

WORKING PAPER · NO. 2023-01

International Spillover Effects of Air Pollution: Evidence from Mortality and Health Data

Seonmin Will Heo, Koichiro Ito, and Rao Kotamarthi

JANUARY 2022



ENERGY POLICY INSTITUTE
AT THE UNIVERSITY OF CHICAGO
芝加哥大学能源与环境政策研究所



An Affiliated Center of

5757 S. University Ave.
Chicago, IL 60637
Main: 773.702.5599
bfi.uchicago.edu

International Spillover Effects of Air Pollution: Evidence from Mortality and Health Data*

Seonmin Will Heo

Koichiro Ito

Rao Kotamarthi

UC Santa Barbara

University of Chicago and NBER

Argonne National Laboratory

This version: January 4, 2023.

Abstract

We study the international spillover effects of air pollution by developing a framework that integrates recent advances in atmospheric science into econometric estimation with microdata on mortality and health. Combining transboundary particle trajectory data with the universe of individual-level mortality and emergency room visit data in South Korea, we find that transboundary air pollution from China significantly increases mortality and morbidity in South Korea. Using these estimates, we show that a recent Chinese environmental policy “war on pollution” generated a substantial international spillover benefit. Finally, we examine China’s strategic pollution reductions and provide their implications for the potential Coasian bargaining.

*Heo: University of California, Santa Barbara, 2127 North Hall, Santa Barbara, CA 93106 (e-mail: sheo@ucsb.edu). Ito: Harris School of Public Policy, University of Chicago, 1307 East 60th St., Chicago, IL 60637, and NBER (e-mail: ito@uchicago.edu). Kotamarthi: Argonne National Laboratory (E-mail: vrkotamarthi@anl.gov). We would like to thank Keisuke Ito and David Xu for excellent research assistance, and Severin Borenstein, Susanna Berkouwer, Judson Boomhower, Maureen Cropper, Olivier Deschênes, Dave Donaldson, Michael Greenstone, Rema Hanna, Danae Hernández-Cortés, Kelsey Jack, Ryan Kellogg, Shanjun Li, Kyle Meng, Joe Shapiro, Shaoda Wang, and seminar participants at UC Berkeley Energy Camp, the Griffin Conferences on Socioeconomic Effects of Air Pollution, and the Coase Project Conference for their helpful comments. We gratefully acknowledge financial support from the Global Energy Challenge by Argonne National Laboratory and the Energy Policy Institute at the University of Chicago and the Griffin Applied Economics Incubator on the Global Energy Challenge.

1 Introduction

Air pollution is one of the most pressing global challenges that have been affecting many lives in the world. In the United States, air quality has improved substantially in the last few decades largely thanks to a variety of environmental regulations (Chay and Greenstone, 2003; Shapiro and Walker, 2018). However, air pollution from recent wildfires has been creating new negative impacts on economic outcomes (Wang et al., 2021; Borgschulte, Molitor and Zou, 2022; Wen and Burke, 2022).¹ In developing countries, severe air pollution is considered to be one of the most crucial burdens for economic development (Jayachandran, 2009; Greenstone and Hanna, 2014; Chen, Ebenstein, Greenstone and Li, 2013; Greenstone and Jack, 2015; Jack, 2017; Ito and Zhang, 2020; Berkouwer and Dean, 2022).

A fundamental challenge of air pollution is its international transboundary nature. A country's air pollution could travel over the country's borders and affect neighboring countries. It also implies that a country's environmental policy may have international spillover benefits to other countries. International organizations including the World Bank recognize the international spillover effects of air pollution to be the first order problem to economic development (World Bank, 2022). However, the economics literature mostly has not incorporated this spillover effect when evaluating the cost of air pollution and the benefit of environmental regulation. For example, the benefits of US environmental regulations are usually estimated based on the domestic benefits. Similarly, the benefits of recent ambitious environmental policies in China and India may have substantial impacts on environmental quality in the surrounding countries, but these spillovers are not typically incorporated into the evaluations of these policies.

In this paper, we study the international spillover effects of air pollution and examine the extent to which conventional economic analysis would understate the cost of air pollution as well as the benefit of environmental regulation. Our framework integrates recent advances in atmospheric science into econometric estimation and microdata on mortality and health. We use the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT) to obtain data on hourly particle trajectories from China to South Korea.² Combining these particle trajectory data with hourly $PM_{2.5}$ data in China and Korea, we estimate how the transboundary $PM_{2.5}$ from China affects $PM_{2.5}$ in South Korea. We then connect these data with the universe of individual-level mortality data and emergency room visit data in South Korea to quantify the

¹In addition to air pollution, wildfires also caused significant damages on lives and properties by the spread of fire by itself (Baylis and Boomhower, 2023).

²Although it is not in the context of international spillovers, a growing number of recent economics studies use HYSPLIT for the analysis of air pollution (Hernandez-Cortes and Meng, 2023; Fowlie, Rubin and Wright, 2021).

mortality and health impacts of transboundary air pollution.

We begin by presenting descriptive and visual evidence that transboundary air pollution from China plays a significant role in the level of $PM_{2.5}$ in South Korea. In East Asia, fall and winter are known to be the seasons when the prevailing west wind called the “westerlies” persist, and therefore, South Korea receives persistent west wind from China. In these seasons, we find that $PM_{2.5}$ is substantially higher in the northwest region of South Korea than the southeast region. By contrast, $PM_{2.5}$ in these regions are similar in the spring and summer. We use HYSPLIT to quantitatively confirm this relationship by identifying the hourly particle trajectories from China to South Korea. The northwestern cities such as Incheon and Seoul have trajectories coming from China more than half of the hours in our sample period. By contrast, cities in the southeast such as Busan have much lower frequency of trajectories from China.

We statistically estimate this relationship by regressing the hourly $PM_{2.5}$ in South Korean cities on the hourly transboundary $PM_{2.5}$ from China to each city. We find that a $1 \mu\text{g}/\text{m}^3$ increase in transboundary $PM_{2.5}$ from China results in a $0.122 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ in South Korean cities on average. The estimate is robust and stable to the choice of fixed effects and control variables. Furthermore, our binned scatter plots suggest a strong and robust relationship between these two variables both in the raw data and residualized data.

Combining these data with the universe of individual-level mortality data, we estimate the mortality impact of transboundary air pollution. Our reduced-form estimates indicate that a $1 \mu\text{g}/\text{m}^3$ increase in transboundary $PM_{2.5}$ from China in the past 70 days results in an increase in hourly mortality in South Korea by 3.56 per billion people for the overall population (an increase in annual mortality by 31.2 per million people). This effect implies a 0.6% increase in mortality with respect to a $1 \mu\text{g}/\text{m}^3$ increase in transboundary $PM_{2.5}$, relative to the baseline mortality rate for this population.

In addition to the overall population, we also provide results for the elderly (ages 65 and above), infants (ages below 1), and those with respiratory and cardiovascular diseases as the cause of death. The marginal effect on mortality is higher for infants (a 2.1% increase in mortality with respect to a $1 \mu\text{g}/\text{m}^3$ increase in transboundary $PM_{2.5}$ in the past 70 days) and those with respiratory and cardiovascular diseases as the cause of death (a 1.1% increase in mortality). Our analysis also suggests that both of the contemporaneous and lagged transboundary $PM_{2.5}$ affect mortality, though the lagged effects diminish around 70 days.

Using the transboundary $PM_{2.5}$ from China as an instrumental variable (IV) for the local $PM_{2.5}$ in South Korea, we also identify the effect of $PM_{2.5}$ on mortality in South Korea. Our IV estimates indicate that a

1 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ in the past 70 days results in an increase in hourly mortality by 9.09 per billion people for the overall population. This implies an increase in annual mortality by 79.7 per million people and a 1.5% increase in mortality relative to the mean. The marginal effect as a percent increase in mortality is larger for infants (a 5.5% increase) and those with respiratory and cardiovascular diseases as the cause of death (a 2.9% increase).

In addition to the impact on mortality, air pollution could also increase morbidity (Barwick, Li, Rao and Zahur, 2018). In particular, the short- and medium-run increases in air pollution are believed to affect the acute symptoms of asthma and rhinitis (Eguiluz-Gracia et al., 2020; Kuiper et al., 2021). Thus, the increase in transboundary $\text{PM}_{2.5}$ from China to South Korea may increase such symptoms in South Korean population. To investigate this question, we collected data that include the universe of emergency room (ER) visits in South Korea between 2013 and 2017 for the patients admitted due to atopic dermatitis, rhinitis, or asthma. We find that transboundary $\text{PM}_{2.5}$ results in increases in ER visits for asthma and rhinitis. We do not find such an impact on atopic dermatitis. The reduced-form results imply that a 1 $\mu\text{g}/\text{m}^3$ increase in transboundary $\text{PM}_{2.5}$ from China to South Korea results in an increase in daily ER visits by 50.0 and 482.6 per billion people (or annual ER visits by 18.3 and 176.1 for million people) for asthma and rhinitis, respectively, which are 0.5% and 3.4% increases relative to the means.

Our empirical findings suggest that transboundary air pollution from China has substantial impacts on mortality and morbidity in South Korea. A key policy implication of these findings is that a country's environmental regulation may have an international spillover effect on other countries. This international spillover effect has not been incorporated in the conventional cost-benefit analysis of environmental regulations in the economics literature. To highlight this point, we consider an implication of a prominent environmental policy recently implemented in China, known as the "war on pollution" (Greenstone, He, Li and Zou, 2021). The Chinese government has rolled out a nationwide air pollution reduction program since 2014. Our data suggest that $\text{PM}_{2.5}$ in China had a long-run decline during our sample period. Our data also show that this reduction resulted in a decline in transboundary $\text{PM}_{2.5}$ from China to South Korea. Based on the data we obtained from the HYSPLIT model, we find that transboundary $\text{PM}_{2.5}$ from China to South Korea declined by 9.63 $\mu\text{g}/\text{m}^3$ during our sample period from 2015 to 2019.

We use our estimates and the value of a statistical life estimated in the literature to quantify the spillover benefits of the Chinese environmental regulation for South Korea. We find that a 9.63 $\mu\text{g}/\text{m}^3$ reduction in transboundary $\text{PM}_{2.5}$ from China to South Korea implies the spillover benefit of \$2.62 billion per year for

South Korea based on the avoided mortality. This result suggests that the international spillover benefit of environmental regulation is economically substantial.

Finally, we investigate China's strategic reductions in air pollution and its implications for the Coasian Bargaining. For water pollution, several previous studies find that a county or local government may take advantage of the spillovers of water pollution and strategically allocate the flow of the pollution in trans-boundary rivers (Sigman, 2002; Lipscomb and Mobarak, 2016; Wang and Wang, 2021; He, Wang and Zhang, 2020). To our knowledge, such strategic allocation of pollution has not been investigated for air pollution. In theory, it is possible to observe such a phenomenon for air pollution. If China made such a strategic decision on where they reduced air pollution during the "war on pollution", China may have prioritized reducing air pollution for its citizens, and therefore air pollution may have decreased less for those who live in neighboring countries. This strategic decision could lower the potential international spillover benefits.

We indeed find empirical evidence of China's strategic reductions in air pollution during the war on pollution. We find that the reduction in $PM_{2.5}$ during our sample period was $9.29 \mu\text{g}/\text{m}^3$ in Chinese cities from which most air pollution has gone outside the country border. This reduction in $PM_{2.5}$ is lower than the nationwide average reduction ($14.07 \mu\text{g}/\text{m}^3$) and much lower than the reduction in Chinese cities from which most air pollution remained within China ($18.32 \mu\text{g}/\text{m}^3$). This strategic pollution reduction implies that the international spillover benefit found in our analysis may have been lower than a counterfactual scenario in which such strategic decision was absent or China and South Korea had the Coasian bargaining to address this problem. We show that the additional international spillover benefit of the war on pollution could have been up to \$2.36 billion per year for South Korea.

Related literature and our contributions— Our study builds on and contributes to four strands of the literature. First, we provide a new framework that integrates recent advances in atmospheric science into econometric estimation with microdata on mortality and health to study the international spillover effects of air pollution. Previous studies in economics use indirect measures of transboundary air pollution such as an interaction term between wind direction and air pollution or a dummy variable of particular events such as yellow dust or wildfires (Sheldon and Sankaran, 2017; Jia and Ku, 2019; Cheung, He and Pan, 2020). This is because it has been considered to be difficult to obtain direct measurements of transboundary air pollution. For example, Jia and Ku (2019) describe that "tracing winds from the vast area of China to a specific district within South Korea is difficult and such data do not exist." We address this challenge by

obtaining location-specific hourly transboundary $PM_{2.5}$ data using HYSPLIT and integrate the data with the universe of mortality and ER visits data in South Korea.

Second, our study adds new findings to the recent studies that use detailed data on air pollution, mortality, and health to estimate the mortality and health impact of air pollution. For example, [Deryugina, Heutel, Miller, Molitor and Reif \(2019\)](#) estimate the mortality effect of $PM_{2.5}$ for the elderly in the United States from 1999 to 2013 using the Medicare data and wind direction as an instrument. Both of this paper and our study connect microdata on mortality or health outcomes with detailed data on air pollution. Our study differs from previous studies in this literature in two ways. First, our research question is on the international spillover effects of air pollution. Second, we use data on the direct measures of particle trajectories based on HYSPLIT rather than wind direction to trace air pollution trajectories.

Third, we provide new evidence to the literature on the international spillover of environmental externalities. In the economics literature, the focus of this topic has been water pollution in transboundary rivers ([Sigman, 2002](#); [Lipscomb and Mobarak, 2016](#); [Wang and Wang, 2021](#); [He, Wang and Zhang, 2020](#)). This is partly because measuring transboundary air pollution has been more challenging than measuring transboundary water pollution. Our framework addresses this challenge by integrating HYSPLIT with econometric estimation. We find evidence that China may have strategically reduced more air pollution in Chinese cities where most air pollution has stayed inside the country borders and reduced less in cities where most air pollution has gone outside the country borders. Based on this finding, we provide implications for the potential Coasian bargaining for transboundary air pollution.

Finally, our framework benefits from recent advancement in atmospheric science in modeling and estimating particle trajectories. Many recent studies in atmospheric science use HYSPLIT or similar models to estimate the trajectory of particles ([Lee, Ho, Lee, Choi and Song, 2013](#); [Oh et al., 2015](#); [Lee et al., 2017](#); [Bhardwaj et al., 2019](#); [Han, Cai, Zhang and Wang, 2021](#)). Studies in atmospheric science, however, usually do not intend to estimate the impacts of transboundary air pollution on mortality or other economic and health outcomes. We contribute to this literature by connecting transboundary air pollution data from HYSPLIT with microdata on mortality and health to shed light on the economic implications of international air pollution spillovers.

2 Data and Descriptive Evidence

In this section, we describe our data and provide descriptive evidence of transboundary air pollution from China to South Korea.

2.1 $PM_{2.5}$ in South Korea and China

We obtain hourly $PM_{2.5}$ concentrations in Chinese cities from Berkeley Earth’s air pollution data. Berkeley Earth collects hourly levels of $PM_{2.5}$ at the city level that are regionally interpolated from real-time observations made by ground-level monitoring stations. The air pollution data have a good coverage on $PM_{2.5}$ concentrations in China, as shown in Figure A.3.³

Hourly $PM_{2.5}$ concentrations in South Korean cities are obtained from Korea Environment Corporation’s air pollution data. The data contain hourly concentrations of pollutants such as $PM_{2.5}$, PM_{10} , SO_2 , CO , O_3 , and NO_2 . The data have been collected at the monitor level from 153 monitors since 2001 and are validated by National Institute of Environmental Research in South Korea. Although PM_{10} has been collected since 2001, collection of $PM_{2.5}$ only began in 2015 as part of the Clean Air Conservation Act that was passed in October 2013. We show monitor locations in Figure A.4.⁴

Figure 1 provides suggestive evidence that transboundary air pollution from China may play a significant role in the level of $PM_{2.5}$ in South Korea. The figure shows the time-series variation in $PM_{2.5}$ in China and South Korea between January 2015 and December 2020. We split South Korea into northwest regions (i.e., regions closer to China) and southeast regions (i.e., regions relatively far from China) to examine how $PM_{2.5}$ in China are correlated with $PM_{2.5}$ in northwest and southeast regions in Korea differently.⁵

[Figure 1 about here]

The figure suggests that $PM_{2.5}$ in China had persistent declines in our sample period. Many previous studies find that large part of this reduction can be attributable to an aggressive environmental regulation implemented in China, known as “war on pollution” (Greenstone, He, Li and Zou, 2021). Our data suggest that the average reduction in $PM_{2.5}$ in China from 2015 to 2019 was $14.07 \mu\text{g}/\text{m}^3$.

³The air pollution data are available at the Berkeley Earth website: <http://berkeleyearth.org>. Accessed February 10, 2022.

⁴Data is available at AirKorea, a webpage operated by Korea Environment Corporation: <https://www.airkorea.or.kr/web>.

⁵As we show in Figure 3, we find that transboundary pollution from China arrives at northwest regions in South Korea more frequently than southeast regions.

