



Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Journal of Asian Economics

journal homepage: www.elsevier.com/locate/asiecoCOVID-19, commuting flows, and air quality[☆]Munseob Lee^{a, *}, Rachel Finerman^b^a University of California San Diego, 9500 Gilman Drive #0519, La Jolla, CA 92093-0519, USA^b ICEYE, Irvine, CA, USA

ARTICLE INFO

JEL classification:

Q53

R11

R41

Keywords:

COVID-19

Commuting Flows

Transportation

Air Pollution

ABSTRACT

Fossil-fuel burning transportation methods significantly contribute to air pollution. During the COVID-19 pandemic, South Korea experienced a 10-20% decline in commuting flows, even without government-mandated stay-at-home orders. This paper quantifies the impact that decreased commuting flows have on PM_{2.5}, PM₁₀, NO₂, CO, and SO₂, using municipality level commuting data. We find that a 1% decrease in commuting flows decreases air pollutants by 0.08-0.17%, after controlling for seasonality and time-varying local production. The effect was higher in regions with high initial pollution, and people recognized air quality improvements. These results emphasize the importance of encouraging cleaner transportation methods after the pandemic.

1. Introduction

Transportation methods that burn fossil fuels significantly contribute to the release of air pollution particles and gases that cause harmful effects on human health and environmental ecosystems. Fossil fuel-burning vehicles increase the amount of particulate matter (PM_{2.5} and PM₁₀) and other harmful gases such as nitrogen dioxide (NO₂) and carbon monoxide (CO) in the air that are inhaled by humans. These pollutants, along with several others, are known to cause major health issues for human respiratory systems. While several countries are working on making the switch to alternative fuel transportation to decrease pollution levels, the primary sources of transportation today involve fossil fuel-burning methods.

One way to understand the impacts of transportation on pollution is to examine the flow of people across different places, or commuting flow. Commuting flow gives insight into how the number of people traveling across municipalities or provinces can impact air quality in those regions. As many people traveling across places use cars or other transportation methods such as buses that burn fossil fuels, we suggest that changes in commuting flows can create changes in air pollution levels. Studies have shown that particles and gases that comprise air pollution are associated with the number of vehicles on the road (Lau, Hung, Cheung, & Yuen, 2008; Kim & Guldmann, 2011). Understanding the impact of commuting flow on air quality informs the importance of transitioning from fossil fuel-burning to cleaner transportation methods.

Throughout the COVID-19 outbreak, commuting flows were greatly affected all over the world. Some countries created stay-at-home policies that required people to work from home if possible and only leave their houses for essential trips. Naturally, the amount of people traveling on the streets decreased. Time-series data show that pollution levels decreased in some places during the

[☆] Munseob Lee is the lead author. We use proprietary data from SK Telecom and thank Geovision at the SK Telecom for their assistance with the data.

* Corresponding author.

E-mail addresses: munseoble@ucsd.edu (M. Lee), rachel.finerman@iceye.com (R. Finerman).

<https://doi.org/10.1016/j.asieco.2021.101374>

Received 3 April 2021; Received in revised form 11 July 2021; Accepted 29 August 2021

Available online 4 September 2021

1049-0078/© 2021 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

climax of stay-at-home orders with the least number of people contributing to pollution through transportation or industrial work, for example. Some countries, conversely, did not impose stay-at-home policies, including South Korea. Although government intervention was not involved in decreased commuting flows in these countries, people naturally decreased travel due to an abundance of caution and fear of contracting the sometimes-deadly virus.

This paper takes the approach of examining the flow of people across municipalities before and during the COVID-19 outbreak in South Korea to better understand how transportation can contribute to harmful air quality. With decreased personal vehicle use due to less people traveling throughout the country, we expect air quality to improve. Understanding the changes in pollution with the changes in commuting flows during the COVID-19 pandemic contributes to the broader discussion of how improving commuting patterns and transportation use can lead to better air quality in the long-term rather than only in the pandemic short-term. The results of this study can provide the basis for developing ways to enhance transportation and encourage changed commuting flows in order to maintain lower levels of pollution as people begin to leave their houses once again.

We use South Korea in this study for several reasons. First, the commuting flows dataset from South Korea that we have provides real-time information on change in people's movement, which considerably contributes to our analysis and this study's approach. Second, we find that aggregate air quality across the country experiences only a little change, which encourages us to unpack the massive heterogeneity across regions. If policymakers do not investigate this, they may end up with the wrong conclusions, which is especially disadvantageous when establishing ways to decrease pollution in different areas. Third, without government-mandated stay-at-home orders, people voluntarily changed their commuting behaviors, which gives an idea of what may happen in other countries while they open their economies again.

In this paper, we quantify the impact that the 10-20% decline in commuting flows during COVID-19 in South Korea has on $PM_{2.5}$, PM_{10} , NO_2 , CO , and SO_2 . We find that there is endogenous change in commuting flows based on the spread of the virus in South Korea without stay-at-home or lockdown measures. We also find that a 1% decrease in commuting flows decreases $PM_{2.5}$ by 0.11%, PM_{10} by 0.17%, NO_2 by 0.14%, and CO by 0.09%, after controlling for seasonality and local production. We also use our panel regression model to understand the heterogeneity in the municipalities depending on the municipalities' air pollution levels prior to the pandemic. We find that municipalities that were in the 90th percentile for air pollution emissions prior to COVID-19 experience a larger impact of commuting flows on $PM_{2.5}$, PM_{10} , and CO . We also report survey evidence that a substantial amount of people recognized air quality improvements. The share of recognition is positively correlated with the residential location's number of COVID-19 cases.

The analysis and results presented in this paper have broad implications because declining air pollution as a consequence of declining commuting flows has received relatively less attention in the media and related literature than other consequences of responses to the pandemic, such as GDP loss, unemployment, and supply chain disruption. Although many of the consequences from the pandemic are negative, recognizing the impact that changed commuting flows has on pollution during the COVID-19 outbreak can be helpful in understanding how changing commuting flows during non-pandemic times could further benefit air quality.

This paper contributes to the literature on transportation and air quality. [Faiz, Weaver, and Walsh \(1996\)](#) provide a comprehensive review of vehicle emissions, standards, and implementation of cleaner alternative fuels. [Fenger \(1999\)](#) discusses worsening air pollution that is accompanied by urbanization and notes that the increasing number of private cars has a major impact on air pollution. [Colville, Hutchinson, Mindell, and Warren \(2001\)](#) present effects of the transportation sector on air pollution. [Zhang and Batterman \(2013\)](#) model risk of vehicle traffic on human health due to pollution. This paper expands on existing literature by examining air quality changes based on changed commuting flows due to an unexpected exogenous reason.

[Shrivastava, Neeta, and Geeta \(2013\)](#) examine air pollution in India due to road transportation and suggest ways that India could improve its transportation systems to help reduce air pollution. Similarly, [Titos et al. \(2015\)](#) study the effect of transportation policies to encourage more public rather than private transportation usage in two European cities, Granada (Spain) and Ljubljana (Slovenia). They find that air pollution, specifically black carbon and PM_{10} , decreased in both cities after the policies were implemented. These findings acknowledge that transportation is a large source of air pollution, and reducing emissions by altering transportation routes and enhancing policies may help to improve air quality. Although our paper takes a different approach from these two papers in the transportation and air pollution conversation, these papers acknowledge that our findings align with existing literature on the impacts of transportation on air quality. Rather than providing suggestions on ways to change transportation systems to improve air pollution, we aim to quantify the impact of transportation and commuting on air pollution to gain a deeper understanding of the impact based on the natural experiment of COVID-19. By examining literature about transportation and air pollution in different countries, we gain a broader understanding of the impact of transportation, regardless of the location and specific transportation patterns.

Additionally, [Krupnick, Rowe, and Lang \(1997\)](#) highlight the broader environmental impacts of air pollution from transportation. This broader paper provides us with a solid foundation for our hypothesis that by decreasing transportation usage in a commute, air quality will improve. While [Krupnick et al. \(1997\)](#) provides the effects of transportation emissions, we acknowledge the fact that such emissions may be reduced with decreased transportation usage.

In our analysis, we primarily take the stance that the decreased commuting flows means decreased vehicles on the road. Although a limitation in our data is that we do not know what transportation method is associated with each of the commuting flows, we provide additional research and data-supported assumptions to address this limitation. [Lee et al. \(2020\)](#) study the decline in vehicle traffic in the first three months of 2020 due to COVID-19 compared to the first three months of 2019. Overall, they find that traffic from January 1 to March 31 in 2020 was on average 9.7% lower than in the same months in 2019, with varying fluctuations within these months in 2020. Additionally, in the survey produced by [Belot et al. \(2020\)](#), we turn to the results of one of the survey sections, about volunteering activities and attending religious events. At least 75% of all respondents said that during the pandemic they do not at all do any volunteering activities, such as bringing groceries or medicines to friends or family, in critical risk or not, nor do they attend religious services. Since these activities could be seen as important reasons to travel, this survey evidence leads us to believe that people decided

not to travel, regardless of transportation method, during the pandemic, contributing to the decrease in commuting flows. Finally, because the COVID-19 mitigation strategy established by the South Korean government relied on text messages to residents highlighting where and when an infected person had just been, it was easy for people to see where the virus was spreading and choose to decrease travel in any way to avoid getting the virus.

