Saving the world from your couch: The heterogeneous medium-run benefits of COVID-19 lockdowns on air pollution

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Abstract

In Spring 2020, COVID-19 led to an unprecedented halt in public and economic life across the globe. In an otherwise tragic time, this provides a unique natural experiment to investigate the environmental impact of such a (temporary) "de-globalization". Here, we estimate the medium-run impact of a battery of COVID-19 related lockdown measures on air quality across 162 countries, going beyond the existing short-run estimates from a limited number of countries (11, 36, 34, 1, 4, 7, 9, 22, 28, 31). In doing so, we leverage a new dataset categorizing lockdown measures and tracking their implementation and release, extending to August 31st 2020. We find that domestic and international lockdown measures overall led to a decline in PM2.5 pollution by 45 percent and 35 percent, respectively. This substantial impact persists in the medium-run, even as lockdowns are lifted. There is substantial heterogeneity across different types of lockdown measures, different countries, and different sources of pollution. We show that some country trajectories are much more appealing (with fewer COVID-19 casualties, less economic downturn and bigger pollution reductions) than others. Our results have important policy implications and highlight the potential to "build back better" a sustainable economy where pollution can be curbed in a less economically costly way than during the COVID-19 pandemic.

1 Introduction

Major pandemics do not only bring great harm and suffering to humanity, but also allow for opportunities in innovation and to "build back better". If the plague spurred on a series of medical and organizational innovations, such as quarantines and modern public administrations, then the current COVID-19 pandemic has championed remote working, various dimensions of digitalization, and virtual meetings. Altered patterns of mobility, work organization, and slow-downs in production could be cornerstones for more wide-ranging societal changes and new approaches to saving the environment.

Air pollution is among the most severe environmental problems. It causes several million deaths every year, disproportionately affecting the global poor (21). Pollution is also directly related to economic activity and air quality is therefore likely to improve with economic restrictions, which have been the primary response to the COVID-19 pandemic. Such restrictions, termed non-pharmaceutical interventions (NPIs), range in stringency from school closures to full economic shutdowns and curfews. Throughout this paper, we use the term 'lockdown' and 'NPI' interchangeably, and specify when referring to a specific type of measure. Although the relationship between economic activity and air pollution is thought to be generally positive, the strength of this relationship could vary across the globe in intricate ways. Heterogeneity in the response to air pollution across regions, or lockdown measures that target specific economic activities, can therefore inform us on possibilities in improving the environment without sacrificing economic prosperity.

In order to assess how various facets of COVID-induced lockdowns have impacted air pollution in the short- and medium-run, one needs a global study of the impact of a whole arsenal of lockdown measures for the entire globe, and covering the period from the COVID-19 pandemic beginning until today.

While there exist pioneering estimates of the lockdowns' impact on environmental outcomes, most studies focus on a single country (11, 36, 34, 1, 4, 7, 9, 22, 28, 31), or lump together the whole range of NPIs into one aggregate variable (35, 23, 12, 14). Only one paper (26) studies the impact of 8 types of lockdown measures on pollution levels, covering the time period from the 1st of January to the 5th of July for 76 countries.

Contrary to existing articles, here we focus not just on short-run but also on medium-run consequences of lockdown measures. This longer-run impact assessment allows us to evaluate the sustainability of particular policies for bringing the environment "back on track". Medium-run evidence provides precious information on the extent of air quality improvements that are attainable—key information for "building back better" our societies and economies post-COVID-19.

More precisely, by building on existing work, we extend the framework of analysis in several dimensions. Our data covers a time period that is several months longer than those of existing papers, which allows us to move beyond short-run effects and assess whether potential environmental benefits extend to the medium run. In doing so, we explore the question of whether lockdown releases in many countries over the summer 2020 (2) have reversed previous environmental gains, or if they persist even after lockdowns were lifted.

The first key data source to assess the pollution impact of specific lockdown measures is a dataset covering a global sample of 162 countries, and distinguishing several types of measures ranging from partial to full lockdowns and from within-country (hereafter, 'inside') measures, such as school closures and curfews, to international (hereafter, 'outside') measures, such as national border closures. Such detailed information on lockdown measures allows us to discuss whether and how the strictness of a policy matters to its air quality impact. Starting from a new and fine-grained dataset on lockdown measures (3), we extend the time horizon of this data, and add information on lockdown releases. This makes ours the first paper that studies not only the impact of COVID-19 related lockdowns on air pollution, but also of lockdown releases.

To generate the data, we relied on a custom-coded JAVA web scraping program that extracted all news headlines per country from October 31st 2019 to August 31st 2020. From this, we coded the lockdown/lockdown release measures. These were further cross-checked with COVID-19 announcements from the US embassy COVID-19 bulletin, which provides news coverage for all countries. Our lockdown/lockdown release dataset: i.) allows precise identification of the governmental measures that significantly hamper the movement of individuals, ii.) identifies the earliest date when a measure was activated (for lockdowns) or deactivated (for lockdown release), and iii.) differentiates between inside and outside lockdown/lockdown release measures that impacted the movement of individuals.[1] Further details on this data are provided below in Section *Materials*.