In addition, $PM_{2.5}$ in China is almost always higher than $PM_{2.5}$ in South Korea and generally higher in fall and winter than summer and spring. This is because fall and winter heating is a major source of air pollution in China (Ito and Zhang, 2020). In East Asia, fall and winter are also known to be seasons when the prevailing west wind called the “westerlies” persist. In Figure A.2, we use wind data in South Korea to show that this is in fact the case—in South Korea, wind blows from west to east in over 70% of the hours in fall and winter. The wind speed is also particularly stronger in fall and winter than spring and summer (Figure A.2).

The combination of the higher fall and winter $PM_{2.5}$ in China and the seasonal westerlies can be a reason why systematic deviations in $PM_{2.5}$ exist between the northwest and the southeast regions of South Korea only in fall and winter. The levels of $PM_{2.5}$ are similar between the northwest and the southeast regions during spring and summer. By contrast, the northwest region has substantially higher $PM_{2.5}$ than the southeast region in fall and winter when the level of $PM_{2.5}$ in China tends to be high and the westerlies tend to be persistent. In the next section, we provide more formal analysis of this point by using air pollution trajectory data from atmospheric science.

2.2 Transboundary Air Pollution from China to South Korea

As we discussed in the introduction, previous studies in economics typically use indirect measures of transboundary air pollution when studying international spillovers of air pollution. By contrast, researchers in atmospheric science have recently developed several ways to obtain direct measures of transboundary air pollution.

One of the state-of-the-art methods is the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT), which has been developed by the National Oceanic and Atmospheric Administration (NOAA) Air Resources Laboratory. HYSPLIT has been used in a variety of applications to describe atmospheric transport, dispersion, and deposition of pollutants. The model can compute trajectories of particles to determine how far and to where particles will travel. The model can also trace emitted radioactive material, wildfire smoke, dust, and other pollutants.⁶

⁶There are various atmospheric transport models that can simulate pollution dispersion. We choose HYSPLIT, because it is both reliable and computationally tractable that makes it most suitable for our project. At the expense of not accounting for secondary chemical reactions, HYSPLIT can track particles in a computationally efficient manner. AERMOD, a steady-state Gaussian-plume dispersion, incorporates chemical reactions, but it is designed for short-range particle dispersion up to 50 km. Other atmospheric dispersion models that incorporate chemical reactions such as CMAQ and WRF-chem incorporate chemical reactions but require significantly intensive computational power.

Using meteorological data, HYSPLIT can provide data on forward or backward pollution trajectories.⁷ The forward trajectories trace the movement of particles from a given point and time. The backward trajectories trace the movement of particles backward in time from the arrival location. These two trajectories are useful to answer different questions. For example, forward trajectories are useful when we analyze the effect of emission from a point source such as a factory or a volcano. On the other hand, backward trajectories can be used to determine possible sources that might contribute to high levels of pollution in one area. We use backward trajectories in most of our analysis and forward trajectories in Section 4. We provide a detailed description of HYSPLIT and its application to our analysis in [Appendix A](#).

In Figure 2, we show a few examples of backward trajectories obtained by HYSPLIT. We use Seoul as an example destination to plot backward trajectories for three different hours. For example, the red line shows the backward trajectory that arrived at Seoul at 8 pm on June 15, 2015. HYSPLIT provides the particle trajectory's data on its longitude, latitude, and height every hour. For each city in South Korea, we obtain backward trajectories for every hour in our sample period. Each hourly backward trajectory starts from a city's centroid and traces the particle trajectory backward. With this process, we obtain 6.57 million backward trajectories in total ($24 \text{ hourly trajectories} \times 365 \text{ days} \times 5 \text{ years} \times 228 \text{ cities in South Korea}$). This is a computationally-intensive data collection, but we use parallel computing to obtain millions of trajectories in about a week.

[Figure 2 about here]

In Figure 3, we present how often South Korean cities had backward trajectories from China. For each of South Korean cities, we calculate the percent of hours in which the city had trajectories that originated from China during our sample period.⁸ The denominator is the total number of hours from January 1, 2015 to December 31, 2019, and the numerator is the total number of hours in which the backward trajectories came from China. The figure indicates substantial heterogeneity among South Korean cities. Cities in the northwest such as Incheon and Seoul have trajectories coming from China more than half of the hours in our sample period. By contrast, cities in the southeast such as Busan have much fewer frequency of trajectories from China.

[Figure 3 about here]

⁷For the meteorological data, we use the NCEP/NCAR Reanalysis data. We include its description in [Appendix A](#).

⁸We consider that a backward trajectory comes from China if the trajectory is from the inside of China's country borders at a height below 1 km.

In Figure 4, we show how often Chinese cities have trajectories that arrive at any South Korean city. For each city in China, we calculate the ratio, in which the denominator is the total number of hours from January 1, 2015 to December 31, 2019, and the numerator is the total number of hours in which a trajectory went from the city in China to any city in South Korea. We observe higher fractions of trajectories coming from the northeastern part of mainland China, particularly the Liaoning province. This is because of the persistent west wind in this region (the westerlies) and the proximity to South Korea. This map indicates that transboundary air pollution from these regions is more likely to matter to South Korean cities.

[Figure 4 about here]

We also investigate how many hours each trajectory took to travel from China to South Korea. For each trajectory that went from China to South Korea, we calculate the number of hours it took from the last grid point in China to a city in South Korea and show the histogram in Figure A.5. The median is 38 hours, and we observe substantial variation in the duration (the 25th and 75th percentiles are 22 and 69 hours). This substantial heterogeneity suggests that it is important to obtain the direct information of each trajectory from HYSPLIT, and a commonly-used indirect approach (e.g. using average air pollution in China one day or two days ago as a proxy for transboundary air pollution) may not be able to properly capture transboundary air pollution.⁹

We construct a variable $\text{TransboundaryPM}_{ct}$ based on the hourly backward trajectory data and $\text{PM}_{2.5}$ data in China. For each hour t in city c in South Korea, we observe if the backward trajectory comes from China. If the trajectory does not come from China, we define $\text{TransboundaryPM}_{ct}$ to be zero because the focus of our paper is the transboundary air pollution from China. When the trajectory comes from China, we observe the trajectory's location and time in China. By merging this information with data on hourly $\text{PM}_{2.5}$ in China, we can obtain $\text{PM}_{2.5}$ at the origin of the trajectory. We use this value to be $\text{TransboundaryPM}_{ct}$. For example, suppose that a pollution trajectory travels for 24 hours from Beijing to Seoul and arrives at hour t . Then, $\text{TransboundaryPM}_{ct}$ equals to $\text{PM}_{2.5}$ in Beijing in hour $t - 24$.

How much of $\text{TransboundaryPM}_{ct}$ eventually arrives in city c in South Korea and how it affects the city's local $\text{PM}_{2.5}$ are unknown from the trajectory data. Our idea is that we can empirically estimate this relationship by regressing the local $\text{PM}_{2.5}$ in Korean cities on $\text{TransboundaryPM}_{ct}$ with or without control

⁹This distribution also suggest that most trajectories from China to South Korea are less than 100 hours. Therefore, we use 200 hours as the maximum run-time to obtain relevant trajectories for our analysis.

variables. In section 3.1, we find a strong systematic relationship between these two variables and show that this relationship is robust to the inclusions of various fixed effects and control variables.¹⁰

2.3 Mortality in South Korea

We collect South Korean mortality microdata from the MicroData Integrated Service (MDIS), which is operated by Statistics Korea, a South Korean national statistical agency. The microdata include the universe of individual-level mortality information from January 1997 to December 2019, including each individual's date and hour of death, age at death, sex, city of death, and cause of death.¹¹

2.4 Emergency Hospital Admissions in South Korea

We obtain data on emergency hospital admissions in South Korea between 2013 and 2017 where patients are admitted due to atopic dermatitis, rhinitis, or asthma. Provided by National Health Insurance Service (NHIS) in South Korea, the data include all the emergency hospital admissions at the district and daily level. NHIS provided this high-frequency, high-resolution data in 2020 to assist researchers in studying illnesses that are caused by harmful pollutants in the air such as asthma and atopic dermatitis. The data are representative of the whole South Korean population, because almost all (97%) eligible South Korean citizens are beneficiaries of this national insurance policy (Kim and Kim, 2021).

2.5 Other Data

For some of our analysis, we use hourly South Korean meteorological data from January 2001 to December 2019. This monitor-level dataset, produced by the Korea Meteorological Administration, includes wind speed and direction, temperature, and precipitation. The data are collected from 612 ground-level monitors that include Automated Synoptic Observing Stations and Automatic Weather Stations, which are installed to gain a wide coverage on weather conditions in South Korea (their coverage is shown in Figure A.4).

¹⁰In the HYSPLIT, we need to specify the starting height of the backward trajectories. We follow the literature in atmospheric science to use 500 meters for our main results and examine the robustness of the results in Table A.4. Results in Table A.4 suggest that the results are robust to heights over 500 meters and the Kleibergen-Paap rk Wald F-statistic is highest with 500 meters. Similarly, we need to specify the height of the trajectories in China (the height in the origin location of the backward trajectory) with which we determine where the trajectory came from. Studies in atmospheric science use 1000 meters for this height, and we find that indeed this height at the origin location produces the highest Kleibergen-Paap rk Wald F-statistic in our first stage regression.

¹¹Data are available at MDIS: <https://mdis.kostat.go.kr>.

To create maps, we obtain shapefiles for China from the United Nations Office for the Coordination of Humanitarian Affairs and OSM-Boundaries, and a shapefile for South Korea from Geoservice Inc., a research institute that provides technology on GIS, three-dimensional visualization, and deep learning.¹²

2.6 Summary Statistics

Table 1 provides the summary statistics. The average $PM_{2.5}$ in our sample period is $45.05 \mu\text{g}/\text{m}^3$ in China and $24.99 \mu\text{g}/\text{m}^3$ in South Korea. The transboundary trajectory indicator variable at the city-hour level equals one if a backward pollution trajectory from a South Korean city came from China. The average of this variable (0.39) indicates that 39 percent of the trajectories came from China in our sample period. The mortality data suggest that about a quarter of mortality in South Korea is due to respiratory or cardiovascular illnesses.

[Table 1 about here]

3 Empirical Analysis and Results

In this section, we present our econometric analysis and results. We begin by estimating the first-stage regression in section 3.1 to estimate the impact of the transboundary air pollution on local air pollution in South Korea. We then estimate the reduced-form in section 3.2 to identify the impact of the transboundary air pollution on mortality in South Korea. Finally, in section 3.3, we run the instrumental variable (IV) estimation to estimate the effect of local air pollution on mortality in South Korea.

3.1 First-stage Regression

We use PM_{ct} to denote hourly $PM_{2.5}$ in South Korean city c in hour t and $\text{Transboundary}PM_{ct}$ to denote hourly transboundary $PM_{2.5}$ that reached city c in hour t . In the first-stage regression, we estimate the impacts of the transboundary air pollution from China on local air pollution in South Korea by running the Ordinary Least Squares (OLS) regression for the following equation:

$$PM_{ct} = \alpha \text{Transboundary}PM_{ct} + X_{ct}\gamma + u_{ct}, \quad (1)$$

¹²These shapefiles are available online at <https://data.humdata.org/dataset/china-administrative-boundaries>. and <http://www.gisdeveloper.co.kr>.

where X_{ct} is a vector of control variables for city c and hour t and u_{ct} is the error term. We include a set of control variables to control for potential confounding factors such as seasonality and weather. In the most restrictive specification, we include city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, and city-by-temperature quartile fixed effects. The identifying assumption is that the error term is uncorrelated with the transboundary air pollution given the control variables and fixed effects in the equation. We cluster standard errors at the city level.

In Figure 5, we provide a binned scatter plot of PM_{ct} against $TransboundaryPM_{ct}$ to non-parametrically examine the relationship of these two variables. Panel A shows the binned scatter plot of the raw data without controls. We use $1 \mu\text{g}/\text{m}^3$ of $TransboundaryPM_{ct}$ as the bin size to calculate the average PM_{ct} for each bin. The figure suggests that there is a strong relationship between the two variables and that the relationship is close to linear. In Panel B, we residualize PM_{ct} by city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, and city-by-temperature quartile fixed effects. The positive relationship between PM_{ct} and $TransboundaryPM_{ct}$ is robust to these controls.

[Figure 5 about here]

Table 2 shows the regression results of equation (1). The results suggest that the estimate is robust and stable to the choice of fixed effects and control variables. The coefficient in column 5 implies that a $1 \mu\text{g}/\text{m}^3$ increase in transboundary $PM_{2.5}$ from China on average results in a $0.122 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ in South Korean cities. The Kleibergen-Paap rk Wald F-statistic is 5812, suggesting that there is a strong first-stage relationship between these two variables.

[Table 2 about here]

3.2 Reduced-form Estimation

To identify the impact of transboundary air pollution from China on mortality in South Korean cities, we estimate the following equation by OLS:

$$\text{Mortality}_{ct} = \sum_{j=0}^J \beta_j \text{TransboundaryPM}_{c,t-j} + X_{ct}\gamma + u_{ct}, \quad (2)$$

where Mortality_{ct} is the hourly mortality (deaths per billion people) in city c in hour t . We include both the concurrent ($j = 0$) and lagged ($j > 0$) transboundary air pollution to estimate β_j for $j = 1, \dots, J$. These

coefficients estimate the short-run and medium long-run effects of transboundary air pollution on mortality. We include the same set of fixed effects and control variables as the ones included in the most restrictive specification (the final column) of Table 2 and cluster the standard errors at the city level. We show that our results are robust to the choice of different control variables and fixed effects in Table A.2.

Table 3 shows the estimation results of equation (2). In Panel A, we include the average of hourly transboundary PM_{2.5} from China in the past 70 days to estimate the average effect of concurrent and lagged transboundary PM_{2.5}.¹³ The estimate for the overall population (the final column) suggests that a 1 µg/m³ increase in transboundary PM_{2.5} from China in the past 70 days results in an increase in hourly mortality in South Korea by 3.56 per billion people. Because the average hourly mortality is 618 per billion people in our sample, this marginal effect indicates a 0.6% increase in mortality with respect to a 1 µg/m³ increase in transboundary PM_{2.5}. In the final row of the table, we also show the implied marginal effect on annual mortality per million people. For the overall population, our estimate implies that a 1 µg/m³ increase in transboundary PM_{2.5} in the past 70 days results in an increase in annual mortality by 31.2 per million people.

[Table 3 about here]

In addition to the overall population, we also provide results for the elderly (ages 65 and above), infants (ages below 1), and those with respiratory and cardiovascular diseases as the cause of death. The marginal effect on mortality is higher for infants (a 2.1% increase in mortality with respect to 1 µg/m³ increase in transboundary PM_{2.5}) and those with respiratory and cardiovascular diseases as the cause of death (a 1.1% increase in mortality).

In Panel B, we estimate the weekly lagged effects of transboundary PM_{2.5} on mortality. We include a set of 7-day average hourly transboundary PM_{2.5} from China. We find that transboundary air pollution that arrived in the past 14-63 days tends to have the largest partial effects on mortality, although pollution that arrived in the past 0-14 days also has significant effects. This effect decays as we consider lagged effects beyond 63 days and becomes statistically insignificant. This finding is consistent with the medium-long run mortality effect of PM_{2.5} found in the literature. For example, although the context is different from international air pollution spillover effects, [Deryugina, Heutel, Miller, Molitor and Reif \(2019\)](#) find that exposure to PM_{2.5} has medium-long run effects on mortality for Medicare recipients in the United States

¹³We show the results with the the average of hourly transboundary PM_{2.5} from China in the past 70 days in Panel A because we find that the lagged effects decay after the past 70 days in Panel B.

but these lagged effects diminish over time.¹⁴

In Figure 6, we visualize these weekly lagged effects and 95% confidence intervals. These weekly lagged effects are also useful to examine the possibility of the “harvesting effect” frequently discussed in the literature (Deschenes and Moretti, 2009). The harvesting effect implies the possibility that air pollution may not cause more deaths in total but only cause forward displacement of mortality. That is, air pollution may only result in the death of the sick who would have died a few days later anyway even in the absence of air pollution. This is why previous studies suggest that researchers should estimate the longer-run average effect (such as our Panel A) rather than the short-run effect or estimate the series of lagged effects joint with the contemporary effect (such as our Panel B).

[Figure 6 about here]

If there is a substantial harvesting effect, we would observe positive effects in shorter lags followed by negative effects in longer lags, creating a U-shaped line in Figure 6. Our estimation results, however, show positive and significant effects in all the lags for the past 70 days, resulting in an inverted U-shaped line. This evidence suggests that the harvesting effect is unlikely to be substantial in our context.

3.3 Instrumental Variables Estimation

Figure 5 and Table 2 show a strong first-stage relationship between transboundary PM_{2.5} from China to South Korea and PM_{2.5} in South Korea. This suggests that we could use transboundary PM_{2.5} as an instrument for PM_{2.5} to estimate the effect of PM_{2.5} on mortality in South Korea. The exclusion restriction assumption required for this instrumental variables (IV) estimation is that transboundary PM_{2.5} affects mortality only through PM_{2.5} given the set of control variables included in the estimation.

We estimate the following equation by the IV regression:

$$\text{Mortality}_{ct} = \sum_{j=0}^J \phi_j \text{PM}_{c,t-j} + X_{ct}\gamma + u_{ct}, \quad (3)$$

where we use TransboundaryPM_{c,t-j} as an instrumental variable for PM_{c,t-j}. We include the same set of fixed effects and control variables included in equation (2) and cluster the standard errors at the city level.

