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The impacts of human migration and city lockdowns on specific air pollutants during the COVID-19 outbreak: A spatial perspective

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\textbf{ABSTRACT}

The outbreak of COVID-19 continues to bring unprecedented shock to mankind’s socioeconomic activities, and to the wider environment. China, as the early epicenter of the pandemic, locked down one-third of its cities in an attempt to prevent the rapid spread of the virus. Human migration patterns have subsequently been radically altered and many regions have seen perceived improvements in air quality during the lockdowns. This study empirically examines the relationship between human migration and air pollution and further evaluates the causal impacts of the lockdowns. A spatial econometric method and a spatial explicit counterfactual framework are employed in this study. The key findings are as follows: i) a considerable amount of variation in AQI, PM
\textsubscript{2.5}, and NO\textsubscript{x} concentration can be explained by human migration but we fail to find suggestive evidence in the cases of SO\textsubscript{2} and CO; ii) the implementation of lockdown measures led to a significant reduction in AQI (18.1%), PM\textsubscript{2.5} (22.2%), NO\textsubscript{x} (20.5%), and PM\textsubscript{10} (10.7%), but has no meaningful impacts on SO\textsubscript{2}, CO and O\textsubscript{3} levels; iii) further analysis indicates that the impacts of lockdown policies varied by control stringency and by regional heterogeneity. Our findings are of great importance for the Chinese government to create a stronger and more coherent framework in its efforts to tackle air pollution.

\section{1. Introduction}

While COVID-19 is creating all kinds of chaos for human’s socioeconomic activities, for our environment, it is a reprieve (Dffenbaugh et al., 2020). As the early epicenter of the COVID-19 pandemic, China imposed a range of lockdown measures on one-third of its cities in an attempt to reduce the transmission and minimize the impact of the virus (He et al., 2020). In cities under lockdown, inter-jurisdictional borders were closed and populations were confined to their homes, with unnecessary travel within local city areas also banned (Chinazzi et al., 2020; Kraemer et al., 2020; Tian et al., 2020). As could be expected, governmental intervention policies dramatically altered human migration patterns. Human mobility even dropped by 69.85% after the government implemented travel bans (Bao and Zhang, 2020). One side effect of these measures that became apparent was a perceived improvement in air quality (Bao and Zhang, 2020; Cole et al., 2020).

We know that air pollution can lead to pernicious health effects on (Taghizadeh-Hesary and Taghizadeh-Hesary, 2020; Zeng et al., 2020), including heart attacks, strokes (Shah et al., 2015), diabetes, lung cancer (Guo et al., 2016; Yang et al., 2020), and high blood pressure (Maomao et al., 2018). These have also been identified among the pre-existing medical conditions that raise the chances of death from COVID-19 infection (Coccia, 2020; Cole et al., 2020; Conticini et al., 2020; Ogen, 2020; Petroni et al., 2020; Setti et al., 2020; Travaglio et al., 2020; Wang et al., 2020a; Wu et al., 2020; Yao et al., 2020a, b). Humans are suffering from a respiratory virus. Humanity can no longer afford for its air to be polluted. In the context of China, however, 180 of 338 cities at or above prefecture level (APL cities), i.e. 53.4%, failed to meet national air quality standards in 2019.\textsuperscript{2} The outbreak of COVID-19 brought unprecedented impacts on human activities, and in turn on the environment (Mostafa et al., 2021), which is expected to increase general understanding of current environment conditions and to trigger new

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\textsuperscript{3} Air quality meeting the standard: the ambient air quality meets the standard when the concentrations of all 6 pollutants under assessment meet the standard, among which, \textsubscript{SO\textsubscript{2}}, \textsubscript{NO\textsubscript{2}}, \textsubscript{PM\textsubscript{10}}, and \textsubscript{PM\textsubscript{2.5}} were evaluated according to the annual average concentration, and \textsubscript{CO} and \textsubscript{O\textsubscript{3}} were evaluated according to the percentile.

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strategies for reducing pollution. In the specific context of the COVID-19 pandemic, both satellite observations and a few quantitative estimates of the changes in air pollution have found supportive evidence that coronavirus-related lockdowns led to a reduction in air pollution (Le Quéré et al., 2020). For example, Finland’s Centre for Research on Energy and Clean Air reported that measures to contain the spread of COVID-19 in China produced a 25% drop in CO₂. Europe is now seeing the same drop in air pollution that occurred in China. Scientists from the Royal Netherlands Meteorological Institute (KNMI), using satellites to monitor both weather and pollution over Europe, found that emissions of NO₂ dropped in Paris as well as in Madrid. There is a growing literature studying and trying to estimate the impact of the pandemic on air pollution. Evidence of reductions in air pollution following the outbreak of the pandemic was found in many regions, such as Egypt (Mostafa et al., 2021), the USA (Liu et al., 2021), the UK (Ropkins and Tate, 2021), and India (Singh et al., 2020; Vadrevu et al., 2020). In the context of China, several recent studies found similar evidence that the variation in air pollution concentration in many regions of China dropped significantly during the pandemic (Bao and Zhang, 2020). A drop in greenhouse gases (GHGs) shows furthermore that the reduction extends beyond traditional air pollutant emissions (Liu et al., 2020).

However, existing studies are insufficient for understanding the overall effects of the coronavirus lockdown. Scientists from around the world are expected to work on more detailed analyses as satellite data or images have many uncertainties (Schwander et al., 2017). Another reason is that recent emerging studies lose sight on the presence of spillover effects and regional effects in air pollution (Bi and Zeng, 2019; Chen et al., 2016; Du et al., 2020; Feng et al., 2020; Gong and Zhang, 2019; Yue et al., 2019; Zeng et al., 2019, 2021), which may invalidate the results (Kolak and Anselin, 2019). Many questions remain, including: Do spillover effects in air pollution exist in China during the pandemic? And if yes, which model can be considered as the appropriate model for improving the efficiency and accuracy of analysis? Emissions from human-related activities, including road traffic, heating supply etc., have been identified as the dominant sources of air pollution. Another empirical question we specifically aim to address is: Will human migration be a driving factor in variation of air pollution levels during the outbreak? Moreover, lockdown measures taken to mitigate the spread of the virus brought human’s production and consumption activity almost to a standstill. Whether there are causal impacts of the lockdowns on air pollution, and if any, what is their extent? Also, which pollutants have seen their levels fall? In addition, what are the likely heterogeneous impacts in cities exhibiting variations across socioeconomic and environmental dimensions? Any answer to these questions must consider the inherently spatially and temporally dynamic, interactively active nature of air pollution.