The second key data for our analysis is data on pollution. While pollution monitoring networks exist worldwide, they only offer sparse geographic coverage. We overcome this by taking advantage of daily, high-resolution satellite-based pollutant retrievals from NASA (15). The data product assimilates satellite-measured aerosols into a gridded ($0.5° \times 0.625°$), high-frequency dataset with complete global coverage. We restrict our PM2.5 ($\mu g/nm^3$) measure to urban areas, where lockdowns are expected to starkly reduce pollution-generating human activity.

A key concern in the environmental economic literature is the spatial correlation of economic activity and pollution. With regards to COVID-19, the timing of economic lockdowns is arguably correlated between nearby countries, and pollution in one country will be affected by the lockdown of its neighbour. Previous studies on COVID-19 and air quality have not accounted for such indirect channels. Here, we advance the literature by tracking corresponding NPI timelines for all adjacent countries and separate out the indirect effect in our analysis. As such, in addition to accounting for lockdown release, we are also the first to disentangle spatial spillovers.

For our pollution indicator, we focus on PM2.5 because it stands out as the pollutant with the most acute mortality consequences. Indeed, the World Health Organization uses PM2.5 as its main indicator of population exposure to pollution. Furthermore, we opt for remotely sensed data over ground monitor data—which has been used in previous global studies of lockdown impacts ((26), (35))— and that is for two reasons. First, the number and location of monitors varies widely by country, and are often endogenously placed avoiding areas of high pollution (16). In contrast, our gridded data is more representative—equivalent to placing a monitor roughly every 50km worldwide. Second, pre-publication QA/QC protocols vary widely and efforts to synthesize monitor data provide little guidance on data flagging, while the atmospheric model underlying our data ensures a unified pollution measure based on consistent physical and chemical transport properties. Further details on the pollution data used are provided in the next section.

2 Data

2.1 Lockdown Data

The lockdown data from (3) assembled information on each country's lockdown policies, relying on web-scraping, and drawing on news headlines published between 31st October 2019 to 15th of October 2020, provided by Lexis-Nexis. They crosschecked this data with country information from COVID-19 bulletins issued by the United States Embassy. Their final dataset contains the dates of implementation and release for a series of specific non-pharmaceutical interventions (NPI) designed to stop the spread of the COVID-19. The following categories of NPI are distinguished: within country regional lockdown, partial selective lockdown (prohibiting some activities), curfew and state of emergency, country national lockdown, selective border closure stage 1 and 2, and country international lockdown. This

[1] This differs from alternative (and complementary) approaches such as the one followed by (19) that considers a broad range of NPIs, including some that are less related to mobility patterns. Given that our research question focuses on mobility and pollution, our data is more suitable for the precise purpose of the current study.

dataset was extended here, with similar methods, to include the lockdown release period.

Further more we also control in the analysis for a series of sanitary indicators. Specifically, data on COVID-19 fatalities stems from the Johns Hopkins University (13), which is arguably the most complete and reliable source available.

The final dataset covers 162 countries over the time spanning from the 1st of November 2019 to the 31st of August 2020.

2.2 Pollution Data

The dependent variable of interest is fine particulate matter (PM2.5). Novel remote sensing techniques provide fine-grained estimates of the aerosol components of PM2.5, but not concentrations of PM2.5 directly. Here, we use data on aerosol species from the Modern Era Retrospective Analysis for Research and Applications (MERRA-2) ((15)) product. We build up PM2.5 concentrations based on known contributions of measured aerosol species to overall PM2.5 levels following the formula in (5).

Existing satellites, such as the MODIS instrument aboard NASA's Aqua and Terra spacecrafts, measure Aerosol Optical Depth (AOD). AOD measures sunlight reflected by suspended particulates in the atmosphere and is often used in place of PM2.5 ((29), (17), (25)). However, this equivalence is limited because AOD is an atmospheric measure whereas PM2.5 is a surface measurement. Furthermore, cloud contamination and sensor-specific data gaps lower AOD data quality. MERRA-2 offers a major advancement by assimilating raw AOD retrievals through a global atmospheric circulation model to provide a unified set of ground-level estimates of 5 particulate species.

We collect MERRA-2 data from the M2T1NXAER files distributed by NASA [2]. These provide hourly aerosol concentrations on a global grid at $0.5^\circ \times 0.625^\circ$ resolution. We produce a daily pollution panel in three steps. First, we aggregate hourly data to the daily mean in each grid cell for the period November 1st 2019-August 31, 2020. Second, we extract pollution over urban areas using shapefiles of urban extent as identified by ((33)). There are 11,878 urban areas, and we extract daily mean pollution over each area for our study period. Lastly, we identify the country of each urban area using a digital world map from `www.naturalearthdata.com`, and aggregate daily average pollution from urban centres in each country. Our final pollution dataset is a country-day panel of mean PM2.5 in urban areas.