We show that our results are robust to the choice of different control variables and fixed effects in Table A.3.

¹⁴Deryugina, Heutel, Miller, Molitor and Reif (2019) note, “the increase in the effect of a 1-day shock appears to level off after about 14 days, suggesting that the effects of acute exposure do not cause additional deaths beyond this point.”

Table 4 shows the estimation results of equation (3). The last column of Panel A indicates that a $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ in the past 70 days results in an increase in hourly mortality by 9.09 per billion people for the overall population. This implies an increase in annual mortality by 79.7 per million people and a 1.5% increase in mortality relative to the mean. The marginal effect as a percent increase in mortality is larger for infants (a 5.5% increase) and those with respiratory and cardiovascular diseases as the cause of death (a 2.9% increase).

[Table 4 about here]

Our reduced-form and IV estimates provide new evidence on the mortality impact of transboundary air pollution. For the IV estimate, we could compare ours to recent estimates of the mortality impacts of $\text{PM}_{2.5}$ in other contexts and discuss what could make these estimates similar or different. For example, [Deryugina, Heutel, Miller, Molitor and Reif \(2019\)](#) estimate the mortality effect of $\text{PM}_{2.5}$ for the elderly in the United States from 1999 to 2013 using the Medicare data and wind direction as an instrument. They find that a $1 \mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ exposure for one day causes 0.69 additional deaths per million elderly individuals over the three-day window that spans the day of the increase and the following two days. Panel B in our Table 4 suggests that the contemporary marginal effect of $\text{PM}_{2.5}$ for the elderly is an increase in hourly mortality by 4.05 per billion people, which implies an increase in three-day mortality by 0.29 per million people.¹⁵ This implies that the magnitude of our IV estimate is on the same order of magnitude but slightly smaller than the IV estimate in [Deryugina, Heutel, Miller, Molitor and Reif \(2019\)](#). There are a few possible reasons that could explain this difference. First, the two studies use different instrumental variables, and therefore, estimate different local average treatment effects ([Angrist and Imbens, 1995](#)). Second, the elderly in South Korea are known to have fewer underlying health conditions than the Medicare population, which could make them relatively less vulnerable to the exposure to $\text{PM}_{2.5}$.¹⁶

3.4 Mortality Impacts by Age Group

The impact of air pollution on mortality can be substantially different across ages. Such heterogeneity is important to quantify for our analysis of policy implication in Section 4. To determine heterogeneous effects

¹⁵This is because $4.05 \cdot 24 \cdot 3/1000 = 0.29$.

¹⁶Another possibility is that the harmfulness of $\text{PM}_{2.5}$ can be different between two locations because the toxicity in the small particles can be different. For example, [Hsiang, Lee and Wilson \(2022\)](#) find empirical evidence on this possibility.

of transboundary air pollution on mortality across ages, we divide our mortality data into age groups and estimate the equations (2) and (3) separately for each group.

In Table 5, we find that the mortality impact of transboundary air pollution is statistically and economically significant for infants and individuals over 30 years of age and insignificant for individuals between 1 and 29 years of age. Note that the baseline mortality is low for individuals between 1 and 29 years of age, which could make the impact relatively more challenging to be detected.

[Table 5 about here]

The marginal effect on mortality in terms of percent increases relative to the baseline mortality level in each group is the largest for infants. However, the marginal effects in terms of increased death counts per billion people are higher for the elderly. We incorporate this heterogeneity in our analysis of policy implication in Section 4.

3.5 Impacts on Emergency Room Visits

In addition to its impact on mortality, air pollution could increase morbidity (Barwick et al., 2018). In particular, the short- and medium-run increases in air pollution are believed to affect the acute symptoms of asthma and rhinitis (Eguiluz-Gracia et al., 2020; Kuiper et al., 2021). Thus, the increase in transboundary PM_{2.5} from China to South Korea might cause such symptoms to be more prevalent in the South Korean population.

In Table 6, we test this hypothesis by using data on daily emergency room (ER) visits. The outcome variable is the counts of ER visits by diagnosis at the city-day level. We use the same specification as Panel A in Tables 3 and 4 to estimate the reduced-form and IV regressions. Because the seasonal pollen (oak, pine, and weed) are also known to be related to the ER visits in South Korea, we include these three variables as additional controls in our estimation, although we find that the inclusion of these controls does not have substantial effects on our estimates.

[Table 6 about here]

We find that transboundary PM_{2.5} results in increases in ER visits for asthma and rhinitis. We do not find such an impact on atopic dermatitis. The reduced-form results imply that a 1 $\mu\text{g}/\text{m}^3$ increase in transboundary PM_{2.5} from China to South Korea results in an increase in daily ER visits by 50.0 and 482.6

per billion people for asthma and rhinitis, respectively, which are 0.5% and 3.4% increases relative to the means.

4 Policy Implications

4.1 International Spillover Benefits of Environmental Regulation

Our empirical findings suggest that transboundary air pollution from China has substantial impacts on mortality in South Korea. A key policy implication of these findings is that a country's environmental regulation may have an international spillover effect on citizens in other countries. As we discussed in the introduction, this spillover effect has not been incorporated in economic analysis of environmental regulation in the economics literature.

To highlight this point, we consider an implication of a prominent environmental policy recently implemented in China, known as the “war on pollution” (Greenstone, He, Li and Zou, 2021). The Chinese government has rolled out a nationwide air pollution reduction program since 2014. As shown in Figure 1, our data suggest that $PM_{2.5}$ in China had a long-run decline during our sample period. This reduction also resulted in a decline in transboundary $PM_{2.5}$ from China to South Korea. Based on the data we obtained from the HYSPLIT model, we find that the annual average of transboundary $PM_{2.5}$ from China to South Korea declined by $9.63 \mu\text{g}/\text{m}^3$ during our sample period, which is from 2015 to 2019.

We quantify South Korea's economic benefit from this reduction in transboundary $PM_{2.5}$ based on the following procedure. Table 6 provides estimates for the age-specific impacts of transboundary air pollution on mortality. We use these coefficients to calculate the benefit from a $9.63 \mu\text{g}/\text{m}^3$ reduction in transboundary $PM_{2.5}$ on mortality in each age group in South Korea. We then use the value of a statistical life (VSL) in the literature to obtain implied economic values that come from the reductions in mortality. Working on the age-specific estimates—as opposed to using the average estimate—is important for two reasons. First, as we find in Table 6, the mortality effects of $PM_{2.5}$ are heterogeneous across age groups. Second, the VSL can be different across age groups as noted by Murphy and Topel (2006).

To our knowledge, no previous studies provide age-specific VSLs for South Korea. We find three economic studies that estimate South Korea's average VSL. We therefore make the following assumptions to obtain age-specific VSL estimates. We calculate an average of the VSL estimates for South Korea from three studies in the literature, Shin and Joh (2003), Kim et al. (2003), and Lee et al. (2011). This average VSL is

\$511 thousand in 2019 US dollars.¹⁷ We then use the method in developed in [Murphy and Topel \(2006\)](#) to obtain VSL estimates for each age group.¹⁸ The age-specific VSL estimates obtained by this approach are provided in Table [A.7](#).

In Table [7](#), we present the result of this calculation in the first row. We find that a $9.63 \mu\text{g}/\text{m}^3$ reduction in transboundary $\text{PM}_{2.5}$ from China to South Korea implies the economic benefit of \$2.62 billion per year for South Korea, based on the avoided mortality. This result suggests that the international spillover benefit of environmental regulation is economically substantial. The overall spillover benefit can be even larger than our estimate because our calculation does not include other potential benefits such as reductions in morbidity costs and negative effects on productivity and educational outcomes ([Chang, Graff Zivin, Gross and Neidell, 2019](#); [Ebenstein, Lavy and Roth, 2016](#); [Greenstone et al., 2015](#); [Bedi, Nakaguma, Restrepo and Rieger, 2021](#); [Borgschulte, Molitor and Zou, Forthcoming](#); [Hanna and Oliva, 2015](#)).

[Tables [7](#) about here]

4.2 Strategic Reductions in Air Pollution and Implications for Coasian Bargaining

For water pollution, several previous studies find that a country or local government might take advantage of pollution spillovers and strategically allocate the flow of their water pollution ([Sigman, 2002](#); [Lipscomb and Mobarak, 2016](#); [Wang and Wang, 2021](#); [He, Wang and Zhang, 2020](#)). To our knowledge, such strategic allocation of pollution has not been investigated for air pollution, although in theory it is possible because a country or a local government is likely to have incentives to do so. If China made such a strategic decision on where they reduced air pollution for the “war on pollution,” China may have prioritized reducing air pollution for its citizens, and therefore air pollution may have decreased less for those who live in neighboring countries. This strategic decision could lower the potential international spillover benefit.

To test this hypothesis, we use the HYSPLIT model to calculate the “in-China ratio” of the air pollution trajectories for each of 783 cities in China. The in-China ratio is calculated by the following approach. For each city, day, and hour, we use HYSPLIT to obtain forward trajectories of air pollution. We then compute

¹⁷The VSL estimates in [Shin and Joh \(2003\)](#), [Kim et al. \(2003\)](#), and [Lee et al. \(2011\)](#) are 466, 463, and 277 million in South Korean Won. We use the CPI (Consumer Price Index) in South Korea (which are 71.50, 73.11, 88.08, are 115.16 for the years 1999, 2000, 2006, and 2019, respectively) and the exchange rate in 2019 (1165.36 KRW to 1 USD) to convert them to USD in 2019. These values are \$630, \$520, and \$383 thousand in 2019 US Dollars, respectively.

¹⁸Figure 3 in [Murphy and Topel \(2006\)](#) shows the values of remaining lives at each age for the US population. We make an assumption that the curvature of these age-specific values can be applied to the South Korean population and scale the function by the ratio of the South Korea’s VSL relative to the US VSL in [Murphy and Topel \(2006\)](#).

the in-China ratio based on the number of forward trajectories that stayed within China divided by the total number of trajectories. We consider that a pollution trajectory stayed within China if the trajectory fell inside the latitude and longitude boundaries of China or if the trajectory's height is persistently below 1 km since the start of the forward trajectory. In Figure 7, we divide Chinese cities into four groups based on the quartile of the in-China ratio. For example, cities in the first group have the lowest in-China ratio, meaning that air pollution trajectories are less likely to fall within China. We compare the declines in $PM_{2.5}$ relative to 2015 among the four groups. The figure suggests that the first quartile group had a reduction in $PM_{2.5}$ by $9.29 \mu\text{g}/\text{m}^3$, which is similar to the reduction in transboundary $PM_{2.5}$ for South Korea ($9.63 \mu\text{g}/\text{m}^3$). By contrast, the fourth quartile group had a reduction in $PM_{2.5}$ by 18.32. In Table A.6, we show that these differences in the reduction in $PM_{2.5}$ between the first quartile group and other groups are statistically significant.

This result provides suggestive evidence that China may have indeed made a strategic decision on where they reduced air pollution for the “war on pollution.” As a result, the international spillover benefit we calculated in the previous section may have been reduced due to this strategic decision compared to a counterfactual scenario in which such strategic decision was absent, or that in which China and South Korea had the Coasian bargaining to address this problem.

Coase (1960) describes that one of the challenging issues of the Coasian bargaining in practice is the measurement of the bargaining benefit. This is especially true for environmental externalities in international contexts. For the international spillover of air pollution from China to South Korea, our result can be used to measure this potential benefit. In the second and third rows of Table 7, we consider two counterfactual scenarios and calculate the potential benefits of China's air pollution reductions.

Suppose if China reduced its transboundary $PM_{2.5}$ by $14.07 \mu\text{g}/\text{m}^3$, which was the average reduction in $PM_{2.5}$ in China during our sample period. In this case, the benefit of this reduction is \$3.83 billion per year for South Korea. In addition, we could also consider a scenario in which China reduced its transboundary $PM_{2.5}$ by $18.32 \mu\text{g}/\text{m}^3$, which was the average reduction in $PM_{2.5}$ for cities with the highest in-China ratio in Figure 7. In this case, the benefit would have been \$4.98 billion per year for South Korea. While there can be many other obstacles to have the Coasian bargaining in practice, the results in Table 7 provide key measurements for these countries to consider whether a certain form of agreement and compensation scheme on transboundary air pollution can be worth the consideration.¹⁹

¹⁹The average $PM_{2.5}$ level in China during our sample period was $45.05 \mu\text{g}/\text{m}^3$, which is still very high compared to the level that was recommended by the World Health Organization in its global air quality guidelines in 2019 ($10 \mu\text{g}/\text{m}^3$ for the annual mean).

5 Conclusion

In this paper, we develop a framework that integrates recent advances in atmospheric science into econometric estimation with microdata on mortality and health to study the international spillover effects of air pollution. Combining transboundary particle trajectory data with the universe of individual-level mortality and emergency room visit data in South Korea, we find that transboundary air pollution from China significantly increases mortality and morbidity in South Korea. Using our estimates, we quantify that a recent Chinese environmental regulation the “war on pollution” had a substantial international spillover benefit. Finally, we examine China’s strategic pollution reductions and provide its implications for the potential Coase bargaining.

References

- Angrist, Joshua D., and Guido W. Imbens.** 1995. "Identification and estimation of local average treatment effects." National Bureau of Economic Research.
- Barwick, Panle Jia, Shanjun Li, Deyu Rao, and Nahim Zahur.** 2018. "The morbidity cost of air pollution: evidence from consumer spending in China." *Available at SSRN 2999068*.
- Baylis, Patrick, and Judson Boomhower.** 2023. "The Economic Incidence of Wildfire Suppression in the United States." *American Economic Journal: Applied Economics*, 15(1): 442–73.
- Bedi, Arjun S, Marcos Y Nakaguma, Brandon J Restrepo, and Matthias Rieger.** 2021. "Particle pollution and cognition: Evidence from sensitive cognitive tests in Brazil." *Journal of the Association of Environmental and Resource Economists*, 8(3): 443–474.
- Berkouwer, Susanna B, and Joshua T Dean.** 2022. "The impact of reduced charcoal usage on indoor air quality and health in Nairobi, Kenya."
- Bhardwaj, Piyush, Seo J Ki, Youn H Kim, Jung H Woo, Chang K Song, Soon Y Park, and Chul H Song.** 2019. "Recent changes of trans-boundary air pollution over the Yellow Sea: implications for future air quality in South Korea." *Environmental Pollution*, 247: 401–409.
- Borgschulte, Mark, David Molitor, and Eric Zou.** 2022. "Air pollution and the labor market: Evidence from wildfire smoke." National Bureau of Economic Research.
- Borgschulte, M, D Molitor, and EY Zou.** Forthcoming. "Air pollution and the labor market: Evidence from wildfire smoke." *Review of Economics and Statistics*.
- Chang, Tom Y, Joshua Graff Zivin, Tal Gross, and Matthew Neidell.** 2019. "The effect of pollution on worker productivity: evidence from call center workers in China." *American Economic Journal: Applied Economics*, 11(1): 151–72.
- Chay, Kenneth Y, and Michael Greenstone.** 2003. "The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession." *The quarterly journal of economics*, 118(3): 1121–1167.
- Chen, Yuyu, Avraham Ebenstein, Michael Greenstone, and Hongbin Li.** 2013. "Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy." *Proceedings of the National Academy of Sciences*, 110(32): 12936–12941.
- Cheung, Chun Wai, Guojun He, and Yuhang Pan.** 2020. "Mitigating the air pollution effect? The remarkable decline in the pollution-mortality relationship in Hong Kong." *Journal of environmental economics and management*, 101: 102316.
- Coase, RH.** 1960. "The Problem of Social Cost." *The Journal of Law & Economics*, 3: 1–44.
- Deryugina, Tatyana, Garth Heutel, Nolan H Miller, David Molitor, and Julian Reif.** 2019. "The mortality and medical costs of air pollution: Evidence from changes in wind direction." *American Economic Review*, 109(12): 4178–4219.
- Deschenes, Olivier, and Enrico Moretti.** 2009. "Extreme weather events, mortality, and migration." *The Review of Economics and Statistics*, 91(4): 659–681.

