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

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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 department 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 the 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.

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1 Introduction

Air pollution is one of the most pressing global challenges that continues to affect many lives worldwide. 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 resulted in 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 still 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. Air pollution emissions from a country are not confined to its borders and affect neighboring nations, which also implies that a country's environmental policy may have international spillover benefits on other countries. International organizations including the World Bank recognize the international spillover effects of air pollution to be the first order problem in economic development (World Bank, 2022). However, the economics literature generally 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 considered while evaluating these policies.

In this study, we investigate the international spillover effects of air pollution and examine the extent to which conventional economic analysis can understate the cost of air pollution as well as the benefits of environmental regulations. Our framework integrates recent advances in atmospheric science into econometric estimation with microdata on mortality and health. Specifically, we obtain data on hourly particle trajectories from China to South Korea using the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT).[2] Combining these particle trajectory data with hourly $PM_{2.5}$ data in China and South Korea, we estimate how transboundary $PM_{2.5}$ from China affects $PM_{2.5}$ in South Korea.[3] We then connect

[1] In addition to air pollution, the uncontrolled spread of wildfires significantly impacts human safety and damages properties (Baylis and Boomhower, 2023).

[2] Although outside the context of international spillovers, a growing number of recent economics studies use HYSPLIT to analyze air pollution (Hernandez-Cortes and Meng, 2023; Fowlie, Rubin and Wright, 2021).

[3] $PM_{2.5}$ refers to fine particles in the air that are two and one half microns or less in width.

these data with the universe of individual-level mortality data and emergency department visit data in South Korea to quantify the mortality and health impacts of transboundary air pollution.

We begin by presenting descriptive and visual evidence that transboundary air pollution from China is likely to play a significant role in $PM_{2.5}$ in South Korea. In East Asia, fall and winter are known as the seasons characterized by prevailing west wind, called "the westerlies," as a result of which, South Korea receives persistent west winds 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, these regions have similar $PM_{2.5}$ levels in 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 in South Korea, such as Incheon and Seoul, have trajectories coming from China more than half of the times in our sample period. By contrast, cities in the southeast, such as Busan, experience trajectories from China at a lower frequency.

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, on average, a 1 $\mu g/m^3$ increase in transboundary $PM_{2.5}$ from China results in a 0.122 $\mu g/m^3$ increase in $PM_{2.5}$ in South Korean cities. 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 $\mu g/m^3$ 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 of 31.2 per million people). This effect implies a 0.6% increase in mortality with respect to a 1 $\mu g/m^3$ increase in transboundary $PM_{2.5}$, relative to the baseline mortality rate for this population.

In addition to the mortality impact on the overall population, we also estimate the impacts on 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 $\mu g/m^3$ 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 the contemporaneous and lagged transboundary $PM_{2.5}$ affect mortality, although the lagged effects diminish at 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 $\mu g/m^3$ increase in $PM_{2.5}$ in the past 70 days results in an increase in hourly mortality by 9.09 per billion people for the overall population. This effect implies an increase in annual mortality of 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).

Besides 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 $PM_{2.5}$ from China to South Korea may increase such symptoms in the South Korean population. To investigate this issue, we collected data on the universe of emergency department (ED) visits in South Korea between 2013 and 2017 for patients who received medical treatment in the ED for atopic dermatitis, rhinitis, or asthma. We find that transboundary $PM_{2.5}$ results in increased ED visits for asthma and rhinitis but atopic dermatitis. The reduced-form results imply that a 1 $\mu g/m^3$ increase in transboundary $PM_{2.5}$ from China to South Korea results in an increase in daily ED visits by 50.0 and 482.6 per billion people (or annual ED visits by 18.3 and 176.1 per 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 regulations may have international spillover effects on other countries. However, these spillover effects have 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). Since 2014, the Chinese government has rolled out a nationwide air pollution reduction program. Our data suggest that $PM_{2.5}$ in China had a long-run decline during our sample period. Our data also show that this reduction resulted in a decline in transboundary $PM_{2.5}$ from China to South Korea. Based on the data we obtained from the HYSPLIT model, we find that transboundary $PM_{2.5}$ from China to South Korea declined by 9.63 $\mu g/m^3$ 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 $\mu g/m^3$ reduction in transboundary $PM_{2.5}$ from China to South Korea implies a 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 their 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 transboundary rivers (Sigman, 2002; Lipscomb and Mobarak, 2016; Wang and Wang, 2021; He, Wang and Zhang, 2020). To the best of our knowledge, such strategic allocation of pollution has not yet been investigated for air pollution. However, in theory, it is possible to observe such a phenomenon for air pollution. If China made such a strategic decision during the war on pollution, China may have been primarily focused on reducing air pollution more for its citizens and less for those who live in other countries, thus potentially lowering the potential international spillover benefits.

We indeed find empirical evidence of China's strategic reductions in air pollution during the war on pollution. We show that the reduction in $PM_{2.5}$ during our sample period was 9.29 $\mu g/m^3$ in Chinese cities from which most air pollution has gone outside the national border. This reduction in $PM_{2.5}$ is lower than the nationwide average reduction (14.07 $\mu g/m^3$) and much lower than the reduction in Chinese cities from which most air pollution has remained within China (18.32 $\mu g/m^3$). This strategic pollution reduction implies that the international spillover benefits our analysis revealed may have been lower than a counterfactual scenario in which such a strategic decision was absent or China and South Korea employed 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 researchers find it 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 integrating them with the universe of mortality and ED visit data in South Korea.

Second, our study expands on the findings of recent studies that use detailed data on air pollution, mortality, and health to estimate the mortality and health impacts 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 Medicare data with wind direction as an instrumental variable. Both these papers and our study connect microdata on mortality or health outcomes with detailed data on air pollution. Our study differs from these previous studies 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 on the international spillovers of environmental externalities. In the economics literature, the focus of this topic has been primarily on 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 is more difficult 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 remains within the country borders than in cities where most air pollution travels beyond the national boundaries. Based on this finding, we provide implications for the potential Coasian bargaining for transboundary air pollution.

Finally, our framework benefits from recent advancements in atmospheric science. Many recent studies in atmospheric science use HYSPLIT or similar models to obtain particle trajectories (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 transbounadry 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 $PM_{2.5}$ at the city level that are regionally interpolated from real-time observations made by ground-level monitoring stations. The air pollution data provide good coverage of $PM_{2.5}$ concentrations in China, as shown in Figure A.3.[4]

Hourly $PM_{2.5}$ concentrations in South Korean cities are obtained from the 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 National Institute of Environmental Research in South Korea collects data from 153 monitors, with records dating back to 2001. 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.[5]

Figure 1 provides suggestive evidence that transboundary air pollution from China may play a significant role in the $PM_{2.5}$ levels in South Korea. It 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 two regions: northwest (i.e., regions closer to China) and southeast (i.e., regions relatively far from China) to examine how $PM_{2.5}$ in China correlate differently with $PM_{2.5}$ in the northwest and southeast regions in South Korea.

[Figure 1 about here]

The figure suggests that $PM_{2.5}$ in China persistently declined during our sample period. Many previous studies find that a large part of this reduction is attributable to aggressive environmental regulation implemented in China, known as "the 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 $\mu g/m^3$.

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 in summer and spring. This is because heating in fall and winter is a major source of air

[4] The air pollution data are available at the Berkeley Earth website: http://berkeleyearth.org. Accessed February 10, 2022.
[5] Data is available at AirKorea, a webpage operated by Korea Environment Corporation: https://www.airkorea.or.kr/web.

pollution in China (Ito and Zhang, 2020). In East Asia, fall and winter are also known to be seasons when the prevailing west winds 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, the wind blows from west to east in over 70% of the time in fall and winter. The wind speed is also stronger in fall and winter than in spring and summer (Figure A.2).

The combination of the higher $PM_{2.5}$ in China and the seasonal westerlies could explain why systematic deviations in $PM_{2.5}$ exist between the northwest and the southeast regions of South Korea only in fall and winter. The $PM_{2.5}$ levels are similar in the northwest and the southeast regions during spring and summer. By contrast, the northwest region has substantially higher $PM_{2.5}$ levels than the southeast region in fall and winter, in which the $PM_{2.5}$ levels in China tend to be high and the area is prone to persistent westerlies. In the next section, we provide a 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 examining international spillovers of air pollution. However, 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 to use the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT) 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 particle trajectories to determine the distance and locations to which particles travel. The model can also trace emitted radioactive material, wildfire smoke, dust, and other pollutants.[6]

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, while the backward

[6]There are various atmospheric transport models that can simulate pollution dispersion. We choose HYSPLIT, because it is both reliable and computationally tractable, which makes it the 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 only 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.

[7]For the meteorological data, we use the NCEP/NCAR reanalysis data. Further details are available in Appendix A.

