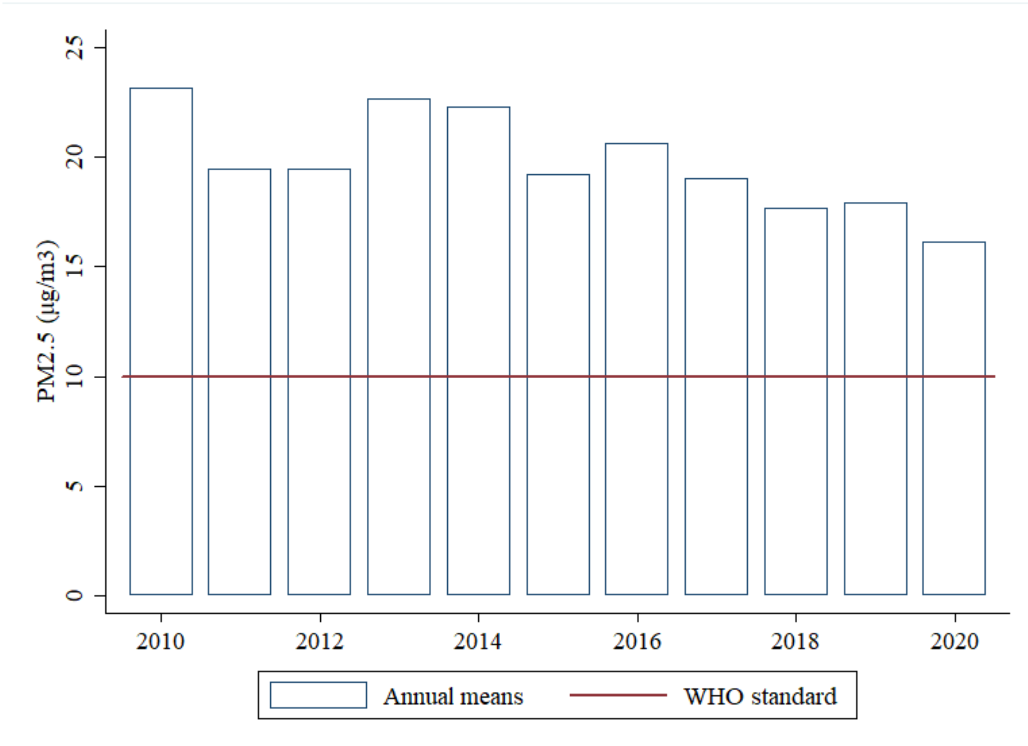

Figure 1: Population-weighted average annual ambient PM2.5 concentration in Bogotá, by year and World Health Organization (WHO) standard