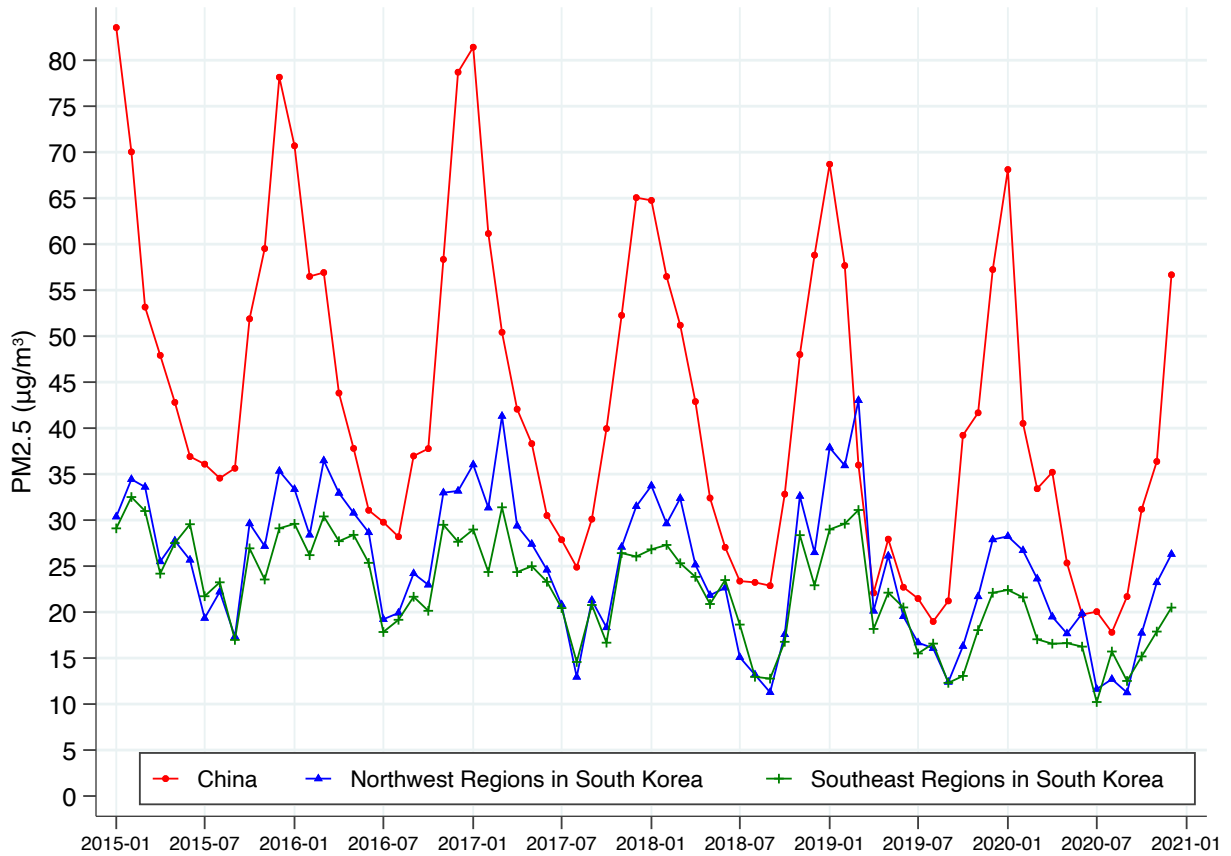
- Ebenstein, Avraham, Victor Lavy, and Sefi Roth.** 2016. “The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution.” *American Economic Journal: Applied Economics*, 8(4): 36–65.
- Eguiluz-Gracia, Ibon, Alexander G Mathioudakis, Sabine Bartel, Susanne JH Vijverberg, Elaine Fuertes, Pasquale Comberiat, Yutong Samuel Cai, Peter Valentin Tomazic, Zuzana Diamant, Jørgen Vestbo, et al..** 2020. “The need for clean air: the way air pollution and climate change affect allergic rhinitis and asthma.” *Allergy*, 75(9): 2170–2184.
- Fowlie, Meredith, Edward A Rubin, and Katie Wright.** 2021. “Air Pollution Co-Benefits and Regulatory Rebound.” *Presentation at UC Berkeley Energy Camp*.
- Greenstone, Michael, and B. Kelsey Jack.** 2015. “Envirodevonomics: A Research Agenda for an Emerging Field.” *Journal of Economic Literature*, 53(1): 5–42.
- Greenstone, Michael, and Rema Hanna.** 2014. “Environmental regulations, air and water pollution, and infant mortality in India.” *American Economic Review*, 104(10): 3038–72.
- Greenstone, Michael, Guojun He, Shanjun Li, and Eric Yongchen Zou.** 2021. “China’s war on pollution: Evidence from the first 5 years.” *Review of Environmental Economics and Policy*, 15(2): 281–299.
- Greenstone, Michael, Janhavi Nilekani, Rohini Pande, Nicholas Ryan, Anant Sudarshan, and Anish Sugathan.** 2015. “Lower pollution, longer lives: life expectancy gains if India reduced particulate matter pollution.” *Economic and Political Weekly*, 40–46.
- Hanna, Rema, and Paulina Oliva.** 2015. “The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City.” *Journal of Public Economics*, 122: 68–79.
- Han, Xiao, Juzhen Cai, Meigen Zhang, and Xiaofei Wang.** 2021. “Numerical simulation of interannual variation in transboundary contributions from Chinese emissions to PM_{2.5} mass burden in South Korea.” *Atmospheric Environment*, 256: 118440.
- He, Guojun, Shaoda Wang, and Bing Zhang.** 2020. “Watering down environmental regulation in China.” *The Quarterly Journal of Economics*, 135(4): 2135–2185.
- Hernandez-Cortes, Danae, and Kyle C Meng.** 2023. “Do environmental markets cause environmental injustice? Evidence from California’s carbon market.” *Journal of Public Economics*, 217: 104786.
- Hsiang, Solomon, Jaecheol Lee, and Andrew Wilson.** 2022. “Simultaneous Estimation of Damage from Transboundary and Domestic Air Pollution.” *Presentation at the Coase Project Conference*.
- Ito, Koichiro, and Shuang Zhang.** 2020. “Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China.” *Journal of Political Economy*, 128(5): 1627–1672.
- Jack, B Kelsey.** 2017. “Environmental economics in developing countries: An introduction to the special issue.” *Journal of Environmental Economics and Management*, 86(C): 1–7.
- Jayachandran, Seema.** 2009. “Air quality and early-life mortality evidence from Indonesia’s wildfires.” *Journal of Human resources*, 44(4): 916–954.
- Jia, Ruixue, and Hyejin Ku.** 2019. “Is China’s pollution the culprit for the choking of South Korea? Evidence from the Asian dust.” *The Economic Journal*, 129(624): 3154–3188.

- Kim, Ye-Shin, Yong-Jin Lee, Hoa-Sung Park, and Dong-Chun Shin.** 2003. “Risk-Based Damage Cost Estimation on Mortality Due to Environmental Problems.” *Journal of Preventive Medicine and Public Health*, 36(3): 230–238. Publisher: The Korean Society for Preventive Medicine.
- Kim, Yong-Ik, and Sun-Min Kim.** 2021. *2020 National Health Insurance Statistical Yearbook*. Health Insurance Review & Assessment Service, National Health Insurance Service.
- Kuiper, Ingrid Nordeide, Cecilie Svanes, Iana Markevych, Simone Accordini, Randi J Bertelsen, Lennart Bråbäck, Jesper Heile Christensen, Bertil Forsberg, Thomas Halvorsen, Joachim Heinrich, et al.** 2021. “Lifelong exposure to air pollution and greenness in relation to asthma, rhinitis and lung function in adulthood.” *Environment international*, 146: 106219.
- Lee, Hyung-Min, Rokjin J Park, Daven K Henze, Seungun Lee, Changsub Shim, Hye-Jung Shin, Kwang-Joo Moon, and Jung-Hun Woo.** 2017. “PM_{2.5} source attribution for Seoul in May from 2009 to 2013 using GEOS-Chem and its adjoint model.” *Environmental Pollution*, 221: 377–384.
- Lee, Seungmin, Chang-Hoi Ho, Yun Gon Lee, Hyoung-Jin Choi, and Chang-Keun Song.** 2013. “Influence of transboundary air pollutants from China on the high-PM₁₀ episode in Seoul, Korea for the period October 16–20, 2008.” *Atmospheric Environment*, 77: 430–439.
- Lee, Yong Jin, Young Wook Lim, Ji Yeon Yang, Chang Soo Kim, Young Chul Shin, and Dong Chun Shin.** 2011. “Evaluating the PM damage cost due to urban air pollution and vehicle emissions in Seoul, Korea.” *Journal of Environmental Management*, 92(3): 603–609.
- Lipscomb, Molly, and Ahmed Mushfiq Mobarak.** 2016. “Decentralization and pollution spillovers: evidence from the re-drawing of county borders in Brazil.” *The Review of Economic Studies*, 84(1): 464–502.
- MicroData Integrated Service.** 1997–2019. “Causes of Death Statistics (Public Use).” <https://doi.org/10.23333/P.101054.001>. (Accessed March 23, 2022).
- Murphy, Kevin M, and Robert H Topel.** 2006. “The value of health and longevity.” *Journal of Political Economy*, 114(5): 871–904.
- National Health Insurance Sharing Service.** 2013–2017. “Environmental Illness Database.” (Accessed August 30, 2021).
- Oh, Hye-Ryun, Chang-Hoi Ho, Jinwon Kim, Deliang Chen, Seungmin Lee, Yong-Sang Choi, Lim-Seok Chang, and Chang-Keun Song.** 2015. “Long-range transport of air pollutants originating in China: A possible major cause of multi-day high-PM₁₀ episodes during cold season in Seoul, Korea.” *Atmospheric Environment*, 109: 23–30.
- Shapiro, Joseph S, and Reed Walker.** 2018. “Why is pollution from US manufacturing declining? The roles of environmental regulation, productivity, and trade.” *American Economic Review*, 108(12): 3814–54.
- Sheldon, Tamara L, and Chandini Sankaran.** 2017. “The impact of Indonesian forest fires on Singaporean pollution and health.” *American Economic Review*, 107(5): 526–29.
- Shin, Young Chul, and Seunghun Joh.** 2003. “Estimating the Willingness-to-Pay and the Value of a Statistical Life for Future Mortality Risk Reduction : The Value of a Statistical Life for Assessing Environmental Damages and Policies.” *Environmental and Resource Economics Review*, 12(1): 49–74. Publisher: Korean Resource Economics Association.

- Sigman, Hilary.** 2002. “International spillovers and water quality in rivers: do countries free ride?” *American Economic Review*, 92(4): 1152–1159.
- Stein, AF, Roland R Draxler, Glenn D Rolph, Barbara JB Stunder, MD Cohen, and Fong Ngan.** 2015. “NOAA’s HYSPLIT atmospheric transport and dispersion modeling system.” *Bulletin of the American Meteorological Society*, 96(12): 2059–2077.
- Wang, Daoping, Dabo Guan, Shupeng Zhu, Michael Mac Kinnon, Guannan Geng, Qiang Zhang, Heran Zheng, Tianyang Lei, Shuai Shao, Peng Gong, et al..** 2021. “Economic footprint of California wildfires in 2018.” *Nature Sustainability*, 4(3): 252–260.
- Wang, Shaoda, and Zenan Wang.** 2021. “The environmental and economic consequences of internalizing border spillovers.”
- Wen, Jeff, and Marshall Burke.** 2022. “Lower test scores from wildfire smoke exposure.” *Nature Sustainability*, 5(11): 947–955.
- World Bank.** 2022. *Striving for Clean Air: Air Pollution and Public Health in South Asia*. Washington, D.C.:World Bank Group. <http://documents.worldbank.org/curated/en/099030312132233780/P1682370b4ac4a0270ac2702e1cfb704198>.

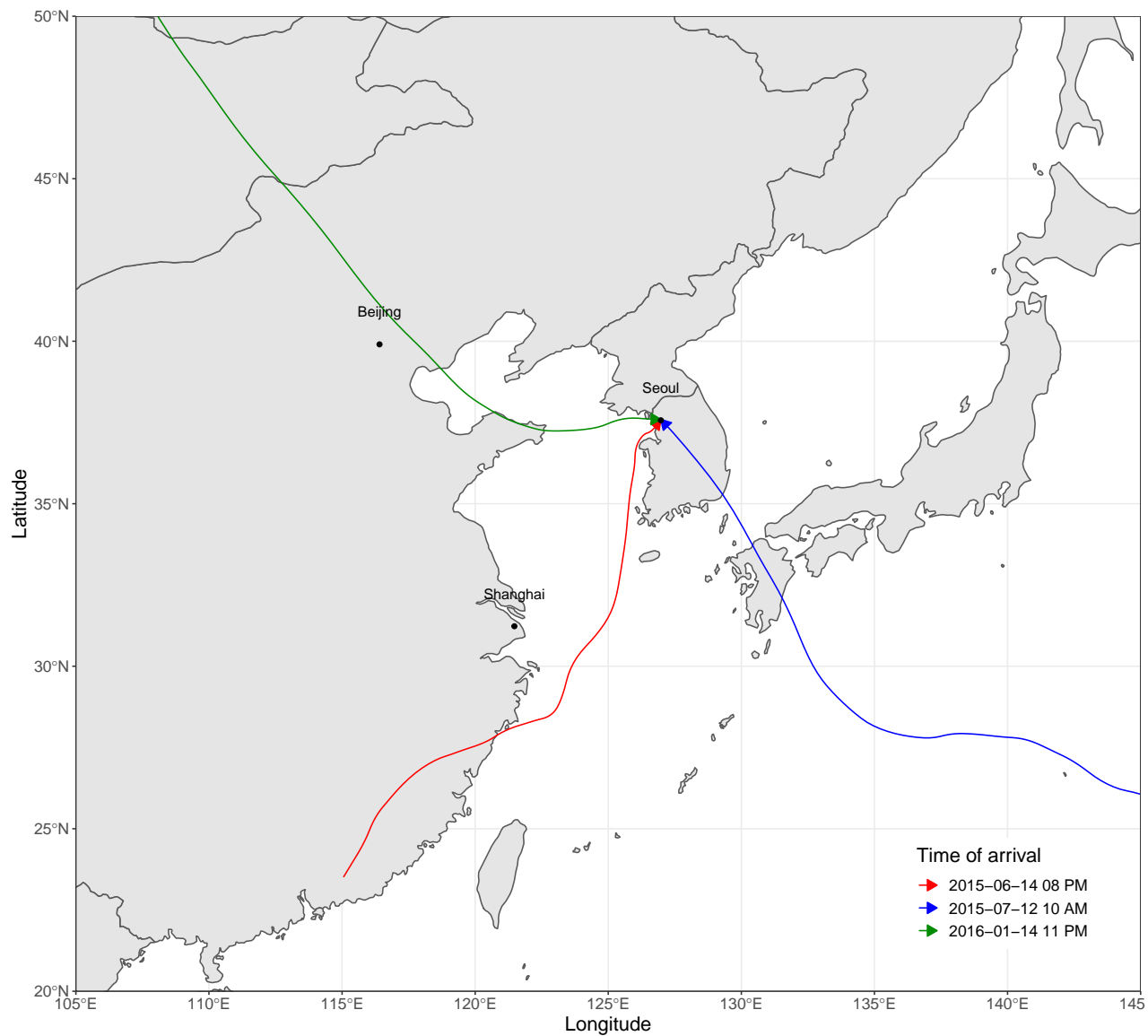
Figures

Figure 1: PM_{2.5} in China and South Korea



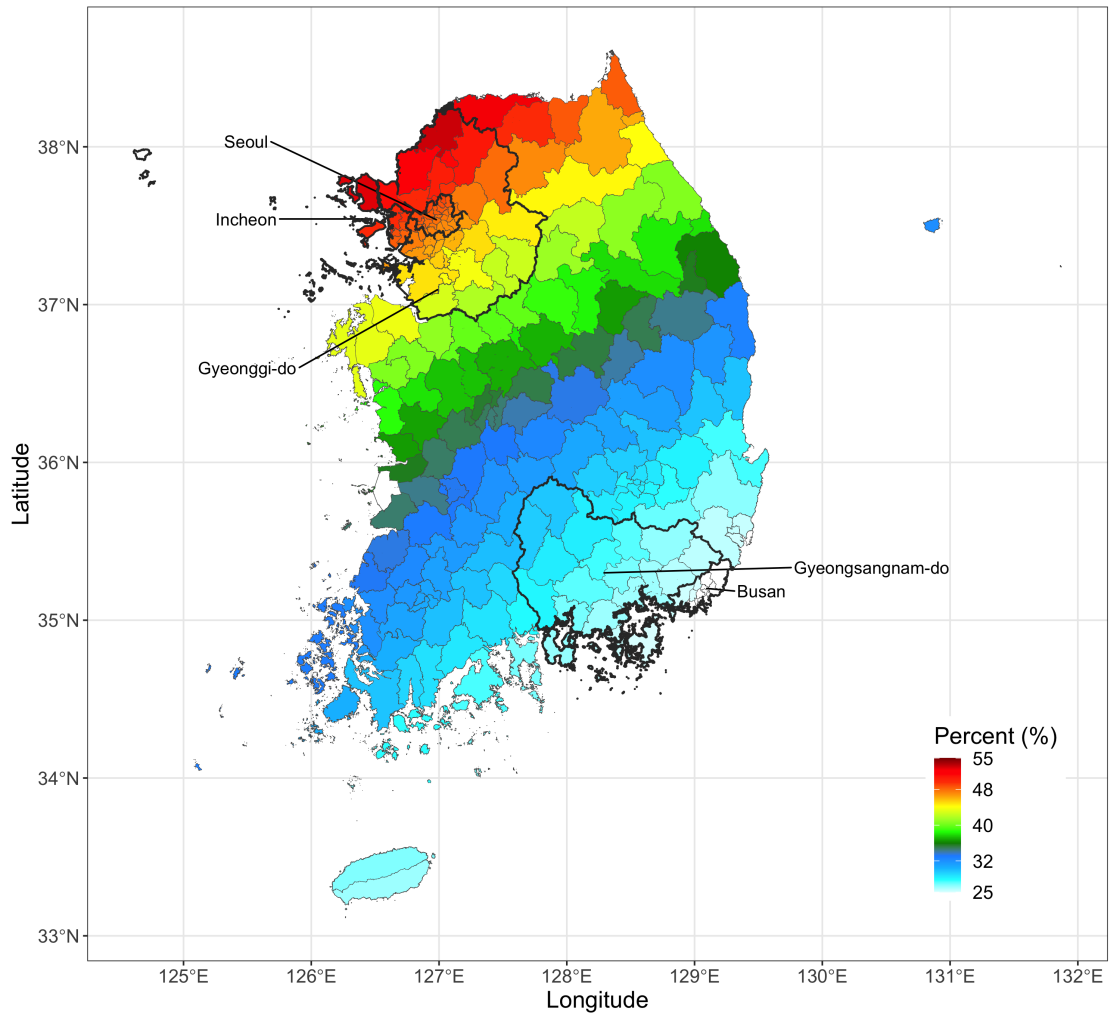
Note: This figure illustrates the evolution of monthly average hourly PM 2.5. The Northwest region in South Korea is defined as cities in South Korea that have more than or equal to 35% of frequency of trajectories coming from China in Figure 3. The Southwest region in South Korea is defined as cities with less than 35% of frequency of trajectories coming from China.