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 can be used to analyze the effect of emissions from a point source such as a factory or a volcano. On the other hand, backward trajectories help 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 from HYSPLIT using Seoul as an example to plot backward trajectories for three different hours. For instance, the red line shows the backward trajectory that arrived at Seoul at 8 pm on June 15, 2015. HYSPLIT provides data on the particle trajectory's 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 hourly trajectories $\times$ 365 days $\times$ 5 years $\times$ 228 cities in South Korea). While this is a computationally-intensive data collection, parallel computing allows us to obtain millions of trajectories in about a week.

[Figure 2 about here]

In Figure 3, we present how often South Korean cities have backward trajectories from China. For each city in South Korea, we calculate the percentage of hours in which the city had trajectories originating 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 time in our sample period. By contrast, cities in the southeast, such as Busan, have significantly fewer frequency of trajectories from China.

[Figure 3 about here]

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

[8] We 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.

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 South Korean city. We find higher fractions of trajectories coming from the northeastern part of mainland China, particularly the Liaoning Province owing to 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 affect South Korean cities.

[Figure 4 about here]

We also investigate how many hours each trajectory takes to travel from China to South Korea. For each trajectory that went from China to a South Korean city, we observe how many hours it took to move from the last grid point in China to the city in South Korea. We present the distribution of this duration in Figure A.5. The median is 38 hours, and there is 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 direct information on each trajectory from HYSPLIT and that commonly-used indirect approaches (e.g. using average air pollution in China one or two days ago as a proxy for transboudnary air pollution) may not be able to accurately capture transboundary air pollution.[9]

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

The particle trajectory data by itself does not uncover how transboundary air pollution affects local air pollution in South Korea. Our idea is that we can empirically estimate this relationship by regressing the local hourly PM$_{2.5}$ levels in South Korean cities on TransboundaryPM$_{ct}$ with and without control variables. In section 3.1, we find a strong systematic relationship between these two variables and demonstrate that this relationship is robust to the inclusions of various fixed effects and control variables.[10]

[9] This distribution also suggests 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.

[10] In the HYSPLIT, we need to specify the starting height of the backward trajectories. We follow the literature in atmospheric

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 Department Visits in South Korea

We obtain data on emergency department (ED) visits in South Korea between 2013 and 2017 for patients admitted due to atopic dermatitis, rhinitis, or asthma. The National Health Insurance Service (NHIS) in South Korea provides data on all ED admissions at the district and daily level. 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 levels. The data are collected from 612 ground-level monitors, including automated synoptic observing stations and automatic weather stations, installed to gain a wide coverage on weather conditions in South Korea. Figure A.4 displays their coverage.

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 geographic information systems (GIS), three-dimensional visualization, and deep learning.[12]

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science to use 500 meters for our main results and examine their robustness in Table A.4. The results in Table A.4 suggest that they are robust to heights over 500 meters and that the Kleibergen-Paap rk Wald F-statistic is highest with 500 meters. Similarly, we need to specify the heights of the trajectories in China (the height at the origin of the backward trajectory) to determine the origin of the trajectory. Studies in atmospheric science use a height of 1,000 meters, and we find that indeed this height at the origin produces the highest Kleibergen-Paap rk Wald F-statistic in our first stage regression.

[11] Data are available at MDIS: https://mdis.kostat.go.kr.

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

2.6 Summary Statistics

Table 1 provides the summary statistics. The average $PM_{2.5}$ in our sample period is 45.05 $\mu g/m^3$ in China and 24.99 $\mu g/m^3$ 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 comes from China. The average of this variable (0.39) indicates that 39% of the trajectories came from China in our sample period. The mortality data suggest that approximately 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 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 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 $\text{TransboundaryPM}_{ct}$ 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:

$$\text{PM}_{ct} = \alpha \text{TransboundaryPM}_{ct} + X_{ct}\gamma + u_{ct}, \tag{1}$$

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 not correlated 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 $\text{TransboundaryPM}_{ct}$ to non-parametrically examine the relationship between these two variables. Panel A shows the binned scatter plot of the raw data without controls. We use 1 $\mu\text{g/m}^3$ of $\text{TransboundaryPM}_{ct}$ as the bin size to calculate the average PM_{ct} for each bin. The figure suggests a strong relationship between the two variables that is close to linear. In Panel B, we residualize these variables 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. We find that the relationship between PM_{ct} and $\text{TransboundaryPM}_{ct}$ 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, on average, a 1 $\mu\text{g/m}^3$ increase in transboundary $\text{PM}_{2.5}$ from China on average results in a 0.122 $\mu\text{g/m}^3$ increase in $\text{PM}_{2.5}$ in South Korean cities. The Kleibergen-Paap rk Wald F-statistic is 5,812, 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:

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

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 $j = 1, ..., J$. These coefficients estimate the short- and medium long-run effects of transboundary air pollution on mortality. We include the same set of fixed effects and control variables—those 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 one $\mu g/m^3$ increase in transboundary $PM_{2.5}$ from China in the past 70 days results in a 3.56 per billion people increase in hourly mortality in South Korea. 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 $\mu g/m^3$ 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 $\mu g/m^3$ increase in transboundary $PM_{2.5}$ in the past 70 days results in a 31.2 per million people increase in annual mortality.

[Table 3 about here]

In addition to the overall population, we also provide results for the elderly (ages 65 and above), infants (ages 1 and under), 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 $\mu g/m^3$ 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 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 useful to examine the possibility of the "harvesting effect" frequently discussed in the

[13] We show the results with 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 70 days in Panel B.

[14] Deryugina, 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."

literature (Deschenes and Moretti, 2009). The harvesting effect implies that air pollution may not cause more total deaths 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 even in the absence of air pollution. Therefore, previous studies suggest that researchers estimate either the longer-run average effect (such as our Panel A) or the series of lagged effects jointly with the contemporaneous 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 $PM_{2.5}$ levels 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 variable (IV) estimation is that given the set of control variables included in the estimation, transboundary $PM_{2.5}$ affects mortality only through $PM_{2.5}$.

We estimate the following equation using the IV regression:

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

We use $\text{TransboundaryPM}_{c,t-j}$ as an instrumental variable for $\text{PM}_{c,t-j}$, 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.

Table 4 presents the estimation results of Equation (3). The last column of Panel A indicates that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ in the past 70 days results in a 9.09 per billion people increase in hourly mortality for the overall population. This implies a 79.7 per million people increase in annual mortality and a 1.5% increase in mortality relative to the mean. The marginal effect in terms of a percentage 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. We can compare our IV estimate to recent estimates of the mortality impacts of $PM_{2.5}$ in other contexts and discuss what makes these estimates similar or different. 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 with wind direction as an instrument. They find that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ exposure for one day causes 0.69 additional deaths per million elderly individuals over a three-day window that spans the day of the increase and the following two days. Panel B in our Table 4 suggests that the contemporaneous marginal effect of $PM_{2.5}$ on the elderly is a 4.05 per billion people increase in hourly mortality, which implies a 0.29 per million people increase in three-day mortality.[15] This implies that the magnitude of our IV estimate is similar to but slightly smaller than the IV estimate in Deryugina, Heutel, Miller, Molitor and Reif (2019). There are several possible explanations for this difference. First, the two studies use different instrumental variables and thus 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 in the United States, which could make them relatively less vulnerable to exposure to $PM_{2.5}$.[16]

3.4 Mortality Impacts by Age Group

The impact of air pollution on mortality can substantially differ across ages. Such heterogeneity is important to quantify for our analysis of policy implication in Section 4. To estimate the heterogeneous effects 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 aged 1–29

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

[16] Another possibility is that the harmfulness of $PM_{2.5}$ can differ between two locations because the toxicity of the small particles could vary. For example, Hsiang, Lee and Wilson (2022) find empirical evidence that supports this possibility.

years. Note that the baseline mortality is low for those between 1–29 years, which could make statistically detecting the impact relatively more challenging.

[Table 5 about here]

The marginal effect on mortality in terms of percentage 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 Department Visits

In addition to its impact on mortality, air pollution may 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 using data on daily emergency department (ED) visits. The outcome variable is the number of ED 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 seasonal pollen (oak, pine, and weed) is also known to be related to the ED visits in South Korea, we include these three variables as additional controls in our estimation but find that including these controls does not substantially change our estimates as shown in Table A.5.

[Table 6 about here]

Results in Table 6 suggest that transboundary $PM_{2.5}$ results in increases in ED visits for asthma and rhinitis. We do not find such an impact on atopic dermatitis. The reduced-form results imply that a 1 $\mu g/m^3$ increase in transboundary $PM_{2.5}$ from China to South Korea results in increases in daily ED visits of 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 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). In 2014, the Chinese government began to roll out a nationwide air pollution reduction program. As shown in Figure 1, our data suggest that $PM_{2.5}$ levels in China exhibited 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 $\mu g/m^3$ during our sample period (2015–2019).