This study thus aims to investigate the impacts of COVID-19 on our atmospheric environment. Specifically, we are to quantify the relationship between the variation in human movements caused by city lockdowns and air pollution concentration during the confinement period by considering the spillover effects on air pollution. In addition, we will investigate the causal impacts of lockdowns on air pollution to increase our understanding of the epidemic’s impact on the environment. To achieve these results, two main datasets were used: real-time monitoring human mobility data (intra-/inter-city migrants) extracted from Baidu Maps and sets of air pollution indicators (AQI, SO₂, PM₂.₅, PM₁₀, NO₂, CO) collected from the China National Environment Monitoring Center. Our data covers 283 Chinese APL cities for the 100 days ranging from 1 January to April 9, 2020. A core challenge for our empirical analysis was that regional diffusion effects may exist in air pollution. We thus used a spatial econometric framework to incorporate these spatiotemporal factors into our model. Another empirical issue in our estimating procedure is that any reduction in air pollution may have been caused by local environment regulations and a reduction in human movements as the result of panic effects or virus effects which went unobserved. To address this endogeneity concern, we develop a difference-in-difference (DID) framework to make a causal inference by means of a natural experiment, which exploits regional and temporal variation in the adoption of lockdown measures.

Our results found, in brief, that: First, a considerable amount of variation in air pollution is explained by population migration. A one-unit (10 million people) increase in inter-city population movements was associated with 305.9%, 69.0%, 250.5%, and 76.8% increases in AQI, PM₁₀, PM₂.₅, and NO₂, and a 110.2% decrease in O₃ respectively, but had no meaningful impacts on SO₂ and CO levels. Regression results for intra-city migration offered similar evidence. Second, relative to cities that were not locked down, transmission control measures taken in the cities under lockdown led to a significant reduction in AQI (~18.1%), PM₂.₅ (~22.2%), and NO₂ (~20.5%) concentration and a smaller reduction in PM₁₀ (~10.7%), but no significant drop in SO₂ and CO levels. Further analysis revealed that the impacts of the lockdowns varied by control levels and specific pollutants. Complete lockdowns in eleven cities on average reduced AQI, PM₂.₅, PM₁₀, and NO₂ by 26.5%, 26.9%, 32.3%, and 68.2%, respectively, relative to the 40 cities that adopted partial lockdown measures. Finally, heterogeneity analysis demonstrated that the effects of lockdown on specific air pollutants varied largely throughout different types of cities with multiple dimensions of attributes.

Our study provides three potential contributions to the literature. The first is its consideration of the inherently spatially and temporally dynamic, interactive nature of air pollution being studied. Many studies have suggested that air pollution has spillover effects and regional impacts. This study investigates the impacts of human migration and lockdown policies on air pollution by incorporating spatial effects into formal causal inference modeling, leading to a deeper understanding of the relationship between coronavirus lockdown and air pollution. The second contribution concerns the identification strategy. An empirical concern is the potential bias and loss of efficiency that can result invalidation when dependence in both space and time are ignored in the causal investigation of the relationship between human mobility and air pollution. A Spatial Autoregressive (SAR) model was used to propel our causal estimation strategy. Turning to a causal exploration that the lockdown had on environmental outcomes is challenging, as well, since the air pollution concentration of a city at any point in time is shaped by various weather conditions and confounding factors like local environmental regulations. We developed a set of SAR-DID models to address this issue. The third is that our findings provide important policy implications for the ongoing discussion of air pollution control in China. Our findings highlight that, to reduce SO₂ and CO concentration, it is important to accelerate the growth of clean energy and continually combat excessive coal consumption in the power and industrial sectors.

This paper is organized as follows. The second section introduces variables and details the empirical strategy. The third section presents our main empirical results. The fourth section presents results on heterogeneous effects with final conclusions and policy implications provided in the fifth section.

2. Materials and methods

2.1. Data and variables

2.1.1. Air pollution

We use air pollution concentration as a measure of air quality. The original dataset was collected from the China National Environment Monitoring Center (http://datacenter.mee.gov.cn), a real-time monitoring data system operated by the MEE, including the air quality index (AQI) and six other kinds of primary air pollutants. We aggregated the concentrations of daily air pollutants data into weekly values by following (He et al., 2020).
2.1.2. Human migration

Our data on population migration cover 100 days—1 January to April 9, 2020—and were obtained from Baidu Maps (https://qianxi.baidu.com/), provided by the dominant Chinese search engine Baidu. This dataset contains two daily migration intensity indices: the inter-city migration intensity index aggregated by the inflow and outflow migration intensity index, and the intra-city migration intensity index. Fig. 1-a and 1-b plot the overall average variation trend of population migration across 283 Chinese APL cities respectively in 2020 and the same period of 2019, respectively, the latter when adjusted for the lunar calendar. Compared to the same sample period in 2019, the average inter-city and intra-city migration dramatically declined in 2020 after the implementation of the Wuhan lockdown on 23 January.

2.1.3. City lockdowns

We collected each city’s lockdown information from various news media and local government-run websites. To ensure the reliability and validity of the data, we compared our data with the data offered by previous studies for verification purposes (Fang et al., 2020; He et al., 2020). Detailed information of the lockdowns is illustrated in Fig. 2. Further information about city lockdowns is provided in Table SF-1 (see supplementary files, SF-A) owing to spatial constraints.

As shown in Fig. 2, by February 12, 2020, 133 of 283 Chinese APL cities (red zones) in 26 provinces had adopted different degrees of lockdown measures. Among them, 11 cities, including Wuhan in Hubei province, announced a total lockdown, which meant that both public and private transportation were suspended, nonessential individual movements in and out of communities were limited, and industrial factories and other public places were closed. 40 cities adopted partial lockdown measures, which meant that most public transportation was suspended, community units in most areas kept only one entrance and exit point open, and each household was allowed limited numbers of entrances and exits. 92 cities set up checkpoints and quarantine zones, which meant that while main line traffic maintained normal operation, people entering and exiting were required to wear masks and receive temperature checks. The rest of the 150 cities (blue zones) were under regular conditions, which meant that local governments in these places did not issue any type of lockdown measures in an official way. This context provides us with a unique opportunity to take advantage of the natural experiments resulting from regional and temporal differences in lockdown policy adoption in various cities to examine the effects of transmission control measures taken in mainland China on air pollution.

2.1.4. Weather conditions

Changes in the concentration levels of pollutants are strongly influenced by multiple meteorological factors. We therefore collected a set of daily weather condition data as our control variables to remove the impact of the local weather conditions on air pollution. Daily history weather data, including maximum and minimum temperatures, maximum wind and gust speeds, and records of rainfall and snow cover, were collected from the website freemeteo.com (https://freemeteo.cn/). This website provides comprehensive weather information for all regions of the world. We collapsed the daily data to weekly city-level datasets according to the same method used to aggregate the air pollution data.

2.1.5. Summary statistics

Table 1 summarizes variables and their definitions, data sources, and summary statistics. Panel A in Table 1 shows descriptive statistics for the seven air pollution indicators selected as our dependent variables and illustrates that there were large variations in air pollution
concentrations in different cities. For example, PM$_{2.5}$, one of the six major air pollutants, had an average concentration of 46.2 $\mu$g/m$^3$, exceeding WHO guidelines and even WHO’s least-stringent target (35 $\mu$g/m$^3$), with a minimum concentration of 7.369 $\mu$g/m$^3$ and a maximum concentration of 238 $\mu$g/m$^3$.

