Forest fires and impacts of COVID-19 lockdowns on air quality in four Latin American megacities

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Abstract
Latin America, as other regions in the world, imposed mobility restrictions to tackle the COVID-19 pandemic. Although recent research has analyzed the effect of mobility restrictions on air quality in several regions, a scarce literature explores the causal effects of the lockdowns in Latin America at a city scale whose results may guide local policymaking. This article, based on a quasi-experimental approach, estimates the causal short-term impacts of lockdowns on air quality considering the influence of forest fires on pollution in four megacities in Latin America (Bogotá, Mexico City, Santiago, and Sao Paulo). Results show that nitrogen oxides and carbon monoxide consistently declined (from 16% to 68%), nevertheless, fine particles rarely decreased across cities. Only Bogotá exhibited an overall reduction in fine particles (45% for PM$_{2.5}$). Mexico City obtained the lowest reduction in pollutants, whereas Bogotá outperformed other cities in several pollutants. Evidence from mobility statistics supports the decrease in air pollution by a reduction in driving, transit use, and other mobility indicators.

1. Introduction
Many countries imposed lockdowns to mitigate the coronavirus disease (COVID-19) infection at the beginning of the current pandemic. Lockdowns unintendedly mimic sudden and temporary policy interventions to cut air pollution and reduce health effects$^1$ by restricting driving or industry operations.

Recent research has examined the impacts of lockdown on air quality at a global scale. Using satellite or ground station data in econometric models, Dang and Trinh [1], Venter et al [2], and Liu et al [3] found that mobility restrictions decrease fine particulate matter (PM$_{2.5}$) or nitrogen dioxide (NO$_2$) concentrations. Lenzen et al [4], employing a global multi-regional macro-economic model, show that nitrogen oxides (NO$_x$) and PM$_{2.5}$ emissions also decline during lockdown. The results of these studies differ in the magnitude of air pollution effects. For instance, Dang and Trinh [1] report a global reduction of 5% for NO$_2$ and 4% for PM$_{2.5}$, whereas Venter et al [2] find a decrease of 60% for NO$_2$ and 31% for PM$_{2.5}$. At regional scale, Hammer et al [5] used a chemical transport model showing that China exhibited a reduction of up to 15 $\mu$g m$^{-3}$ in PM$_{2.5}$, while decreases in Europe and the United States (US) were lower$^2$. Other works conduct country-specific analyses for some countries, mainly to assess the effect on NO$_2$ or particles. He et al [6], Cole et al [7], Almond et al [8], Liu et al [9], and Lu et al [10] investigate mobility restrictions in China; Brodeur et al [11] in the US; Briz-Redón et al [12] in Spain; Singh et al [13], Dhaka et al [14], and Vadrevu et al [15] in India; Higham et al [16] in the UK; and Dang and Trinh [17] in Vietnam. Several of these studies use econometric models (difference-in-difference, regression discontinuity, or synthetic control methods) to estimate

$^1$ Several epidemiological studies highlight the air pollution-related risk of mortality for low respiratory infections, chronic obstructive pulmonary disease, ischemic heart disease, stroke, among other causes [41].

$^2$ Recent research assesses whether air quality impacts induced by the lockdown persist when mobility restrictions are lifted. In this case, effects on air quality are analyzed considering a time period that is several months longer than the first month of lockdown implementation [42].
the causal effects of lockdown on air quality, whose calculated reductions range between 12% and 63% depending on the pollutant.

Although this emerging literature examines the effect of lockdowns on air quality, a scarce literature analyzes the case of Latin American cities. Studying Latin America is important as the region exhibits high levels of pollution exceeding the World Health Organization’s (WHO) guidelines. Furthermore, several Latin American cities periodically implement temporary driving or industry bans to tackle air pollution spikes. Rodríguez-Urrego and Rodríguez-Urrego [18] assessed the impact of lockdowns in 50 cities including four Latin American cities. Comparing a week before and after the lockdown, the authors found that fine particles decreased 57%, 10% and 2% in Bogotá, Santiago and Mexico City, respectively. In another study, Sahraei et al [19] examined the effect of lockdowns in 21 cities, including Sao Paulo, Mexico City, Santiago and Guadalajara. Using data of 2019 for the same period of the lockdown as the reference year, they found that the frequency of hazardous levels of the air quality index slightly decreased during lockdown for some cities. These works offer prior estimates of the effects of the lockdown, however, they do not estimate the causal impact of the mobility restrictions or do not account for possible confounders, for example, forest fires.