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 $\mu g/m^3$ 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 arising 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 differ 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. Therefore, we 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; 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

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

obtain VSL estimates for each age group.[18] We present the age-specific VSLs obtained from this approach in Table A.7.

In Table 7, we present the result of this calculation in the first row. We find that a 9.63 $\mu g/m^3$ reduction in transboundary $PM_{2.5}$ from China to South Korea implies an 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 by strategically allocating 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, but 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 to reduce air pollution for "the war on pollution," it 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 HYSPLIT to calculate the "in-China ratio" of the air pollution trajectories for each of 783 cities in China. We obtain the in-China ratio using the following approach. For each city, day, and hour, we use HYSPLIT to obtain forward trajectories of air pollution. We then compute the in-China ratio based on the number of foward trajectories that stayed within China divided by the total number of trajectories. We consider that a pollution trajectory stayed within China if the trajectory remained inside

values are $630, $520, and $383 thousand in 2019 US dollars, respectively.

[18] Figure 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 latitude and longitude boundaries of China or if its height is persistently below 1 km from 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 $PM_{2.5}$ leves relative to 2015 among the four groups. The figure suggests that the first quartile group experienced a reduction in $PM_{2.5}$ by 9.29 $\mu g/m^3$, which is similar to the reduction in transboundary $PM_{2.5}$ levels for South Korea (9.63 $\mu g/m^3$). By contrast, the fourth quartile group had a $PM_{2.5}$ reduction of 18.32. In Table A.6, we show that these differences in $PM_{2.5}$ reductions 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 to reduce air pollution for "the war on pollution." Consequently, 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 a 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 measuring 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 the potential benefit from this bargaining. 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 China reduced its transboundary $PM_{2.5}$ by 14.07 $\mu g/m^3$, which was the average reduction in $PM_{2.5}$ levels 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 can consider a scenario in which China reduced its transboundary $PM_{2.5}$ by 18.32 $\mu g/m^3$, 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 may be many other obstacles to employ 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]

[19]The average $PM_{2.5}$ level in China during our sample period was 45.05 $\mu g/m^3$, 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 $\mu g/m^3$ for the annual mean).

5 Conclusion

In this study, 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 department 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 their implications for the potential Coasian bargaining.

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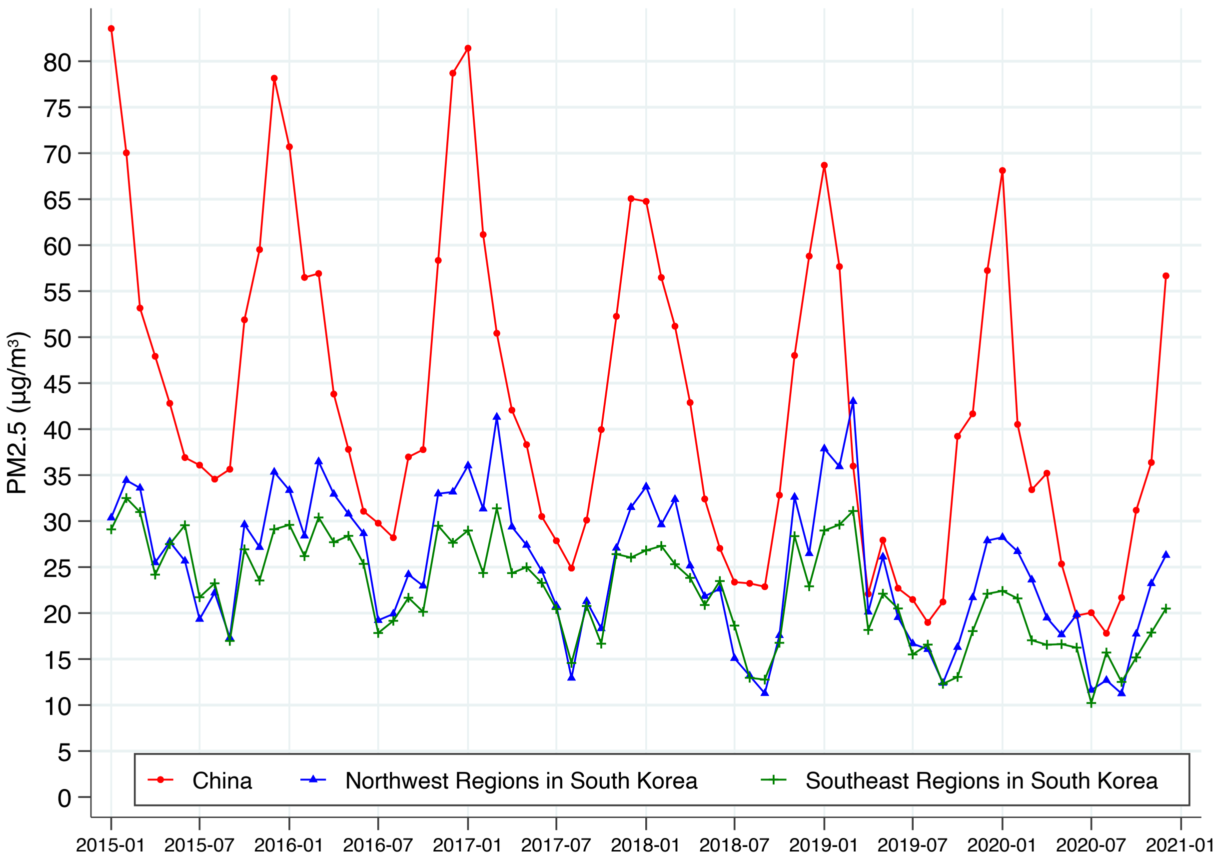
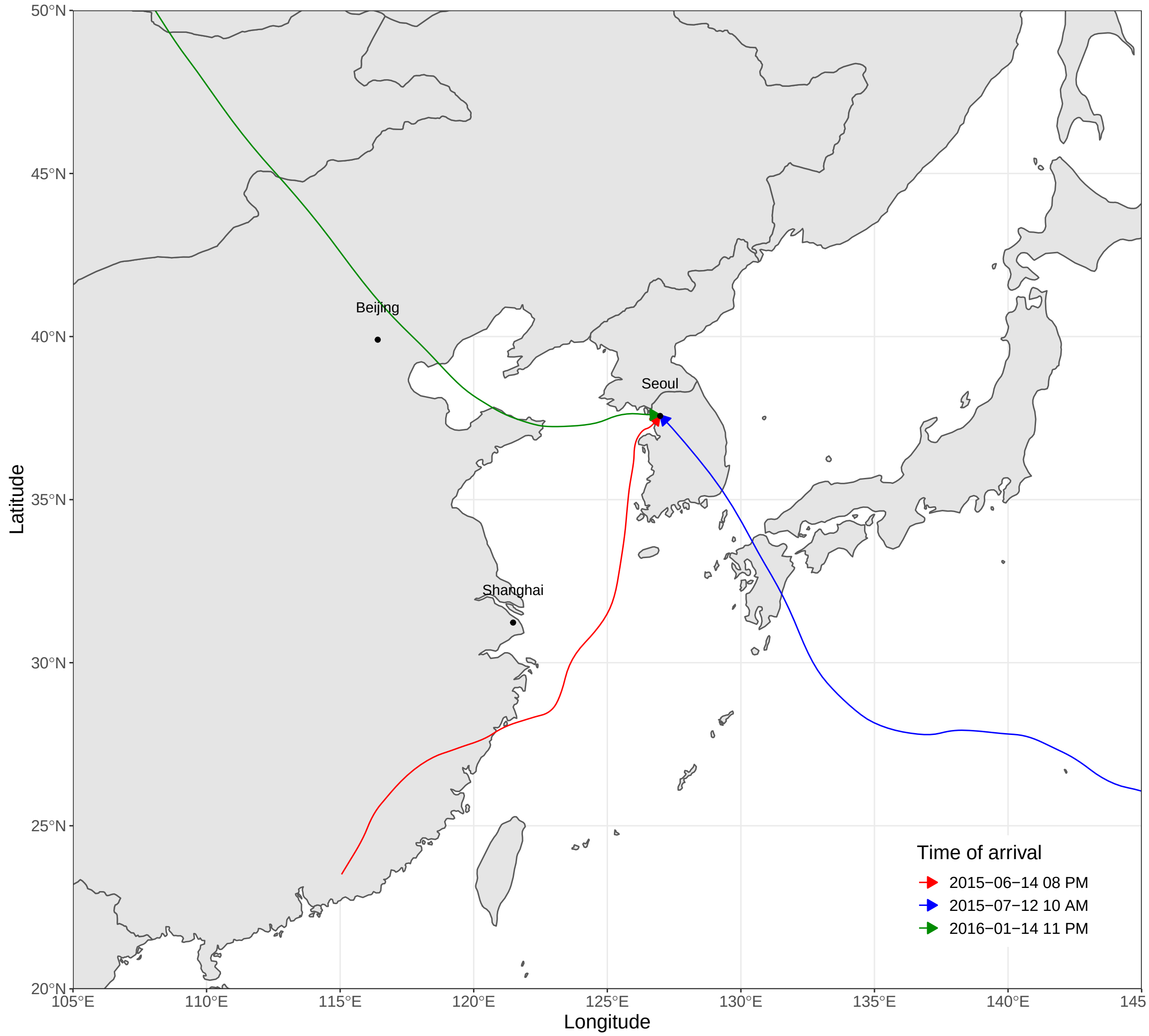
Figures