This paper is most closely related to recent works linking COVID-19 and environmental issues. [Cicala, Holland, Mansur, Muller, and Yates \(2020\)](#) study the effects of decreased electricity consumption and personal travel due to COVID-19 in the United States on pollution-related mortality and find that the significant decrease in travel and electricity consumption would lead to a 25% decrease in mortality caused by personal travel-related air pollution. [Muhammad, Long, and Salman \(2020\)](#) present changes in air pollution due to COVID-19 in several cities around the world using satellite data and show that pollution in the pandemic's epicenters decreased by up to 30%. [He, Pan, and Tanaka \(2020\)](#) examine the effects of lockdown policies in cities in China that did and did not implement lockdown policies. They conclude that cities with different characteristics experienced different lockdown effects on pollution but also that changes in pollution were experienced due to other COVID-19 mitigation strategies regardless of the severity of the lockdown policies. These papers use data for a few weeks or months at the very beginning of the pandemic. Instead, we use two years of data, from January 2019 to December 2020, to investigate the systematic relationship between commuting flows and air quality. This paper adds to the literature by examining the environmental effects of decreased travel due to COVID-19 and takes a different approach by exploiting within a country across regions, with detailed information on commuting patterns, to estimate the effect more precisely.

This paper is also related to recent works on quantifying consequences of COVID-19 and mitigation strategies. [Wilder-Smith and Freedman \(2020\)](#) and [Alvarez, Argente, and Lippi \(2020\)](#) discuss different pandemic responses and the economic and social impacts of COVID-19 mitigation measures. [Dingel and Neiman \(2020\)](#) examine the feasibility of working from home in the United States, as a strategy to limit the spread of the virus. This paper examines mobility throughout South Korea considering that the government did not implement stay-at-home orders. It adds to the literature by examining how commuting flows changed due to the pandemic without government intervention and the impact of those changed commuting flows on air pollution.

This paper also uses mobile phone data to understand commuting flows across South Korea during the pandemic. [Couture, Dingel, Green, Handbury, and Williams \(2020\)](#) examine the possibility of using smartphone data to identify spread of the COVID-19 virus throughout the United States. [Brinkman and Mangum \(2021\)](#) use county-level data from cellular devices to understand movement across the United States in relation to the spread of the virus. They find that travel throughout the United States dropped as number of cases increased, and people specifically avoided high-transmission areas regardless of government mandates in those regions. [Argente, Hsieh, and Lee \(2020\)](#) quantify the impact of South Korea's public disclosure of newly discovered COVID-19 cases via text messages on commuting flows across the country. Like those papers, we use mobile phone data to measure change in people's movement across regions within a country. Instead of quantifying the data's contribution to virus transmission, we quantify its contribution to air quality improvements.

This paper proceeds as follows. [Section 2](#) provides background to our analysis, and we introduce the number of COVID-19 cases in South Korea along with the commuting flows and air quality data that we use throughout the rest of our paper. [Section 3](#) presents our empirical findings for the change in commuting flows and air quality as well as the impact that the spread of the disease has on commuting flows. In [Section 4](#), we present our panel regression model for the analysis and examine the impact of changed commuting flows on air pollution. [Section 5](#) presents a discussion of the heterogeneity in our results from South Korean municipalities in the 90th percentile of air pollution levels as well as a look into people's perception of air pollution changes during the pandemic. [Section 6](#) concludes.

2. Background and data

We introduce the data that we use in our analysis by examining the number of COVID-19 cases and changes in commuting flows due to the pandemic in South Korea. These initial statistics provide background for the following sections and show that our primary question for the analysis is supported by the confirmed decrease in commuting flows from 2019 to 2020. We also introduce the air quality data and explain our use of $PM_{2.5}$, PM_{10} , NO_2 , CO , and SO_2 as air pollutants of interest in the analysis. We include a summary table of the variables we use in our primary specification in [Appendix Table A.1](#) and a summary table of our samples in [Appendix Table A.2](#).

2.1. COVID-19 in South Korea

South Korea saw its first confirmed case on January 20, 2020. With a quick and effective pandemic response, the government was able to slow the spread of the virus, despite the continuous increase in number of cases. The number of cases increased most drastically from November to December 2020, in what some might call a "second wave" of the virus. Before November, the cumulative number of cases increased steadily and slightly each month after the first confirmed case in January. By December 2020, South Korea had over 60,000 cumulative cases, and the cumulative number of cases in each province ranged from less than 1,000 to over 15,000, with Seoul having the highest number of cases by December 2020 than any other region in South Korea¹.

South Korea's response to COVID-19 was effective in reducing the spread and maintaining relatively stable economic performance.

¹ [Appendix Fig. A.1](#) and [A.2](#) show the cumulative number of COVID-19 cases in South Korea in total and by province.

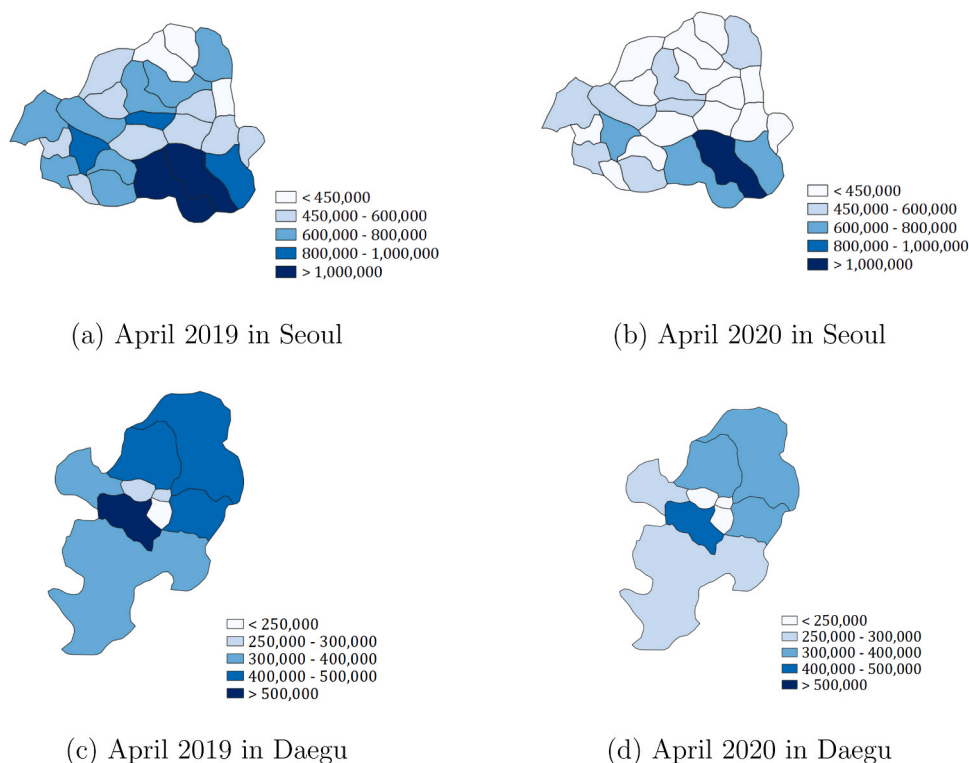


Fig. 1. Gross commuting flows in Seoul and Daegu Provinces, in units of average number of commuting people. Notes: The figure shows gross commuting flows, in units of number of commuting people, averaged across weekdays and weekends, in Seoul and Daegu provinces in April 2019 and April 2020. Seoul has 25 municipalities and Daegu has 9 municipalities.

Many countries implemented stay-at-home or lockdown policies that significantly affected the economies of those countries as many people lost their jobs and stopped circulating money through the economy by way of traveling, dining at restaurants, and shopping. Instead of implementing a country-wide lockdown, South Korea experienced the benefits of public disclosure during the pandemic. By notifying citizens via cellular phone text messages and sharing information on websites about newly discovered cases in addition to aggressive testing for the virus, the government was able to control the spread without implementing lockdown policies.² We take South Korea's relative success in handling the pandemic into account for our analysis, acknowledging that lockdown policies may have an even greater effect on air pollution as people's lifestyles changed more drastically than they did with South Korea's strategy.

2.2. Commuting flows data

We measure commuting flows from proprietary data provided by the SK Telecom mobile phone company.³ Based on the location of mobile phones, SK Telecom calculates daily bilateral flows of people in 250 municipalities across 17 provinces in South Korea.⁴ A person's movement is included when she or he stays in the origin municipality for more than two hours, commutes to another municipality and stays in that municipality for more than two hours. If a person moves multiple times during the day, the data records the

² In an author's other paper, [Argente et al. \(2020\)](#) weigh the costs of public disclosure and lockdown policies on public welfare, number of COVID-19 cases and deaths, and the economy, using Seoul as the example for public disclosure. They find that public disclosure and lockdown policies result in about the same number of cases and lives saved compared to a situation with neither regulation but that lockdown policies create much larger negative impacts on welfare and the economy than public disclosure. [Aum, Lee, and Shin \(2021\)](#) examine the impacts of COVID-19 mitigation strategies and use South Korea as an example of a country that used a different mitigation strategy than a lockdown policy. They find that a stricter and longer lockdown could be beneficial for decreasing the spread of the virus as well as increasing GDP in the long run, but South Korea's aggressive COVID-19 testing and public disclosure method is significantly more beneficial in terms of virus spread and economic loss than a lockdown policy. [Aum, Lee, & Shin \(2020\)](#) find that COVID-19 destroyed jobs in Korea even without lockdowns. Appendix [Table A.3](#) shows an example of public disclosure in South Korea. This is the second case in Seoul confirmed on January 30. This information has been available on official website and has been circulated by text alerts for people living in certain districts. Refer to [Argente et al. \(2020\)](#) for more information on disclosure policy and its effectiveness.