We summarize statistical results of our independent variables in Panel B, including two population migration indicators and a lockdown dummy variable of our interest. By following Fang et al. (2020), who estimated that one index unit in inter-city and intra-city migration corresponds to 90,848 and 2,182,264 migrants, respectively, we calculated the number of population flow in and out of a city and the number of population travel within a city. We then multiplied these two migration intensity indices by 90,848 and 2,182,264. The average number of intra-city migrants in locked-down cities is significantly lower than that of unlocked-down cities. Additionally, across the 283 cities, 47% of cities implemented lockdown, and travel was restricted for 1249 weeks, accounting for 30% of the sample period.

The bottom of Table 1 shows descriptive statistics for the control variables i.e. weather conditions. The temperature and wind speed values of treated cities is clearly somewhat larger than that of untreated cities.

### 2.2. Empirical methods

The potential bias and loss of efficiency that can result when spatial effects such as spatial autocorrelation and spatial heterogeneity of air pollution are ignored in the estimation process have been taken into accounts, and all empirical models have been developed within a spatial econometric framework.

#### 2.2.1. Measurements of spatial correlations

The specification of a spatial weighting matrix (represented by $W$) plays an important role in determining the appropriate form of the spatial model, which summarizes spatial relations among all spatial units. According to Tobler’s First Law of Geography (1970), this study calculates an inverse distance weight matrix by using the Euclidean distance from center cell as the measure of the correlation of spatial units. The premise of this weight matrix is that observations further away should have their contributions diminished according to how far away they are. It is calculated as follows:

$$W_{ij} = f(\theta, dis_{ij})$$  \hspace{1cm} (1)

In which $dis_{ij}$ is the distance between spatial unit $i$ and spatial unit $j$. $\theta$ is the given distance decay parameter.

Earlier research has demonstrated that air pollution has spillover effects and regional impacts among the spatial units (Chen et al., 2016; Zeng et al., 2019). Once released, air pollutants are dispersed by the weather and can travel long distances within and between cities. Emissions from distant and local sources can accumulate into high local concentrations of pollution. To measure such spatial autocorrelation of air pollutants, Global Moran’s I Index (GMI) and Local Moran’s I Index (LMI), both ranging from −1 (perfect dispersion) to +1 (perfect correlation), are calculated. The formula of GMI is as follows:

$$GMI = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - \bar{x})(x_j - \bar{x})}$$

(2)

where $n$ is the total number of spatial units; $x_i$ and $x_j$ stand for air pollution indicators of $i$-th and $j$-th sample cities. $\bar{x}$ is the sample mean of the variable $x$, and $W_{ij}$ is the spatial weight matrix ($n \times n$) of the connection between the $i$-th and $j$-th sample cities.

The general form of the LMI can be written as:

$$LMI_i = \sum_j W_{ij} Z_j (i \neq j)$$

(3)

In which, $Z_i$ and $Z_j$ are the standardized values of air pollution indicators in the $i$-th and $j$-th administrative cities, respectively. $W_{ij}$ have the same meanings as in formula (2).

#### 2.2.2. Human migration and air pollution

It is common practice to consider the SAR specification to account for possible spatial spillover effects in air pollution among different regions. The SAR model assumes the dependent variable is spatially autocorrelated. In our study, we consider air pollutants to be autocorrelated across cities, as explained not only by its associated attributes, but also partially by the traits of the “neighboring” cities. The traits of the “neighbors” are described in terms of contiguity. Compared to traditional spatial
econometrics literature, whose literature is interested primarily in the
development among observations across space, an obvious difference of this
study is that we are model both spatial dependence (neighbors,
distance, links, etc.) and temporal dependence (time) in the same
equation. We assume that air pollution in a certain city is not only
explained by its neighbors, but also by its precursors (previous air
pollution levels), especially for our city-week data. Thus, considering the
spatial effects and time-period specific effects of air pollution, we first
employed a dynamic spatial autoregression (SAR) model to investigate
the relationship between the population movements and air pollution
emissions. Formally, the model is:

$$\begin{align*}
\text{Ln}(\text{Air}_{i,t}) &= \tau \cdot \text{Ln}(\text{Air}_{i,t-1}) + \rho \cdot \text{W} \cdot \text{Ln}(\text{Air}_{i,t}) + \eta \cdot \text{W} \cdot \text{Ln}(\text{Air}_{i,t-1}) \\
&+ \beta \cdot \text{Ln(Intercity / Intraicity)} + \lambda \cdot \text{Weather}_{i,t} + \text{city}_{i} + \text{week}_{t} + \epsilon_{i,t}
\end{align*}$$

(4)

We considered three spatial/temporal lag terms to include potential
spatial effects of air pollution in Eq. (4). The parameters \(\tau\), \(\rho\), and \(\eta\) are
the response parameters of the dependent variable, successively, the
dependent variable lagged in time, that is \(\text{Ln}(\text{Air}_{i,t-1})\), which captures the
serial dependence between the air pollution of each city over time; the
dependent variable lagged in space, that is \(W^{*}\text{Ln}(\text{Air}_{i,t})\), which captures the contemporaneous outcomes in neighboring cities; and the
dependent variable lagged in both space and time, that is \(W^{*}\text{Ln}(\text{Air}_{i,t-1})\), which captures the unobservable spatial and time-period specific effects
from neighboring cities. \(\text{Ln(Intercity / Intraicity)}\) are exogenous explanatory
variables of our interest, \(\text{Weather}_{i,t}\) is an \(N \times 6\) matrix of weather
condition variables, \text{city} stands for spatial fixed effects, and \text{week} stands for
city-by-week fixed effects. \(\epsilon_{i,t}\) is a disturbance term. This model
suggests that the concentration of air pollutants in any given city is a
function of the pollution situation both in that city and all the other
cities in the system.