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



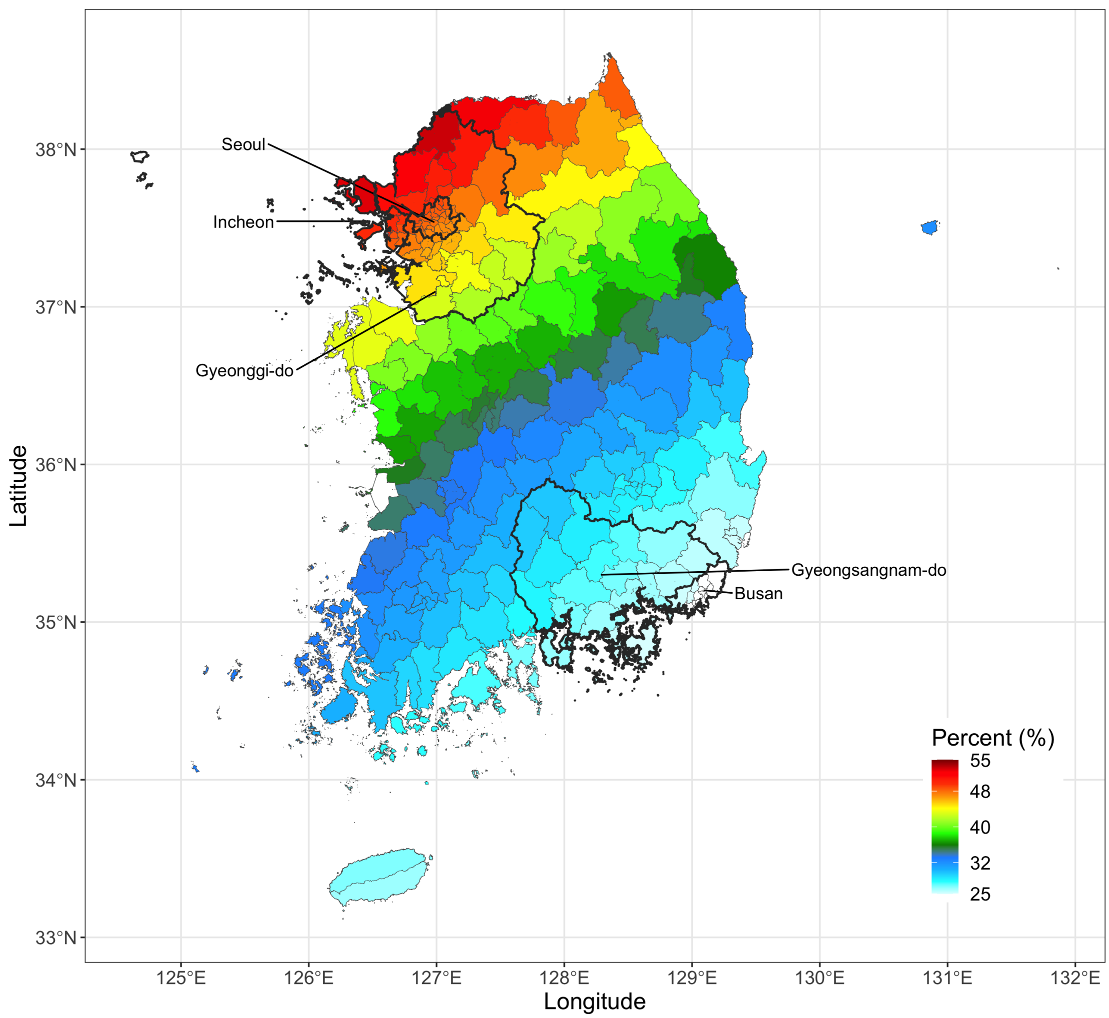
Note: This figure illustrates the evolution of monthly average hourly PM 2.5. The Northwest region in South Korea is defined as cities in South Korea that have more than or equal to 35% of frequency of trajectories coming from China in Figure 3. The Southwest region in South Korea is defined as cities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

Figure 2: Examples of Backward Trajectories



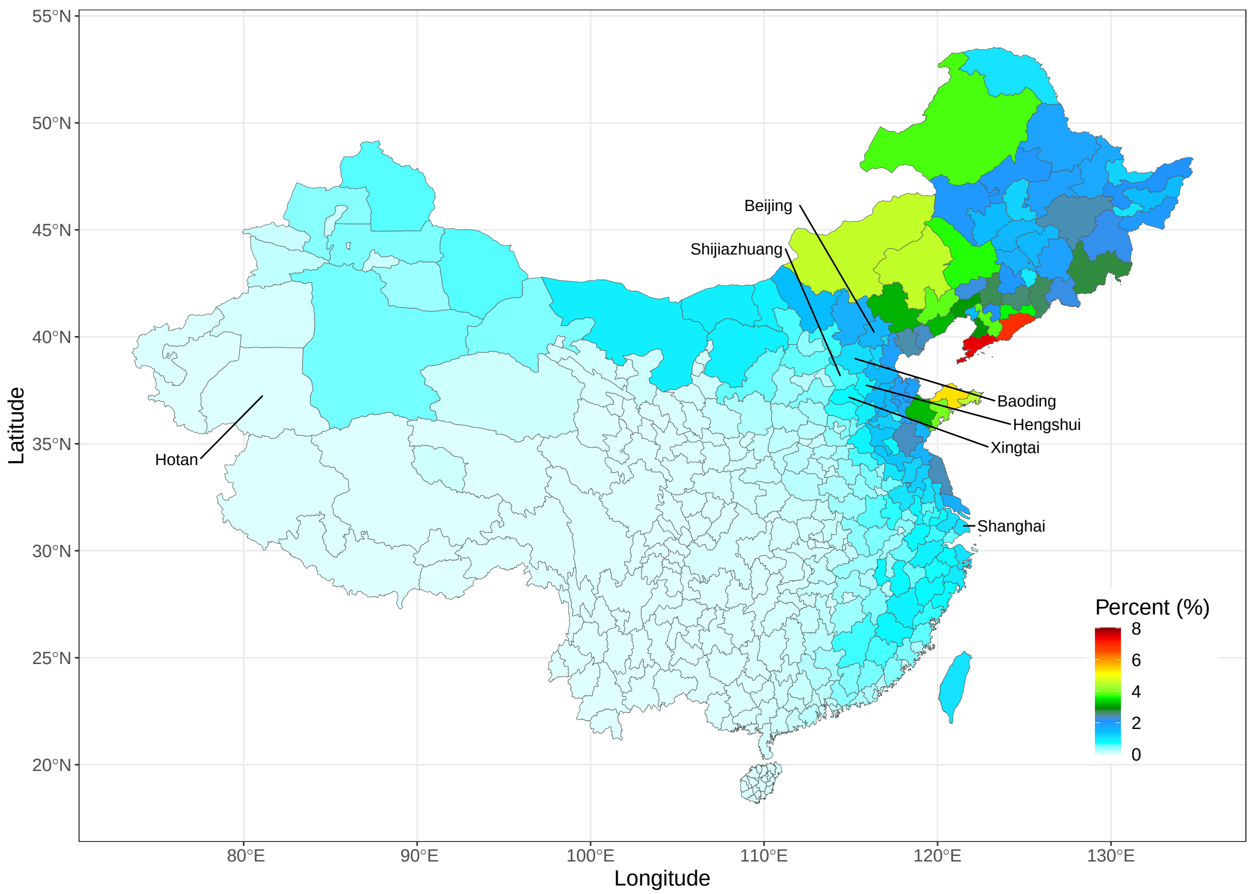
Note: This figure shows three examples of the backward trajectories obtained from HYSPLIT. For example, the green trajectory came from northern China, passed through Beijing, and reached Seoul at 11 pm on January 14, 2016.

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.