Our data is generated by the MERRA-2 reanalysis product, which combines satellite-measured aerosol and meteorological variables with the GEOS-5 chemical transport model to produce ground-level particulate estimates. GEOS-5 is detailed climate model that includes atmospheric circulation, oceanic, and land components ((30)). Crucially, it also incorporates aerosol processes based on the Goddard Chemistry, Aerosol, Radiation, and Transport (GOCART) model which assimilates bias-corrected AOD retrievals from NASA's MODIS instrument ((8)). The algorithm uses a neural net scheme to fill in data gaps from cloud contamination and translate cloud-cleared MODIS reflectances into ground-monitor calibrated aerosol levels.

The GOCART module of GEOS-5 simulates five types of aerosols which we use to estimate PM2.5: dust, sea salt (SS), black carbon (BC), organic carbon (OC), and sulfate (SO_4). We follow (5) and calculate PM2.5 as:

$$PM2.5 = [DUST_{2.5}] + [SS_{2.5}] + [BC] + 1.4[OC] + 1.375[SO_4] \tag{1}$$

(5) also evaluate the PM2.5 data quality against 150 ground monitors in the U.S. between 2003-2012. They find a correlation coefficient of 0.8. Overall, we believe our data represent an improvement over existing particulate data sources with global coverage, and accurately depict ground-level concentrations relevant for human health.

The data on the main source of air pollution are from the Extended Data Figure 1 of (24).

[2] retrieved from: https://disc.gsfc.nasa.gov/

2.3 GDP and COVID-19 Mortality Data

Quarterly real GDP data are from the OECD reported by individual countries according to the 2008 System of National Accounts. The data on the number of Covid deaths are from the European Centre for Disease Prevention and Control accessed through the "our World in Data" website. We restrict the number of deaths to the number of death in the second quarter of 2020.

2.4 Meteorological Covariates

A key empirical concern is that the cascade of global COVID-19 lockdowns is correlated with contemporaneous changes in atmospheric conditions that also affect PM2.5 levels. To isolate the lockdown channel, we collect data on a range of time-varying meteorological variables and control for them in the analysis.

We obtain daily satellite data for weather (rainfall and temperature), surface wind speed, humidity, and the planetary boundary layer (PBL) during our study period. Controlling for temperature is important because high temperatures increase photochemical reactions among precursors of PM2.5. Changing wind speed and humidity affects the diffusion of dust particles that make up PM2.5 ((6), (10)). Lastly, the PBL, which is the lowest portion of the troposphere, regulates the upward dispersion of pollutants and has been shown to correlate with PM2.5 formation ((27)).

Data on rainfall is from the NASA-operated GPM Level-3 product, which provides daily precipitation estimates (in mm) on a 0.1×0.1 degree grid (20). All other variables are obtained from the MERRA-2 M2T1NXFLX data files, which are provided at the same resolution as the pollution data. Surface wind speed is measured in m/s, temperature is measured in Kelvin, humidity is measured as the fraction of water vapor in dry air, and PBL is measured in metres. All covariates are assembled into a country-day panel over urban centers following the same procedure described in 2.2.

3 Methods

3.1 Causal Identification Strategy

Studying the impact of lockdown measures on air quality is statistically challenging, because of related variables affecting both (e.g. a right-wing government both opposed to certain sanitary measures and in favor of relaxing environmental protection). Furthermore, seasonal changes in pollution—such as lower air quality in warmer temperatures—make it difficult to separate the lockdown effect from the onset of summer in the Northern Hemisphere.

We address endogeneity, omitted variable bias, reverse causality and measurement errors with a large battery of controls and fixed effects. Notably, our fine-grained panel data enables the use of country-month fixed effects, which account for unobserved, country specific factors common across all days of the month. This geographic dimesion of this demanding specification accounts for the confounding impacts of: geography, industry shares, pollution regulations, population size, topographic features, and any other time-invariant geographic feature entangling the lockdown-pollution relationship. The separate intercept by month removes time-varying biases accruing over wider time scales across the country, such as: the evolution of public perception of the virus, response to global announcements, and changes to the healthcare system.

Beyond fixed effects, we control for a range of meteorological determinants of PM2.5 formation that change during the same period as lockdown: rainfall (mm), humidity (%), temperature (K), wind speed (m/s) and planetary boundary layer height (PBLH) (m). See the section titled *Meteorological Covariates* for more details. Crucially, we also account for spatial correlation by controlling for the proportion of bordering countries having implemented an NPI in each time period. We do this to separate the impact of a country's lockdown on its own pollution from the indirect impact from the lockdown of its neighbors. Lastly, we control for the number of deaths within the country, a metric widely accessible to the population, which might drive the preventative behaviour of citizens and firms even in the absence of strict NPI measures.