³ In January 2020, its market share was 41.9%, followed by KT with 26.4% and LG U+ with 20.6% (source: Korea Communications Commission).

⁴ The presence of subscribers in a given municipality is based on any of their cellular phone activity including calls, texts, and the internet connection. The location of a user is inferred by cellular tower triangulation.

main movement. We obtained data on monthly average of daily bilateral commuting flows for weekdays and weekends separately from January 2019 to December 2020, covering all municipalities in South Korea. This dataset provides valuable insights as it shows real-time information on change in people's movement across the country during the COVID-19 pandemic.

Although there is the potential for estimation bias without within municipality commuting flows, the main way we control for this is using municipality fixed effects. With municipality fixed effects, we take into account the potential variations of commuting flows within each municipality, given the data that we have. We also cluster standard errors at the municipality level to take into account the commuting flows that happen beyond what we have available in our data. We acknowledge that this dataset does not contain all information about commuting flows, mobility, and travel during the chosen time period, but it provides a valuable understanding from a prominent South Korean mobile phone company of how commuting flows have generally changed due to COVID-19.

We calculate gross commuting flows for each municipality by summing all inflows to and outflows from that municipality. Suppose that ϕ_{ij} is the number of people who moved from a municipality i to a municipality j . Then, the gross commuting flows in a municipality k , π_k , is defined as

$$\pi_k \equiv \sum_i \phi_{ik} + \sum_j \phi_{kj} \quad (1)$$

where $\sum_i \phi_{ik}$ is the sum of inflows to the municipality k from all other municipalities and $\sum_j \phi_{kj}$ is the sum of outflows from the municipality k to all other municipalities. Fig. 1 shows average commuting flows in April 2019 and April 2020 in both Seoul and Daegu provinces, averaged across weekdays and weekends. We use these two provinces for the initial examination of commuting flows because Seoul province has 20% of the South Korean population, and both Seoul and Daegu provinces had the largest number of COVID-19 cases throughout 2020 than any other South Korean province. As seen in panel (a) and (b) of Fig. 1, Seoul experienced a substantial decrease in commuting flows in April 2020 compared to April 2019, where average commuting flows in April 2020 were about 70% of what they were in April 2019. Daegu experienced a similar decrease in commuting flows as well, as seen in panel (c) and (d) of Fig. 1, where average commuting flows in April 2020 were about 76% of what they were in April 2019. We hypothesize that the substantial decrease in commuting flows will have an impact on air pollution. We also note that the changes in commuting flows in South Korea were voluntary and not imposed by government orders or restrictions. Commuting flows may be significantly more impacted in other countries that had lockdown policies.

In addition to the changes in commuting flows shown in Fig. 1, we use data from Google's Global Community Mobility Reports to further provide motivation for our assumption that commuting flows decreased during the outbreak of COVID-19. The data in the mobility reports show that mobility related to transit stations and workplaces decreased from February to December 2020. Appendix B presents the decline in mobility related to transit stations and workplaces in Seoul, Manhattan, and Tokyo and shows that Seoul's mobility decreased slightly compared to the baseline throughout 2020, and Manhattan's and Tokyo's declined even more. Therefore, we suggest that the results presented in our analysis may translate to other cities or countries based on decreased mobility data during COVID-19.

2.3. Air quality data

We collect data from the World Air Quality Index, which sources its South Korea data from Korea Air Environment Corporation.⁵ The data come with the Air Quality Index (AQI) for several air pollution measures: PM_{2.5}, PM₁₀, NO₂, CO, SO₂, and O₃. After reviewing similar studies, we focus on PM_{2.5}, PM₁₀, NO₂, CO, and SO₂. Cicala et al. (2020) examine PM_{2.5}, SO₂, nitrogen oxides, and volatile organic compounds (VOCs), paying particular attention to PM_{2.5}. In their study of the relationship between personal vehicle travel, electricity use, and PM_{2.5}-associated mortality during COVID-19, they calculate the amount of emissions and number of deaths per billion miles of travel for each measure of air pollution based on the average emission rates for light duty vehicles and trucks. They find that nitrogen oxides, which include NO₂, have the highest number of deaths per billion miles of travel. Based on similar studies and health effects of the pollutants themselves, we focus on PM_{2.5}, PM₁₀, NO₂, CO, and SO₂ because of their proven harmful effects on human health and their relevance to the transportation sector and vehicle emissions.

3. Empirical findings

We provide motivation for our analysis by examining the change in commuting flows and air quality during the pandemic as well as how the spread of the disease impacted commuting flows. We find that commuting flows substantially decreased from 2019 to 2020 and that the increase in the number of confirmed cases contributed to the decline in commuting flows. We acknowledge that the analysis and results may contain endogeneity bias. However, with the set of fixed effects, along with controlling for seasonality and local production, we provide robust results throughout the following sections of this paper.

3.1. Change in commuting flows and air quality

Panel (a) of Fig. 2 shows the year-on-year log change in commuting flows from 2019 to 2020, averaged across the municipalities. It shows that commuting flows in South Korea in 2020 were lower on average across the municipalities compared to commuting flows in

⁵ <https://waqi.info>; <https://www.airkorea.or.kr>

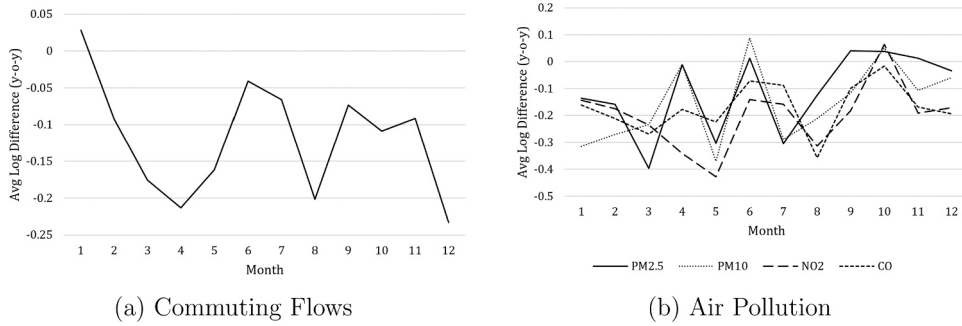


Fig. 2. Year-on-year change in commuting flows and air pollution from 2019 to 2020. Notes: Panel (a) shows average year-on-year change in commuting flows in South Korea from 2019 to 2020, represented by average log difference of commuting flows for each month of each year. Panel (b) shows average year-on-year change in air quality values of PM_{2.5}, PM₁₀, NO₂, and CO in South Korea, represented by average log difference of each of the air quality measures for each month of each year.

Table 1
Spread of disease and decline in commuting flows.

	$\ln\pi_{jkt}$ (1)	(2)	(3)	(4)
$\ln(C_{jkt} + 1)$	-0.0257*** (0.0008)	-0.0258*** (0.0030)		
$\mathbb{I}[C_{jkt} > 0]$			-0.1374*** (0.0049)	-0.0102* (0.0059)
Municipality FEs	Yes	Yes	Yes	Yes
Weekday/weekend FEs	No	Yes	No	Yes
Time FEs	No	Yes	No	Yes
Cluster	Municipality	Municipality	Municipality	Municipality
Observations	5,999	5,999	5,999	5,999
R-squared	0.3165	0.4501	0.2791	0.5530

Notes: The table reports regression results for Eq. (2) in columns (1) and (2) and for Eq. (3) in columns (3) and (4). Column (1) does not include weekday/weekend or time fixed effects for Eq. (2). Column (2) includes all fixed effects for municipality, weekday/weekend, and time. Column (3) does not include weekday/weekend or time fixed effects for Eq. (3). Column (4) includes all fixed effects for municipality, weekday/weekend, and time. All results have clustered standard errors at the municipality level. The ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

2019. Even though South Korea did not have stay-at-home orders or related government intervention on mobility restriction, this figure clarifies that people traveled less during this time compared to the same months in the previous year. Year-on-year log change in commuting flows fluctuated in different months likely due to the varying degrees of concern the virus posed on society. Some months, there were significantly fewer new COVID-19 cases arising, so mobility would likely increase. When there were months that saw an increase in COVID-19 cases, mobility likely decreased as people stayed at home more to keep themselves safe.

Panel (b) of Fig. 2 shows the year-on-year log change in four of the air pollution measures of interest, PM_{2.5}, PM₁₀, NO₂, and CO from 2019 to 2020, averaged across the provinces. It shows that all four air pollution measures' levels were generally lower in 2020 than in 2019, which may be attributed to declines in commuting flows. The trends of the commuting flows and air pollution measures seem to roughly correlate, contributing to our hypothesis that the decline in commuting flows during COVID-19 in South Korea may have contributed to a decline in air pollution. We acknowledge that the changes in commuting flows and air pollution vary across provinces and municipalities, and therefore the national average masks massive heterogeneity. We account for the spatial variation in our panel regression model in Sections 4 and 5.