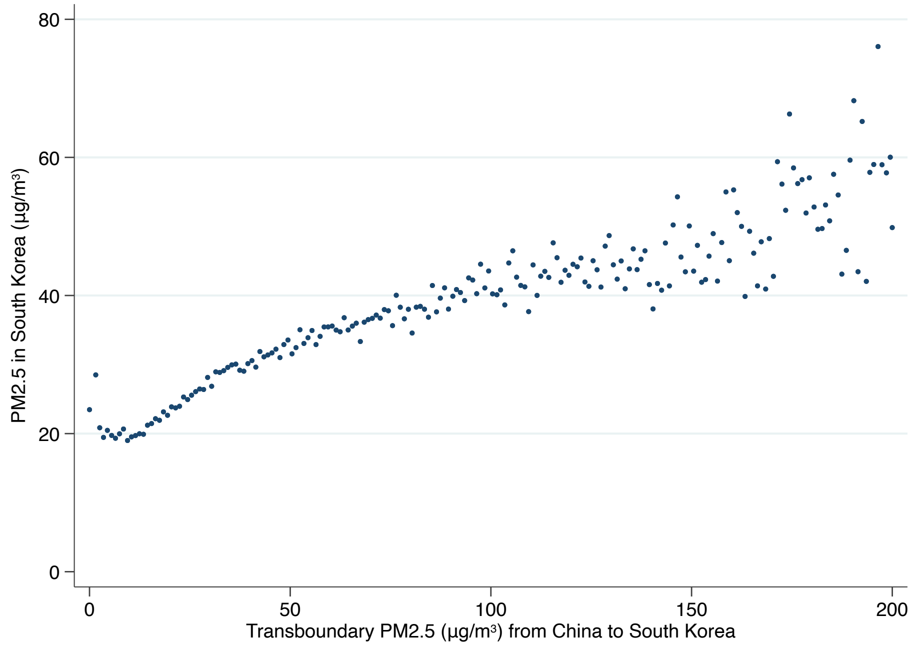
Figure 4: Paths of Trajectories that Traveled Through China and Reached South Korea



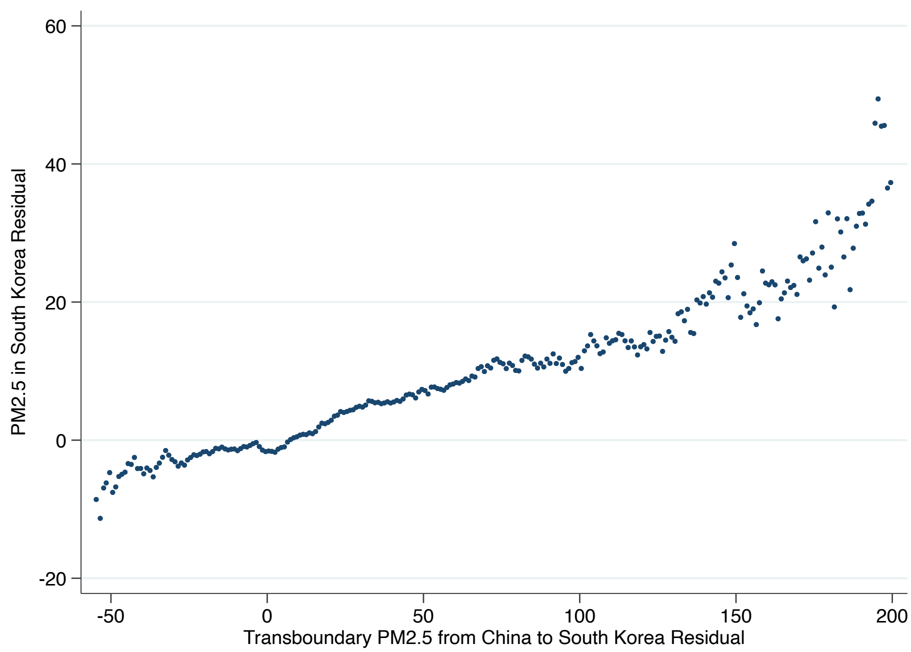
Note: This figure shows how often each city in China had a trajectory that passed the city and reached South Korea. For each city in South Korea, we use the HYSPLIT model to obtain backward trajectories for each day-hour during our sample period (January 2015 to December 2019). We then compute how often 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