This article employs mobility-restriction policies to estimate and compare the causal short-term impacts of the lockdown on air quality for four megacities in Latin America: Bogotá, Mexico City, Santiago, and Sao Paulo. The causal effect is assessed using a regression discontinuity approach for a time window of 28 days before and 28 days after the lockdown (i.e. from the lockdown start), and follows a set of robustness exercises. This study includes some additional evidence to explain the magnitude of the outcome effects.

This research contributes to the existing literature on two fronts. First, this study examines individually and with more detail the effect of lockdown in some Latin American cities, accounting for some confounders. This study provides a causal estimate using an econometric approach, analyzes intraday variation of air quality, and computes the health benefit/cost of pollution changes. This research uses high frequency data from ground-monitoring stations for a wide range of pollutants: carbon monoxide (CO), NO₂, NO₃, PM₁.₅, and particulate matter with a diameter equal to or smaller than 10 µm (PM₁₀), and adds the effect of forest fires on air quality equation, besides the effect of local weather. Estimates provide lockdown effects not only for all hours of the day, but also for intraday time slots (morning peak, evening peak, and off peak). Splitting the sample in this way makes it possible to analyze the effects of mobility restrictions considering the dynamics of pollutant sources in intraday periods. As far as the author knows based on the cited literature, most research uses daily observations of pollutants, and from those studies that employ hourly data [7, 13, 16], only Singh et al [13] exploits intraday variation to estimate the effects of the lockdown during peak hours. Recent literature highlights the problem of transboundary pollution caused by fire smoke. For instance, Sheldon and Sankaran [20] found that smoke from forest fires in Indonesia travels to Singapore increasing air pollution and polyclinic attendance. In Latin America, Rincón-Riveros et al [21] demonstrate that forest fires in the Amazon region strongly correlate with air quality in Bogotá. Forest-fire smoke contains several compounds including PM₁.₅, CO and NOₓ. Moreover, Aguilera et al [22] suggest that PM₁.₅ from forest fires becomes more harmful for human health than other PM₁.₅ sources. All these elements point to forest-fire smoke being a confounder. Hence, including forest fires as a covariate is intended to improve estimates.

Second, this study estimates the effect of mobility restrictions at their maximum potential, i.e. when lockdowns were at their most stringent (when stay-at-home requirements were imposed). Studying the impact under such circumstances sheds light on the greatest impacts that may be achieved due to critical mobility (and industry operation) restrictions. Estimations are conducted using the donut approach [23], which consists of excluding some observations to account for people’s anticipation response, because citizens may reduce mobility to avoid contagion before the lockdown begins. Time-series structural break tests are employed to empirically define the beginning of anticipation behavior before lockdown. Most studies provide an estimate of the effects of lockdown at global and country scale, or across several cities, revealing an average overview of the policy impacts. However, the specific use of those results at city scale is limited, making them less informative for local policymakers.

Estimating effects for each city offers useful lessons considering site-specific conditions and opens the debate on potential actions that could make current air-pollution abatement policies effective. This research also assembles information

3 Annual PM₁.₅ concentrations in several capital cities in Latin America are between 1.5 and 3 times the WHO’s standard of 10 µg m⁻³. Data retrieved from https://whoairquality.shinyapps.io/AmbientAirQualityDatabase/ (accessed in July 2020). Moreover, poverty and inequality has favored the spread of the virus in the region [43, 44]. Latin America has faced high COVID-19 mortality rates (above 190 fatalities per hundred thousand inhabitants). Data retrieved from https://coronavirus.jhu.edu/data/mortality (accessed in August 2021).

4 For a detailed explanation of the AQI and its estimation method see section 2.2 of Sahraei et al [19].

5 Among several studies, Vadrevu et al [15] obtain estimates for specific cities in India. However, they use an autoregressive moving average model with intervention, which differs from the classical econometric methods for impact evaluation.
from the Oxford COVID-19 Government Response Tracker (OxCGRT) and mobility outcome variables from Google and Apple reports to analyze stringency of the lockdown and mobility indicators.

2. Methods

2.1. Data

Lockdowns imply a set of policies that restrict people’s movement. Restrictions induce changes in mobility by modifying citizens’ travel destination and transport mode, or the normal industry operations. These policies vary in the degree of stringency. The four cities studied began to cancel and restrict big events and gatherings, close schools, and recommend teleworking. They then banned smaller events and gatherings, closed some workplaces, and encouraged people to reduce mobility. The most stringent policy consisted of mandatory stay-at-home requirements. An aggregated indicator of the policies implemented by governments to contain contagion is the stringency index. The OxCGRT provides daily scores between 0 and 100 of the stringency of policy responses [24]. Although the index is mainly available at country level, it is widely determined by policies in the largest cities studied. By the end of May, Colombia, Mexico, Chile and Brazil were a cluster of nations with high levels of the stringency index (see figure A1, supporting information (SI)).