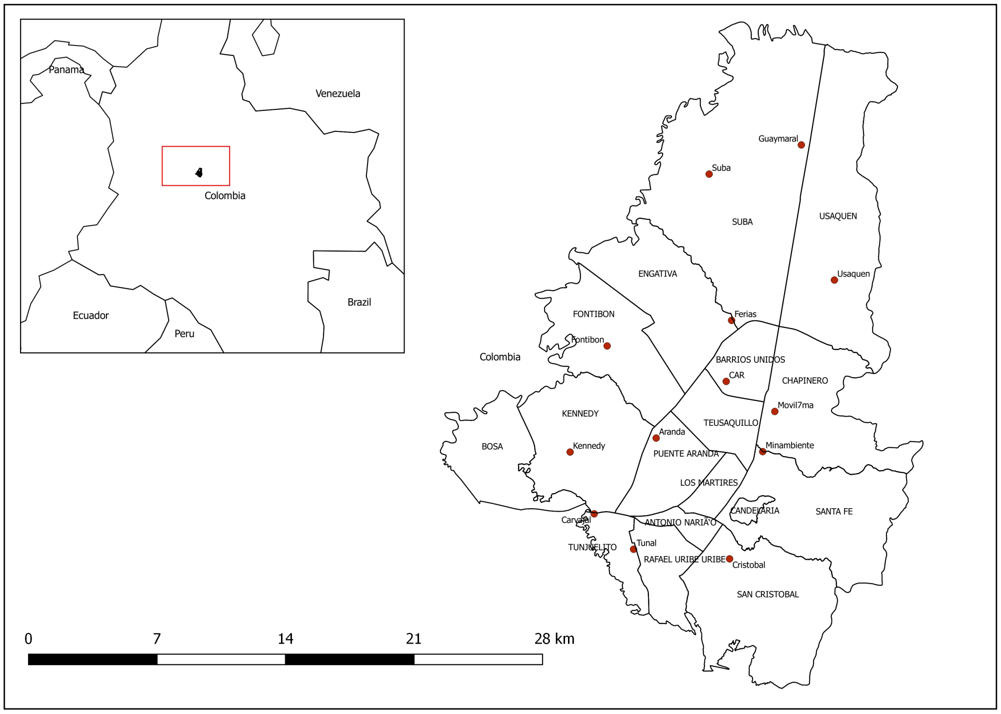

Figure 2: *Localidades* (polygons) and monitoring stations (red points) in Bogotá. This figure excludes southern *localidades* (Sumapaz, Usme, and Ciudad Bolívar)