Panel A: Raw data

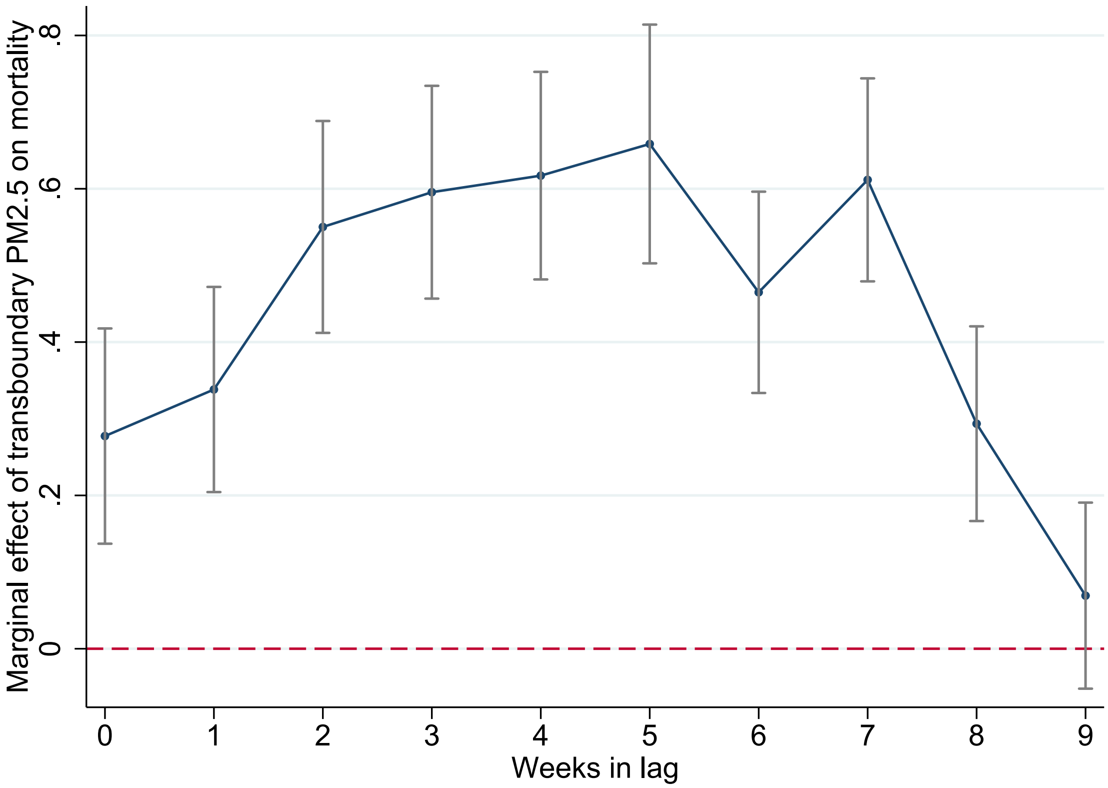


Panel B: Residuals



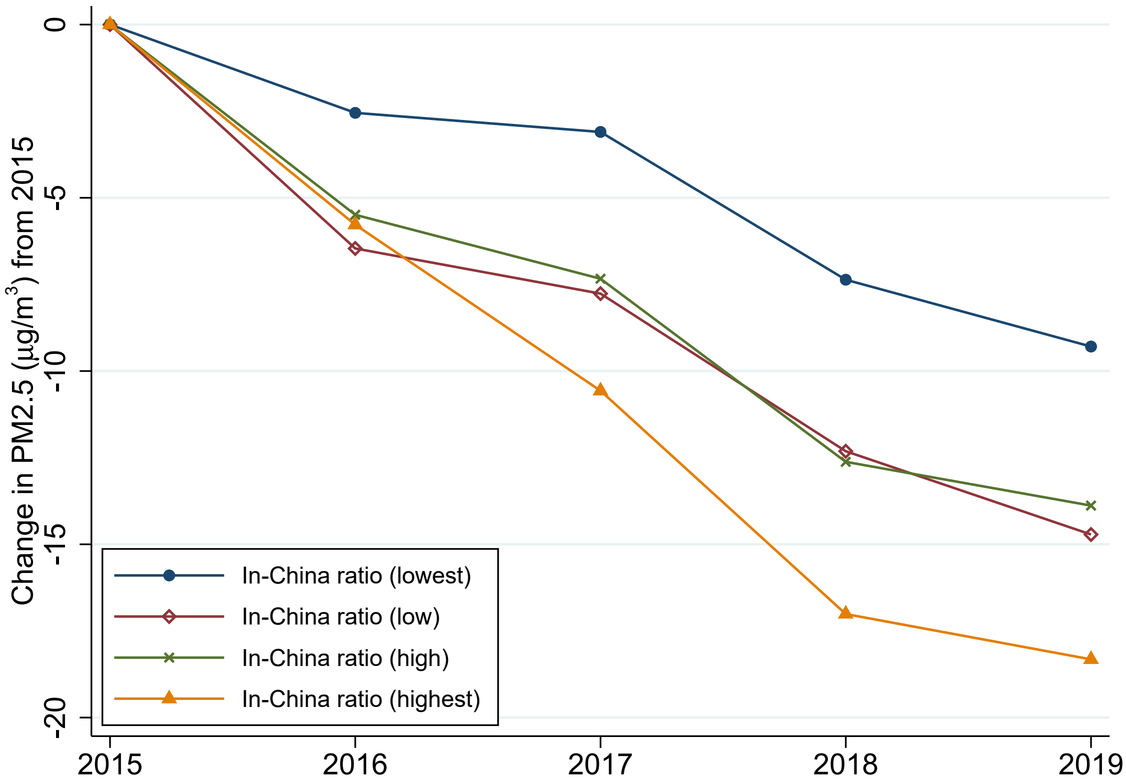
Note: Panel A plots the mean of PM 2.5 within each bin against bins of transboundary PM 2.5 with bins of size 1. Panel B plots the mean of residuals (from a regression of PM 2.5 in South Korea on city-by-year-by-month fixed effects, city-by-day of week fixed effects, city-by-rainfall quartile fixed effects, 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
$PM_{2.5}$ ($\mu g/m^3$) in Chinese cities	45.05	38.40
$PM_{2.5}$ ($\mu g/m^3$) in Korean cities	24.99	18.06
Transboundary $PM_{2.5}$ ($\mu g/m^3$) 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 ($^\circ$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	0.129	0.129	0.129	0.122
	(0.003)	(0.002)	(0.002)	(0.002)	(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	19.00	6.68	3.56
	(0.17)	(2.17)	(3.33)	(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	1.35	0.90	0.28
	(0.04)	(0.48)	(0.58)	(0.07)
Transboundary $PM_{2.5}$ (past 7-14 day)	0.21	1.93	0.37	0.34
	(0.03)	(0.47)	(0.64)	(0.07)
Transboundary $PM_{2.5}$ (past 14-21 day)	0.25	3.16	2.02	0.55
	(0.04)	(0.45)	(0.64)	(0.07)
Transboundary $PM_{2.5}$ (past 21-28 day)	0.25	3.59	-0.36	0.60
	(0.03)	(0.46)	(0.59)	(0.07)
Transboundary $PM_{2.5}$ (past 28-35 day)	0.23	3.61	1.18	0.62
	(0.04)	(0.49)	(0.70)	(0.07)
Transboundary $PM_{2.5}$ (past 35-42 day)	0.27	3.81	0.10	0.66
	(0.04)	(0.51)	(0.69)	(0.08)
Transboundary $PM_{2.5}$ (past 42-49 day)	0.14	2.41	1.21	0.46
	(0.03)	(0.44)	(0.75)	(0.07)
Transboundary $PM_{2.5}$ (past 49-56 day)	0.22	3.50	0.87	0.61
	(0.03)	(0.45)	(0.70)	(0.07)
Transboundary $PM_{2.5}$ (past 56-63 day)	0.12	1.74	0.42	0.29
	(0.03)	(0.40)	(0.57)	(0.06)
Transboundary $PM_{2.5}$ (past 63-70 day)	0.09	-0.09	0.67	0.07
	(0.03)	(0.42)	(0.64)	(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	48.60	17.44	9.09
	(0.47)	(5.72)	(8.63)	(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	4.05	2.08	0.78
	(0.10)	(1.37)	(1.63)	(0.21)
$PM_{2.5}$ (past 7-14 days)	0.52	3.68	0.24	0.69
	(0.09)	(1.27)	(1.67)	(0.19)
$PM_{2.5}$ (past 14-21 days)	0.62	7.10	5.15	1.23
	(0.12)	(1.42)	(1.96)	(0.22)
$PM_{2.5}$ (past 21-28 days)	0.67	8.24	-1.41	1.37
	(0.11)	(1.52)	(1.77)	(0.23)
$PM_{2.5}$ (past 28-35 days)	0.52	7.88	3.48	1.31
	(0.10)	(1.35)	(1.83)	(0.20)
$PM_{2.5}$ (past 35-42 days)	0.66	9.77	0.12	1.63
	(0.10)	(1.29)	(1.66)	(0.20)
$PM_{2.5}$ (past 42-49 days)	0.43	7.50	3.01	1.37
	(0.10)	(1.32)	(1.94)	(0.21)
$PM_{2.5}$ (past 49-56 days)	0.78	13.01	3.78	2.23
	(0.11)	(1.37)	(2.22)	(0.23)
$PM_{2.5}$ (past 56-63 days)	0.49	8.94	1.12	1.42
	(0.09)	(1.20)	(1.74)	(0.20)
$PM_{2.5}$ (past 63-70 days)	0.21	-0.03	2.11	0.20
	(0.08)	(1.12)	(1.61)	(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	0.18	-0.14	0.04	0.94	0.61
	(3.33)	(0.17)	(0.19)	(0.26)	(0.32)	(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	4.60	13.85	39.63	110.42	185.48
	(0.73)	(1.23)	(2.64)	(7.78)	(31.68)	(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	0.46	-0.35	0.09	2.43	1.61
	(8.63)	(0.43)	(0.49)	(0.66)	(0.82)	(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	11.62	35.13	101.91	285.67	467.04
	(1.92)	(3.20)	(6.75)	(20.52)	(81.68)	(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 Department Visits

Panel A: Reduced-form Estimation

	Asthma	Rhinitis	Atopic
Transboundary PM $_{2.5}$ (past 0-60 days)	50.0	482.6	-2.8
	(10.2)	(54.3)	(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	2066.7	-11.8
	(45.6)	(258.9)	(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 2017. The dependent variables are the numbers of daily ED 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 $\mu g/m^3$	2.62	0.12	0.04	1.50	0.97
Counterfactual Scenario 1:					
Reduction of Transboundary $PM_{2.5}$ by 14.07 $\mu g/m^3$	3.83	0.18	0.05	2.19	1.41
Counterfactual Scenario 2:					
Reduction of Transboundary $PM_{2.5}$ by 18.3 $\mu g/m^3$	4.98	0.23	0.07	2.85	1.83

Note: This table shows the internaitonal spillover benefits of reudctions 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 a 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 $\mu g/m^3$). The first counterfactual scenario is based on the national-average pollution reduction in China during our sample period (14.07 $\mu g/m^3$), and the second counterfactual scenario is based on the pollution reduction in Chinese cities where most air pollution remained within China (18.3 $\mu g/m^3$).

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:

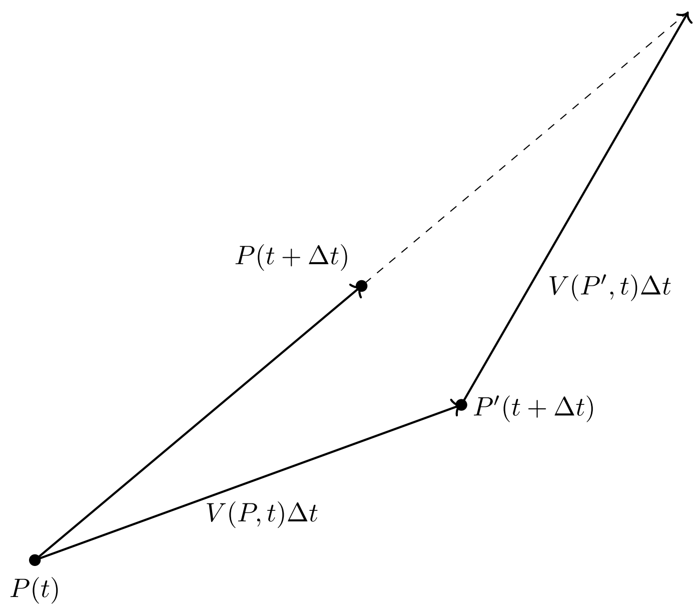
$$P(t + \Delta t) = P(t) + \frac{V(P,\ t) + V(P',\ t + \Delta t)}{2} \cdot \Delta t.$$

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

[20]The 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.