3.2. Spread of disease and decline in commuting flows

In order to systematically investigate the relationship between spread of disease and decline in commuting flows, we run the following regression equation:

$$\Delta \ln \pi_{jkt} = \beta \ln(C_{jkt} + 1) + \theta_j + \varphi_k + \gamma_t + \epsilon_{jkt} \tag{2}$$

where $\Delta \pi_{jkt}$ is year-on-year change in gross commuting flow in a province j during $k = \{\text{weekdays or weekends}\}$ in a month t , C_{jkt} is the number of newly confirmed cases in the month t , θ_j is municipality fixed effects, φ_k is weekday/weekend fixed effects, and γ_t is month fixed effects. We cluster standard errors by municipalities. Note that we aggregate the commuting flows up to the provinces because the number of confirmed cases are available by province, not by municipality. This specification allows us to understand the relationship

between monthly averages in our data.

Additionally, we test whether the decline in commuting flows comes either from the intensive or extensive margin, by running the following regression:

$$\Delta \ln \pi_{jkt} = \beta \mathbb{1}[C_{jkt} > 0] + \theta_j + \varphi_k + \gamma_t + \epsilon_{jkt} \quad (3)$$

where $\mathbb{1}[C_{jkt} > 0]$ is an indicator function that is one when there is at least one confirmed case. Therefore, β represents the change in commuting patterns with respect to change in the extensive margin. Table 1 reports regression results. Columns (2) and (4) show the results with all fixed effects from the above equations. The results come mostly from the intensive margin as the result from the extensive margin is not significant, seen in Column (4). With the intensive margin, a 1% increase in confirmed cases significantly decreases average gross commuting flow by 0.026%. These results clarify that declines in commuting flows are more closely related to the severity of the spread of the virus after controlling for overall spread of the virus.⁶

This result is reasonable because people would be traveling less during the time of the pandemic in order to stop the spread of the virus and avoid contracting it themselves, leading to a decline in commuting flow to and from provinces with large numbers of confirmed cases during that time. Although a 0.026% decline in commuting flows does not initially seem substantial, we know that commuting flows did decrease in respective months from 2019 to 2020, and this result helps to qualify that the decline in commuting flows was due, at least in significant part, to the severity of the spread of COVID-19 in each province.⁷

To further the claim we make in this paper about commuting flows primarily including personal vehicle use, we provide additional research and data-supported assumptions. Lee et al. (2020) study the decline in vehicle traffic in the first three months of 2020 due to COVID-19 compared to the first three months of 2019. Overall, they find that traffic from January 1 to March 31 in 2020 was 9.7% lower than in the same months in 2019, with varying fluctuations within these months in 2020.

Additionally, in the survey produced by Belot et al. (2020), we turn to the results of one of the survey sections, about volunteering activities and attending religious events. At least 75% of all respondents said that during the pandemic they do not at all do any volunteering activities, such as bringing groceries or medicines to friends or family, in critical risk or not, nor do they attend religious services. Since these activities could be seen as important reasons to travel, this survey evidence leads us to believe that people decided not to travel, regardless of transportation method, during the pandemic, contributing to the decrease in commuting flows.⁸

Finally, the COVID-19 mitigation strategy established by the South Korean government relied on text messages to residents highlighting where and when an infected person had just been. Therefore, it was simple and in real-time for people to see where the virus was spreading and choose to decrease travel to avoid getting the virus, regardless of the type of travel.

4. Commuting flows and air quality

After testing for the change in commuting flows during the COVID-19 outbreak, we quantify the impact of commuting flows on air pollution. We find that the relationships between commuting flows and four of the five air quality measures of interest are positive and significant. These results primarily align with our hypothesis that the decreased commuting flows during COVID-19 led to decreased air pollution.

We acknowledge the potential bias in our estimates by taking year-on-year log changes of commuting flows and air pollution. Therefore, we use a variable that represents the percent change in air pollution from 2019 to 2020 in order to avoid misinterpreting the results that are simply seasonal changes in commuting flows and air pollution.⁹ The variable we use reflects the difference between the log of the average air quality measure for each month of 2019 and of 2020.

Our primary analysis involves quantifying the impact of the decline in commuting flows from January 2019 to December 2020 on PM_{2.5}, PM₁₀, NO₂, CO, and SO₂. We use the following regression equation for this part of our analysis:

$$\Delta \ln AQ_{ikt} = \beta \Delta \ln \pi_{ikt} + \theta_i + \varphi_k + \gamma_t + X_{it} + \epsilon_{ikt} \quad (4)$$

where ΔAQ_{ikt} is year-on-year change in air quality in a municipality i during $k = \{\text{weekdays or weekends}\}$ in a month t , $\Delta \ln \pi_{ikt}$ is year-on-

⁶ In Appendix Table A.4, we provide regression results for the same equation, using day 16 of the previous month through day 15 of the current month as a robustness check. The results show the monthly average relationship between spread of disease and decline in commuting flows with a two-week lag to address the potential lag between increase of cases and decrease in commuting flows, taking into consideration people's varying decisions to travel based on cumulative cases during a given time period before the trip. The results of this robustness check align with the results of the original regression, where a 1% increase in confirmed COVID-19 cases significantly decreases average gross commuting flow by 0.018%.

⁷ In Appendix C, we provide survey evidence showing that about 40% of respondents who were employed in South Korea had to either stop working or switch to telework due to the pandemic, which would contribute to a decline in commuting flows throughout the week in relation to the spread of the virus.

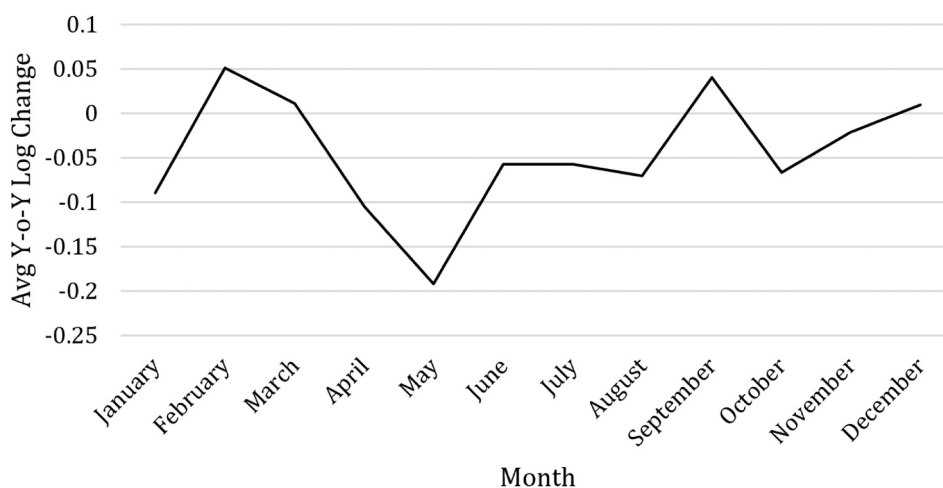
⁸ The survey question that led to these results reads: **With what weekly frequency have you done any of the following activities since the Covid 19 outbreak in your country?** It lists four different types of activities: Bought groceries or medicines for friends or family in quarantine; Bought groceries or medicines for friends or family members in critical risk groups (e.g. elderly immunocompromised); Other volunteer activities; Attended religious services. The response options for each of these activities are: not at all, at least once, almost every day, or every day.

⁹ One example of where potential bias could come from is "yellow dust," which is a meteorological phenomenon that is most prominent in the spring months. Seasonally, South Korea experiences dust storms, or "yellow dust," commonly known to be coming from China and Mongolia, as described by Chung (1992)

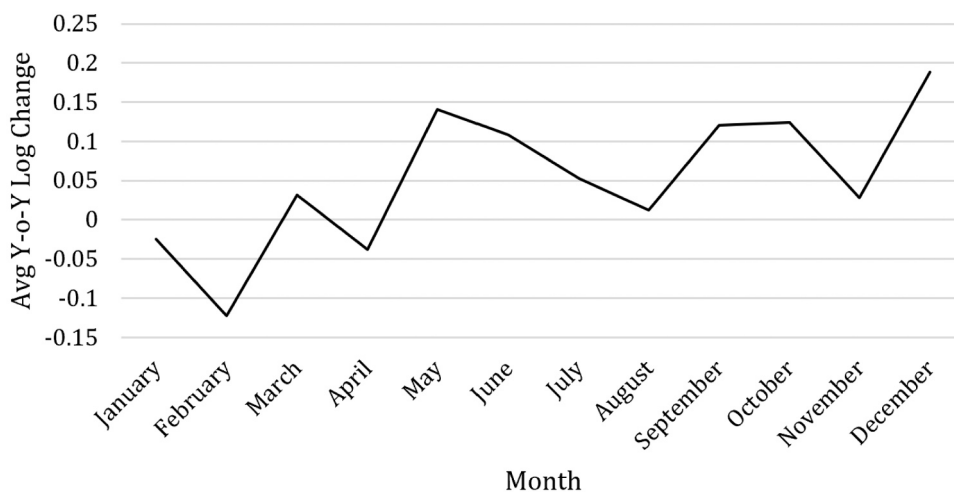
Table 2
Commuting flows and air quality.