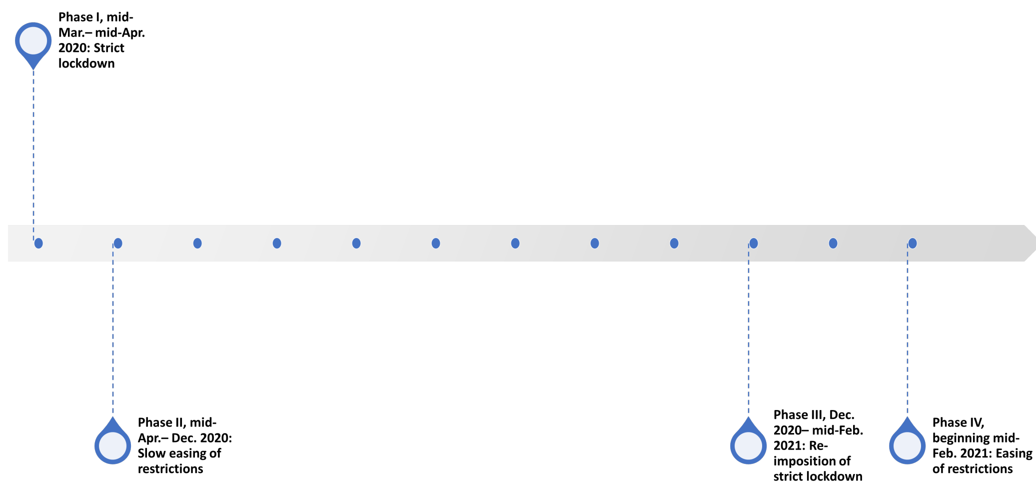

Figure 3: Timeline of Bogotá's Covid-19 lockdown

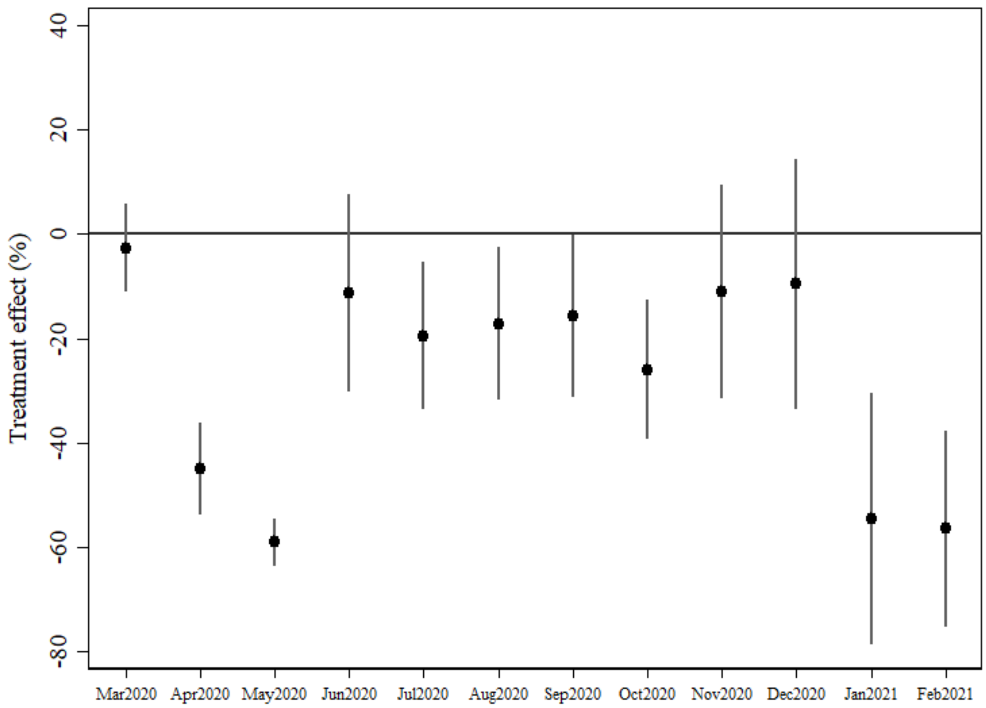

Figure 4: Estimated effect of Covid-19 lockdown on PM2.5 concentration. City-level model with treatment effects by lockdown month. Point estimates and 95% confidence intervals.

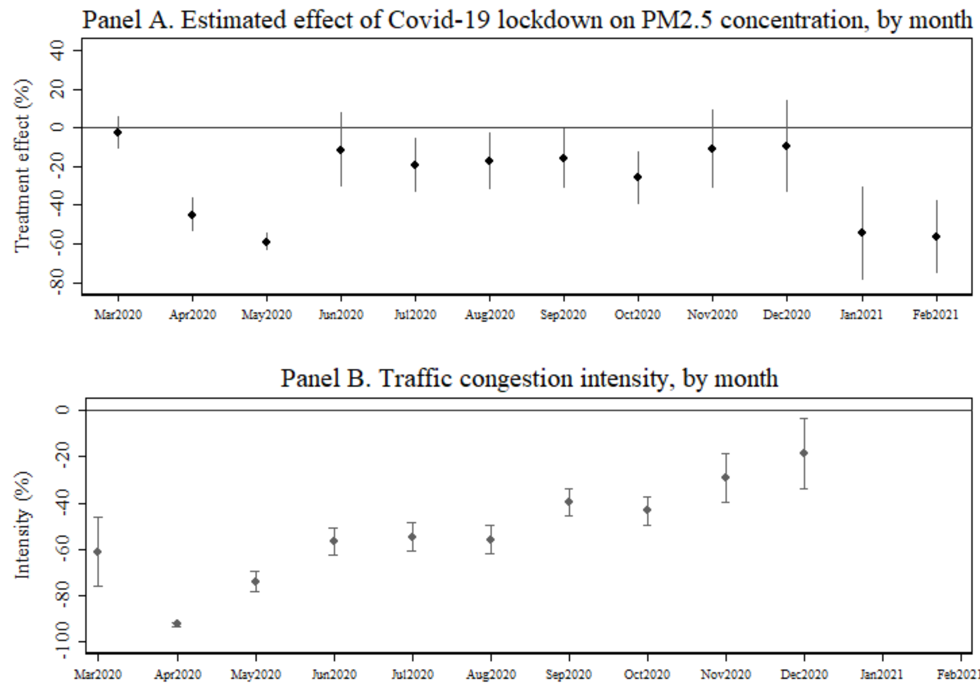

Figure 5: Comparison between effect of Covid-19 lockdown on PM2.5 concentration, point estimates, and 95% confidence intervals (Panel A) and traffic congestion using Waze data, means, and standard deviation (Panel B). Traffic congestion intensity is the monthly average of daily percentage change with respect to the week March 2–8, 2020 (IDB/IDB-Invest 2020). Data available from March 9, 2020, to December 12, 2020.