[21]For 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 $2.5° \times 2.5°$ 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 hourly trajectories/day $\times$ 365 days/year $\times$ 5 years $\times$ 228 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^1_{ct} 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^2_{ct} is constructed by interacting Z^1_{ct} 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^2_{ct} 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

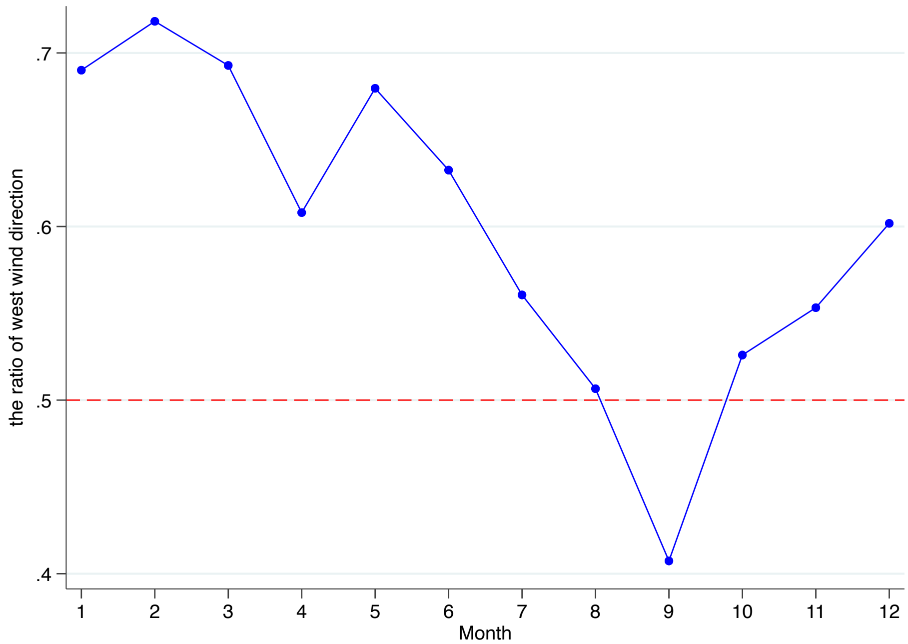
In this online appendix, we provide additional figures and tables from our analysis.

List of Figures in Appendix

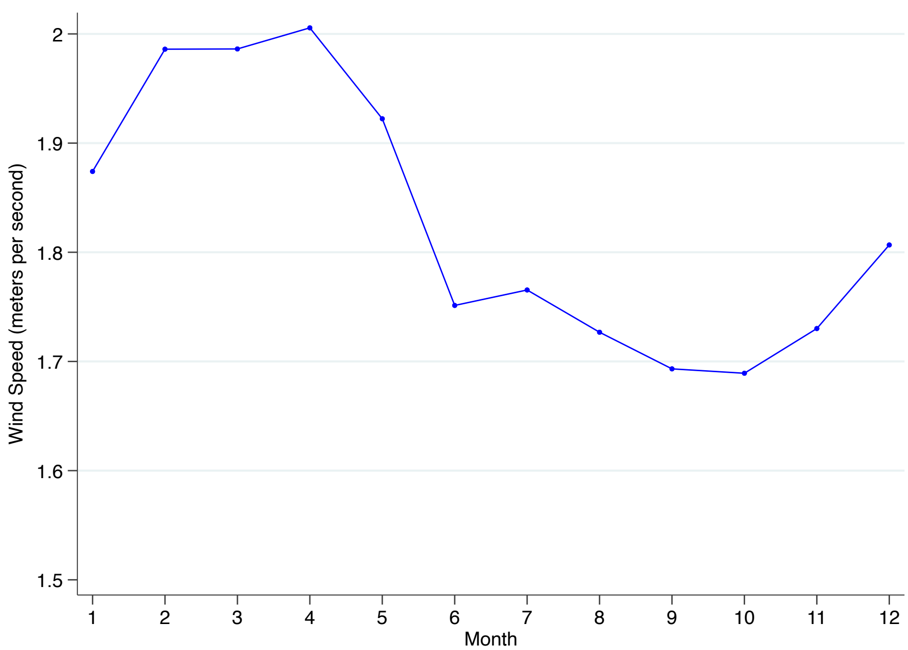
List of Tables in Appendix

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

Panel A: Ratio of West Wind



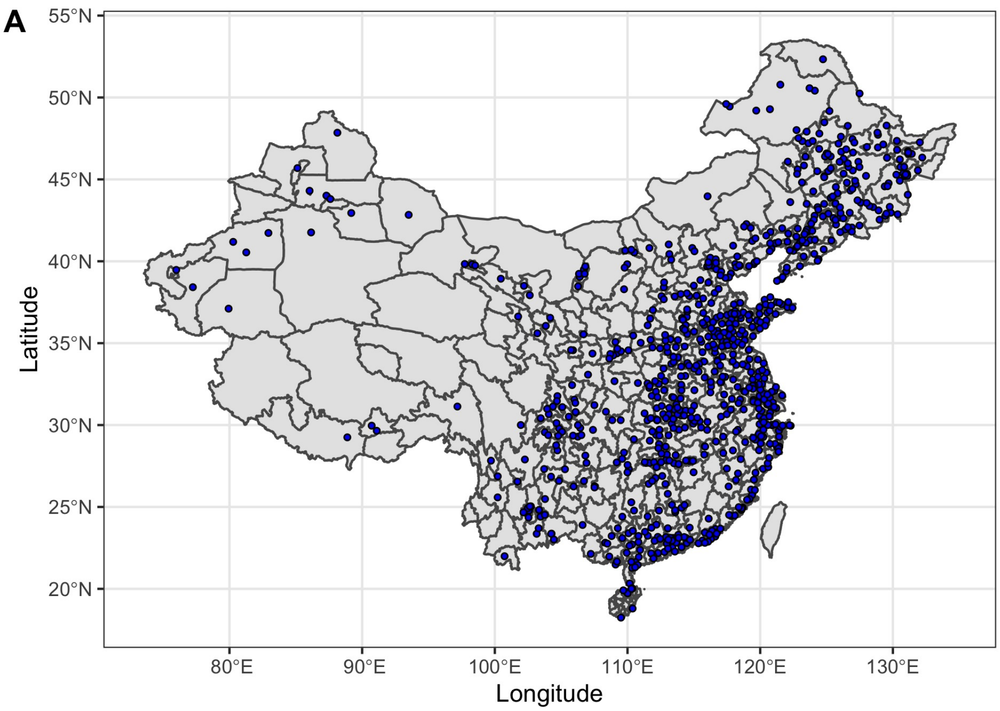
Panel B: Wind Speed



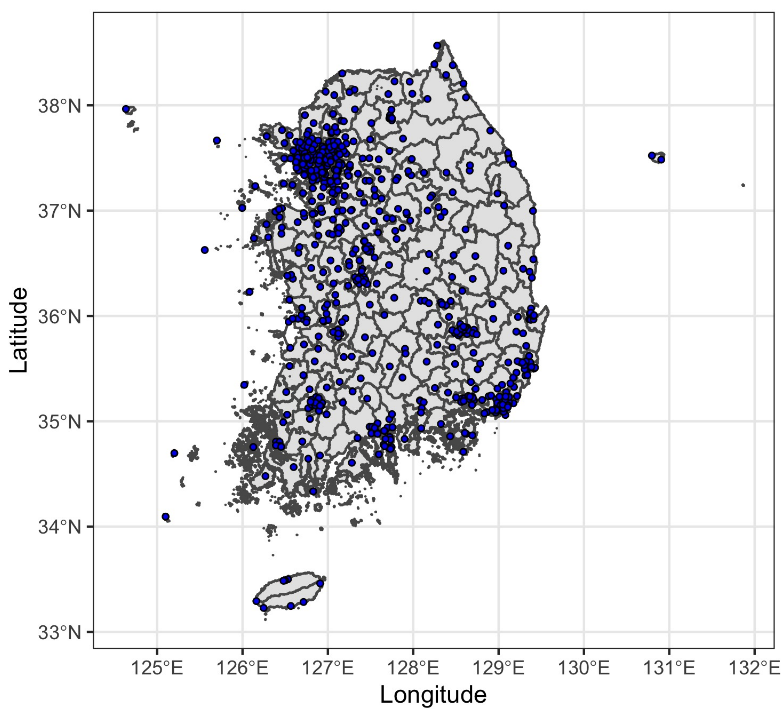
Note: The figure shows monthly percentage of each west wind direction in Seoul. Sample includes all South Korean cities between January 2015 and December 2019.