Figure 2: Examples of Backward Trajectories



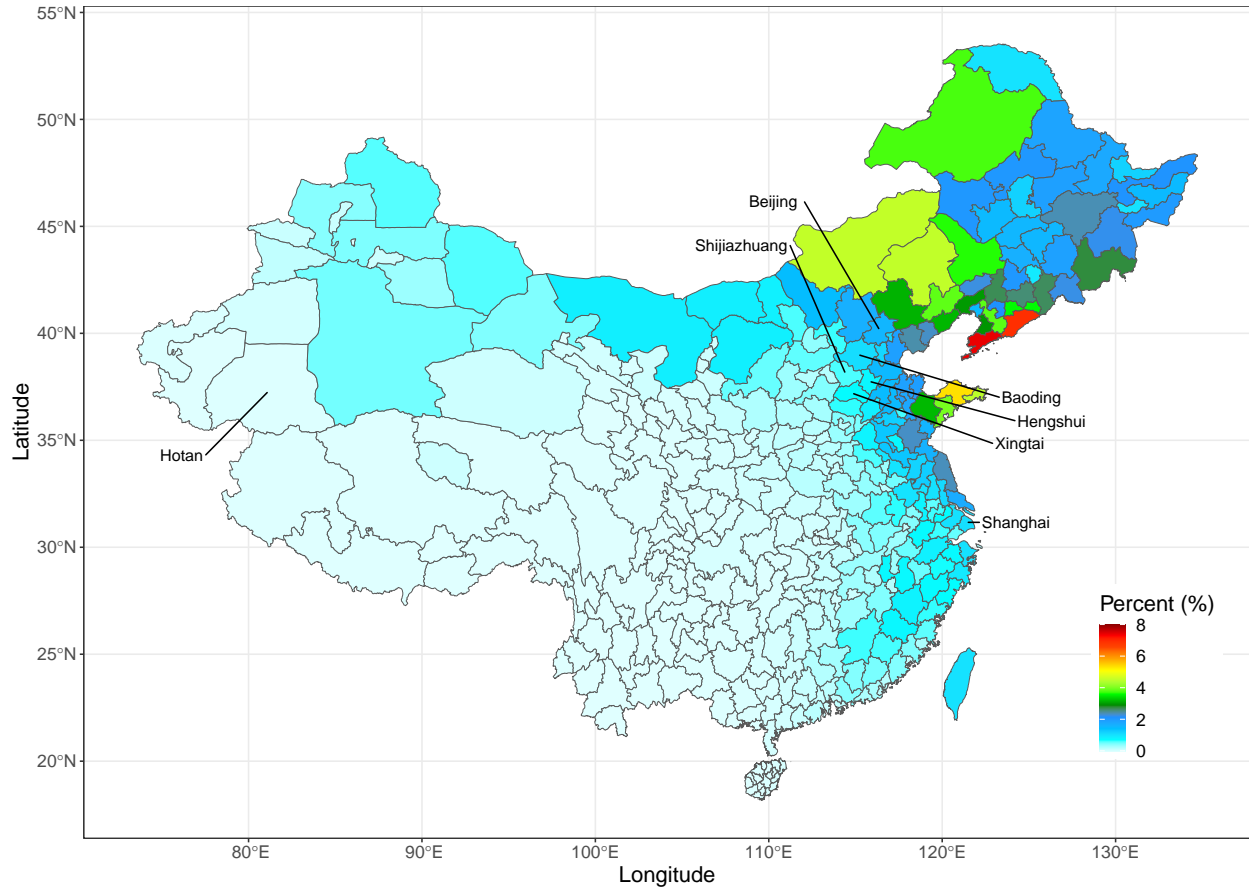
Note: This figure shows three examples of the backward trajectories obtained from the HYSPLIT model. For example, the green trajectory came from northern China, passed through Beijing, and reached Seoul at 11 pm on January 14, 2016.

Figure 3: Frequency of Trajectories Coming from China



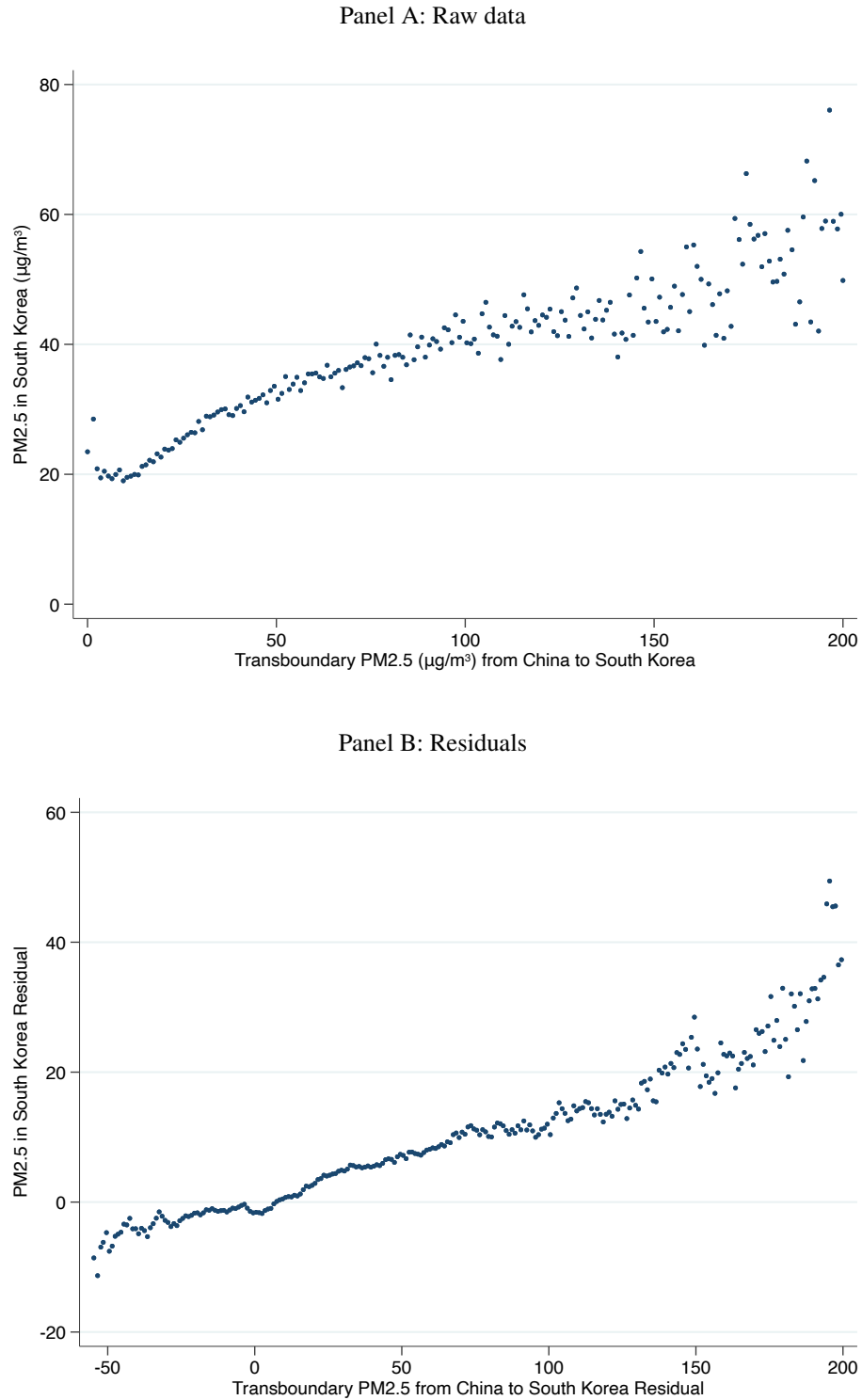
Note: This figure shows the percentage of hours in which each city in South Korea had trajectories coming from China during our sample period (January 2015 to December 2019). For each city in South Korea, we use the HYSPLIT model to obtain backward trajectories for each day-hour. We then compute the percentage of the backward trajectories that came from China. That is, the denominator is the total number of hours from January 1, 2015 to December 31, 2019, and the numerator is the total number of hours in which the trajectories came from China. The duration of the backward trajectories we use is 200 hours. For example, if this value is 50% for a city in South Korea, it means that in half of the total hours in our sample period, this city had the trajectories coming from China.

Figure 4: Paths of Trajectories that Traveled Through China and Reached South Korea



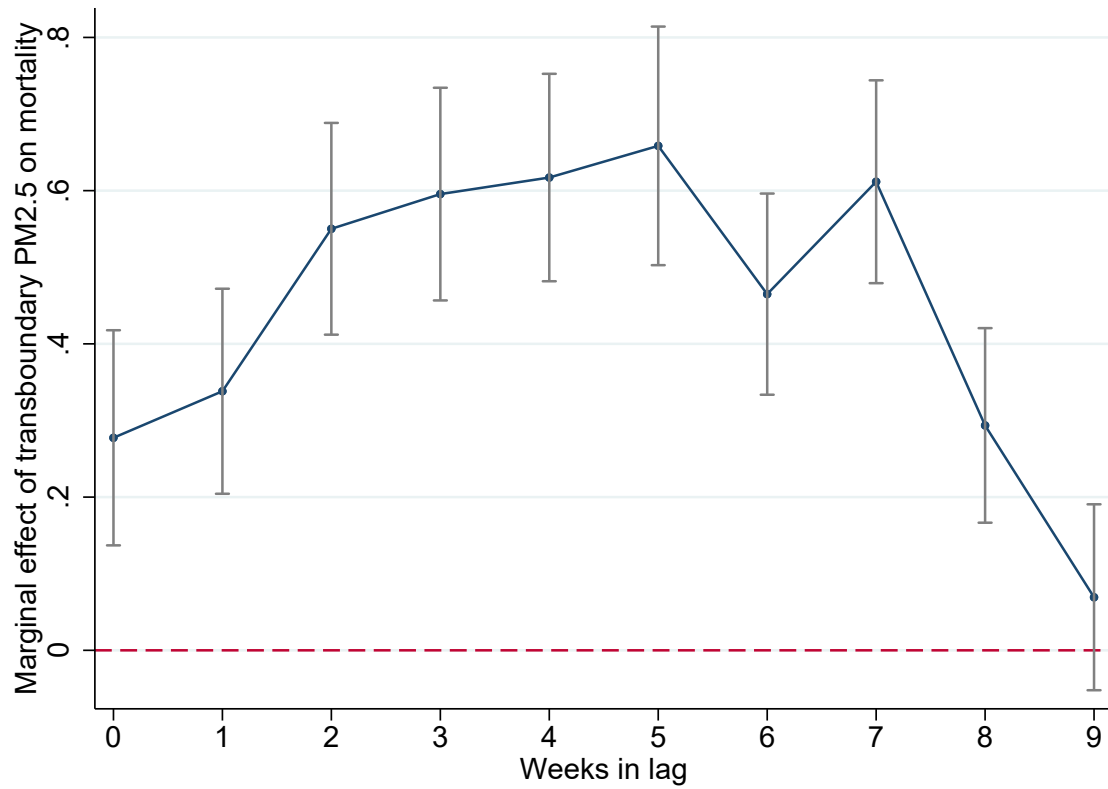
Note: This figure shows how often each city in China had a trajectory that passed the city and reached South Korea. For each city in South Korea, we use the HYSPLIT model to obtain backward trajectories for each day-hour during our sample period (January 2015 to December 2019). We then compute how often these backward trajectories passed each city in China. That is, the denominator is the total number of hours from January 1, 2015 to December 31, 2019. The numerator is the total number of hours in which a trajectory passed a city in China and reached cities in South Korea. The duration of the backward trajectories we use is 200 hours. For example, if this value is 5% for a city in China, it means that in 5% of the total hours in our sample period, a trajectory passed this city and reached a city in South Korea.

Figure 5: Scatter Plot of PM_{2.5} in South Korea and Transboundary PM_{2.5} from China



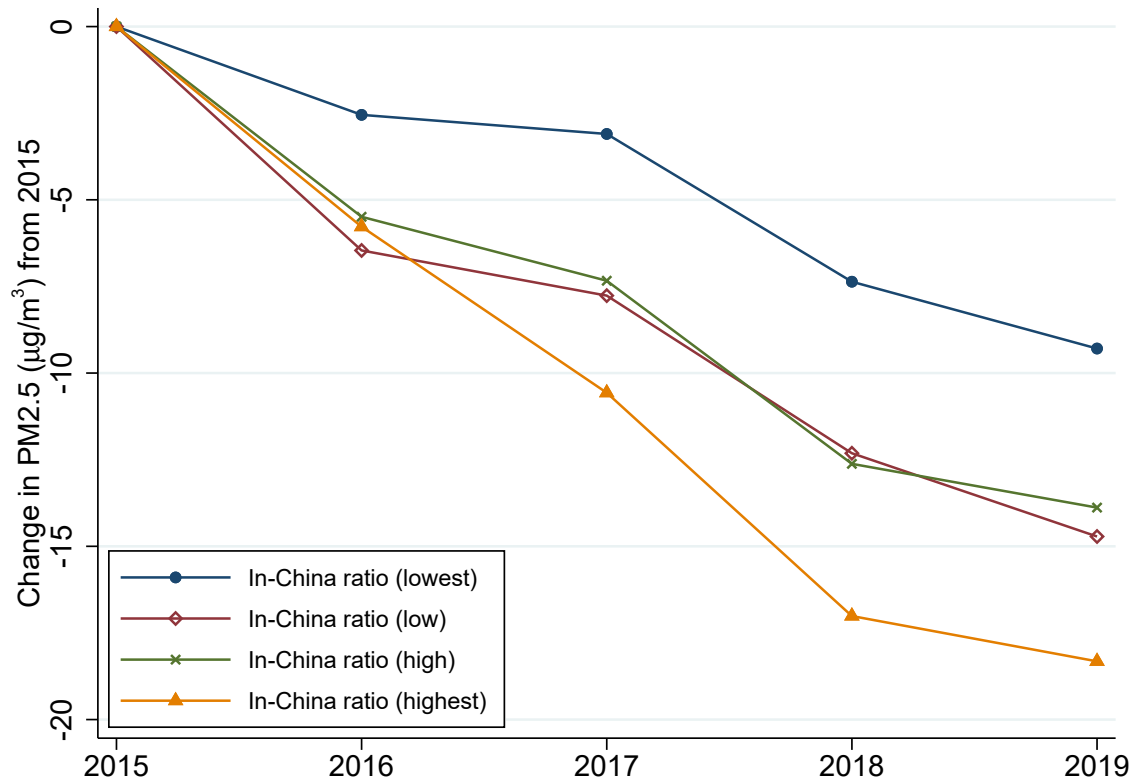
Note: Panel A plots the mean of PM 2.5 within each bin against bins of transboundary PM 2.5 with bins of size 1. Panel B plots the mean of residuals (from a regression of PM 2.5 in South Korea on city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, and city-by-temperature quartile fixed effects) against bins of residuals (from a regression of transboundary PM 2.5 on city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, and city-by-temperature quartile fixed effects).

Figure 6: Weekly Lagged Effects of the Transboundary Air Pollution on Mortality



Note: This figure plots the estimates and 95% confidence intervals presented in Panel B of Table 3. Each point estimate indicates the partial lagged marginal effect of Transboundary PM_{2.5} (from China to Korea) on hourly mortality per billion people in South Korea.

Figure 7: Testing for Strategic Air Pollution Reductions in China



Note: This figure plots the change in $PM_{2.5}$ relative to 2015 level for Chinese cities by the quartile groups of in-China ratio. The in-China ratio is calculated by the following approach. For each city, day, and hour, we use HYSPLIT model to obtain forward air pollution trajectories. We then compute the in-China ratio based on the number of trajectories that entered China divided by the total number of trajectories. A pollution trajectory is considered to have fallen within China if the trajectory falls inside the latitude and longitude boundaries of China or if the trajectory's height is persistently below 1 km since the start of the forward trajectory.