	PM _{2.5}		PM ₁₀		NO ₂		CO		SO ₂	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta \ln \pi_{ikt}$	0.0999*** (0.0230)	0.1142*** (0.0255)	0.0052 (0.0304)	0.1710*** (0.0266)	0.3842*** (0.0304)	0.1425*** (0.0345)	0.2791*** (0.0284)	0.0887** (0.0389)	-0.0020 (0.0475)	-0.0311 (0.0520)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday/weekend FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cluster	Municipality		Municipality		Municipality		Municipality		Municipality	
Observations	5,371	5,371	5,373	5,373	5,373	5,373	5,374	5,374	5,374	5,374
R-squared	0.1073	0.5039	0.1284	0.5021	0.2124	0.4010	0.2493	0.3531	0.2746	0.3590

Notes: The table reports regression results for Eq. (4). Columns (1), (3), (5), (7), and (9) show the results without the use of weekday/weekend and time fixed effects for the five dependent variables, PM_{2.5}, PM₁₀, NO₂, CO, and SO₂ respectively. Columns (2), (4), (6), (8), and (10) show the results that include all fixed effects for municipality, weekday/weekend, and time for the same dependent variables. We control for time-varying local level industry production and unemployment rate. All results have clustered standard errors at the municipality level. The ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.



(a) Industry Production



(b) Unemployment Rate

Fig. 3. Change in industry production and unemployment rate in South Korea from 2019 to 2020. Notes: Panel (a) shows the provincial average year-on-year log change in industry production index in South Korea from 2019 to 2020. Panel (b) shows the provincial average year-on-year log change in unemployment rate in South Korea from 2019 to 2020.

year change in gross commuting flow, θ_i is municipality fixed effects, φ_k is weekday/weekend fixed effects, and γ_t is time fixed effects. X_{it} is time-varying local level control variables (industry production index and unemployment rate). We cluster standard errors by municipalities.

The overall results in Table 2 show that when commuting flows increase, four of the five air quality measures of interest significantly increase as well. The results take into account important explanatory and control variables that provide robustness and confidence to our results. In addition to municipality, weekday/weekend, and time fixed effects, the results include year-on-year log change in industry production and year-on-year log change in unemployment rate, calculated the same way as year-on-year log change in air quality from 2019 to 2020.

Including South Korea's industry production and unemployment rate as control variables for this regression accounts for other economic activity that could potentially affect air quality. While industry production provides a control variable for economic activity relating to manufacturing, unemployment rate provides a proxy for additional economic activity in the region. The trends in year-on-year log change in industry production from 2019 to 2020 in respective months of each year show that, generally, industry production was slightly lower in 2020 than in 2019. The trends in year-on-year log change in unemployment rate from 2019 to 2020 in respective

Table 3
Commuting flows and air quality: heterogeneity by initial level of pollution.

	PM _{2.5} (1)	PM ₁₀ (2)	NO ₂ (3)	CO (4)
$\Delta \ln \pi_{ikt}$	0.1079*** (0.0261)	0.1659*** (0.0272)	0.1380*** (0.0355)	0.0768* (0.0399)
$\Delta \ln \pi_{ikt} \times D_i$	0.1298** (0.0612)	0.1172* (0.0652)	0.0524 (0.0573)	0.1494* (0.0770)
Municipality FEs	Yes	Yes	Yes	Yes
Weekday/weekend FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Cluster	Municipality	Municipality	Municipality	Municipality
Observations	5,371	5,373	5,373	5,374
R-squared	0.5041	0.5023	0.4010	0.3535

Notes: The table reports regression results for Eq. (5). Columns (1), (2), (3), and (4) show the results for the four dependent variables, PM_{2.5}, PM₁₀, NO₂, and CO respectively. We include municipality fixed effects, weekday/weekend fixed effects, and time fixed effects. We control for time-varying local level industry production and unemployment rate. All results have clustered standard errors at the municipality level. The ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

months of each year show that, generally, unemployment rate was slightly higher in 2020 than in 2019. Fig. 3 provides a visualization of year-on-year log change from 2019 to 2020 for both variables.

Table 2 reports regression results. Examining the results from columns (2), (4), (6), and (8), we examine robust significant increases in four air quality measures when there is a 1% increase in year-on-year log change in commuting flows. Year-on-year log change of PM_{2.5}, PM₁₀, NO₂, and CO increases by about 0.11%, 0.17%, 0.14%, and 0.09%, respectively. As these pollutants are often emitted through vehicle use, particularly vehicles that burn fossil fuels, we expect to see a decrease in the amount of these pollutants when there is a decrease in commuting flows and, therefore, decreased personal vehicle use, such as during the COVID-19 pandemic. The results for those four air quality measures are consistent with our expectation.¹⁰

The relationship between commuting flows and SO₂ is not significant. This may be the case because of the other ways this pollutant gets emitted, such as through industrial plants. Perhaps industrial plants have a stronger impact on SO₂ emissions compared to PM_{2.5}, PM₁₀, NO₂, and CO, which are known to be more directly linked to vehicle use. Therefore, as we examine commuting flows, and consequently personal vehicle use, we see more of an impact on those four air quality measures compared to SO₂ that may be more heavily impacted by other factors.

According to the United States Environmental Protection Agency, United States average concentrations of PM_{2.5} and CO have decreased by 23%, and United States average concentrations of PM₁₀ and NO₂ have decreased by 17% from 2010 to 2019, which implies an average 2% decrease yearly for four significant air quality measures.¹¹ With a 10–20% decrease in commuting flows, such as from 2019 to 2020 due to COVID-19, our results show that PM_{2.5} likely declined by about 1.1–2.2%, PM₁₀ likely declined by about 1.7–3.4%, NO₂ likely declined by about 1.4–2.8%, and CO likely declined by 0.9–1.8% in South Korea within one year. Comparing these values to those in the United States, these percentages are substantial and show that making changes to transportation and personal vehicle use could lead to important decreases in these pollutants in addition to the decreases that are already happening as countries around the world work to implement various other environmentally sustainable policies.

A limitation of our data is that we cannot account for public holidays separate from regular weekdays due to the monthly frequency of our data. To address this limitation, we examine our primary specification without two months with major South Korean holidays: January with Korean New Year (*Seollal*) and October with Harvest Festival (*Chuseok*). We find that the results do not change drastically, except CO no longer has a positive and significant relationship with commuting flows, which would be helpful future research to understand how CO may differ from the other air quality measures during these months with major holidays. Considering the general strength of our specification even without accounting for public holidays, we are confident that our specification is robust. Additionally, we cannot make a strong claim about our regression results without January and October since these do not fully account for the public holidays and subtract two out of the twenty-four months we examine. These results simply provide robustness to our primary specification. We provide the results in Appendix Table A.5.

5. Discussion

5.1. Heterogeneity by initial level of pollution

For the four air pollutants that yielded significant results in our primary specification, we define D_i to categorize municipalities with

¹⁰ In Appendix D, we include the results for the other air pollution measures from the data. We find that there is a significant inverse relationship between commuting flows and O₃ emissions, and a positive and significant relationship between commuting flows and O_x (NO₂ + O₃). These findings are consistent with atmospheric chemistry.

¹¹ <https://www.epa.gov/air-trends/particulate-matter-pm25-trends>; <https://www.epa.gov/air-trends/carbon-monoxide-trends>; <https://www.epa.gov/air-trends/particulate-matter-pm10-trends>; <https://www.epa.gov/air-trends/nitrogen-dioxide-trends>

high initial level of pollution before the COVID-19 pandemic. D_i is one if the average air pollutant in municipality i during the year of 2019 is above the 90th percentile among 250 municipalities. We use the following regression equation to quantify heterogeneity by initial level of pollution:

$$\Delta \ln AQ_{ikt} = \beta \Delta \ln \pi_{ikt} + \lambda \Delta \ln \pi_{ikt} \times D_i + \theta_i + \varphi_k + \gamma_t + X_{it} + \epsilon_{ikt} \quad (5)$$

where λ quantifies the heterogeneity. All other variables are the same as equation 4.

The results in Table 3 show that the change in commuting flows during the COVID-19 pandemic had a larger effect on the air quality measures in municipalities that were in the 90th percentile among the other municipalities for air pollution emissions before the COVID-19 pandemic. For municipalities in the 90th percentile of air pollution, a 1% decrease in commuting flows leads to a 0.13% further decline in $PM_{2.5}$, a 0.12% further decline in PM_{10} , and a 0.15% further decline in CO. The results for NO_2 are positive but not significant for the municipalities in the 90th percentile. These results present the heterogeneity in the data within the different South Korea municipalities based on pollution experience before the pandemic. They show that the effect of commuting flows on $PM_{2.5}$, PM_{10} , and CO was larger in municipalities that had more air pollution before the start of the pandemic. Therefore, we hypothesize that it will be more effective encouraging cleaner transportation methods in those areas after the pandemic.

5.2. Perception on air pollution reduction

After acknowledging that the decline in commuting flows during the COVID-19 pandemic led to decreased air pollution, we examine a survey conducted in the third week of April 2020 by Belot et al. (2020) that included a question about people's perception of air quality reduction. 45% of 963 respondents stated that they recognized a decline in air pollution.¹²

To further understand people's perception of air pollution in relation to the spread of COVID-19, we look at the correlation between the number of compound cases by mid April 2020 in 17 provinces and the share of people who noted in the survey that they saw air pollution reduction. We find small but positive correlation of 0.11. This is consistent with our findings on association between COVID-19 and air quality improvements.