Air quality information consists of ground level measurements of hourly CO, NO₂, NO₃, PM₁₀ and PM₂.₅ concentrations from 1 January to 31 May 2020. Data is downloaded from the webpages of the Bogotá Air Quality Monitoring Network [25], the Mexico City Atmospheric Monitoring System [26], the Santiago Air Quality Monitoring Network [27], and the Sao Paulo Air Quality Monitoring Network [28] (figure A2, SI). All networks provide a wide coverage of pollution and include records of weather variables such as wind speed, wind direction, temperature and relative humidity. The data cleaning procedure excludes stations with few observations around the lockdown dates. A comparison of pollution among cities in the pre-pandemic period indicates that Latin American cities largely differ in air quality for most pollutants. The highest daily average concentrations of CO, NO₂, and PM₂.₅ are observed for Bogotá (0.95 ppm, 39.5 ppb and 28 µg m⁻³, respectively), of NO₂ (25.4 ppb) for México City, and of PM₁₀ (65 µg m⁻³) for Santiago.

Data on daily active forest fires is taken from The National Aeronautics and Space Administration (NASA)’s Fire Information for Resource Management System [29], which provides near real-time records of fires across the globe based on satellites. This study uses the Visible Infrared Imaging Radiometer Suite aboard the joint NASA/National Oceanic and Atmospheric Administration (NOAA) Suomi National Polar-orbiting Partnership (Suomi NPP) product given its high resolution (375 m pixel). To infer the amount of forest fire emissions that may be transported by wind for long distances to each city, this article computes the total upwind fire radiative power (UFRP) within a 1500 × 1500 Km² centered on each city¹. Information on wind direction from airport weather stations within the same 1500 × 1500 Km²,⁸ obtained from NOAA [30], is used to approximate the trajectory of the forest fire emissions that may reach each city⁹. Figure A3-SI shows UFRP for the four cities. It is observed that upwind forest fires for Bogotá are larger than those for Mexico City, Santiago and Sao Paulo.

Mobility variables are taken from Google COVID-19 Community Mobility Reports [31] and Apple COVID-19 Mobility Trends Reports [32]. Google uses aggregate and anonymized data to compute the daily percentage change in visits at several places with respect to 3 January–6 February 2020. It includes information on mobility indicators for grocery stores and pharmacies, retail and recreation spaces (restaurants, cafes, etc.), parks, residential, and workplaces. Apple reports the daily change in the volume of user requests for directions on Apple Maps relative to 13 January 2020. Apple reports provide information on mobility indicators for driving, transit, and walking¹⁰. Information on public transport use is supplemented with visits to transit stations from Google reports¹¹. Table A1-SI presents the descriptive statistics for all variables.

2.2. Air quality impacts

Causal short-term impacts of lockdowns on air quality are estimated using regression discontinuity

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¹ This article uses a buffer of 1500 × 1500 Km² to cover a wide range of regional biomass burning transport from wildfires as suggested by Rincón-Riveros et al [21].

⁸ The database includes information from 73, 81, 39 and 187 airport weather stations surrounding Bogotá, Mexico City, Santiago, and Sao Paolo, respectively.

⁹ Total upwind fire radiative power for every city is calculated as follows. First, the 1500 × 1500 Km² is divided into four quadrants, Northeast (NE), Southeast (SE), Southwest (SW), and Northwest (NW). Second, prevailing winds in each quadrant are estimated as the mode of the hourly wind direction (NE, SE, SW, NW) at all airports located in the same quadrant for a specific day. Third, the procedure computes UFRP per day as the sum of fire radiative power for all forest fires across quadrants when quadrant of fire location matches prevailing winds. For example, fires located in SE quadrant are upwind forest fires when prevailing wind direction in that quadrant is SE.

¹⁰ Driving and walking statistics for Bogotá were imputed with country-level figures. Variations in these country mobility variables reasonably capture changes in driving or walking in Bogotá, since the city led the country’s implementation of policies against COVID-19.

¹¹ Apple database does not report transit information for Bogotá and Santiago.
design in time (RD). This consists of using observations before lockdown as a counterfactual of the observations after the lockdown within a narrow time window around the cut-off point. Identification relies on the assumption that unobserved factors change smoothly around the threshold and that the policy analyzed is the only source of sharp change [33]. A key element of the RD method is the definition of the variable that determines treatment and establishes the cut-off point; i.e. the date when the lockdown begins. One alternative is to use the date of the first policy implemented to reduce COVID-19 contagion; however, defining treatment in this form does not provide an estimate of the maximum potential effect of the lockdown. A change just to the right of the cut-off is the average effect of several policies that differ in stringency.