Tables

Table 1: Summary Statistics

	Mean	Standard Deviation
PM _{2.5} (µg/m ³) in Chinese cities	45.05	38.40
PM _{2.5} (µg/m ³) in Korean cities	24.99	18.06
Transboundary PM _{2.5} (µg/m ³) from China to Korean cities	14.19	27.52
Transboundary trajectory indicator variable (1 or 0)	0.39	0.49
Mortality in Korean cities (hourly deaths per billion people)		
Overall	894	3800
Respiratory/Cardiovascular	231	1954
Infant (age < 1)	327	27702
Elderly (age ≥ 65)	3576	14197
Emergency Room Visits (daily visit counts per billion people)		
Atopic	0.08	0.32
Rhinitis	3.27	5.68
Asthma	2.15	2.65
City-level population (in thousands)		
Overall	232	240
Elderly (age ≥ 65)	32.16	25.27
Infant (age < 1)	1.68	1.91
Hourly Temperature (°C)	13.01	10.43
Hourly Precipitation (mm)	0.13	1.00

Note: This table reports summary statistics. All mortality rates are per billion population in the corresponding age group. Sample includes all South Korean cities, and 784 Chinese cities over a period of January 2015 to December 2019.

Table 2: First Stage: Impacts of Transboundary Air Pollution on Local Air Quality in South Korea

Dependent variable: Hourly PM _{2.5} in South Korean cities					
	(1)	(2)	(3)	(4)	(5)
Hourly Transboundary PM _{2.5}	0.170 (0.003)	0.129 (0.002)	0.129 (0.002)	0.129 (0.002)	0.122 (0.002)
Constant	22.776 (0.221)				
Observations	9160118	9107025	9107025	9107025	9107025
KP F-stat	3885	5730	5819	5774	5812
Year-Month-City FE	No	No	Yes	Yes	Yes
Year-Month FE	No	Yes	No	No	No
Month-City FE	No	Yes	No	No	No
Day of week-City FE	No	Yes	Yes	Yes	Yes
Rainfall quartile-City FE	No	Yes	No	Yes	No
Temperature quartile-City FE	No	Yes	No	Yes	No
Rainfall decile-City FE	No	No	No	No	Yes
Temperature decile-City FE	No	No	No	No	Yes
Rainfall quartile FE	No	No	Yes	No	No
Temperature quartile FE	No	No	Yes	No	No

Note: This table shows OLS estimation results for equation (1). Standard errors in parentheses are clustered by city. All models are weighted by the city population. KP F-stat is Kleibergen-Paap rk Wald F statistic. Sample includes all South Korean cities between January 2015 and December 2019.

Table 3: Impacts of Transboundary Air Pollution on Mortality in South Korea (Reduced-form)

Panel A: Average Effect Over the Past 70 Days (Dependent variable: hourly mortality per billion people)

	Respiratory/ cardiovascular	Elderly	Infant	Overall
Transboundary PM _{2.5} (past 0-70 days)	1.66 (0.17)	19.00 (2.17)	6.68 (3.33)	3.56 (0.34)
Observations	9555368	9555368	9555368	9555368
Mean of dependent variable	148	3259	314	618
Marginal effect as % increase in mortality	1.1%	0.6%	2.1%	0.6%
Marginal effect on annual mortality/million	14.5	166.5	58.5	31.2

Panel B: Weekly Lagged Effects (Dependent variable: hourly mortality per billion people)

	Respiratory/ cardiovascular	Elderly	Infant	Overall
Transboundary PM _{2.5} (past 0-7 day)	0.14 (0.04)	1.35 (0.48)	0.90 (0.58)	0.28 (0.07)
Transboundary PM _{2.5} (past 7-14 day)	0.21 (0.03)	1.93 (0.47)	0.37 (0.64)	0.34 (0.07)
Transboundary PM _{2.5} (past 14-21 day)	0.25 (0.04)	3.16 (0.45)	2.02 (0.64)	0.55 (0.07)
Transboundary PM _{2.5} (past 21-28 day)	0.25 (0.03)	3.59 (0.46)	-0.36 (0.59)	0.60 (0.07)
Transboundary PM _{2.5} (past 28-35 day)	0.23 (0.04)	3.61 (0.49)	1.18 (0.70)	0.62 (0.07)
Transboundary PM _{2.5} (past 35-42 day)	0.27 (0.04)	3.81 (0.51)	0.10 (0.69)	0.66 (0.08)
Transboundary PM _{2.5} (past 42-49 day)	0.14 (0.03)	2.41 (0.44)	1.21 (0.75)	0.46 (0.07)
Transboundary PM _{2.5} (past 49-56 day)	0.22 (0.03)	3.50 (0.45)	0.87 (0.70)	0.61 (0.07)
Transboundary PM _{2.5} (past 56-63 day)	0.12 (0.03)	1.74 (0.40)	0.42 (0.57)	0.29 (0.06)
Transboundary PM _{2.5} (past 63-70 day)	0.09 (0.03)	-0.09 (0.42)	0.67 (0.64)	0.07 (0.06)
Observations	9555318	9555318	9555318	9555318
Mean of dependent variable	148	3259	314	618

Note: This table shows OLS estimation results for equation (2). Standard errors in parentheses are clustered by city. The dependent variable is hourly mortality per billion people in each category. All regressions include city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, city-by-temperature quartile fixed effects, and are weighted by city-level population. Sample includes all South Korean cities between January 2015 and December 2019.

Table 4: Impacts of Local Air Quality on Mortality in South Korean Cities (IV Estimation)

Panel A: Average Effect Over the Past 70 Days (Dependent variable: hourly mortality per billion people)

	Respiratory/ cardiovascular	Elderly	Infant	Overall
PM _{2.5} (past 0-70 days)	4.24 (0.47)	48.60 (5.72)	17.44 (8.63)	9.09 (0.94)
Observations	9528960	9528960	9528960	9528960
Mean of dependent variable	148	3258	314	618
Marginal effect as % increase in mortality	2.9%	1.5%	5.5%	1.5%
Marginal effect on annual mortality/million	37.2	425.8	152.8	79.7

Panel B: Weekly Lagged Effects (Dependent variable: hourly mortality per billion people)

	Respiratory/ cardiovascular	Elderly	Infant	Overall
PM _{2.5} (past 0-7 days)	0.37 (0.10)	4.05 (1.37)	2.08 (1.63)	0.78 (0.21)
PM _{2.5} (past 7-14 days)	0.52 (0.09)	3.68 (1.27)	0.24 (1.67)	0.69 (0.19)
PM _{2.5} (past 14-21 days)	0.62 (0.12)	7.10 (1.42)	5.15 (1.96)	1.23 (0.22)
PM _{2.5} (past 21-28 days)	0.67 (0.11)	8.24 (1.52)	-1.41 (1.77)	1.37 (0.23)
PM _{2.5} (past 28-35 days)	0.52 (0.10)	7.88 (1.35)	3.48 (1.83)	1.31 (0.20)
PM _{2.5} (past 35-42 days)	0.66 (0.10)	9.77 (1.29)	0.12 (1.66)	1.63 (0.20)
PM _{2.5} (past 42-49 days)	0.43 (0.10)	7.50 (1.32)	3.01 (1.94)	1.37 (0.21)
PM _{2.5} (past 49-56 days)	0.78 (0.11)	13.01 (1.37)	3.78 (2.22)	2.23 (0.23)
PM _{2.5} (past 56-63 days)	0.49 (0.09)	8.94 (1.20)	1.12 (1.74)	1.42 (0.20)
PM _{2.5} (past 63-70 days)	0.21 (0.08)	-0.03 (1.12)	2.11 (1.61)	0.20 (0.16)
Observations	9274063	9274063	9274063	9274063
Mean of dependent variable	148	3260	315	617

Note: This table shows instrumental variable estimation results for equation (3). Standard errors are clustered by city. The dependent variable is hourly mortality per billion people in each category. All columns include city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, city-by-temperature quartile fixed effects, and are weighted by city-level population. The Kleibergen-Paap rk Wald F statistic is 1816 for all columns in panel A and 356 for all columns in panel B. The sample periods are from January 2015 to December 2019.

Table 5: Impacts of Transboundary Air Pollution on Mortality by Age Group

Panel A: Reduced Form (Dependent variable: hourly mortality per billion people)

	Infant	1-9	10-19	20-29	30-39	40-49
Transboundary PM _{2.5} (past 0-70 days)	6.68 (3.33)	0.18 (0.17)	-0.14 (0.19)	0.04 (0.26)	0.94 (0.32)	0.61 (0.45)
Mean of dependent variable	314	12	18	42	79	169
Marginal effect as % increase in mortality	2.1%	1.5%	-0.8%	0.1%	1.2%	0.4%
Marginal effect on annual mortality/million	58.6	1.6	-1.3	0.3	8.2	5.3

	50-59	60-69	70-79	80-89	90-99	100-109
Transboundary PM _{2.5} (past 0-70 days)	2.70 (0.73)	4.60 (1.23)	13.85 (2.64)	39.63 (7.78)	110.42 (31.68)	185.48 (173.36)
Mean of dependent variable	364	746	2313	7324	19368	16318
Marginal effect as % increase in mortality	0.7%	0.6%	0.6%	0.5%	0.6%	1.1%
Marginal effect on annual mortality/million	23.6	40.3	121.3	347.1	967.3	1624.8

Panel B: IV Estimation (Dependent variable: hourly mortality per billion people)

	Infant	1-9	10-19	20-29	30-39	40-49
PM _{2.5} (past 0-70 days)	17.48 (8.63)	0.46 (0.43)	-0.35 (0.49)	0.09 (0.66)	2.43 (0.82)	1.61 (1.16)
Mean of dependent variable	314	12	18	42	79	169
Marginal effect as % increase in mortality	5.6%	3.7%	-2.0%	0.2%	3.1%	0.9%
Marginal effect on annual mortality/million	153.1	4.0	-3.1	0.8	21.3	14.1

	50-59	60-69	70-79	80-89	90-99	100-109
PM _{2.5} (past 0-70 days)	6.93 (1.92)	11.62 (3.20)	35.13 (6.75)	101.91 (20.52)	285.67 (81.68)	467.04 (444.44)
Mean of dependent variable	364	746	2312	7322	19365	16323
Marginal effect as % increase in mortality	1.9%	1.6%	1.5%	1.4%	1.5%	2.9%
Marginal effect on annual mortality/million	60.7	101.8	307.7	892.8	2502.5	4091.3

Note: Panel A shows age-specific results for the OLS estimation in equation (2), and Panel B shows results for the instrumental variable estimation in equation (3). Standard errors in parentheses are clustered by city. The dependent variable is hourly mortality per billion people in each category. In the OLS estimation, all age groups have 9,555,368 observations, except for the age group 100-109, which has 9,537,950 observations. The age group 100-109 has fewer observations because the population for age over 100 is 0 for some years in some cities in the sample. In the IV estimation, all age groups have 9,528,950 observations, except for the age group 100-109, which has 9,511,542 observations. All regressions include city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, city-by-temperature quartile fixed effects, and are weighted by city-level population. The Kleibergen-Paap rk Wald F statistic for Panel B is 1,814 for all age groups except for age group 100-109 (1,825). The sample includes all South Korean cities between January 2015 and December 2019.

Table 6: The Impact of Transboundary Air Pollution on Emergency Room Visits

Panel A: Reduced-form Estimation			
	Asthma	Rhinitis	Atopic
Transboundary PM _{2.5} (past 0-60 days)	50.0 (10.2)	482.6 (54.3)	-2.8 (1.6)
Observations	235388	235388	235388
Mean of dependent variable	9228.3	14053.4	363.5
Marginal effect as % increase in ER visits	0.5%	3.4%	-0.8%
Marginal effect on annual ER visits/million	18.3	176.1	-1.0

Panel B: Instrumental Variable Estimation			
	Asthma	Rhinitis	Atopic
PM _{2.5} (past 0-60 days)	214.2 (45.6)	2066.7 (258.9)	-11.8 (6.7)
Observations	235388	235388	235388
Mean of dependent variable	9228.3	14053.4	363.5
Marginal effect as % increase in ER visits	2.3%	14.7%	-3.2%
Marginal effect on annual ER visits/million	78.2	754.3	-4.3

Note: Standard errors, clustered by city, are reported in parentheses. All regressions include city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, city-by-temperature quartile fixed effects, city-by-humidity quartile fixed effects, and are weighted by city-level population. Kleibergen-Paap rk Wald F statistic is 750 for all columns in the IV estimation. The sample includes all South Korean cities between January 2015 and December 2018. The dependent variables are the numbers of daily ER visits per billion people due to asthma, rhinitis, and atopic dermatitis, respectively. All columns in this table includes controls for pollen variables (oak, pine and weed pollen). We include results without these control variables in Table A.5, which suggests that results are robust to the exclusions of these control variables.

Table 7: International Spillover Benefits of Reductions in Air Pollution (\$ billion/year)

	Overall	Infant < 1	Youth 1 – 19	Adult 20 – 64	Elderly ≥ 65
Status Quo:					
Reduction of Transboundary PM _{2.5} by 9.63 µg/m ³	2.62	0.12	0.04	1.50	0.97
Counterfactual Scenario 1:					
Reduction of Transboundary PM _{2.5} by 14.07 µg/m ³	3.83	0.18	0.05	2.19	1.41
Counterfactual Scenario 2:					
Reduction of Transboundary PM _{2.5} by 18.3 µg/m ³	4.98	0.23	0.07	2.85	1.83

Note: This table shows the international spillover benefits of reductions in air pollution for three scenarios. The table reports the per-year spillover benefit for South Korea in 2019 US billion dollars. We calculate the benefits based on the estimates of the age-specific impacts of transboundary air pollution on mortality in Table and the age-specific value of statistical life described in Section 4. The status-quo is based on the actual reduction in transboundary air pollution from China to South Korea observed in our data during our sample period (9.63 µg/m³). The first counterfactual scenario is based on the national-average pollution reduction in China during our sample period (14.07 µg/m³), and the second counterfactual scenario is based on the pollution reduction in Chinese cities where most air pollution remained within China (18.3 µg/m³).

Appendix A Details of the HYSPLIT model

In this section, we provide details of the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT), an open-source computer software for simulating atmospheric transport and dispersion.²⁰

Brief description of the HYSPLIT model

Developed by the National Oceanic and Atmospheric Administration (NOAA) Air Resources Laboratory and the Australian Bureau of Meteorology Research Centre in 1998, HYSPLIT computes trajectories of particles to determine how far and where particles will travel. The model can also simulate particle dispersion and compute air concentrations. However, we focus our attention on trajectory computation, because our study is concerned with determining whether pollutants in South Korea passed through China. Particle dispersion is useful when estimating the effect of emission from point sources, such as factories and power plants.

To compute a forward trajectory or a backward trajectory, the model takes a coordinate and a height of a starting location, a starting time, a trajectory duration, and other parameters as inputs and computes a trajectory of a single particle using the mean wind speed and direction of each grid that the particle passes by.²¹ The forward trajectory is calculated by tracking the movement of the air mass in time, whereas the backward trajectory is calculated by tracking the movement of the air mass *back* in time. Forward trajectory analysis is useful for determining the particle dispersion, while back trajectory analysis is useful for determining the origins of pollutants.

Figure A.1 shows how forward trajectories are calculated in the HYSPLIT model. Given the initial position $P(t)$ and the first-guess position $P'(t + \Delta t) = P(t) + V(P, t)\Delta t$ where $V(P, t)$ denote the velocity vector, $V(P, t)$ is linearly interpolated, which is then used to obtain the final position:

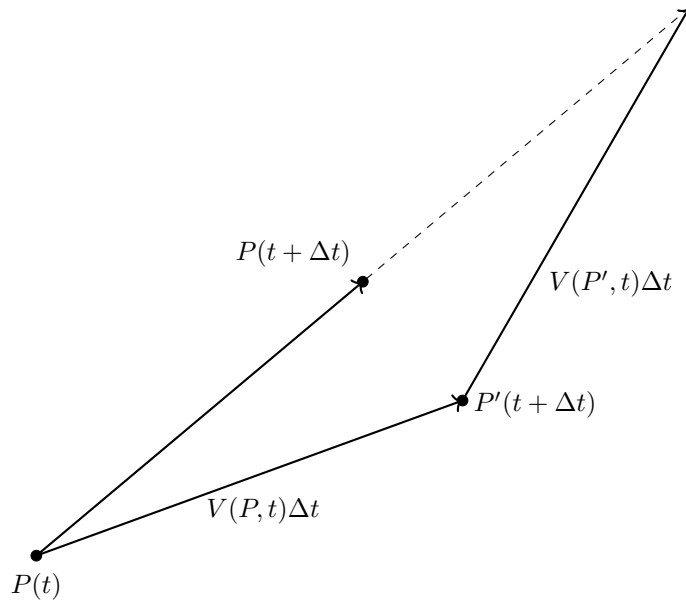
$$P(t + \Delta t) = P(t) + \frac{V(P, t) + V(P', t + \Delta t)}{2} \cdot \Delta t.$$

Backward trajectories are calculated using the same procedure, except that Δt is now negative.

²⁰The authors gratefully acknowledge the NOAA Air Resources Laboratory (ARL) for the provision of the HYSPLIT transport and dispersion model and/or READY website (<https://www.ready.noaa.gov>) used in this publication. See Stein et al. (2015) for more information on HYSPLIT.