Appendix

Table A1: Monitoring stations: Population weights and percentages of observations missing for air quality and weather variables 1/1/2010 to 2/28/2021

Monitoring station	Population weight	*pm2.5*	*wind speed*	*wind direction*	*temperature*	*precipitation*	*temperature20m*
Carvajal	0.03	40	6	5	5	5	100
Centro Alto Rend.	0.06	17	6	5	3	3	100
Fontibón	n/a[a]	81	80	80	80	100	100
Guaymaral	n/a[a]	47	9	6	3	4	6
Kennedy	0.28	8	5	7	4	14	100
Las Ferias	0.11	26	4	5	4	5	100
MinAmbiente	n/a[a]	43	22	22	100	18	100
Móvil 7ma	n/a[b]	56	30	34	33	33	100
Puente Aranda	0.00	65	6	8	1	2	100
San Cristóbal	0.09	47	14	9	8	14	100
Suba	0.16	43	5	5	12	6	100
Tunal	0.20	17	6	4	11	3	100
Usaquén	0.07	20	12	7	35	6	100

Note: Monitoring stations matched to each *localidad*: Carvajal: Puente Aranda; Centro Alto Rend.: Barrios Unidos, Chapinero, Teusaquillo; Kennedy: Bosa, Fontibón, Kennedy; Las Ferias: Engativá; San Cristóbal: Antonio Nariño, La Candelaria, Los Mártires, San Cristóbal, Santa Fé; Suba: Suba; Tunal: Ciudad Bolívar, Rafael Uribe Uribe, Sumapaz, Tunjuelito, Usme; Usaquén: Usaquén. [a]Dropped from the analysis because of missing observations. [b]Dropped from the analysis because located next to a main road.

Table A2: Placebo tests: Effect of Bogotá's lockdown on ambient PM2.5 concentrations; two-way fixed effects city-level regression models (s.e.)

Model	2020-2021	2019-2020	2018-2019	2017-2018
POST (actual)	-0.25*** [0.03]			
POST (placebo)		-0.09 [0.05]		
POST (placebo)			-0.06 [0.05]	
POST (placebo)				0.01 [0.04]
Observations	9371	8189	7013	5974
R-squared	0.53	0.51	0.50	0.50

Note: The dependent variable is the natural logarithm of PM2.5. 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 February 28, 2021, or for the same time period in previous years. Covariates are monitoring station fixed effects (n = 9), four sets of temporal fixed effects (*month, year, week, day-of-week*), and 16 time-varying covariates: *wind speed, windspeed squared, wind direction2–wind direction8, temperature, temperature squared, rainfall, rainfall squared, thermal inversion,* and *upwind fires*. Standard errors are clustered at the monitoring station level. The counterfactual is the population weighted average of the natural logarithm of PM2.5 for all station-days in years preceding the lockdown. ***p<0.01, **p<0.05, *p<0.1.

Table A3: 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)

GDB (2019) cause	Short name	ICD-10 code	Codes available for Colombia (CEPAL/CELADE 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	J09, J11-J13, J15, J16, J18, J20-J22, J85, P23
Tracheal, bronchus, and lung cancer	LC	C33, C34-C34.92, Z12.2, Z80.1-Z80.2, Z85.1-Z85.20	C33-C34
Stroke	Stroke	G45-G46.8, I60-I62, I62.9-I64, I64.1, I65-I69.998, Z82.3	G45, I60-I64, I67,I69
Ischemic stroke	Stroke	G45-G46.8, I63-I63.9, I65-I66.9, I67.2-I67.848, I69.3-I69.4	G45, I63, I67, I69
Diabetes mellitus type 2	Diabetes	E11-E11.1, E11.3-E11.9	E11