Studying the potential impact under the most stringent condition is relevant from the policy perspective because it sheds light on the largest impacts that may be achieved given the critical mobility (and firm production) restrictions. Thus, this study defines lockdown in each city as the mandatory stay-at-home period. Given that this is the most stringent policy, it would induce a sharp change in the outcome variable and no other policy might motivate governments to take additional measures. Bogotá, Mexico City, Santiago, and Sao Paulo implemented mandatory stay-at-home orders on 20 March, 30 March, 27 March, and 24 March 2020, respectively. These cities executed citywide lockdowns, except for Santiago whose stay-at-home policy consisted of dynamic lockdowns that operated in certain times, order, and locations. The lockdown date for Santiago corresponds to the introduction of the first stay-at-home policy in the city.

RD estimation assumes no anticipation effects; otherwise, estimates of the lockdown impact would be biased. There are at least two reasons why citizens may react earlier than the lockdown dates affecting mobility and air pollution. On the one hand, measures taken in other countries and informed through news may influence an earlier response to avoid contagion. On the other, authorities' announcements of future policies and implementation of gradual measures before stay-at-home restrictions induce progressive adjustments in mobility decisions. A statistical approach to assess changes in variable patterns is the estimation of structural breaks. The supremum Wald statistic is used to test for unknown structural breaks for driving variable, since driving is one of the channels influencing pollution and is the only available variable across cities that informs on possible changes in vehicle circulation. For the sake of generality, structural breaks are also estimated for other mobility indicators and stringency. All tests control for day of the week and holidays and examine breaks in mean, intercept or time trend slope, and both. The algorithm chooses the earliest statistically significant break that occurs in March for each variable because the most critical policy announcements for the four cities occurred in this month. The presence of statistically significant breaks before lockdown would be an indication of early mobility response.

This article examines the magnitude of the effects of strict lockdowns compared to a situation in which mobility variables are not influenced by policy measures, referred to as the pre-pandemic period. If there is evidence of structural breaks before lockdowns, the dates of the estimated breaks delimit the end of the pre-pandemic period. With these considerations, RD estimations use the donut approach [23, 34], which obtains the treatment effect by excluding observations within some distance of the threshold to address early behavioral responses. Estimation of the lockdown effect excludes data between the end of pre-pandemic period and the day before the lockdown start. The pre-pandemic period for air pollution analysis is defined by the structural break of driving variable. The effect of lockdowns on air quality for each city is assessed as follows:

$$y_{pdhc} = \delta \text{Lockdown} + \lambda_1 \text{date} + \lambda_2 \text{date} \times \text{Lockdown} + X \phi + F \omega + \alpha_{dow} + \alpha_{hol} + \alpha_h + \epsilon_{pdhc}$$

(1)

where $y_{pdhc}$ is the concentration of pollutant $p$ (in logs) for day $d$, hour $h$ in city $c$. Effects are measured on five pollutants: CO, NO$_2$, NO$_x$, PM$_{10}$ and PM$_{2.5}$. Concentration level is the hourly city average across available monitoring stations, except for Santiago that uses one station affected by the first lockdown$^{12}$. For consistency in the methodology, the same RD equation is applied to the four cities. Lockdown is an indicator variable that takes the value of one from the lockdown date, and is equal to zero otherwise. date is a daily time trend centered on the lockdown start, which takes negative values before the end of the driving break (pre-pandemic period), and positive values after the lockdown begins. date $\times$ Lockdown is the interaction term of date times Lockdown, which allows to account for different time trends before and after lockdown. $\delta$ is the causal short-term effect of lockdown on air quality$^{13}$. In the case of Santiago, $\delta$ provides a city-wide estimate of a local policy. This impact is expec-

$^{12}$ Although, the dynamic scheme of lockdowns in Santiago might be considered to analyze causal effects using an alternative approach such as differences-in-differences (DID), a detailed exploration of the data shows that information on monitoring stations is not always available in areas affected by subsequent lockdowns or in locations where authorities lifted lockdowns, impeding the implementation of a DID estimation.

$^{13}$ To be precise, the causal effect is estimated as $[\exp(\delta) - 1]$ and its standard error through the delta method. Although researchers frequently use $\delta$ as the estimate of the effect, it is not a close approximation of $[\exp(\delta) - 1]$ when absolute values of $\delta$ are relatively large.
Several models were run to assess the model performance to presents the Autocorrelation functions of the residuals suggest that serial correlation is the current and 1-day lag of UFRP within a day of the week, holidays, and hourly-fixed effects. and is equal to zero otherwise.