²¹For the meteorological data for the HYSPLIT model, we use the NCEP/NCAR Reanalysis data, available from 1948 to present. The NCEP/NCAR Reanalysis data set is a continuously updated globally gridded data set that is jointly produced by the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR). This data set is a product of a data assimilation project where the initial states of the atmosphere are “reanalyzed” by incorporating historical observations and using a numerical weather prediction (NWP) model from 1948 to present. This data set has a $2.5^\circ \times 2.5^\circ$ spatial resolution with a timestamp of six hours.

Figure A.1: Description of the Trajectory Equation



Comparison between different methods of analysis in the HYSPLIT model

The purpose of using the HYSPLIT model is to determine whether pollution in South Korea at a given time comes from China. To address this question, we explored a number of possible options using the HYSPLIT model.

First, we discuss the benefits and limitations of forward and backward trajectory analyses. Forward trajectory analysis is useful for determining emission paths or dispersion of pollutants from a point source. For example, [Hernandez-Cortes and Meng \(2023\)](#) computes concentrations of air pollutants for each zip code and year by running forward trajectory simulations from each facility in California. To address our research question, one may imagine running forward trajectory simulations from polluting facilities in China. This method of analysis has its appeals, because we would then be able to determine the effect of anthropogenic transboundary air pollution from Chinese factories and power plants.

However, our research question is to determine the effect of transboundary air pollution from China, which would also include ambient air pollution from the use of coals for heating in winter. Then to capture all the possible paths of pollution flow from China to South Korea, we would ideally simulate forward trajectories from all the coordinates in China. However, we face a number of issues creating the instrument this way. First, simulating from all the coordinates in China at various levels of height makes it computationally less tractable. Second, these forward trajectories may not fully capture all the possible paths of transboundary air movements due to discrete starting points of trajectory simulation.

Backward trajectory analysis is useful for determining the source locations of pollutants. For our research question, we can track back in time trajectories that are simulated from South Korea to determine whether the trajectories reach China. This method is computationally less intensive than the first method, because trajectories can be simulated from each South Korean city at a given height.

However, this method also has limitations. Simulating backward trajectories with a given duration is based on the assumption that pollutants have travelled for that given duration; that is, we cannot determine whether pollution *originated* from China. This is a valid concern in that we cannot ascertain exact sources of air pollution that arrive at South Korea if there are multiple possible polluting sources in the region. However, this is not a grave concern for our study, because we are interested in knowing whether air pollution in South Korea passed through China, not whether it *originated* from China. It is possible that the effect of transboundary air pollution picked up pollution from other neighboring countries of China. Fortunately, there is only the Yellow Sea between South Korea and China, and we can safely assume that there are no polluting sources in the Yellow Sea.

Another limitation is that trajectories of particles from two different source locations may intersect at a city in South Korea, and computing backward trajectories may not correctly identify the source locations. However, this is the limitation of the HYSPLIT model that exists in both forward and backward trajectory analyses. The trajectory calculation relies on the mean wind speed and wind direction at the grid point, and the advection of a particle is computed using the mean of the three-dimensional velocity vectors obtained from the input meteorological conditions. Thus, the trajectory analysis in the HYSPLIT model provides the average locations of the particle back in time, which we believe is a good approximation of the mean locations of the pollutants observed at the pollution monitor in South Korean cities back in time.

One may then ask whether particle dispersion can address our research question better than trajectory calculation. HYSPLIT introduces particle dispersion by calculating the trajectory for many points. However, each trajectory changes its course by the random atmospheric turbulence along its path (where the random shock is provided within the HYSPLIT model), creating dispersion among particles. Due to this way of computation, particle dispersion results in the arrival of a fewer particles as the distance between the source and the destination increases. Thus, we decided that computing backward trajectories is the most suitable way to determine whether air pollution in South Korea at a given time passed through China some time ago in expectation.

Construction of instrumental variables using the HYSPLIT model

To construct instrumental variables, we run backward trajectory simulations in the HYSPLIT model. We compute 200-hour backward trajectories 500 meters off the ground every hour for each South Korean city from January 2015 to December 2019, running 6.57 million trajectories in total ($24 \text{ hourly trajectories/day} \times 365 \text{ days/year} \times 5 \text{ years} \times 228 \text{ cities in South Korea}$).

The height of 500 meters was selected, because if a trajectory starts at a height close to the ground level will most likely not travel anywhere. In atmospheric science, the height of 850 mb (which is about 1 to 1.2 km above surface) is typically used, because if an air parcel reaches that level, the dynamics of the atmospheric boundary layer will bring the parcel down to surface.

We create two instruments using the HYSPLIT model (denote them Z^1 and Z^2). Z_{ct}^1 takes a value of 1 if the 200-hour backward trajectory that is simulated at a South Korean city c at time t reaches China and 0 otherwise. We define that a backward trajectory reaches China if the particle enters the Chinese boundary under the specified height (we use 1 km for the default height, but we test other heights for robustness checks) during the duration of 200 hours. We repeat backward trajectory simulations for every city c and hour t to obtain Z^1 .

Z_{ct}^2 is constructed by interacting Z_{ct}^1 with the PM 2.5 concentrations at the Chinese entry point of the backward trajectory. The PM 2.5 concentrations are retrieved from the nearest monitor to the entry point in China. If the particle reaches China j hours ago, then Z_{ct}^2 takes a value of the PM 2.5 concentration at that entry point at time $t - j$. It takes a value of 0 otherwise.

Appendix B Additional Figures and Tables

In this online appendix, we provide additional figures and tables from our analysis.

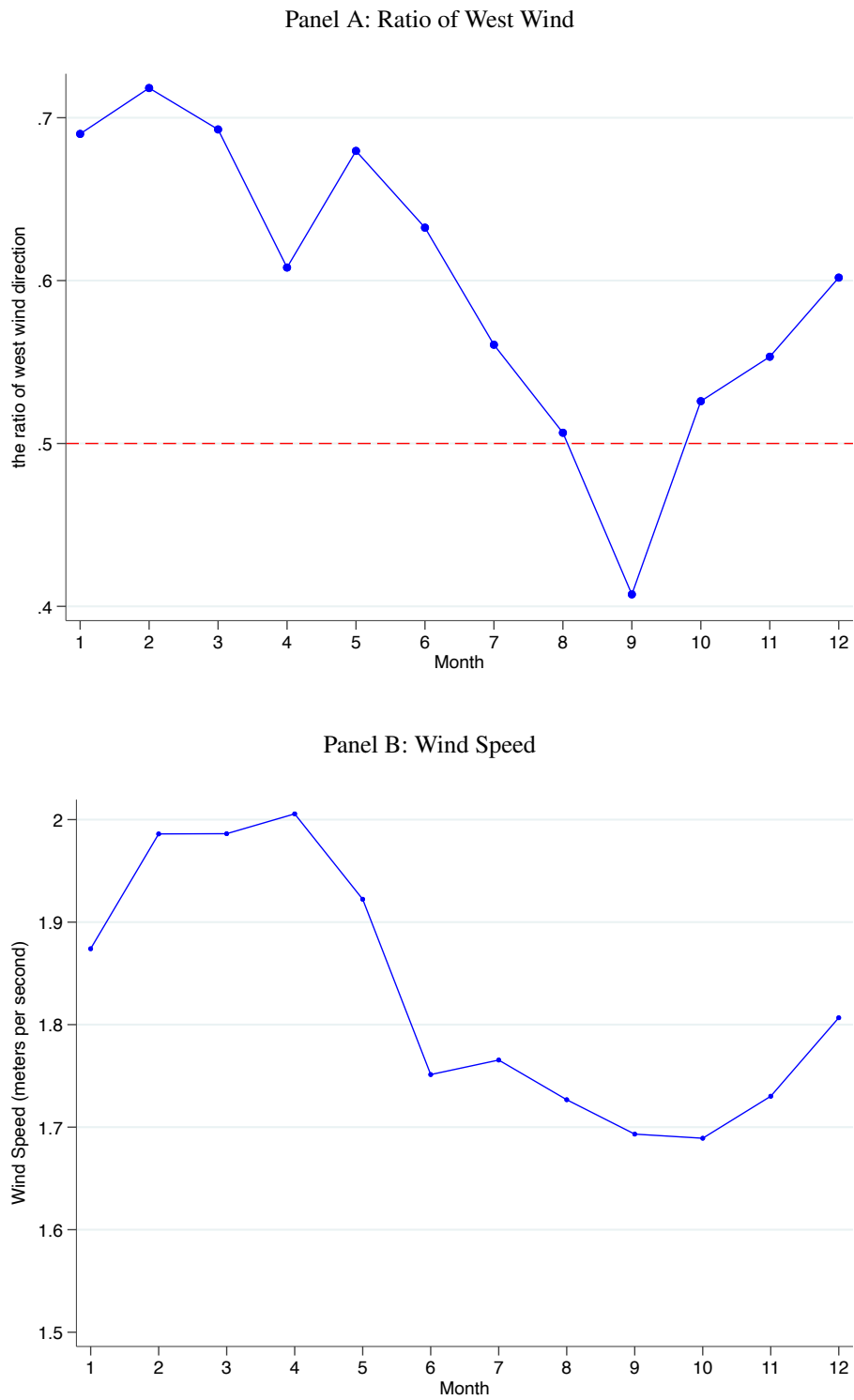
List of Figures in Appendix

A.1	Description of the Trajectory Equation	Appendix: page-2
A.2	Seasonality in Wind Speed and Direction in Seoul	Appendix: page-5
A.3	Map of PM _{2.5} Monitor Locations	Appendix: page-6
A.4	Location of Meteorological Monitoring Stations in South Korea	Appendix: page-7
A.5	Histogram of the Duration of Trajectories from China to South Korea	Appendix: page-8

List of Tables in Appendix

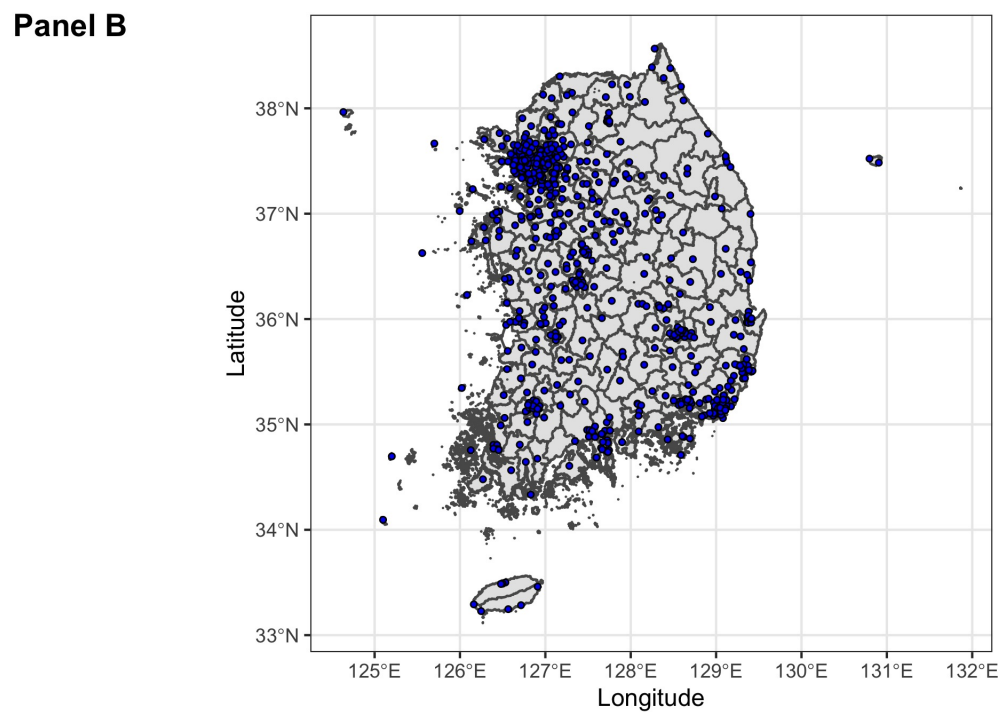
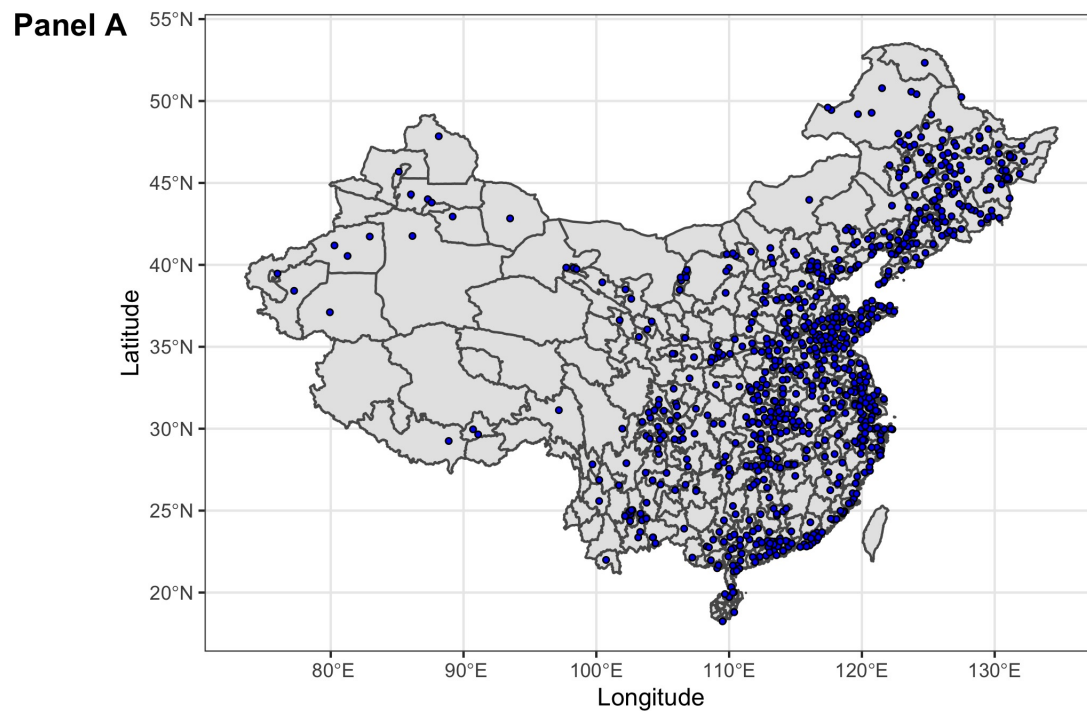
A.1	PM _{2.5} Concentrations by Season and Province	Appendix: page-9
A.2	Robustness Check for the Choices of Different Control Variables for Reduced Form estimation	Appendix: page-10
A.3	Robustness Check for the Choices of Different Control Variables for the IV estimation	Appendix: page-11
A.4	Robustness check of HYSPLIT to Choices of Different Starting Heights from South Korea	Appendix: page-12
A.5	The Impact of Transboundary Air Pollution on Emergency Room Visits (with and without Controls)	Appendix: page-13
A.6	Dependent Variable: PM _{2.5} in China at the city-year-month-day level	Appendix: page-14
A.7	Value of remaining life for each age group in South Korea	Appendix: page-15

Figure A.2: Seasonality in Wind Speed and Direction in Seoul



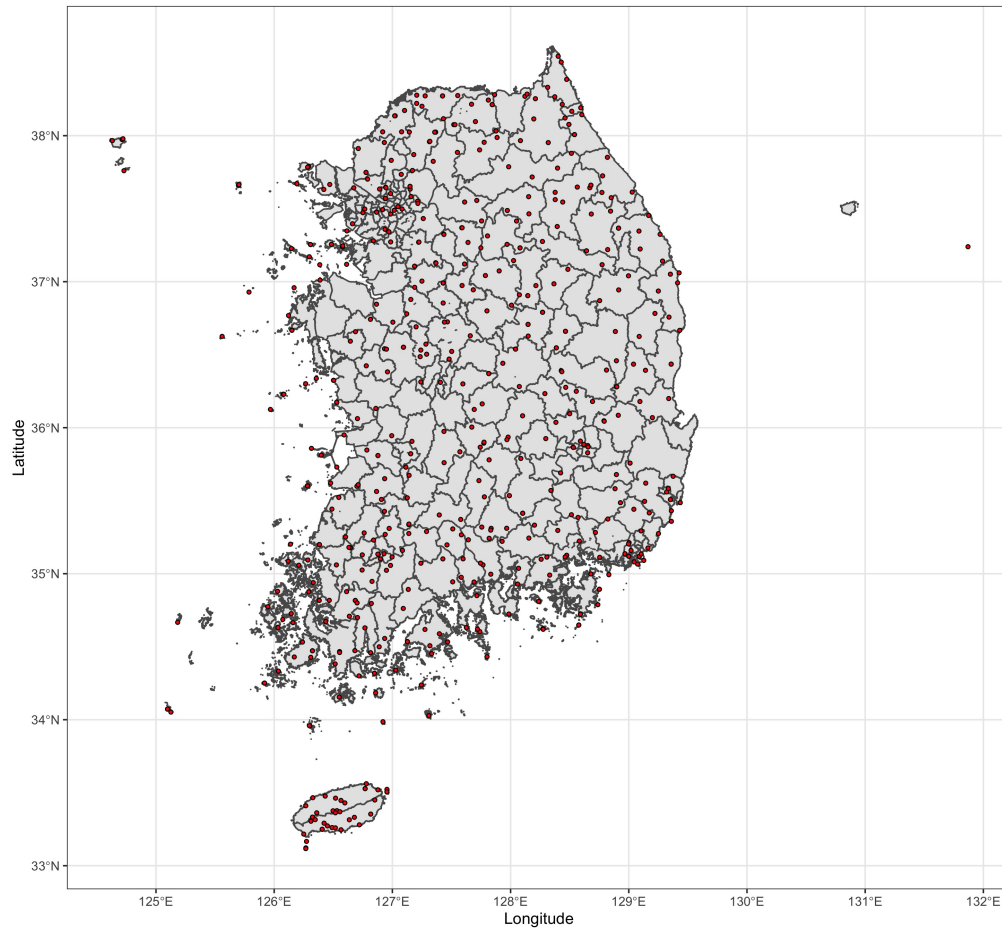
Note: The figure shows monthly percentage of each west wind direction in Seoul. Sample includes all South Korean cities between January 2015 and December 2019.