2.2.3. Lockdown and air pollution

Even though we have established a link between human movements
and air pollution emissions in Eq. (4), it is insufficient for understanding the
variation in air pollution during the pandemic. Now we turn to
investigate how lockdown affected air quality across China’s cities. As
the epicenter at the early phase of the pandemic, a range of lockdown
measures were imposed on one-third of Chinese cities within days of the
Wuhan lockdown. This fact enabled us to identify the causal effects of
city lockdown caused by the pandemic and by the air pollution. But a
key empirical challenge is the endogeneity of city lockdown originating
from various confounding factors that potentially affect the air pollution
level. To be specific, the air pollution levels have been declining in most
cities over the last several years owing to the government’s environ-
mental regulations. As a result, the before-and-after comparison by
satellite observation or sensory evidence could simply capture the
decreasing trend in air pollution caused by regulations. Fortunately, our
DID strategy helps to address this endogeneity issue because cities
without lockdown policies can serve as the counterfactuals, mimicking
what would happen in lockdown cities in the absence of its imple-
mentation. In our case, some cities were exposed to a lockdown policy
(treatment group) and others were not (control group). This background
allows us to apply the logic of causal inference and employ a difference-in-difference (DID) method to identify the plausible causal impact of the
lockdown policy by comparing how the air pollution concentration in
these two groups changed before and after its implementation. Consid-
ering the spatial effects inherent in air pollution, we extended the
traditional SAR model. Showing how a spatially explicit counterfactual
framework can add further insight into the evaluation of treatment ef-
fects as shown in Eq. (5).

$$\begin{align*}
\text{Ln}(\text{Air}_{i,t}) &= \rho \cdot \text{Treat\_lock}_{i,t} + \beta \cdot \text{Weather}_{i,t} + \text{city}_{i} + \text{week}_{t} \\
&+ \text{city}_{i} \cdot \tau + \epsilon_{i,t}
\end{align*}$$

(5)

In essence, Eq. (5) is a spatial panel model with 283 cross-sectional
city observations and 14 time periods, including spatial fixed effects
city) and temporal fixed effects (week), in which the outcome variable
\(\text{Ln}(\text{Air}_{i,t})\) is the mean (by week) of the AQI index and the concentration
of six air pollutants. The treatment \(\text{Treat\_lock}_{i,t}\) is the interaction term of
the lockdown dummy and the period dummy, which captures the
average treatment effect of lockdown measures on air pollution. Other
variables and coefficients without specific interpretation are equal to
those introduced in function (1). In order to relax common trend as-
sumptions to some extent, we followed the approach of Angrist and
Pischke in introducing a city-specific trend as the product of a city
dummy with a time trend term \(t\) into our model (Angrist and Pischke,
2014).

3. Results and discussion

We present our GMI scatter plot for AQI and six air pollutants in
Fig. 3. As illustrated, all GMI of six air pollutants indicators are signifi-
cantly greater than 0 at the 0.05 confidence level, indicating that air
pollution emissions are spatially and positively correlated among the
spatial units – the cities with high air pollution emissions (or low air
pollution emissions) appear close to each other, or clustered together, in
space.

Based on the LMI index, our spatial autocorrelation analysis at the
local scale also provides supportive evidence that air pollutants were
clustered in space. Fig. 4 presents the Moran scatter plot and
geographical distribution of AQI (see Fig. 4-a1 & Fig. 4-a2) and the
concentrations of PM_{2.5} (see Fig. 4-b1 & Fig. 4-b2). We observed that
heavy air pollution was mainly concentrated in northern China. Other
pollutants show similar characteristics. To save space, we offer detailed
information on the measurements of spatial clustering and heterogene-
ity of the other five air pollution indicators in supplementary files
(SF-B).

3.1. Correlating human migration and air pollution

3.1.1. Inter-city migration and air pollution

We considered three spatial/temporal lag terms to include potential
spatial effects of air pollution and developed a dynamic spatial panel
model to capture the effects of population migration on air pollution. For
our study, what we require is a model that allows us to estimate which
percentage of air pollution changes with human mobility. And a log-
linear model, in which the dependent variable is transformed by tak-
ning the natural log of it, allows us to interpret these estimated effects in
percentage terms. Moreover, the contribution of the spatial model is to
breakdown the spatial multiple effects into direct effects, indirect effects
and total effects.

We must note that investigating the spatiotemporal patterns and
socioeconomic drivers of air pollution by using spatial econometric
model is not new. Numerous studies have found evidence for strong
spatial overflow effects (indirect effects) and spatial accumulation

![Fig. 3. GMI scatter plot for AQI and six air pollutants (by week). This figure was plotted with Stata 16.0 software.](image-url)
characteristics in air pollutants among different regions and provided sufficient policy implications such as establishing a regional cooperative governance mechanism. For simplicity, this study thus focuses only on the direct causal relationship between city actions and air pollution which may be more meaningful for local governments when making policies to adapt to the need of their regions. It would, moreover, be overly complicated to report both direct and indirect effects by considering seven proxy indicators of air pollution in the context of spatial econometrics and would reduce the readability of this manuscript.

We report the specific effects incorporating temporal and spatial effects in Table 2. We begin by interpreting the effects of inter-city migration on air pollution. Both spatial and period fixed effects are included in all models. The estimates show that the coefficients of the lagged dependent variable in time \((\text{LnAir}_{i,t-1})\) and the lagged dependent variable in space \((W*\text{LnAir}_{i,t})\) are all positively significant, suggesting that the effects of temporal serial association and the immediate neighbors are to increase air pollution levels, whereas the coefficients of the lagged value in both time and space \((W*\text{LnAir}_{i,t-1})\) suggest the opposite. Nevertheless, the presence of the temporal and spatial effects confirms the validity of our selected model. Again, \(R^2\) and log likelihood of the models suggest that the models fit the data well. As shown at the bottom of Table 2, the dynamic SAR models explain at least 83% of variations in air pollution emissions.

Furthermore, we turn our attention toward the coefficients of our explanatory variable and its decomposed marginal effects. The significant and positive coefficients of inter-city migration on AQI, PM\(_{2.5}\), PM\(_{10}\), and NO\(_2\) imply that human migration among cities may increase the AQI, PM\(_{2.5}\), PM\(_{10}\), and NO\(_2\) levels, and the corresponding direct effects are 3.059, 0.690, 2.505, and 0.768, implying that a one-unit (10 million people) increase in inter-city population movements is associated with 305.9%, 69.0%, 250.5%, and 76.8% increases in AQI, PM\(_{10}\), PM\(_{2.5}\), and NO\(_2\), respectively. The lack of significance of the coefficients on SO\(_2\) and CO suggests that inter-city migration has no impact on SO\(_2\) and CO.

The coefficients on O\(_3\) are negative and statistically significant, which seems somewhat counterintuitive. However, this phenomenon is understandable for two reasons. The first relates to O\(_3\)’s source and formation. O\(_3\) is not emitted directly into the air, but rather is created by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC). O\(_3\) levels occur when precursor emissions (NOx, VOC) react in the presence of sunlight, warm temperatures, and...
Impact of intra-city migration on air pollution.