Kahn, Sun, and Zheng (2020) study people's perception of air pollution changes in China during the pandemic and, consequently, people's environmental engagement potential post-pandemic. They hypothesize that if reduction in air pollution during the COVID-19 pandemic is an experience good, people will actively push for cleaner air and improved environmental protection past the pandemic. With this understanding, our evidence from the survey suggests that a large percentage of people may continue to push for societal changes that could lead to air pollution reduction even after the pandemic is over.

6. Conclusion

This paper uses a panel regression model and real-time commuting flow data to test the effect of decreasing commuting flows on important air pollution measures in South Korea during the COVID-19 outbreak. Exploiting regional variation within a country, we find that the 10-20% decline in commuting flows from 2019 to 2020 due to the country's pandemic mitigation strategy and people's fear of contracting the virus leads to a significant decrease in $PM_{2.5}$, PM_{10} , NO_2 , and CO. A 1% decrease in commuting flows decreases $PM_{2.5}$ by 0.11%, PM_{10} by 0.17%, NO_2 by 0.14%, and CO by 0.09%. These results show that changing commuting patterns and behaviors of personal vehicle use could have a substantial impact on air pollution if those patterns continue once COVID-19 is contained.

Future work must be done to understand the long-term impacts of COVID-19 consequences on air quality. Despite decreased vehicle use as people travel within and across regions less during the pandemic, many governments around the world are relaxing their environmental regulations and standards in order to boost their economies. Many people suspect that the relaxed regulations and standards will contribute to significantly more pollution than if the pandemic did not occur. Additionally, other consequences of COVID-19 also impact air pollution, such as the shut-down and re-opening of industrial factories and other heavily-polluting companies. In this paper, we study the impact of changed transportation patterns, but other COVID-19 consequences must be examined in order to have a complete picture of how the pandemic is impacting air pollution and how to potentially maintain better air quality once everything re-opens again. We note that changing transportation and commuting flow patterns is only one aspect of decreasing pollution. Other factors must be studied in order to understand other changes countries can make post-pandemic to maintain decreased air pollution and better air quality.

Researchers, companies, and think tanks are collaborating on ways to translate the environmental lessons from COVID-19 to the post-pandemic world. Experiences during the pandemic have allowed for increased environmental research, and the pandemic has created a real-world study for people to understand and learn from in order to make the world more environmentally sustainable. This paper joins other studies in showing ways to benefit air quality by making societal changes to transportation and necessary commutes.

About 5 million people prematurely die from pollution-related causes worldwide each year, estimated by the World Health Organization. He, Fan, and Zhou (2016) quantify the impact in their study by concluding that 285,000 yearly premature deaths in China could be prevented if PM_{10} concentrations decrease by about 10% from the country's current levels. Understanding the harm that pollution does to human health and using COVID-19 as a learning experience, we must continue to find ways to improve air quality.

¹² The survey question for this is: Have you experienced any positive non-financial effects from the societal changes occurring due to the epidemic, such as (select all that apply): Enjoying more free time, Enjoying time with family, Reduction of air pollution, Reduction of noise pollution, Other, None of the above.

Taking lessons from COVID-19 environmental impacts and working to establish long-term sustainability will lead to improved human health and saved lives.

Data availability

The authors do not have permission to share data.

Appendix A. Appendix Figures and Tables

Table A.1

Table A.1
Summary of Variables.

Variables	Description
Year-on-year change in air quality	This variable is our dependent variable. We use five air quality measures: PM _{2.5} , PM ₁₀ , NO ₂ , CO, and SO ₂ . We calculate this variable by taking the average log difference of each of the air quality measures for each month of 2019 and 2020 respectively.
Year-on-year change in gross commuting flow	This variable is our primary independent variable. We calculate this variable by taking the average log difference of commuting flows for each month of 2019 and 2020 respectively.
Municipality fixed effects	Fixed effects for each municipality in South Korea.
Weekday/Weekend fixed effects	Fixed effects to take into account differing travel patterns and reasons on weekdays versus weekends.
Time fixed effects	Fixed effects at the monthly level.
Time-varying local level control variables: Year-on-year change in industry production index and year-on-year change in unemployment rate	We calculate these two variables by taking the average log difference of each variable for each month of 2019 and 2020 respectively. These variables account for other economic activity that could potentially affect air quality.

Table A.2

Table A.2
Summary of Samples.

Data	Samples
Commuting flows data	Daily bilateral flows of people in 250 municipalities across 17 provinces in South Korea from January 2019 to December 2020. Data produced by SK Telecom.
Air quality data	Air Quality Index (AQI) for five air pollution measures: PM _{2.5} , PM ₁₀ , NO ₂ , CO, and SO ₂ from January 2019 to December 2020. Air quality data for this time frame was available for 191 out of 250 municipalities, so this is the number of municipalities we use in our regression analysis. Data collected from the World Air Quality Index.

Fig. A.1

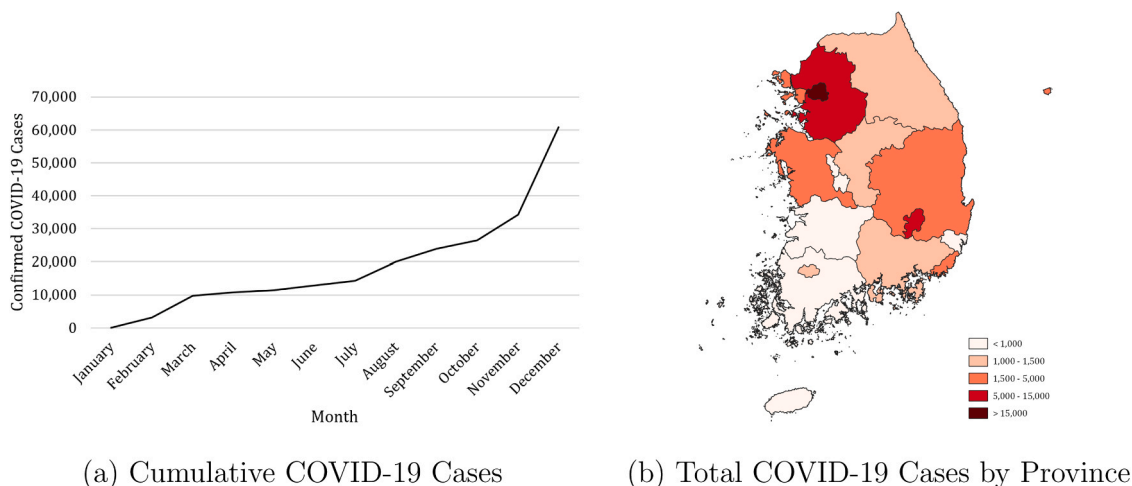


Fig. A.1. Total confirmed COVID-19 cases. Note: Panel (a) shows the total cumulative number of confirmed cases in South Korea by month in 2020. Panel (b) shows total confirmed cases in South Korea as of December 31, 2020 by province.