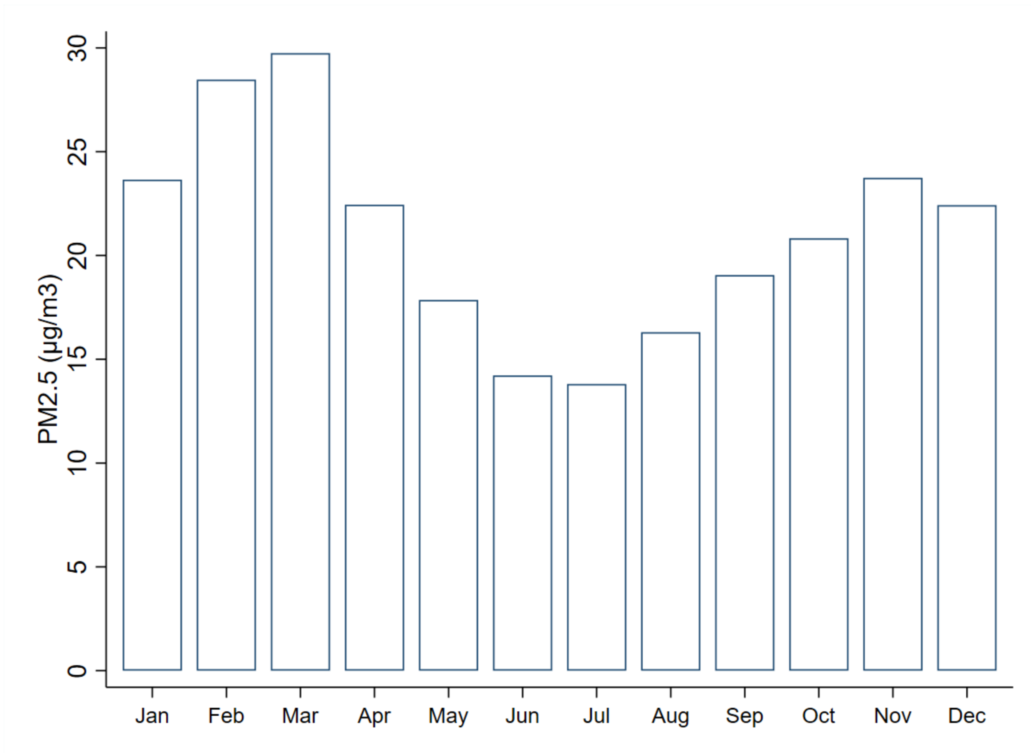

Figure A1: Population-weighted average monthly ambient PM2.5 concentration in Bogotá, by month

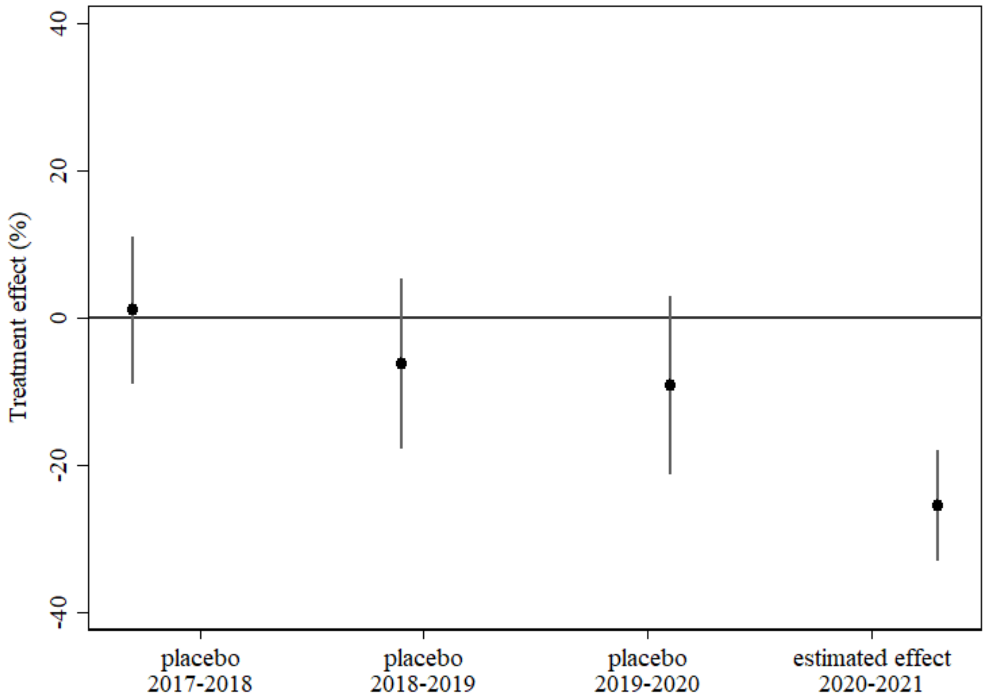

Figure A2: Placebo tests: Effect of actual Covid-19 lockdown in 2020-2021 and effects of placebo treatments in 2017-2018, 2018-2019, and 2019-2020; Two-way fixed effects city-level regression models, point estimates and 95 percent confidence intervals.