Table 3

| Variables | (1) Ln(AQI) | (2) Ln(SO₂) | (3) Ln(PM₂.₅) | (4) Ln(PM₁₀) | (5) Ln(NO₂) | (6) Ln(CO) | (7) Ln(O₃) |
|-----------|-------------|-------------|----------------|-------------|-------------|------------|------------|
| LnAir(t-1) | 1.010*** (10.379) | 1.003*** (10.567) | 1.029*** (10.768) | 1.003*** (10.646) | 1.037*** (11.572) | 1.041*** (9.656) | 1.039*** (11.091) |
| W*lnAirt | 0.407*** (13.822) | 0.554*** (27.122) | 0.378*** (12.564) | 0.361*** (11.143) | 0.470*** (21.373) | 0.470*** (20.836) | 0.350*** (17.534) |
| W*lnAir(t-1) | -0.913*** (-7.314) | -0.773*** (-5.391) | -0.886*** (-7.411) | -0.843*** (-6.272) | -0.774*** (-5.702) | -0.756*** (-5.088) | -0.712*** (-7.560) |
| Inter-city Migration (direct effects) | 3.059** (1.959) | -0.148 (-0.423) | 0.690 (0.739) | 2.505** (2.773) | 0.768** (2.242) | -0.117 (-0.346) | -1.102*** (-3.426) |
| Minmet | -0.014*** (-6.486) | -0.026*** (-11.377) | -0.013*** (-5.196) | -0.022*** (-9.208) | -0.022*** (-11.554) | -0.005*** (-3.462) | -0.007*** (-4.980) |
| Maxmet | 0.012*** (6.729) | 0.023*** (12.997) | 0.066*** (2.388) | 0.021*** (10.494) | 0.015** (9.818) | -0.003*** (-0.188) | 0.018*** (13.462) |
| Maxgust | -0.015** (-10.735) | -0.010*** (-8.051) | -0.020*** (-12.128) | -0.014*** (-9.290) | -0.014*** (-11.790) | -0.007*** (-7.417) | 0.004*** (4.048) |
| Rain | -0.010*** (-6.523) | -0.003** (-1.989) | -0.013*** (-6.961) | -0.015*** (-8.162) | -0.003*** (-2.395) | -0.002*** (-1.506) | -0.009*** (-7.668) |
| Snow | 0.018* (1.035) | 0.011 (1.023) | 0.031** (2.167) | 0.023* (1.826) | 0.030*** (2.709) | 0.016* (1.926) | 0.035*** (3.491) |
| Spatial FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3679 | 3679 | 3679 | 3679 | 3679 | 3679 | 3679 |
| R-squared | 0.844 | 0.904 | 0.850 | 0.851 | 0.901 | 0.854 | 0.831 |
| log-likelihood | -109.025 | 354.602 | -702.218 | -471.759 | 649.467 | 1152.325 | 1200.267 |

Notes: t statistics in parentheses, standard errors are clustered at city level (283 clusters) *p < 0.10, indicates significance at 10% levels, **p < 0.05, indicates significance at 5% levels, ***p < 0.01, indicates significance at 1% levels. The matrix W is an inverse distance space weight matrix of dimension 283 (the same as in Table 2).

Impact of inter-city migration on air pollution.

Table 2

| Variables | (1) Ln(AQI) | (2) Ln(SO₂) | (3) Ln(PM₂.₅) | (4) Ln(PM₁₀) | (5) Ln(NO₂) | (6) Ln(CO) | (7) Ln(O₃) |
|-----------|-------------|-------------|----------------|-------------|-------------|------------|------------|
| Intra-city Migration (direct effects) | 0.601*** (5.563) | 0.027 (0.809) | 0.403*** (4.228) | 0.686*** (6.340) | 0.334*** (10.256) | -0.044 (-1.305) | -0.147*** (-4.598) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Spatial FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3679 | 3679 | 3679 | 3679 | 3679 | 3679 | 3679 |
| R-squared | 0.844 | 0.904 | 0.850 | 0.851 | 0.901 | 0.854 | 0.831 |
| log-likelihood | -99.784 | 355.798 | -699.072 | -464.089 | 657.281 | 1144.931 | 1208.091 |

Notes: To save space, the results of the spatial terms and control variables are not reported here, but are available upon request.

light winds. Unfortunately, we fail to prove whether the precursors affect the O₃ level due to the lack of data for NOx and VOC. The second is that previous studies have found that there is a trade-off between ambient PM₂.₅ and O₃ concentrations. For instance, Li et al. (2020) found that O₃ concentrations in the North China Plain are reduced by about 25 ppb (part per billion) relative to PM₂.₅-free conditions when PM₂.₅ exceeds 80 μg/m³. Another also provides evidence for the negative relations of ambient PM₂.₅ and O₃ in cold seasons (December, January and February) in an urban area of East China. These analyses support the inverse relations between O₃ and PM₂.₅ in our case (Jia et al., 2017). Nevertheless, we must we must interpret this result with caution because considering chemical reactions will make matters more complicated.

3.1.2. Intra-city migration and air pollution

In Table 3, we reported the effects of intra-city migration on air pollution. As with the results presented in Table 2, the coefficients of AQI, PM₂.₅, PM₁₀, and NO₂ are positive and statistically significant at the 0.01 level, and the predicted direct effects of one-unit change in intra-city migration on these four air pollution indicators are 60.1%, 40.3%, 68.6%, and 33.4%, respectively. The coefficients of O₃ remain negative as before. We again fail to find suggestive evidence for SO₂ and CO.

The results in Tables 2 and 3 suggest that a considerable amount of the variation in AQI, PM₂.₅, PM₁₀, NO₂, and O₃ is partially explained by population migration, while population migration into or within cities does not bear a significant influence on SO₂ and CO emissions. This conclusion is consistent with the fact that PM₂.₅, PM₁₀, and NO₂ released from human activity overwhelmingly derive from the raising of dust from road transport and soot from vehicle exhausts, but almost all SO₂ and CO are emitted as a result of the combustion of fossil fuels.

3.2. Quantifying the impact of the lockdown on air pollution

As revealed in the previous section, human movements measured by the human migration intensity index are strongly associated with the concentration of the pollutants PM₂.₅, PM₁₀, NO₂, and O₃. However, shedding more light on how human-made activity impacts air pollution is challenging. The exogenous shock in human mobility resulting from lockdown during the COVID-19 outbreak provides a useful research environment for us to examine the potential mechanism between human movements and air pollution emissions. We employ a set of spatial DID estimations to disentangle the lockdown effects on air pollution reductions.

3.2.1. 133 lockdown cities vs. 150 non-lockdown cities

By considering the spatial effects of air pollution, a spatial-autoregression difference-in-difference (SAR-DID) model was considered as a plausible empirical design. For this analysis, we divide our data...
Notes: To save space, the results of the spatial terms and control variables are not reported here, but are available upon request (the same as in the following tables).