Each dummy variable takes the value of one if wind direction (in degrees) falls into one of those bins, and is equal to zero otherwise. \( \alpha_{\text{dow}}, \alpha_{\text{hol}} \) and \( \alpha_{\text{h}} \) are day of the week, holidays, and hourly-fixed effects. \( F \) is the current and 1-day lag of UFRP within a 1500 \( \times \) 1500 Km\(^2\) centered on each city. \( \epsilon_{\text{pdeh}} \) is the error term.

All regressions obtain estimates with a rectangular kernel. In order to use the same bandwidth for all variables and account for seasonality and a reasonable narrow window around the lockdown date, regressions provide estimates based on a 28-day time window before the end of pre-pandemic period and 28 days after the lockdown. Additional exercises—running a regression assuming a longer range transport influence of forest fires than the buffer of 1500 \( \times \) 1500 Km\(^2\), using a shorter 14-day bandwidth, and including weather covariates in quartics—assess the sensitivity of the coefficients. Models address heteroskedasticity and autocorrelation with Newey–West standard errors up to 2-day lags. High frequency information on pollutants also allows a detailed analysis of the effects in different time slots. Estimations of the impact on pollutants during all hours of the day (overall), morning peak (5:00 a.m.–10:00 a.m.), off peak (10:00 a.m.–4:00 p.m.) and evening peak (4:00 p.m.–9:00 p.m.) assess the magnitude of the effects in periods of high and low traffic demand.

3. Results

3.1. Structural breaks

Table A2-SI presents the results of the structural breaks for driving, other mobility variables and stringency index for each city. The supremum test statistic rejects the null hypothesis of no structural break (either in mean or in slope, or both) at the 1% significance level for all mobility variables and stringency index across cities. In general, the first variable to respond in the beginning of the pandemic after the implementation of mobility-restriction policies was driving. The lockdown dates happened after those variable breaks. The government response, measured through the stringency index, started in the second week of March. The exception to this pattern is Mexico City, where government response to COVID-19 came several days after people's reaction in mobility variables. Mobility variables for most cities responded between one and nine days after the stringency index break or between one and 15 days before lockdown date (figure A4, SI). The evidence of structural breaks in driving suggests that people adjusted their mobility patterns before lockdown.

3.2. Air quality effects

Figure A5-SI displays the RD graphs using raw data of daily concentrations for five pollutants (CO, NO\(_2\), NO\(_x\), PM\(_{10}\) and PM\(_{2.5}\)) and four cities (from panels (A) to (D)). It is salient that, across cities, pollutants such as NO\(_2\) and NO\(_x\) declined when lockdown was in place. CO also appears to decrease during lockdown for some cities. However, particles (PM\(_{10}\) and PM\(_{2.5}\)) seem to be less responsive to lockdowns than the other pollutants. Although these graphs show general patterns, they do not control for other factors and confounders that affect pollution. Table 1 presents the estimates of the lockdown effect on air pollutants considering the influence of forest fires. Across cities, NO\(_2\) and NO\(_x\) declined (from 20% to 59%), CO also decreased for three of the cities studied (from 29% to 37%), while particles rarely diminished. Compared to estimations that exclude the effect of forest fires (see table A5, SI), adding forest fire controls in the estimations changes the magnitude and statistical significance of lockdown effects. The most important
show that CO decreases in all four

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Overall

Off-peak

Morning peak

−0.291***

(0.036)

−0.624***

(0.033)

−0.561***

(0.035)

−0.486***

(0.070)

−0.425***

(0.116)

Evening peak

−0.393***

(0.038)

−0.584***

(0.037)

−0.596***

(0.031)

−0.536***

(0.066)

−0.470***

(0.104)

Effects on CO reflect the impact of reduced driving. Overall, lockdown decreased PM2.5 in Bogotá by 45%, compared to pre-pandemic levels. Slight variations in coefficient magnitude and significance occur for other pollutants. Regarding the intraday impacts of lockdowns, the results in table 1 show that CO decreases in all four cities during the morning peak. These estimates are statistically different from zero at the 1% significance level. The CO reduction for the morning peak ranges from 26% in Sao Paulo to 56% in Santiago. Given that CO is as a tracer of gasoline-engine vehicle combustion and the association between CO and car use is strong during the morning peak [35, 36], lockdown effects on CO reflect the impact of reduced driving. Table 1. Lockdown effect on air pollutants.