A remaining concern is that our study period, which extends to the medium term (90-120 days), includes the period when many countries had lifted their respective lockdowns. This generates an offsetting increase in pollution that may negate initial air quality gains, leaving the net effect ambiguous. To guard against this, we use our custom scraped release data to separate out the impact of lockdown from lockdown release. Specifically, we control for the lockdown release timeline.

3.2 Event Study Specification

To study the impact of COVID-19 lockdown measures on global air quality, we implement the following panel OLS regression:

$$
\begin{aligned}
Log(PM2.5_{it}) = \beta_k \sum_{k=-60}^{120} 1[t - NPI_{ij} = k] \qquad (2) \\
+ \beta_1[Release_{ijt}] + \beta_2[log(Death_{it} + 1 \\
+ \beta_3[Nbr_{it}] + \beta_4[M_{it}] + \gamma_{im} + \epsilon_{it}
\end{aligned}
$$

where $Log(PM2.5_{it})$ is the log of PM2.5, normalized by standard deviations, in country i at date t. NPI_{ij} is the date of lockdown of type j (e.g. inside measures, outside measures, state of emergency, etc), and $1[t - NPI_{ij} = k]$ is a dummy that switches on k periods before or after the measure is implemented. The period $k = -1$ is omitted so that all coefficients β_k are relative to the day before the lockdown event. $Release_{ijt}$ is a dummy equal to one from the day country i released measure j. Nbr_{it} is the proportion of countries bordering i having implemented any NPI at time t, and controls for spatial spillovers. $log(Death_{it} + 1)$ captures the timeline of COVID-19 deaths and controls for the evolution of the virus within country i. M_{it} is a vector of meteorological controls including rainfall, temperature, wind speed, humidity, and PBLH. γ_{im} are country-month fixed effects and ϵ_{it} is the error term, clustered at the country level.

Our coefficients of interest are the set of β_k's. These represent the global average percentage change in PM2.5 at k days before or after lockdown, relative to the day before lockdown, after controlling for covariates and fixed effects. Importantly, the regression is weighted by the number of urban regions in each country. We do this because, in some countries with few urban areas, our pollution measure is a mean over one or two places (less precise) compared with larger countries where pollution is a mean over hundreds of cities (more precise). Weighting the regression by number of urban areas gives each observation influence over coefficients in proportion to its measurement precision rather than be treated equally.

4 Results

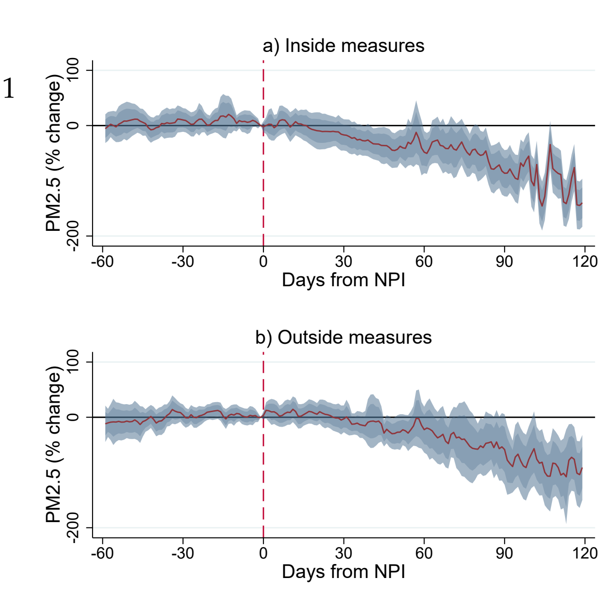

Figure 1: Lockdown measures reduced PM2.5 on the medium term similarly for inside measures (within country) and measures towards the outside (blocking borders). 90% and 99% confidence intervals are shown in different shades of blue. The vertical dashed line shows the day when the measure was implemented.

Figure 1 presents our main results. It depicts the short-run (1 to 60 days) and medium-run (61 to 120 days) global impact of COVID-19 lockdowns on air quality. Two categories of measures are distinguished: Panel a) reports findings for inside measures, while panel b) displays the results for outside measures. For each country, we control for the varied timing of lockdown release as well as the proportion of bordering countries having implemented any type of NPI on a given day. Our results can thus be interpreted as a net effect after adjusting for the offsetting effect of lifting lockdowns and removing spatial spillovers.

There are three noteworthy results. First, both inside (panel a) and outside mobility restrictions (panel b) improve air quality over the short and medium run. Over the full period, on average, inside and outside lockdowns reduce PM2.5 concentrations by 45% and 35%, respectively, relative to the day before its implementation.[3] Second, in the absence of lockdown, the pollution trend cannot be statistically distinguished from zero, suggesting the post-lockdown pollution decline is a result of reduced human activity and not merely a continuation of a pre-existing pollution trend. Third, the pollution impact accumulates over time, showing the strongest reduction of around 100% at 90-120 days into lockdown. Crucially, countries that released their restrictions do not upward bias these results. Our release covariate ensures the release effect is subtracted away before identifying the lockdown effect.