### Table 4: Impact of lockdown on air pollution.

| Variables | (1) Ln(AQI) | (2) Ln(SO$_2$) | (3) Ln(PM$_{2.5}$) | (4) Ln(PM$_{10}$) | (5) Ln(NO$_2$) | (6) Ln(NO$_x$) | (7) Ln(No$_x$) |
|-----------|-------------|----------------|-------------------|------------------|----------------|----------------|----------------|
| **TW (LnAir$_i$)** | 0.998*** (1670.617) | 0.995*** (850.868) | 0.998*** (1670.459) | 0.998*** (1670.827) | 0.995*** (855.958) | 0.997*** (1301.862) | 0.997*** (1263.794) |
| **Treat_Lock** | -0.181*** | 0.017 | -0.222*** | -0.107** | -0.205** | -0.048 | -0.004 |
| **MinFe** | -4.324 | (9.321) | (4.380) | (2.175) | (3.912) | (1.430) | (6.103) |
| **MaxFe** | -14.674 | (-24.002) | -6.100 | (-21.508) | (-10.119) | (-3.673) | (-15.473) |
| **Maxtemp** | 0.018** | 0.038*** | 0.005* | 0.037*** | 0.027*** | 0.002 | 0.017*** |
| **Maxwind** | -10.487 | (187755) | 2.152 | (18375) | (11720) | (1143) | (12849) |
| **Maxgust** | -18.909 | (-4.583) | -21.241 | -17.069 | -7.163 | -7.751 | (5.628) |
| **Rain** | 0.001 | 0.001 | 0.002*** | 0.000 | -0.002** | 0.000 | 0.001*** |
| **Snow** | 0.006 | -0.023 | 0.016 | -0.001 | 0.059* | 0.036* | 0.009 |
| **Spatial FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Week FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Constants** | 0.117*** | -0.320*** | 0.335*** | -0.036 | -0.219*** | 0.020 | -0.082* |
| **Observations** | 3962 | 3962 | 3962 | 3962 | 3962 | 3962 | 3962 |
| **R-squared** | 0.527 | 0.462 | 0.530 | 0.493 | 0.310 | 0.463 | 0.556 |
| **log-likelihood** | -1074.674 | -2250.585 | -1831.420 | -1651.560 | -2263.506 | -351.280 | -88.022 |

Additionally, the focus of this paper is the variation of the other six specific air pollutants and we provide a comprehensive analysis for each air pollutant in subsequent sections. The baseline results demonstrate that, relative to the control group, transmission control measures taken in the cities under lockdown led to a large and significant reduction in AQI, PM$_{2.5}$, and NO$_x$ concentrations and a smaller reduction in PM$_{10}$ but no significant drop in SO$_2$, CO, and O$_3$ levels. These results confirm our earlier findings and are consistent with previous research, as well. In the case of the concentration of SO$_2$, which did not significantly decline following the lockdown, it likely reflects the fact that China heavily relies on fossil fuels for its energy needs, and the fact that residents burned more coal for heating in the colder period we studied. It is less clear why CO, a pollutant largely emitted from transport, and O$_3$, a pollutant not directly emitted but rather formed in the air, did not fall following the lockdown.

#### 3.2.2. Stringency of lockdown measures and air pollution

In response to the rapid transmission of COVID-19, different levels of prevention and control measures were imposed on various cities within days of the Wuhan lockdown on 23 January. As the epicenter, eleven cities under the jurisdiction of Hubei province announced complete lockdown, 40 cities adopted partial lockdown measures, and 92 cities set up checkpoints and quarantine zones.

In order to isolate the effects of different degrees of stringency in lockdown measures, we implemented two sets of regression that differ in the selection of air pollution indicators. We substituted our explained variables up to six main pollutants (PM$_{2.5}$, PM$_{10}$, CO, SO$_2$, NO$_2$, and O$_3$). AQI is thus too general for describing specific effects of air pollution. Furthermore, the focus of this paper is the variation of the other six specific air pollutants and we provide a comprehensive analysis for each air pollutant in subsequent sections. The baseline results demonstrate that, relative to the control group, transmission control measures taken in the cities under lockdown led to a large and significant reduction in AQI, PM$_{2.5}$, and NO$_x$ concentrations and a smaller reduction in PM$_{10}$ but no significant drop in SO$_2$, CO, and O$_3$ levels. These results confirm our earlier findings and are consistent with previous research, as well. In the case of the concentration of SO$_2$, which did not significantly decline following the lockdown, it likely reflects the fact that China heavily relies on fossil fuels for its energy needs, and the fact that residents burned more coal for heating in the colder period we studied. It is less clear why CO, a pollutant largely emitted from transport, and O$_3$, a pollutant not directly emitted but rather formed in the air, did not fall following the lockdown.

### Table 5: Impact of lockdown on 24-h concentration mean of six air pollutants.

| Variables | (2) Ln(SO$_2$ 24 h) | (3) Ln(PM$_{2.5}$ 24 h) | (4) Ln(PM$_{10}$ 24 h) | (5) Ln(NO$_2$ 24 h) | (6) Ln(NO$_x$ 24 h) | (7) Ln(No$_x$ 24 h) |
|-----------|-------------------|----------------|-------------------|------------------|----------------|----------------|
| **Treat_Lock** | 0.041 | -0.222*** | -0.118*** | -0.037*** | 0.009 | 0.006 |
| **Control variables** | (0.252) | (-5.025) | (-2.819) | (-3.710) | (0.498) | (0.405) |
| **Spatial FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Week FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Constants** | -0.324*** | 0.335*** | -0.040 | -0.342 | -0.094*** | -0.132*** |
| **Observations** | 3962 | 3962 | 3962 | 3962 | 3962 | 3962 |
| **R-squared** | 0.462 | 0.528 | 0.489 | 0.296 | 0.585 | 0.585 |
| **log-likelihood** | -2249.933 | -1817.766 | -1629.764 | -2291.204 | 1158.821 | 1158.821 |
Heterogeneity analysis.

Cities are inherently heterogeneous entities. To gain further insight into the impacts of city lockdown on air pollution better, we turn our focus to understand heterogeneous effects on air pollution from four factors – population distribution, industrial development, winter heating supply, and transportation demand – that are most relevant to this study. We specifically explore heterogeneity between different cities through sub-city typologies based on Eq. (5). In presenting the results, we consider each dimension in turn.

### Table 6: Stringency of lockdown measures and air pollution.

| Variables | (1) Ln(AQI) | (2) Ln(SO\(_2\)) | (3) Ln(PM\(_{2.5}\)) | (4) Ln(PM\(_{10}\)) | (5) Ln(NO\(_2\)) | (6) Ln(CO) | (7) Ln(O\(_3\)) |
|-----------|-------------|-----------------|---------------------|-------------------|----------------|-----------|-------------|
| Panel A: 11 complete lockdown cites vs. 40 partially locked-down cities |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.265*** | -0.077 | -0.269*** | -0.323*** | -0.628*** | 0.232*** | 0.269*** |
| (4.471) | (1.551) | (-4.001) | (-5.002) | (-10.352) | (6.657) | (6.329) |
| R-squared | 0.472 | 0.598 | 0.525 | 0.443 | 0.437 | 0.562 | 0.600 |
| log-likelihood | -150.091 | -314.661 | -274.650 | -243.115 | -270.477 | 74.400 | -72.451 |
| Panel B: 11 complete lockdown cites vs. 92 checkpoints cities |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.064 | -0.165*** | -0.019 | -0.101** | -0.421*** | 0.171*** | 0.229*** |
| (1.215) | (-2.897) | (-3.371) | (-2.012) | (-6.369) | (4.283) | (6.214) |
| R-squared | 0.502 | 0.366 | 0.529 | 0.453 | 0.342 | 0.414 | 0.570 |
| log-likelihood | -345.021 | -739.890 | -575.994 | -537.696 | -769.241 | -200.246 | -158.799 |