| Model               | (1) CO          | (2) NO₂         | (3) NOx         | (4) PM₁₀        | (5) PM₂.₅       |
|---------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| BOGOTÁ              |                 |                 |                 |                 |                 |
| Overall             | −0.371***       | −0.594***       | −0.572***       | −0.468***       | −0.452***       |
|                     | (0.044)         | (0.034)         | (0.031)         | (0.075)         | (0.114)         |
| Morning peak        | −0.463***       | −0.513***       | −0.652***       | −0.384***       | −0.270*         |
|                     | (0.038)         | (0.036)         | (0.030)         | (0.091)         | (0.146)         |
| Off-peak            | −0.291***       | −0.624***       | −0.561***       | −0.486***       | −0.425***       |
|                     | (0.036)         | (0.033)         | (0.035)         | (0.070)         | (0.116)         |
| Evening peak        | −0.393***       | −0.584***       | −0.596***       | −0.536***       | −0.470***       |
|                     | (0.038)         | (0.037)         | (0.031)         | (0.066)         | (0.104)         |
| MEXICO CITY         |                 |                 |                 |                 |                 |
| Overall             | −0.066          | −0.220***       | −0.202***       | −0.107          | 0.118           |
|                     | (0.086)         | (0.083)         | (0.050)         | (0.136)         | (0.158)         |
| Morning peak        | −0.370***       | −0.209***       | −0.303***       | −0.082          | 0.032           |
|                     | (0.056)         | (0.039)         | (0.069)         | (0.130)         | (0.157)         |
| Off-peak            | 0.042           | −0.219***       | −0.181**        | −0.002          | 0.250           |
|                     | (0.169)         | (0.078)         | (0.088)         | (0.121)         | (0.171)         |
| Evening peak        | 0.090           | −0.172**        | −0.163*         | −0.023          | 0.268           |
|                     | (0.188)         | (0.087)         | (0.093)         | (0.154)         | (0.168)         |
| SANTIAGO            |                 |                 |                 |                 |                 |
| Overall             | −0.331***       | −0.500***       | −0.503***       | −0.084          | 0.058           |
|                     | (0.042)         | (0.045)         | (0.039)         | (0.089)         | (0.122)         |
| Morning peak        | −0.563***       | −0.556***       | −0.683***       | −0.448***       | −0.238*         |
|                     | (0.040)         | (0.071)         | (0.048)         | (0.050)         | (0.134)         |
| Off-peak            | −0.274***       | −0.300**        | −0.313**        | 0.019           | −0.069          |
|                     | (0.073)         | (0.140)         | (0.124)         | (0.097)         | (0.113)         |
| Evening peak        | −0.391***       | −0.489***       | −0.465***       | −0.105          | −0.031          |
|                     | (0.055)         | (0.082)         | (0.091)         | (0.131)         | (0.148)         |
| SAO PAULO           |                 |                 |                 |                 |                 |
| Overall             | −0.292***       | −0.337***       | −0.389***       | −0.190**        | −0.162          |
|                     | (0.029)         | (0.037)         | (0.039)         | (0.092)         | (0.101)         |
| Morning peak        | −0.260***       | −0.293***       | −0.242***       | −0.219***       | −0.115          |
|                     | (0.059)         | (0.057)         | (0.061)         | (0.080)         | (0.122)         |
| Off-peak            | −0.394***       | −0.495***       | −0.568***       | −0.402***       | −0.318**        |
|                     | (0.040)         | (0.046)         | (0.036)         | (0.078)         | (0.105)         |
| Evening peak        | −0.405***       | −0.543***       | −0.615***       | −0.392***       | −0.375***       |
|                     | (0.022)         | (0.029)         | (0.024)         | (0.060)         | (0.082)         |

Note: This table shows the estimates of the lockdown effect on pollution in equation (1) for all hours of the day (overall), morning, evening, and off-peak time slots. Columns (1)–(5) display results for carbon monoxide (CO), nitrogen dioxide (NO₂), nitrogen oxides (NOₓ), and particulate matter with a diameter equal to or smaller than 10 (PM₁₀) and 2.5 μm (PM₂.₅), respectively. Newey–West standard errors robust to heteroscedasticity and 2-day lag serial correlation shown in parenthesis. ***, * p < 0.01, ** p < 0.05, * p < 0.10.

Implication is for PM₂.₅, a pollutant with critical health impacts. Overall, lockdown decreased PM₂.₅ in Bogotá by 45%, compared to pre-pandemic levels. Slight variations in coefficient magnitude and significance occur for other pollutants.