There is a noticeable lag between lockdown implementations and air quality improvements. For inside measures, it takes over 1 month for PM2.5 declines to initiate ($p<0.05$). For outside measures, it takes 2 months ($p<0.05$). The delay is arguably because our categorization combines a continuum of behavioural changes. On one end, domestic lockdown measures include partial constraints like playground closures, and on the other end, full regional shutdowns.

Figure 2 separately shows the impact of various specific lockdown measures, always controlling for all other measures in place. For strict measures, e.g. a domestic regional lockdown (panel a), or a state of emergency with curfew (panel e), the timing of air quality improvements is remarkably coincident with the implementation date. For looser measures, e.g. a partial selective lockdown or a curfew (panels b and d[4]), the improvement in air pollution is only noticeable after a one month delay. Also, the first selective border closure (panel f) improves air quality only after about 45 days, while the second selective border closure already reduces air pollution after about 30 days (panel g). Countries which close their airports and international borders experience improvements in air quality after less than 30 days.

4.1 Geographical heterogeneity

The impact of all NPIs taken together could vary widely between different areas of the world. Figure 3 shows areas of the world colored according to the change in air pollution around the time when the country implemented its first lockdown measure inside the country. Large areas in North and South America, Europe, Southern Africa, East Asia and the Pacific experience improvements in air quality, but the improvements differ across the world.

Figures 4 and 5 display the geographical differences in the evolution of pollution in the short- and medium-run for inside measures and outside measures, respectively. Inside measures improve air quality in East Asia and the Pacific, South Asia, the Middle East, North African Countries, and in Sub-Saharan Africa. Effects of outside measures are imprecisely estimated, and remain often insignificant. Regions with some significant improvements in air pollution include East Asia and the Pacific, South Asia, Latin America and the Caribbean, the Middle

[3] These results refer to the mean of daily coefficients in Figure 1 post-lockdown and are intended only to summarize the event study into a single result.

[4] Although curfew can be considered strict, it is unlikely to starkly impact pollution because human activity is allowed to continue during the day until a specified evening hour.

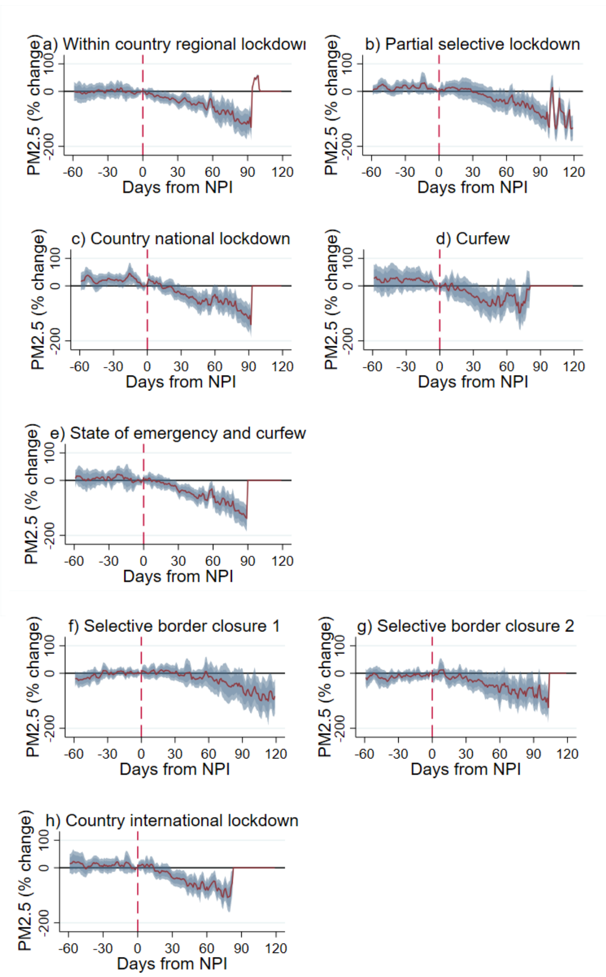

Figure 2: Non-Pharmaceutical Interventions reduced PM2.5 on the medium term similarly for inside measures (within country) and measures towards the outside (blocking the borders). More stringent measures tend to have larger effect (see panel e) and h)). 90% and 99% confidence intervals are shown in different shades of blue. The vertical dashed line shows the day when the measure was implemented and estimates are reported for as long as there is sufficient data to estimate them.