The estimation sample used in regressions reported in Panel A of Table 6 is taken from the eleven completely locked-down cities (treatment group) and 40 partially locked-down cities (control group). In so doing, we compare the extent of the variation of air pollution in cities under complete lockdown to cities under partial lockdown. As illustrated in Panel A of Table 6, the estimated coefficients on Treatment effect remain negative for AQI, PM\(_{2.5}\), PM\(_{10}\), and NO\(_2\), and economically and statistically significant. The estimates suggest that complete lockdown in eleven cities on average reduces AQI, PM\(_{2.5}\), PM\(_{10}\), and NO\(_2\) by 26.5%, 26.9%, 32.3%, and 68.2%, respectively, relative to the 40 cities that adopted partial lockdown measures. We again fail to find suggestive evidence that lockdown impacts SO\(_2\) concentration. Contrary to our expectation, we find the coefficients for CO and O\(_3\) are positively significant, indicating that the concentrations of CO and O\(_3\) in completely locked-down cities increased by 23.2% and 26.9% when separately compared with partially locked-down cities.

The estimation sample in Panel B consists of the eleven cities under complete lockdown (treatment group) and 92 cities that set up checkpoints and quarantine zones (control group). As demonstrated in Panel B of Table 6, lockdown measures reduce PM\(_{10}\) and NO\(_2\) by 10.1% and 42.1%, respectively, and the coefficients of Treatment effect are significant as before. Unexpectedly, we do not observe statistically significant effects for AQI and PM\(_{2.5}\), suggesting that control measures taken by the eleven completely locked-down cities have no significant impacts on AQI and PM\(_{2.5}\), with respect to cities that establish checkpoints and insulating areas. We also find that the coefficients of Treatment effect on CO and O\(_3\) remain positive and statistically significant, which confirm that the concentrations of CO and O\(_3\) increased in completely locked-down cities. The coefficient of SO\(_2\) remains insignificant as before. These results must be interpreted with caution because the sample sizes vary largely in different model settings. Nevertheless, these results highlight that the impacts of the lockdowns varied by control levels and specific pollutants.

### 4. Heterogeneity analysis

Cities are inherently heterogeneous entities. To gain further insight into the impacts of city lockdown on air pollution better, we turn our focus to understand heterogeneous effects on air pollution from four factors – population distribution, industrial development, winter heating supply, and transportation demand – that are most relevant to this study. We specifically explore heterogeneity between different cities through sub-city typologies based on Eq. (5). In presenting the results, we consider each dimension in turn.

### Table 7: Heterogeneity analysis.

| Variables | (1) Ln(AQI) | (2) Ln(SO\(_2\)) | (3) Ln(PM\(_{2.5}\)) | (4) Ln(PM\(_{10}\)) | (5) Ln(NO\(_2\)) | (6) Ln(CO) | (7) Ln(O\(_3\)) |
|-----------|-------------|-----------------|---------------------|-------------------|----------------|-----------|-------------|
| Panel A: 107 cities with high population density (N = 1498) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.073*** | 0.069*** | -0.100*** | -0.038 | 0.100*** | 0.005 | -0.013 |
| (4.135) | (2.844) | (-4.153) | (-1.619) | (4.100) | (0.325) | (-0.217) |
| Panel B: 176 cities with low population density (N = 2464) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.087*** | -0.007 | -0.107*** | -0.064*** | 0.050*** | -0.022 | -0.017 |
| (3.242) | (-0.009) | (-3.982) | (-2.611) | (2.691) | (-1.063) | (-1.021) |
| Panel C: 86 cities with more industrial firms (N = 1204) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.056** | 0.024 | -0.077*** | -0.025 | 0.035 | 0.021 | -0.081*** |
| (2.032) | (0.346) | (-2.585) | (-0.321) | (0.725) | (0.884) | (-0.4082) |
| Panel D: 197 cities with fewer industrial firms (N = 2758) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.035** | 0.052*** | -0.057*** | -0.001 | 0.064*** | -0.020 | 0.020 |
| (2.453) | (2.633) | (-2.789) | (-0.234) | (3.236) | (-1.005) | (1.327) |
| Panel E: 97 cities with heating supply (N = 1358) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.096*** | -0.029 | -0.082*** | -0.103*** | 0.028 | -0.077*** | 0.010 |
| (3.541) | (-0.570) | (-2.641) | (-3.341) | (0.174) | (-3.321) | (0.613) |
| Panel F: 186 cities without heating supply (N = 2604) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.069*** | 0.028 | -0.092*** | -0.037 | 0.106*** | -0.023 | -0.041*** |
| (2.973) | (1.045) | (-4.543) | (-1.547) | (4.368) | (-1.443) | (-2.026) |
| Panel G: 141 cities with a higher transportation demand (N = 1974) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.092*** | -0.014 | -0.115*** | -0.064*** | 0.047 | -0.045*** | -0.039** |
| (4.473) | (-0.065) | (-4.643) | (-2.633) | (1.445) | (-2.691) | (-2.031) |
| Panel H: 142 cities with a lower transportation demand (N = 1988) |  |  |  |  |  |  |  |
| Treat_Lock (direct effects) | -0.028 | 0.079*** | -0.037 | 0.009 | 0.065*** | -0.027 | 0.018 |
| (1.203) | (3.341) | (-1.310) | (0.774) | (2.878) | (-1.640) | (1.548) |

Control variables: Yes Yes Yes Yes Yes Yes Yes

Spatial FE: Yes Yes Yes Yes Yes Yes Yes

Week FE: Yes Yes Yes Yes Yes Yes Yes
Population density measured by the ratio of total urban population to administrative area is one of the most basic attributes of a city. By comparing the local population density with the national mean value, we divide our estimation sample into two sub-city typologies: 107 cities with high population density and 176 cities with low population density. The results of the statistical analyses are reported in Panels A & B of Table 7. As revealed, the direct effects of lockdown measures taken in densely populated cities are −7.3%, −10.0%, and −3.8% for AQI, PM$_{2.5}$, and PM$_{10}$, respectively, corresponding to a reduction ratio of −8.7%, −10.7%, and −6.4% in cities with lower population density. These results suggest that lockdown led to a greater improvement in AQI, PM$_{2.5}$, and PM$_{10}$ in populated cities. We curiously observed evidence that lockdown significantly increased SO$_{2}$ emission by 6.9% in high-density cities but had no obvious impacts on low-density cities. This finding is consistent with the fact that energy consumption, especially coal consumption for heating and domestic burning, is higher in the cities in which people are concentrated, combined with the fact that our sample focuses only on the first quarter of 2020, traditionally the coldest season of the year, due to the availability of our data. Results also show that lockdown policies increased NO$_{2}$ in both cities with high population density and cities with low population density, and that the variation in densely populated cities is greater than in sparsely populated cities. This disparity was likely to be caused by transportation but weakened the rate of increase in cities with low population density. It is understandable as emissions from anthropogenic activity are relatively stable and more people means more pollution emissions, even if a city is locked down.