In the case of NO₂ and NOₓ, lockdowns induced reductions for all the cities studied for the morning, evening, and off peak. Lockdown time-slot effects vary from −17% in Mexico City to −63% in Bogotá for NO₂, and from −16% in Mexico City to −68% in Santiago for NOₓ. Unlike CO, NO₂ and NOₓ do not always exhibit the largest reductions during the morning or evening peak. This can be explained by the fact that NO₂ and NOₓ are reactive in the
atmosphere; i.e. nitrogen oxide formation is influenced by temperature [37], often reaching high values around noon. Particles did not decrease in all cities studied. For instance, in Mexico City, lockdown coefficients for PM_{10} and PM_{2.5} are statistically insignificant at all conventional levels for the three time-slot estimations. In Santiago, PM_{10} and PM_{2.5} only declined during the morning peak (45% and 24%, respectively). For Sao Paulo, PM_{10} diminished in morning, evening, and off-peak periods. For PM_{2.5} in this city, lockdown only reduces concentrations during the evening and off-peak. Unlike other cities, in Bogotá, the effects of lockdown on PM_{10} and PM_{2.5} occur for different time slots. The lockdown impact in Bogotá reduces PM_{10} between 38% and 54% and PM_{2.5} between 27% and 47%. These results differ from those found by Rodríguez-Urrego and Rodríguez-Urrego [18]. They reported effects of lockdown on PM_{2.5} that were larger than those shown in this study for Bogotá, Santiago, and Mexico City. It may be explained not only by the difference in the methodology, but also by the dates Rodríguez-Urrego and Rodríguez-Urrego [18] employed as lockdowns. In the case of Mexico City and Santiago they chose earlier dates for the lockdowns than the dates of the stay-at-home policy used in this study [19].

Table A6-SI displays robustness checks for overall estimates and all pollutants. The first exercise consists of estimating the impact of lockdown considering the influence of upwind forest fires within a 2000 × 2000 Km² (panel (A)) [19]. The results are qualitatively and quantitatively similar to those found with a buffer of 1500 × 1500 Km². This indicates that considering long distances in forest fire emission transport does not affect the main findings. In the second exploration, estimations employ a 14-day bandwidth (panel (B)). Results are analogous to the baseline models for CO, NO₂ and NOₓ. Some differences for particles appear for a few estimates compared to 28-day bandwidth models. Such differences might be associated to the use of a very short bandwidth that does not entirely capture the complete seasonality pattern of this pollutant. Dang and Trinh [1], for instance, use a large 88-day bandwidth for PM_{2.5}, and find that employing a narrow bandwidth also introduces changes in some of the estimates making them insignificant. In the third exercise, specifications add weather covariates in quartics allowing a large degree of nonlinearity (panel (C)). In this analysis, conclusions regarding the lockdown effects remain unaltered.

Findings for air pollutants are consistent with the responses in mobility indicators. Figure A6-SI shows mobility variables and the stringency index over time for the five cities. It is clear that residential variable tends to increase after the stringency index break, while the rest of the mobility variables decline. In all cities, regardless of the stringency level, most variables seem to exhibit their greatest change when lockdown started. RD approach applied to driving indicator and other mobility variables also supports the decrease in air pollutants (table A7, SI). The increase in the residential variable appears to show that the stay-at-home policy was more effective in Bogotá (37%) than in Mexico City (19%). Regarding stringency, the four Latin American cities studied raised their stringency above 60%.

3.3. Relative performance across cities
Another way to compare the results across cities is to explore the relative performance of the studied indicators using the point estimates obtained in the previous section. Figure 1 displays point estimates of the overall lockdown effect on pollutants (y-axis) versus stringency change (upper-left graph), and impacts on residential (upper-right graph), driving (lower-left graph), and workplace (lower-right graph) indicators (x-axis). As explained earlier, pollution may be affected by stringency level and, therefore, through channels such as vehicle and industry activity. Comparing estimates on air quality with driving effects seeks to assess the influence of changes in vehicle emissions. Similarly, comparing the impacts on residential and workplace indicators with the effect on pollutants attempts to examine the relative effect of work restrictions (as a proxy of industry activity) with air quality. Points located on the 45° line imply that the lockdown impact on a pollutant is equally proportional to the change in stringency or other indicators. The graphs show that Mexico City is often positioned above and far from the 45° line, indicating that its air quality improvement during lockdown was the lowest. In the case of the other cities, Bogotá seems to perform well when its pollution outcomes are compared with the changes in driving and residential variables.

4. Additional evidence
The differences found for the four cities may depend on factors such as enforcement, people’s behavior, emission sources, atmospheric chemistry, etc. Table B1-SI presents the contribution of mobile and point sources to air pollution in each city from emission inventories. A comparison of the lockdown estimates on air quality with the emission share for each source sheds lights on which sources may have contributed to reducing specific pollutants during the lockdown (see SI, section B).

18 Results in this article are not directly comparable to those shown by Sahraei et al [19] because of the differences in the metrics used to assess air pollution. Sahraei et al [19] analyzes the changes in each level of health concern (from good to very unhealthy classes) of the air quality index.
19 UFPF is estimated using the same procedure explained in footnote 9. Extending the area to a 2000 × 2000 Km² increases the number of airport weather stations to 101, 141, 59 and 276 for Bogota, Mexico City, Santiago, and Sao Paulo, respectively.
Figure 1. Relative mobility and pollution effects.
Note: Figure shows pollution effects relative to stringency change and mobility impacts. Confidence intervals not shown (see standard errors in table 1).