East and Northern Africa.[5]

Last but not least, Figure 6 plots PM2.5 change against GDP changes during the COVID-19 pandemic, also taking into account the number of COVID-19 fatalities per capita (represented by the size of the dot) and the main sources of pollution (represented by the color of the dot).[6] Several countries including Canada, Italy, Spain and the United States had substantial GDP losses as well as reductions in air pollution (all countries in the grey shaded area), yet there are also exceptions including Brazil, India, Japan and South Korea for which substantial GDP reductions were associated with increases in air pollution (all countries in the red shaded area). These differences may be explained by different sources of air pollution (as discussed in more depth in Section *Discussion*).

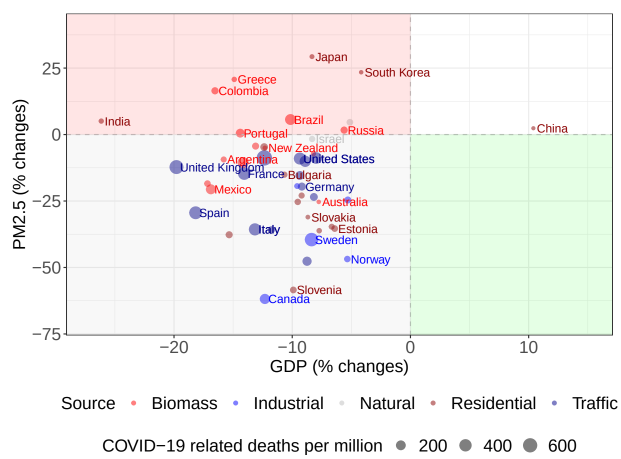

Figure 6: Air quality changes in urban areas, GDP changes, sources of air pollution and COVID-19 related mortality. GDP and PM2.5 are measured as the difference in mean values between the first and second quarter in 2020 relative to the same difference in 2019. COVID-19 related deaths are the sum of deaths in the second quarter of 2020. The sources of air pollution are the sources responsible for the largest impact of PM2.5 on mortality in 2010 (24).

[5] North America also experiences an improvement in air quality, but the number of observations is not sufficiently large to provide a statistical test for North-America.

[6] Change is a "difference-in-differences", i.e. the change between the first and second quarter in 2020 compared to the same change between the first and second quarter in 2019, both for PM2.5 and GDP.

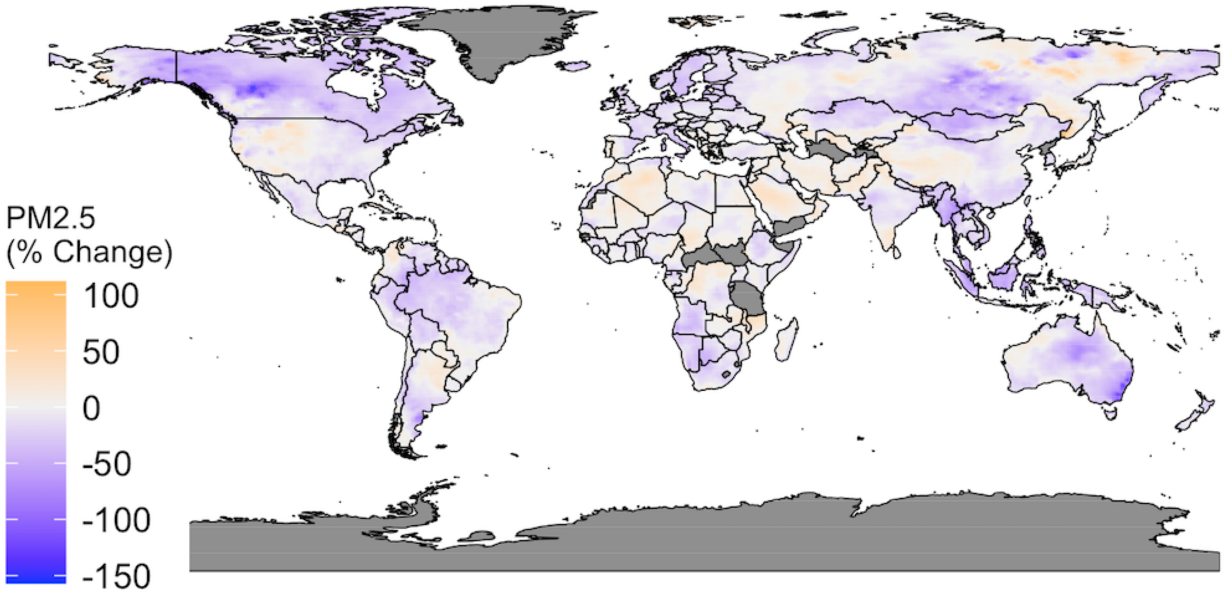

Figure 3: Global distribution of pandemic-induced air quality changes. Cell values describe the difference in mean log-PM2.5 before and after the first inside NPI measure relative to the same pre-post difference in 2019. The "before" period extends to November of the previous year until the lockdown date. The "after" period extends to August 31st.