Fig. A.2

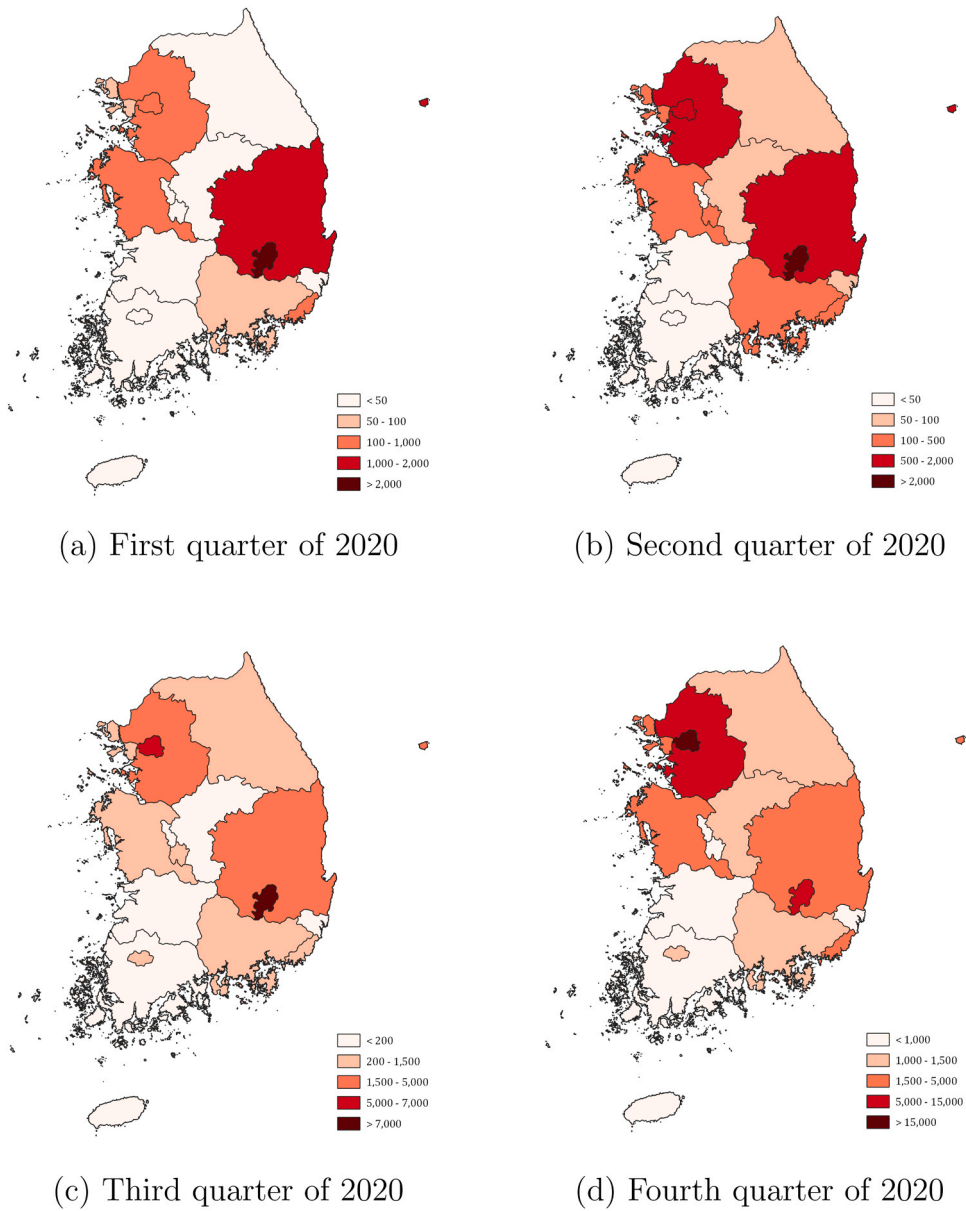


Fig. A.2. Total confirmed COVID-19 cases by quarter. Note: Panel (a) shows the total cumulative number of confirmed cases in South Korea by province by the end of the first quarter, March 31, 2020. Panel (b), (c), and (d) show second, third, and fourth quarters, respectively.

Table A.3

Table A.3
Example of public disclosure.

Korean, male, born in 1987, living in Jungnang district. Confirmed on January 30. Hospitalized in Seoul Medical Center.	
January 24	Return trip from Wuhan without symptoms.
January 26	Merchandise store* at Seongbuk district at 11 am, fortune teller* at Seongdong district by subway at 12 pm, massage spa* by subway in the afternoon, two convenience stores* and two supermarkets*.
January 27	Restaurant* and two supermarkets* in the afternoon.
January 28	Hair salon* in Seongbuk district, supermarket* and restaurant* in Jungnang district by bus, wedding shop* in Gangnam district by subway, home by subway.
January 29	Tested at a hospital in Jungnang district.
January 30	Confirmed and hospitalized.

Notes: The table shows example of public disclosure for the second case in Seoul confirmed on January 30. The * denotes establishments whose exact names have been disclosed.

Table A.4

Table A.4
Spread of disease and decline in commuting flows (from day 16 of previous month and to day 15 of current month).

	$\ln \pi_{jkt}$ (1)	(2)	(3)	(4)
$\ln(C_{jkt} + 1)$	-0.0146*** (0.0015)	-0.0177*** (0.0045)		
$\mathbb{I}[C_{jkt} > 0]$			-0.0056 (0.0092)	0.0982 (0.1289)
Municipality FEs	Yes	Yes	Yes	Yes
Weekday/weekend FEs	No	Yes	No	Yes
Time FEs	No	Yes	No	Yes
Cluster	Municipality	Municipality	Municipality	Municipality
Observations	5,500	5,500	5,500	5,500
R-squared	0.2694	0.4224	0.2479	0.4240

Notes: The table reports regression results for Eq. (2) in columns (1) and (2) and for Eq. (3) in columns (3) and (4), using the month time frame as day 16 of the previous month to day 15 of the current month. Column (1) does not include weekday/weekend or time fixed effects for Eq. (2). Column (2) includes all fixed effects for municipality, weekday/weekend, and time. Column (3) does not include weekday/weekend or time fixed effects for Eq. (3). Column (4) includes all fixed effects for municipality, weekday/weekend, and time. All results have clustered standard errors at the municipality level. The ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table A.5

Table A.5
Commuting flows and air quality (excluding January and October).

	PM _{2.5}		PM ₁₀		NO ₂		CO		SO ₂	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta \ln \pi_{ikt}$	0.0926*** (0.0253)	0.1001*** (0.0272)	0.1211*** (0.0308)	0.1552*** (0.0291)	0.3560*** (0.0343)	0.1010*** (0.0369)	0.2848*** (0.0322)	0.0459 (0.0412)	0.0345 (0.0507)	-0.0797 (0.0562)
Municipality FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday/weekend FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Time FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cluster	Municipality		Municipality		Municipality		Municipality		Municipality	
Observations	4,529	4,529	4,531	4,531	4,531	4,531	4,532	4,532	4,532	4,532
R-squared	0.1122	0.5234	0.1503	0.4724	0.2394	0.3730	0.2685	0.3570	0.3133	0.3732

Notes: The table reports regression results for Eq. (4), excluding January and October that contains Korean New Year (*Seollal*) and Harvest Festival (*Chuseok*). Columns (1), (3), (5), (7), and (9) show the results without the use of weekday/weekend and time fixed effects for the five dependent variables, PM_{2.5}, PM₁₀, NO₂, CO, and SO₂ respectively. Columns (2), (4), (6), (8), and (10) show the results that include all fixed effects for municipality, weekday/weekend, and time for the same dependent variables. We control for time-varying local level industry production and unemployment rate. All results have clustered standard errors at the municipality level. The ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively. These results are very similar to our primary specification including January and October, except amount of CO now no longer has a positive and significant relationship with commuting flows. This is important potential future research to understand these changes and how CO may differ from the other air quality measures during these months.

Appendix B. Global Community Mobility

Data from Google’s Global Community Mobility Reports provide insights into mobility trends and how movement has changed throughout the time period of the COVID-19 pandemic. Data from the report specifically provide an understanding of how visits and length of stay at various places has changed compared to a baseline value. The baseline value is the median for the corresponding day of the week during the period of January 3 to February 6, 2020. Each day of the week has its own baseline, which must be taken into account when evaluating the data from day to day. The data are calculated based on people’s location history attached to their Google Accounts, if they opted into sharing their locations. The location data are only used when there are enough people in the specific region or at the specific place to ensure anonymity of the data and maintain user privacy. The data provided in the reports are the percent change from the baseline value for each of the types of locations. This means that when a day’s value is zero, mobility related to the particular place is about the same as it was in the months prior to the COVID-19 outbreak for the corresponding day of the week. If it is below zero, mobility has decreased in relation to the prior months for the corresponding day of the week, and if it is above zero, mobility has increased. Fig. B.1 shows the average monthly mobility changes in Seoul, Manhattan, and Tokyo in relation to transit stations, shown in panel (a), and workplaces, shown in panel (b), from February to December 2020. The figure shows that mobility in relation to transit stations and workplaces decreased in all three cities, but significantly more in Manhattan and Tokyo than in Seoul. Therefore, people were most likely able to live their more normal lives in at least this region, if not others as well, in South Korea rather than those in the United States or Japan, which provides insight into the South Korean pandemic response compared to that of Japan and the United States. For example, many states in the United States, including New York, implemented strict stay-at-home policies where non-essential workers were required to work from home and people could only go out for essential purposes, such as grocery shopping. Meanwhile, South Korea’s mitigation strategy was focused on public disclosure of the newly found cases as well as aggressive testing, allowing people to choose where and when they traveled based on the COVID-19 information without government intervention.

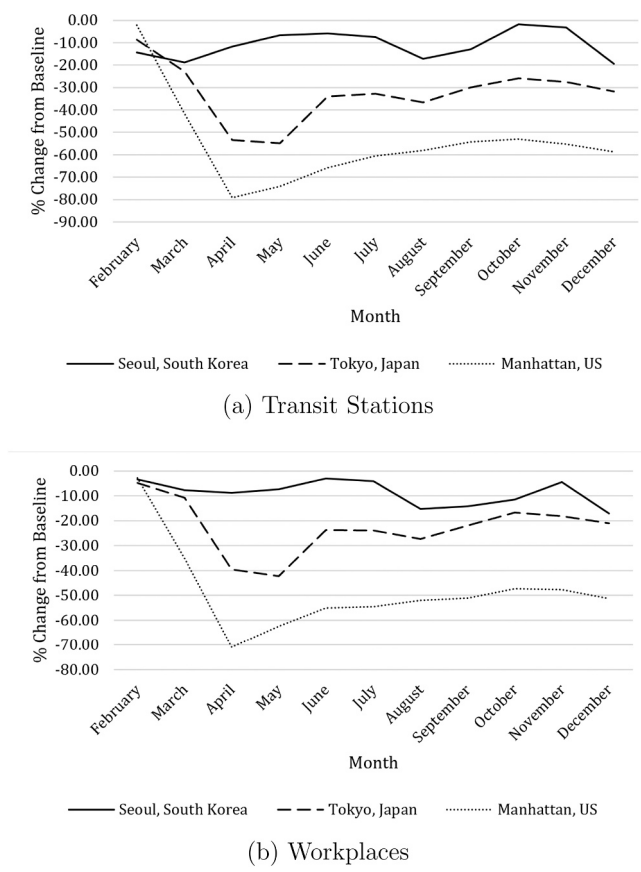


Fig. B.1. Change in mobility from February 2020 to December 2020. Notes: Panel (a) shows the percent change from the January 2020 baseline of people traveling to and from transit stations in February 2020 through December 2020. Panel (b) shows the percent change from the January 2020 baseline of people traveling to and from workplaces in February 2020 through December 2020. The baseline value is the median for the corresponding day of the week during the period of January 3, 2020 to February 6, 2020. The values for Seoul, Manhattan, and Tokyo are the average percent change from baseline for each month.