The magnitude of emission shares and lockdown effects across cities indicate that CO reduction came primarily from decreased automobile use. In Bogotá, most of the effect on particles could be attributed to the decrease in traditional-bus supply during the first months of the lockdown (figure B1, SI) and enforcement to mobility-restriction policies. For Mexico City, the CO and NO₂ decrease during the morning peak is mostly associated with reduced car driving. However, the ineffective response in PM₁₀ and PM₂.₅ may be explained by a weak mobility-restriction enforcement. Table B2-SI shows the effects of the extraordinary Hoy No Circula (HNC) program implemented by Mexico on 23 April as an additional measure to contain the spread of COVID-19. During this phase of HNC, PM₂.₅ declined 28%. In the case of Santiago and Sao Paulo, other factors could have intervened in the fact that fine particles did not decrease. Resuspended dust and firewood combustion in Santiago, and secondary aerosol formation in Sao Paulo become much more important emission sources of fine particles than transport and industrial emissions.

5. Health effects

Table C1-SI displays the health effects of short-term air pollution exposure during 28 days of lockdown for the four cities. Back-of-the-envelope calculations yield estimates for mortality avoided by reduced single or combined exposure to PM₂.₅, NO₂ and CO using The World Bank and Institute for Health Metrics and Evaluation method [38] (see SI, section C for details). Health outcomes consider all causes of mortality (excluding injuries) for PM₂.₅ and NO₂ for all ages, and cardiovascular diseases for CO in the over 5 year-old population. Mean estimates indicate that mortality avoided by reduced combined pollutant exposure ranges between 10 and 53 deaths, which implies benefits of US $26 million and US $79 million, respectively. The greatest number of avoided deaths with reduced PM₂.₅ and CO exposure are found for Bogotá, and with decreased NO₂ for Sao Paulo. Regarding the costs of the lockdown, mean estimates vary from US $2320 million in Bogotá to US $6516 million in Mexico City. Although these calculations do not consider the COVID-19-avoided deaths during the first month of the stay-at-home policies, the magnitude of the figures suggests that the economic costs of the lockdown are remarkable.

6. Conclusion and policy implications

This research assesses the causal short-term effects of lockdowns in Bogota, Mexico City, Santiago, and
Sao Paulo on air quality. To inform policymakers, estimates reveal the magnitude of the effect of stay-at-home measures using a donut-hole RD approach. Baseline results and robustness exercises indicate that air pollution decreased in the four cities compared to the pre-lockdown period. Pollutants such as nitrogen oxides and nitrogen dioxide systematically responded to lockdowns across cities. This result is similar to that found in global, regional, and country-specific studies [1–3, 7, 13, 16]. Carbon monoxide also fell due to the mobility restrictions, particularly during the morning peak. The magnitude of the CO estimates is comparable to that found for India by Singh et al [13], although it is more than twice the size of the global effect reported by Liu et al [3]. In the case of fine particles, only Bogotá showed overall reductions. In this city, the effect on particles was proportionally close to the estimate found by Singh et al [13] for India. In contrast to the global studies that find particle reduction, this study suggests that particles respond differently to mobility restrictions depending on the site-specific conditions. When comparing stringency levels, the general findings indicate that stringent policies do not necessarily induce substantial changes in people’s behavior. Air-pollution abatement policies should be supported by enforcement measures. This article also suggests that the unprecedented restrictions to mobility and economic activity generated short-term air quality benefits, although at a very high cost.

The main lesson learned from the lockdowns in the four selected cities is that improving air quality is not as simple as merely restricting driving and closing firms. Some policy implications emerge from the evidence in this study. First, restrictions to mobility and economic activity affect different pollutants distinctly. Regulators may target several pollutants, however, given the budget constraints to finance abatement plans in Latin American cities, policymakers should focus on the most critical pollutant: PM$_{2.5}$. Thus, since PM$_{2.5}$ did not decrease uniformly across cities during lockdowns, other particle-reduction measures should be studied. Addressing emissions from old diesel engine vehicles such as trucks and buses would enable a greater reduction in air pollution. Second, abating pollution from main combustion sources may not be sufficient to improve air quality as other influencing factors that can make the policy more or less effective are not under the direct control of policymakers. These factors are meteorology, atmospheric chemistry, and regional pollutant transport [39, 40]. Estimates in this article account for meteorology and, to some extent, regional pollutant transport through active forest fires. However, the differential response in terms of particle reduction during the lockdowns, empirically shows the complexity of reducing PM$_{2.5}$.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the author.

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