5 Discussion

The wave of COVID-19 lockdowns provides an unprecedented opportunity, in an otherwise troubled time, to study the environmental consequences of reduced human activity. We document the short- and medium-term impact of this “anthropause” (coined by (32)) on air quality by assembling the largest dataset of country-level NPIs and high-resolution PM2.5 concentrations across 176 countries. We find a global average reduction in PM2.5 concentrations of 35-45% during COVID-19 lockdowns.

Our results mirror the direction of change in previous studies, but suggest larger air quality improvements. China was the first “laboratory” for studying lockdown impacts, as it was the first country to impose this type of measure. A 30-40% reduction in PM2.5 was found in four Chinese cities by (22) during 20 days of lockdown between January and February 2020. In contrast, (18) use a difference-in-difference method in 300 cities and find a more muted reduction of 17%. Our results are more comparable to global studies, that are limited in number. (35) use ground monitor data in 34 countries and find an average PM2.5 reduction of 31%, kicking in immediately after lockdown. (26) use the same monitor data as (35), but cover twice as many countries, and find a PM2.5 reduction half the size.

There are at least two explanations for our disparate results. First, our dataset is substantially richer and spans locations experiencing large air quality reductions not covered by previous studies. For example, (26) cover 597 cities whereas we cover nearly 12,000. Africa, in particular, is virtually missing from both previous global studies, and South America is missing in (26). But, as can be seen in Figure 3, these continents experienced sweeping air quality improvements during their lockdown. Second, shorter timelines in previous studies precluded the inclusion of release data, resulting in biased coefficients that bundle pollution reductions due to lockdown with pollution increases due to release, and appear smaller. In contrast, we separate out the effect of release measures and, as a result, find relatively larger air quality improvements.

Although most countries suffered from substantial economic losses during the first peak of the pandemic (Figure 6) the results with respect to air pollution are heterogeneous. Consistent with a positive association between air pollution and economic activity, many countries suffered substantial GDP losses as well as reductions in air pollution. However, some countries experienced substantial GDP reductions with increases in pollution– so their lockdowns slowed down their economies but did not improve the quality of their air. These differences may be explained by different sources of air pollution. While transportation and industry plays an important role for air pollution in densely populated parts of Europe and North America, air pollution in Latin America and Asia is dominated by biomass burning, agriculture and residential energy use (e.g. Extended Data Figure 1 of (24)). The different sources of air pollution may respond differently to COVID-19 lockdowns. For example, lockdown measures are likely to increase residential energy use (mainly for heating) while they may reduce pollution from transportation including commuting. Biomass burning is largely related to agriculture which was generally little affected by lockdowns. However, Figure 6 also suggests that win-win situations are unlikely to occur as there is no country with increases in GDP and reductions in air pollution (green shaded quadrant). The economic growth of China during the second quarter of 2020 may be attributed to recovery from the earlier COVID-19 outbreak in China.

Figure 6 therefore suggests that a reduction in economic activity or mobility might not necessarily save the environment. In fact, economic downturns can increase air pollution if they lead to a shift to economic activities that are more harmful to the environment. For example, reduced mobility will only lead to substantial improvements in air quality if it is not outweighed by increased air pollution from residential sources such as heating.

Prohibiting economic activity does improve air quality in the majority of countries around the world, but the price is very high, and in some countries air quality does not improve even though the economy comes to a halt. In turn, economic growth may not necessarily lead to environmental degradation. A shift from more polluting activities to less polluting activities during the growth process such as the shift from resource based activities associated with biomass burning to manufacturing, and later services, can simultaneously increase economic prosperity as well as air quality. However, the necessary changes to improve air quality may differ across economies. A policy to discourage commuting may improve air quality in one region while the same policy may have the reverse effect in a region for which increasing decentralized economic activities is associated with elevated pollution levels. These findings underline the importance of market-based environmental instruments such as Pigouvian taxes or cap and trade systems to reduce pollution at the lowest possible costs. However, they also stress the importance of including all economic activities in these regulations as substitution between activities in response to regulation may worsen the situation. Although the pandemic has caused substantial losses in economic prosperity and human lives it has also improved the environment. The large heterogeneity in the relation between economic activity and air quality suggests that improving the environment may not require these sacrifices.