Figure A.3: Map of PM_{2.5} Monitor Locations



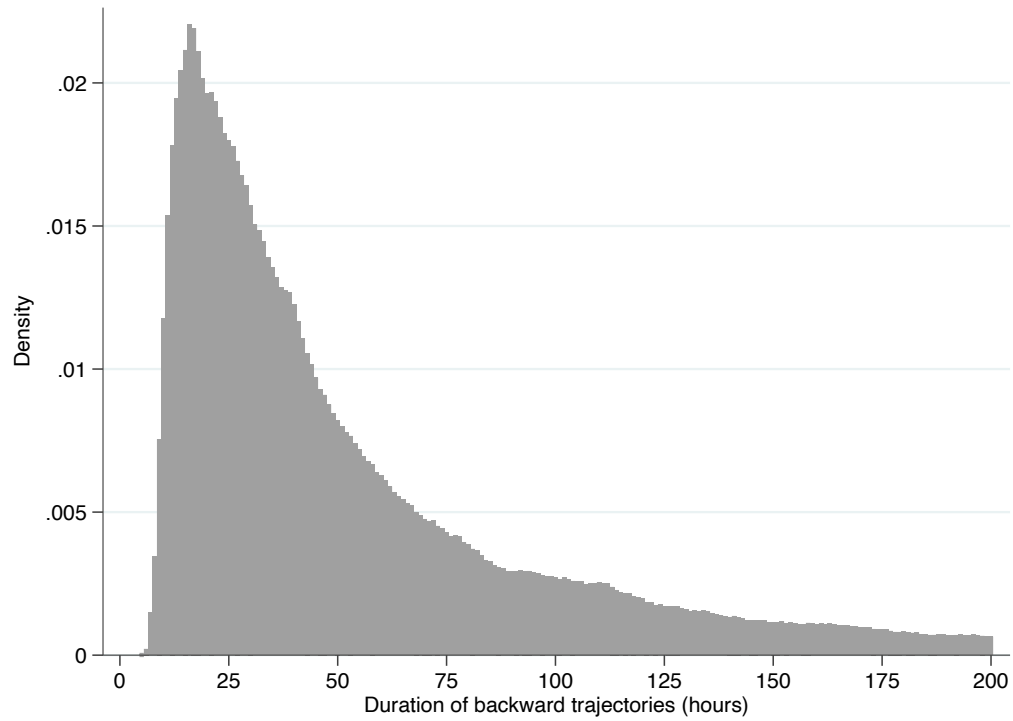
Note: This figure shows the locations of city coordinates available in the Chinese hourly PM_{2.5} concentrations data from Berkeley Earth (Panel A) and the locations of monitors in the South Korean hourly PM_{2.5} concentrations data from the Korea Environment Corporation (Panel B).

Figure A.4: Location of Meteorological Monitoring Stations in South Korea



Note: This figure shows the locations of ground monitoring stations that collect meteorological data in South Korea.

Figure A.5: Histogram of the Duration of Trajectories from China to South Korea



Note: We define the duration of a trajectory as the number of hours it took from the last grid point in China to a city in South Korea. Sample includes trajectories from all South Korean cities between January 2015 and December 2019. The mean is 52 and the median is 38. The 25th percentile is 22 and 75th percentile is 69.

Table A.1: PM_{2.5} Concentrations by Season and Province

Province	Spring	Summer	Fall	Winter
South Korea				
Busan	28.34	22.13	21.63	28.45
Chungcheongbuk-do	29.5	16.85	24.22	34.37
Chungcheongnam-do	26.31	19.71	25.22	30.87
Daegu	25.39	20.02	22.65	29.83
Daejeon	26.17	16.51	20.91	28.48
Gangwon-do	28.62	18.6	20.07	30.57
Gwangju	25.78	18.86	22.74	26.3
Gyeonggi-do	30.58	18.47	23.08	33.55
Gyeongsangbuk-do	26.15	17.84	21.88	27.74
Gyeongsangnam-do	25.81	21.77	20.55	25.94
Incheon	29.15	21.62	23.42	29.16
Jeju	23.52	17.01	18.1	22.02
Jeollabuk-do	31.84	21.27	27.05	33.38
Jeollanam-do	25.68	20.42	20.81	25.46
Sejong	25.4	18.81	19.74	27.3
Seoul	28.3	20.3	20.7	28.84
Ulsan	28.13	23.25	20.64	25.05
China				
Anhui	52.96	33.04	49.19	81.01
Beijing	58.97	43.09	56.18	77.06
Chongqing	41.73	31.19	39.54	75.36
Fujian	31.25	20.29	24.3	35.48
Gansu	39.19	26.39	32.32	53.25
Guangdong	31.97	21.35	33.29	44.03
Guangxi	36.09	23.52	35.44	54.8
Guizhou	34.34	22.19	30.01	48.53
Hainan	21.69	13.37	20.53	29.16
Hebei	60.99	46.93	62.16	97.66
Heilongjiang	33.55	19.67	36.27	52.41
Henan	63.15	41.88	59.75	111.45
Hubei	51.77	32.43	47.62	89.75
Hunan	43.25	27.97	43.51	72.01
Inner Mongolia	32.11	23.93	30.93	42.54
Jiangsu	51.55	33.27	43.17	76.26
Jiangxi	40.41	27.19	38.98	60.22
Jilin	38.63	22.61	39.55	59.39
Liaoning	45.51	29.36	43.94	62.56
Ningsia Hui Autonomous Region	43.87	32.22	44.12	61.5
Qinghai	43	29.9	39.32	62.99
Shaanxi	49.16	32.18	50.34	96.04
Shandong	57.5	37.97	55.16	92.17
Shanghai	47.04	32.73	37	62.76
Shanxi	52.63	41.77	54.48	87.54
Sichuan	44.03	28.74	38.03	74.6
Tianjin	62.84	46.11	61.11	85.08
Tibet	22.53	15.25	20.13	27.89
Xinjiang	62.22	34.79	43.65	76.96
Yunnan	32.04	18.95	22.76	31.77
Zhejiang	41.82	26.54	34.16	57.99

Table A.2: Robustness Check for the Choices of Different Control Variables for Reduced Form estimation

	(1)	(2)	(3)	(4)	(5)
Transboundary PM _{2.5} (past 0-7 day)	0.14 (0.04)	0.15 (0.04)	0.14 (0.04)	0.07 (0.04)	0.07 (0.04)
Transboundary PM _{2.5} (past 7-14 day)	0.21 (0.03)	0.22 (0.03)	0.21 (0.03)	0.12 (0.03)	0.12 (0.03)
Transboundary PM _{2.5} (past 14-21 day)	0.25 (0.04)	0.27 (0.04)	0.25 (0.04)	0.14 (0.03)	0.14 (0.03)
Transboundary PM _{2.5} (past 21-28 day)	0.25 (0.03)	0.27 (0.03)	0.26 (0.03)	0.14 (0.03)	0.14 (0.03)
Transboundary PM _{2.5} (past 28-35 day)	0.23 (0.04)	0.24 (0.04)	0.24 (0.04)	0.11 (0.04)	0.11 (0.04)
Transboundary PM _{2.5} (past 35-42 day)	0.27 (0.04)	0.29 (0.04)	0.28 (0.04)	0.16 (0.03)	0.15 (0.03)
Transboundary PM _{2.5} (past 42-49 day)	0.14 (0.03)	0.16 (0.03)	0.15 (0.03)	0.04 (0.03)	0.04 (0.03)
Transboundary PM _{2.5} (past 49-56 day)	0.22 (0.03)	0.23 (0.03)	0.23 (0.03)	0.13 (0.03)	0.13 (0.03)
Transboundary PM _{2.5} (past 56-63 day)	0.12 (0.03)	0.13 (0.03)	0.12 (0.03)	0.06 (0.03)	0.06 (0.03)
Transboundary PM _{2.5} (past 63-70 day)	0.09 (0.03)	0.10 (0.03)	0.09 (0.03)	0.05 (0.03)	0.05 (0.03)
Observations	9555318	9555318	9555318	9555318	9555318
Dependent variable mean	148	148	148	148	148
Year-Month-City FE	Yes	Yes	Yes	No	No
Year-Month FE	No	No	No	Yes	Yes
Month-City FE	No	No	No	Yes	No
Month-Province FE	No	No	No	No	Yes
Year FE	No	No	No	No	No
Moith FE	No	No	No	No	No
City FE	No	No	No	No	Yes
Day of week-City FE	Yes	Yes	Yes	Yes	No
Rainfall quartile-City FE	Yes	No	No	Yes	Yes
Temperature quartile-City FE	Yes	No	No	Yes	Yes
Rainfall decile-City FE	No	Yes	No	No	No
Temperature decile-City FE	No	Yes	No	No	No
Rainfall quartile FE	No	No	Yes	No	No
Temperature quartile FE	No	No	Yes	No	No

Note: This table shows results for column Column 1 in Table 3 with different choices of control variables. See notes in Table 3. Column 1 in this table replicates column 1 in Table 3, and we show results with with different choices of control variables in columns 2 to 5.

Table A.3: Robustness Check for the Choices of Different Control Variables for the IV estimation

	(1)	(2)	(3)	(4)	(5)
Hourly PM _{2.5} (past 0-7 days)	0.37 (0.10)	0.38 (0.10)	0.37 (0.10)	0.35 (0.14)	0.35 (0.13)
Hourly PM _{2.5} (past 7-14 days)	0.52 (0.09)	0.54 (0.09)	0.53 (0.09)	0.48 (0.11)	0.48 (0.11)
Hourly PM _{2.5} (past 14-21 days)	0.62 (0.12)	0.67 (0.12)	0.64 (0.12)	0.58 (0.14)	0.58 (0.14)
Hourly PM _{2.5} (past 21-28 days)	0.67 (0.11)	0.73 (0.12)	0.70 (0.11)	0.64 (0.14)	0.64 (0.13)
Hourly PM _{2.5} (past 28-35 days)	0.52 (0.10)	0.55 (0.10)	0.55 (0.10)	0.53 (0.18)	0.53 (0.17)
Hourly PM _{2.5} (past 35-42 days)	0.66 (0.10)	0.70 (0.10)	0.68 (0.10)	0.68 (0.15)	0.67 (0.14)
Hourly PM _{2.5} (past 42-49 days)	0.43 (0.10)	0.47 (0.10)	0.47 (0.10)	0.46 (0.17)	0.44 (0.16)
Hourly PM _{2.5} (past 49-56 days)	0.78 (0.11)	0.82 (0.11)	0.82 (0.11)	0.82 (0.20)	0.80 (0.19)
Hourly PM _{2.5} (past 56-63 days)	0.49 (0.09)	0.54 (0.09)	0.51 (0.09)	0.54 (0.16)	0.53 (0.15)
Hourly PM _{2.5} (past 63-70 days)	0.21 (0.08)	0.23 (0.08)	0.21 (0.08)	0.26 (0.11)	0.27 (0.11)
Observations	9,274,063	9,274,063	9,274,063	9,274,063	9,274,063
Dependent variable mean	148	148	148	148	148
KP F-stat	356	357	355	5	6
Year-Month-City FE	Yes	Yes	Yes	No	No
Year-Month FE	No	No	No	Yes	Yes
Month-City FE	No	No	No	Yes	No
Month-Province FE	No	No	No	No	Yes
Year FE	No	No	No	No	No
Moith FE	No	No	No	No	No
City FE	No	No	No	No	Yes
Day of week-City FE	Yes	Yes	Yes	Yes	No
Rainfall quartile-City FE	Yes	No	No	Yes	Yes
Temperature quartile-City FE	Yes	No	No	Yes	Yes
Rainfall decile-City FE	No	Yes	No	No	No
Temperature decile-City FE	No	Yes	No	No	No
Rainfall quartile FE	No	No	Yes	No	No
Temperature quartile FE	No	No	Yes	No	No

Note: This table shows results for column Column 1 in Table 4 with different choices of control variables. See notes in Table 4. Column 1 in this table replicates column 1 in Table 4, and we show results with with different choices of control variables in columns 2 to 5.

Table A.4: Robustness check of HYSPLIT to Choices of Different Starting Heights from South Korea

Dependent variable: Hourly PM _{2.5} in South Korean cities					
	(1)	(2)	(3)	(4)	(5)
Hourly Transboundary PM _{2.5} (from 100m)	0.049 (0.003)				
Hourly Transboundary PM _{2.5} (from 250m)		0.069 (0.002)			
Hourly Transboundary PM _{2.5} (from 500m)			0.100 (0.003)		
Hourly Transboundary PM _{2.5} (from 750m)				0.117 (0.003)	
Hourly Transboundary PM _{2.5} (from 1000m)					0.110 (0.004)
Observations	1553456	1560982	1573289	1585100	1593754
KP F-stat	355	1023	1560	1551	978

Note: Standard errors, clustered by city, are reported in parentheses. All regressions include city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, city-by-temperature quartile fixed effects, and are weighted by city-level population. KP F-stat is Kleibergen-Paap rk Wald F statistic. Sample includes top 50 cities (in terms of number of deaths in 2018) over Mar/2015-Dec/2018.

Table A.5: The Impact of Transboundary Air Pollution on Emergency Room Visits (with and without Controls for Pollen)

Panel A: Reduced-form Estimation						
	Asthma	Asthma	Rhinitis	Rhinitis	Atopic	Atopic
Transboundary PM _{2.5} (past 0-60 days)	28.0 (9.7)	50.0 (10.2)	437.4 (51.4)	482.6 (54.3)	-3.5 (1.5)	-2.8 (1.6)
Observations	235388	235388	235388	235388	235388	235388
Mean of dependent variable	9228.3	9228.3	14053.4	14053.4	363.5	363.5
Marginal effect on ER visits (%)	0.3%	0.5%	3.1%	3.4%	-1.0%	-0.8%
Control for pollens	No	Yes	No	Yes	No	Yes

Panel B: Instrumental Variable Estimation						
	Asthma	Asthma	Rhinitis	Rhinitis	Atopic	Atopic
PM _{2.5} (past 0-60 days)	128.8 (45.7)	214.2 (45.6)	2014.2 (266.0)	2066.7 (258.9)	-16.3 (7.0)	-11.8 (6.7)
Observations	235388	235388	235388	235388	235388	235388
Mean of dependent variable	9228.3	9228.3	14053.4	14053.4	363.5	363.5
Marginal effect on ER visits (%)	1.4%	2.3%	14.3%	14.7%	-4.5%	-3.2%
Control for pollens	No	Yes	No	Yes	No	Yes

Note: This table shows results presented in Table 6 with and without controls for pollen variables. See notes in 6.

Table A.6: Dependent Variable: PM_{2.5} in China at the city-year-month-day level

	(1)	(2)	(3)	(4)
Annual trend	-4.29 (0.12)		-2.52 (0.16)	
Annual trend × in-China ratio	-8.70 (0.98)	-8.69 (0.98)		
Annual trend × Quartile 2 of in-China ratio			-1.71 (0.21)	-1.71 (0.21)
Annual trend × Quartile 3 of in-China ratio			-1.70 (0.28)	-1.71 (0.28)
Annual trend × Quartile 4 of in-China ratio			-3.52 (0.36)	-3.51 (0.36)
N	1328053	1328026	1328053	1328026
Mean of dependent variable	47.83	47.83	47.83	47.83
City FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes

Note: In-China ratio is divided into quartile groups for columns (3) and (4). Quartile 1 has the lowest in-China ratio. Standard errors, clustered by city, are reported in parentheses. Time fixed effect is at the level of year-month-day. All regressions are weighted by city-level population. Sample includes all South Korean cities between January 2015 and December 2019.

Table A.7: Value of remaining life for each age group in South Korea

Age Group	VSL
0 (infant)	509,122
1 – 9	519,632
10 – 19	542,066
20 – 29	569,630
30 – 39	559,651
40 – 49	488,678
50 – 59	366,400
60 – 69	233,030
70 – 79	124,647
80 – 89	57,094
90 – 99	23,995
100 – 109	10,200

Note: The values of remaining life for each group are obtained from Figure 3 in [Murphy and Topel \(2006\)](#). The figure includes values of remaining life by sex for each age between 0 and 110, using the mean VSL value of \$6.3 million. These age-specific VSL estimates are averaged within each age group, divided by the mean VSL value of \$6.3 million, and then multiplied by the average South Korean VSL estimate obtained in 4.1.