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

Panel A

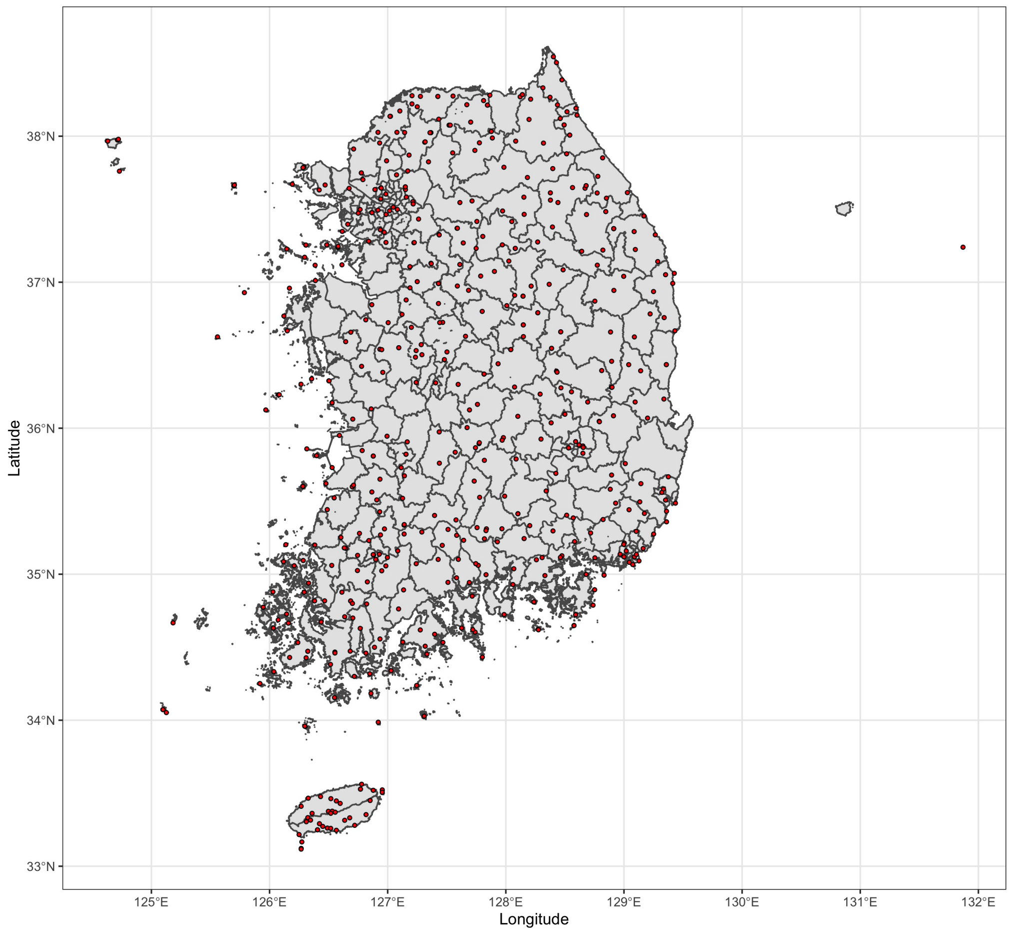


Panel B



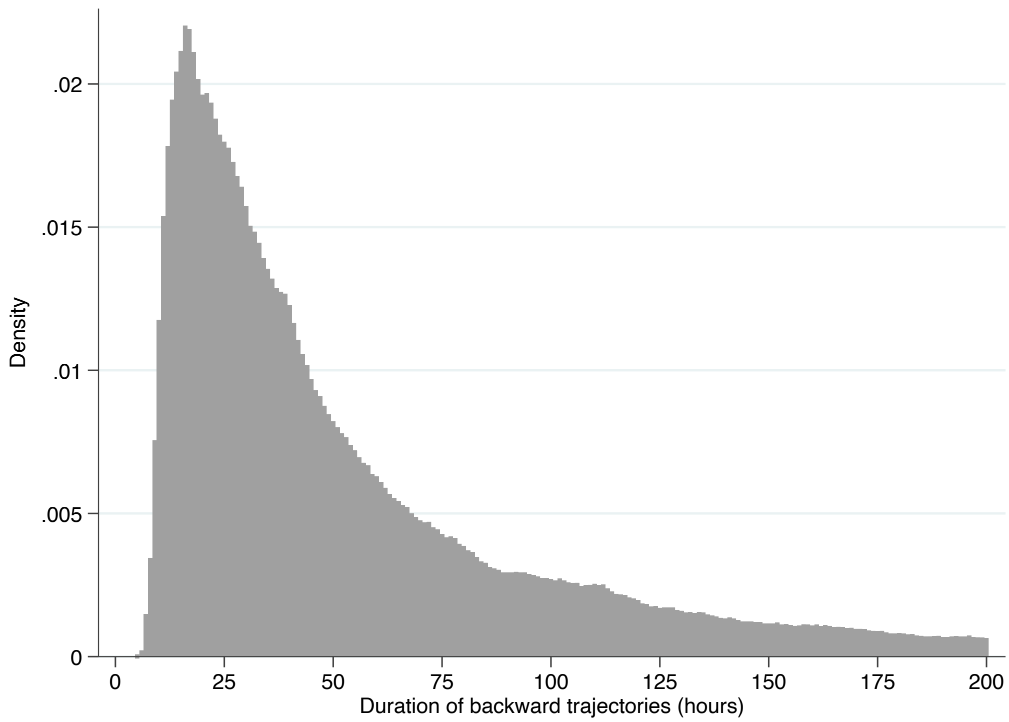
Note: This figure shows the locations of city coordinates available in the Chinese hourly $PM_{2.5}$ concentrations data from Berkeley Earth (Panel A) and the locations of monitors in the South Korean hourly $PM_{2.5}$ concentrations data from the Korea Environment Corporation (Panel B).

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 the 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	0.15	0.14	0.07	0.07
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Transboundary $PM_{2.5}$ (past 7-14 day)	0.21	0.22	0.21	0.12	0.12
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Transboundary $PM_{2.5}$ (past 14-21 day)	0.25	0.27	0.25	0.14	0.14
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Transboundary $PM_{2.5}$ (past 21-28 day)	0.25	0.27	0.26	0.14	0.14
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Transboundary $PM_{2.5}$ (past 28-35 day)	0.23	0.24	0.24	0.11	0.11
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Transboundary $PM_{2.5}$ (past 35-42 day)	0.27	0.29	0.28	0.16	0.15
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Transboundary $PM_{2.5}$ (past 42-49 day)	0.14	0.16	0.15	0.04	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Transboundary $PM_{2.5}$ (past 49-56 day)	0.22	0.23	0.23	0.13	0.13
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Transboundary $PM_{2.5}$ (past 56-63 day)	0.12	0.13	0.12	0.06	0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Transboundary $PM_{2.5}$ (past 63-70 day)	0.09	0.10	0.09	0.05	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(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
Moth 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	0.38	0.37	0.35	0.35
	(0.10)	(0.10)	(0.10)	(0.14)	(0.13)
Hourly $PM_{2.5}$ (past 7-14 days)	0.52	0.54	0.53	0.48	0.48
	(0.09)	(0.09)	(0.09)	(0.11)	(0.11)
Hourly $PM_{2.5}$ (past 14-21 days)	0.62	0.67	0.64	0.58	0.58
	(0.12)	(0.12)	(0.12)	(0.14)	(0.14)
Hourly $PM_{2.5}$ (past 21-28 days)	0.67	0.73	0.70	0.64	0.64
	(0.11)	(0.12)	(0.11)	(0.14)	(0.13)
Hourly $PM_{2.5}$ (past 28-35 days)	0.52	0.55	0.55	0.53	0.53
	(0.10)	(0.10)	(0.10)	(0.18)	(0.17)
Hourly $PM_{2.5}$ (past 35-42 days)	0.66	0.70	0.68	0.68	0.67
	(0.10)	(0.10)	(0.10)	(0.15)	(0.14)
Hourly $PM_{2.5}$ (past 42-49 days)	0.43	0.47	0.47	0.46	0.44
	(0.10)	(0.10)	(0.10)	(0.17)	(0.16)
Hourly $PM_{2.5}$ (past 49-56 days)	0.78	0.82	0.82	0.82	0.80
	(0.11)	(0.11)	(0.11)	(0.20)	(0.19)
Hourly $PM_{2.5}$ (past 56-63 days)	0.49	0.54	0.51	0.54	0.53
	(0.09)	(0.09)	(0.09)	(0.16)	(0.15)
Hourly $PM_{2.5}$ (past 63-70 days)	0.21	0.23	0.21	0.26	0.27
	(0.08)	(0.08)	(0.08)	(0.11)	(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
Moth 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) between March 2015 and December 2018.

Table A.5: The Impact of Transboundary Air Pollution on Emergency Department 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	50.0	437.4	482.6	-3.5	-2.8
	(9.7)	(10.2)	(51.4)	(54.3)	(1.5)	(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	214.2	2014.2	2066.7	-16.3	-11.8
	(45.7)	(45.6)	(266.0)	(258.9)	(7.0)	(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		-2.52	
	(0.12)		(0.16)	
Annual trend × in-China ratio	-8.70	-8.69		
	(0.98)	(0.98)		
Annual trend × Quartile 2 of in-China ratio			-1.71	-1.71
			(0.21)	(0.21)
Annual trend × Quartile 3 of in-China ratio			-1.70	-1.71
			(0.28)	(0.28)
Annual trend × Quartile 4 of in-China ratio			-3.52	-3.51
			(0.36)	(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.