Appendix C. Survey evidence on behavior change

In this section, we document survey evidence on behavior change in Korea. We use the survey by [Belot et al. \(2020\)](#) collected in the third week of April 2020. We compare work-related behavior due to COVID-19 in South Korea and the United States.

In this section of the survey, respondents were asked to identify their current work situation, whether they were teleworking or decided not to work. The question presented in the United States survey reads:

How did your work situation change in the recent weeks as a consequence of the pandemic?

- I do not work anymore
- I started teleworking
- No change
- Other
- Not applicable

Out of the total survey respondents from South Korea, about 60% were able to keep working as normal, 20% switched to telework, and 18% had to stop working. Comparatively, in the United States, 30% could keep working as normal, 30% switched to telework, and 40% had to stop working. The contrasts in these percentages help to show how South Korea's and the United States' pandemic mitigation strategies differed. While the majority of respondents were able to continue going to work as normal in South Korea, this was not the case in the United States. These results also show that different mitigation strategies could have varying effects on the economy, assuming that a large portion of the population having to stop work would lead to a substantial deterioration of the economy. Additionally, the results show that about 40% of employed South Koreans did stop traveling to work in some way, contributing to our analysis results and the overall 10-20% decline in commuting flows from 2019 to 2020.

Appendix D. Other measures on air quality

In the main text, we focus on five air quality measures, PM_{2.5}, PM₁₀, NO₂, CO, and SO₂. Another air quality measure is available in the data, O₃, and the variable O_x can be created by combining NO₂ and O₃, but we do not focus on those based on other literature and the impacts of the measures on human health. Literature on pollution often includes PM_{2.5} and occasionally PM₁₀, NO₂, and CO because of the severe health impacts these four pollutants have, particularly on human respiratory systems. Although other pollutants are harmful as well, the pollutants that we choose to examine in this paper are significantly linked to transportation and personal travel along with bringing some of the most harmful health effects. In this section, we show that we find an inverse relationship between change in commuting flows and change in O₃ and a positive and significant relationship between commuting flows and O_x. [Table D.1](#) reports regression results using Eq. (4). When including all fixed effects, we find that a 1% decrease in commuting flows leads to about a 1.24% increase in O₃. We also find that a 1% decrease in commuting flows leads to about a 0.04% decrease in O_x. This is consistent with the findings of [Shi et al. \(2021\)](#), who state that these findings align with basic atmospheric chemistry. They acknowledge that traffic related reductions in nitrogen oxides lead directly to O₃ concentration increases, due to atmospheric chemistry. They also state that the increases in O₃ will be partially offset by decreases in NO₂ in the future and overall future net O₃ emissions. They also find that O_x decreased while O₃ increased on average during the COVID-19 pandemic.

Table D.1

Commuting flows and air quality: other measures of air quality.

	O ₃ (1)	(2)	O _x (=NO ₂ +O ₃) (3)	(4)
$\ln\pi_{ikt}$	0.0762* (0.0388)	-0.1238*** (0.0284)	0.2665*** (0.0247)	0.0392* (0.0211)
Municipality FEs	Yes	Yes	Yes	Yes
Weekday/weekend FEs	No	Yes	No	Yes
Time FEs	No	Yes	No	Yes
Cluster	Municipality		Municipality	
Observations	5,373	5,373	5,372	5,372
R-squared	0.1118	0.5999	0.1393	0.6276

Notes: The table reports regression results for Eq. (4) using O₃ and O_x(=NO₂+O₃) as the dependent variables respectively rather than our primary pollution measures. Columns (1) and (3) show the results for without the use of weekday/weekend or time fixed effects. Columns (2) and (4) show the results with all fixed effects for municipality, weekday/weekend, and time. We control for time-varying local level industry production and unemployment rate. All the results are clustered at the municipality level. The ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

References

- Alvarez, F. E., Argente, D., Lippi, F. (2020). A Simple Planning Problem for COVID-19 Lockdown, NBER Working Paper No. 26981.
- Argente, D. A., Hsieh, C., Lee, M. (2020). The Cost of Privacy: Welfare Effects of the Disclosure of COVID-19 Cases, NBER Working Paper No. 27220.
- Sangmin, A., Lee, S., Shin, Y. (2020). COVID-19 Doesnot Need Lockdowns to Destroy Jobs: The Effect of Local Outbreaks in Korea, NBER Working Paper No. 27264, 2020.
- Aum, Sangmin, Lee, Sang Yoon (Tim), & Shin, Yongseok (2021). Inequality of fear and self-quarantine: Is there a trade-off between GDP and public health? *Journal of Public Economics*, 194, Article 104354.
- Belot, M., Choi, S., Jamison, J., Papageorge, N., Tripodi, E., van den Broek-Altenburg, E. (2020). Six-Country Survey on Covid-19, IZA Discussion Paper No. 13230.
- Brinkman, J. C, Mangum, K. (2021). The Geography of Travel Behavior in the Early Phase of the COVID-19 Pandemic.
- Chung, Yong-Seung (1992). On the observations of yellow sand (dust storms) in Korea. *Atmospheric Environment. Part A General Topics*, 26(15), 2743–2749.
- Cicala, S., Stephen, P. H., Mansur, E., Muller, N., Yates, A. (2020). Expected Health Effects of Reduced Air Pollution from COVID-19 Social Distancing, NBER Working Paper No. 27135.
- Colville, R. N., Hutchinson, E. J., Mindell, J. S., & Warren, R. F. (2001). The transport sector as a source of air pollution. *Atmospheric Environment*, 35(9), 1537–1565.
- Couture, V., Dingel, J. I., Green, A., Handbury, J., Williams, K. R. (2020). Measuring movement and social contact with smartphone data: a real-time application to COVID-19, NBER Working Paper No. 27560.
- Dingel, Jonathan I., & Neiman, Brent (2020). How many jobs can be done at home? *Journal of Public Economics*, 189.
- Faiz, Asif, Weaver, Christopher S., & Walsh, Michael P. (1996). *Air pollution from motor vehicles: standards and technologies for controlling emissions*. The World Bank.
- Fenger, Jes (1999). Urban air quality. *Atmospheric Environment*, 33(29), 4877–4900.
- He, Guojun, Fan, Maoyong, & Zhou, Maigeng (2016). The effect of air pollution on mortality in China: Evidence from the 2008 Beijing Olympic Games. *Journal of Environmental Economics and Management*, 79, 18–39.
- He, Guojun, Pan, Yuhang, & Tanaka, Takanao (2020). The short-term impacts of COVID-19 lockdown on urban air pollution in China. *Nature Sustainability*, 1–7.
- Kahn, Matthew E., Sun, W., & Zheng, S. (2020). *Clean air as an experience good in urban China*. NBER Working Paper No.27790.
- Kim, Youngkook, & Guldmann, Jean-Michel (2011). Impact of traffic flows and wind directions on air pollution concentrations in Seoul, Korea. *Atmospheric Environment*, 45(16), 2803–2810.
- Krupnick, Alan J., Rowe, Robert D., & Lang, Carolyn M. (1997). Transportation and air pollution: the environmental damages. *The Full Costs and Benefits of Transportation* (pp. 337–369). Springer.
- Lau, J., Hung, W. T., Cheung, C. S., & Yuen, D. (2008). Contributions of roadside vehicle emissions to general air quality in Hong Kong. *Transportation Research Part D: Transport and Environment*, 13(1), 19–26.
- Lee, Hocheol, Park, Sung Jong, Lee, Ga Ram, Kim, Ji Eon, Lee, Ji Ho, Jung, Yeseul, & Nam, Eun Woo (2020). The relationship between trends in COVID-19 prevalence and traffic levels in South Korea. *International Journal of Infectious Diseases*, 96, 399–407.
- Muhammad, Sulaman, Long, Xingle, & Salman, Muhammad (2020). COVID-19 pandemic and environmental pollution: A blessing in disguise? *Science of The Total Environment*.
- Shi, Zongbo, Song, Congbo, Liu, Bowen, Lu, Gongda, Xu, Jingsha, Vu, Tuan Van, ... Harrison, Roy M. (2021). Abrupt but smaller than expected changes in surface air quality attributable to COVID-19 lockdowns. *Science Advances*, 7, 3.
- Shrivastava, R. K., Neeta, Saxena, & Geeta, Gautam (2013). Air pollution due to road transportation in India: A review on assessment and reduction strategies. *Journal of Environmental Research and Development*, 8(1), 69.
- Titos, G., Lyamani, H., Drinovec, L., Olmo, F. J., Močnik, G., & Alados-Arboledas, L. (2015). Evaluation of the impact of transportation changes on air quality. *Atmospheric Environment*, 114, 19–31.
- Wilder-Smith, Annelies, & Freedman, David O. (2020). Isolation, quarantine, social distancing and community containment: pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak. *Journal of Travel Medicine*, 27(2).
- Zhang, Kai, & Batterman, Stuart (2013). Air pollution and health risks due to vehicle traffic. *Science of The Total Environment*, 450, 307–316.