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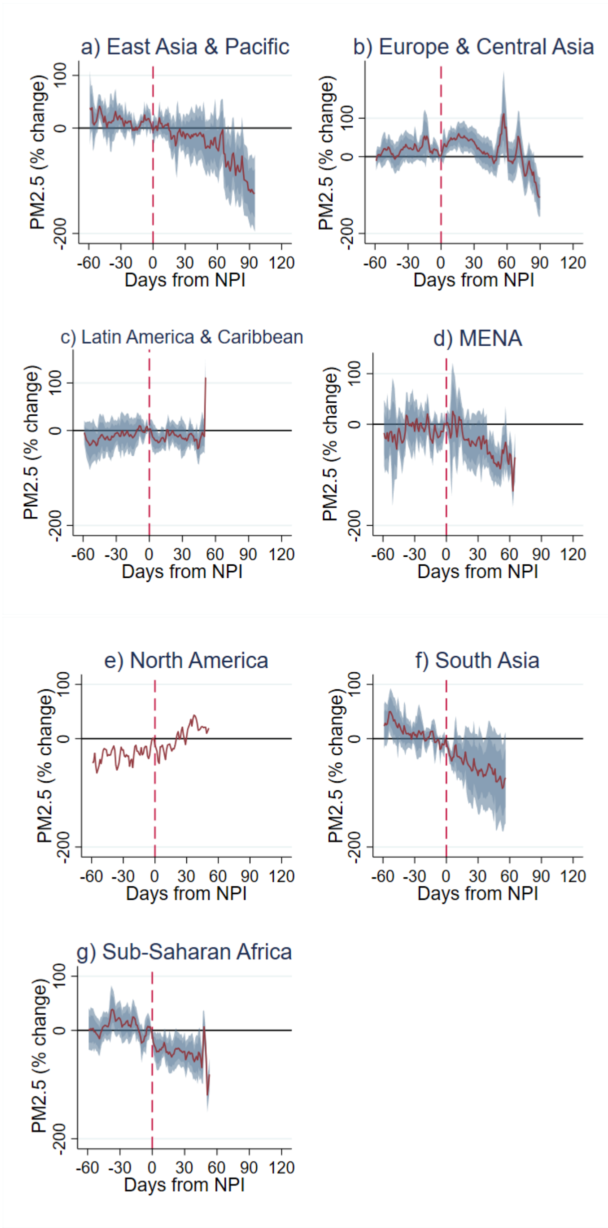

Figure 4: Marginal effect of inside measures (within-country) by region. Non-Pharmaceutical Intervention had a mixed effect on PM2.5 by region. "MENA" stands for Middle East and Northern Africa. 90% and 99% confidence intervals are shown in different shades of blue. The vertical dashed line shows the day when the measure was implemented and estimates are reported for as long as there is sufficient data to estimate them. Note that North America contains too few countries to compute confidence intervals.

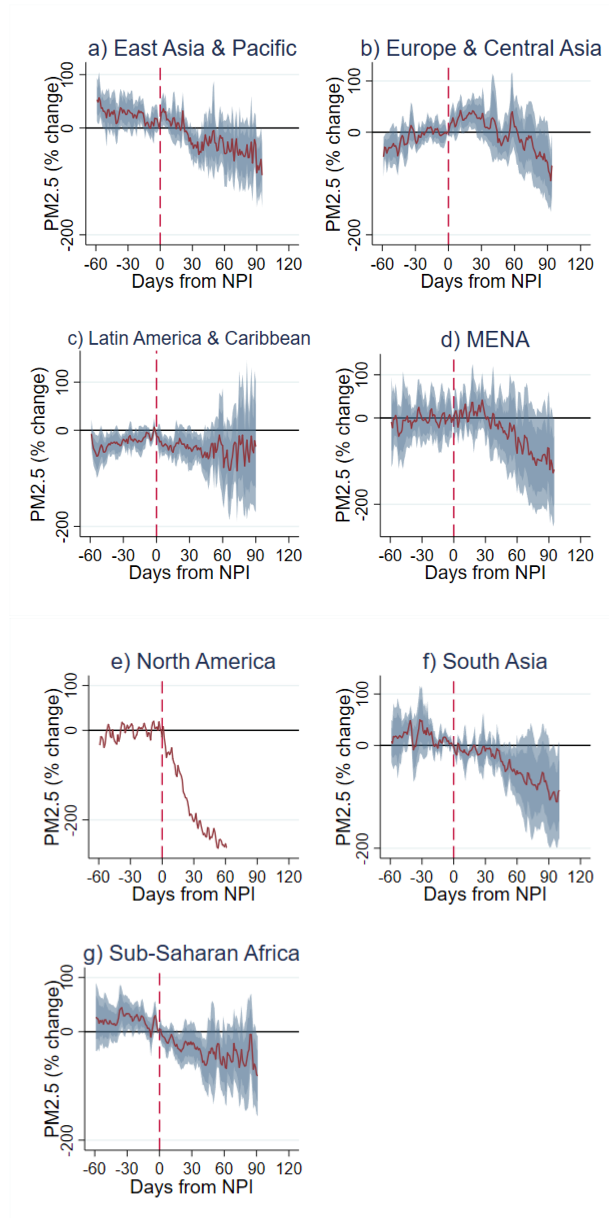

Figure 5: Marginal effect of borders closure (outside measures) by region. 90% and 99% confidence intervals are shown in different shades of blue. The vertical dashed line shows the day when the measure was implemented and estimates are reported for as long as there is sufficient data to estimate them. Note that North America contains too few countries to compute confidence intervals.