The most industrialized areas have always been the most polluted. We obtained the numbers of local industrial firms from the China City Statistical Yearbook 2018 to index regional industrial development levels. Specifically, we use the national mean value to divide our estimation sample into high-industrial-intensity cities and low-industrial-intensity cities. The regression results demonstrated that AQI, PM$_{2.5}$, and O$_{3}$ declined by 5.6%, 7.7%, and 8.1%, respectively, in Panel C, with somewhat smaller decreases (3.5% for AQI, 5.7% for PM$_{2.5}$) in Panel D, when these cities adopted lockdown measures. Some of these differences are due to more industrial emissions from power generation, steel, chemicals, and other manufactured products from fossil fuel combustion. Contrary to our expectation, lockdown increased SO$_{2}$ and NO$_{2}$ concentrations in cities with fewer industrial firms. Cities with more industrial firms recorded a greater reduction in air pollutants, which is likely due to the closure of industrial factories.

In our estimation samples, 97 cities to the north of the Huai River-Qinling Mountains line have received centralized heating supply during cold days each winter, whereas 186 cities to the south have had no heating supply. That China heavily relies on coal combustion and inevitably produces serious air pollution affects air quality. Greater population migration, conducive to more intra-/inter-city migrants, is associated with a larger AQI index and higher PM$_{2.5}$, PM$_{10}$, and NO$_{2}$ pollution concentration, but has no meaningful impacts on SO$_{2}$ and CO levels. A further causal inference provides similar supportive evidence that the adoption of lockdown policies led to a large and significant reduction in AQI (18.1%), PM$_{2.5}$ (22.2%), and NO$_{2}$ (20.5%) concentrations, and a smaller reduction in PM$_{10}$ (10.7%), but had no discernible impact on the concentrations of SO$_{2}$, CO, and O$_{3}$. Results also highlight that the impact of the lockdown varied by control stringency and specific pollutants. Sets of heterogeneity analyses by sample indicate that the impact of city lockdown on air quality is more considerable in cities with a low population density, more industrial firms, higher transportation demand, and a heating-supply system. Our findings are particularly important for China as the country strives to improve air quality and accelerate key measures for the development of a more ecological civilization.

Vehicles are one of the major contributors to urban air pollution in China (Fu and Gu, 2017). Based on this fact, this study uses the annual volume of passengers transported by buses and trolley buses data obtained from the City Statistical Yearbook 2018, to measure regional transportation demand. We first calculate the national volume of passengers per city. Then we use the mean value to separate our sample into two groups of 141 cities with a higher transportation demand and 142 cities with a lower transportation demand. Panels G & H of Table 7 illustrate the changes in seven air pollutant indicators for each group. In Panel G, the direct effects of the adoption of quarantine measures are −9.2%, −11.5%, −6.4%, −4.5%, and −3.9% for AQI, PM$_{2.5}$, PM$_{10}$, CO, and O$_{3}$, respectively, in cities with a greater traffic demand, but we fail to find meaningful impacts on corresponding indicators in cities with a lower transportation demand in Panel G. The difference essentially owes to the fact that transportation demand is concentrated in heavily polluted areas like the 44 cities located in the Beijing-Tianjin-Hebei metropolitan circle and its surroundings, where the number of buses/trolley buses and taxis under operation are 1,233,289 and 232,742, respectively, making up 21.9% and 25.7% of the total. On the contrary, a 7.9% increase in SO$_{2}$ and a 6.5% increase in NO$_{2}$ occurred in cities with a relatively lower transportation demand. Cities with a higher transportation demand witnessed a greater reduction in air pollutants, which is likely due to the suspension of private or public transportation.

5. Conclusion and policy recommendations

In this paper we examine the causal relationship between human migration and air pollution, and in turn the causal impacts of lockdown policies on air quality improvement. Considering the regional diffusion effects of air pollution and potential endogeneity concern of city lockdowns, a dynamic SAR model and spatial counterfactual SAR-DID model were employed. We provide novel causal evidence that human migration affects air pollution concentration. Larger population migration, conducive to more intra-/inter-city migrants, is associated with a larger AQI index and higher PM$_{2.5}$, PM$_{10}$, and NO$_{2}$ pollution concentration, but has no meaningful impacts on SO$_{2}$ and CO levels. A further causal inference provides similar supportive evidence that the adoption of lockdown policies led to a large and significant reduction in AQI (18.1%), PM$_{2.5}$ (22.2%), and NO$_{2}$ (20.5%) concentrations, and a smaller reduction in PM$_{10}$ (10.7%), but had no discernible impact on the concentrations of SO$_{2}$, CO, and O$_{3}$. Results also highlight that the impact of the lockdown varied by control stringency and specific pollutants. Sets of heterogeneity analyses by sample indicate that the impact of city lockdown on air quality is more considerable in cities with a low population density, more industrial firms, higher transportation demand, and a heating-supply system. Our findings are particularly important for China as the country strives to improve air quality and accelerate key measures for the development of a more ecological civilization.

This study provides a few policy implications for the practice of air pollution control. Taken together, the results of the study indicate that the emissions of PM$_{10}$, PM$_{2.5}$, and NO$_{2}$ are strongly associated with human migration. Further analysis provides similar supportive evidence that the implementation of lockdown measures that have changed human migration patterns also led to a significant reduction in PM$_{2.5}$, NO$_{2}$, and PM$_{10}$. There is no denying that air pollutants are released into the atmosphere mainly from road transportation, business activities, and public buildings. An obvious and feasible option for policymakers in cities with higher PM$_{2.5}$, NO$_{2}$, and PM$_{10}$ emissions is the adoption of measures like travel restrictions to reduce emissions. Similar measures were already adopted during the Beijing Olympics (2008) and APEC conference (2014), which proved the effectiveness of such restrictive measures. Curiously, we fail to find suggestive evidence in the cases of SO$_{2}$ and CO, both of which are mainly emitted by fossil energy combustion. An important policy implication to be learned from these results is that in cities with higher SO$_{2}$ and CO emissions, addressing excessive fossil-fuel energy consumption in the power and industry sectors is
essential. Finally, heterogeneity analysis confirms that densely-
populated, industrial-intensive, and heating-supply cities, and those
cities with a high traffic burden, are important sources of air pollution
and highlight the necessity of controlling emissions from these sources
when lockdown measures are lifted.

Credit author statement
Jingjing Zeng, Conceptualization, Methodology, Formal analysis,
Investigation, Writing – review & editing, Supervision, Project admin-
istration, Funding acquisition support. Rui Bao, Data curation, Formal
analysis, Investigation, Writing – original draft, Resources,
Visualization.

Declaration of competing interest
The authors declare that they have no known competing financial
interests or personal relationships that could have appeared to influence
the work reported in this paper.

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Appendix A. Supplementary data
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