Quantifying the mutual contributions of $PM_{2.5}$ pollution and associated population exposure and premature deaths among China, South Korea, and Japan: A dual perspective and an interdisciplinary approach

Jianzheng Liu,[1,#] Fei Yao,[2,3,#] Hongwen Chen,[4,5,]* Hongyan Zhao[6,]*

[1] School of Public Affairs, Xiamen University, Xiamen, Fujian 361005, China.
[2] National Centre for Earth Observation, University of Edinburgh, Edinburgh EH9 3FF, United Kingdom.
[3] School of GeoSciences, University of Edinburgh, Edinburgh EH9 3FF, United Kingdom.
[4] School of Economics, Xiamen University, Xiamen, Fujian 361005, China.
[5] School of Tourism, Nanchang University, Nanchang, Jiangxi 330031, China.
[6] Center for Atmospheric Environmental Studies, School of Environment, Beijing Normal University, Beijing 100875, China.
# these authors contributed equally to this work.
* Correspondence to: hongwen_chen@ncu.edu.cn
* Correspondence to: zhao-hy2021@bnu.edu.cn

Author Contribution

JL and FY contributed equally to this work. JL conceived the project. JL and HC prepared the emission inventory with contributions from FY. FY performed and evaluated GEOS-Chem model simulations with contributions from JL. JL performed the calculations of population-weighted mean $PM_{2.5}$ concentrations, $PM_{2.5}$ population exposure, and $PM_{2.5}$-related premature deaths with contributions from HZ. JL and FY analysed and interpreted the results. JL and FY wrote the manuscript with contributions from HC and HZ. HZ reviewed the manuscript. All authors contributed to the development of the manuscript and approved the final version for publication. JL and FY have verified the underlying data and have full access to all the data in the study.

Declaration of conflicts of interest

The authors declare no competing financial interests.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (42101199 and 42375168).

Abstract

Background:

Transboundary $PM_{2.5}$ pollution in Northeast Asia is causing significant environmental conflicts among China, South Korea, and Japan. However, efforts to address these conflicts have been impeded by a lack of a comprehensive understanding of source-receptor relationship of $PM_{2.5}$ pollution and associated health impacts among these countries.

Objectives:

We quantify the extent to which transboundary $PM_{2.5}$ pollution and associated health impacts are mutual among the three countries in 2015 and 2017 using three metrics (population-weighted mean $PM_{2.5}$ concentration, $PM_{2.5}$ population exposure, and $PM_{2.5}$-related premature deaths) and two accounting perspectives (production and consumption).

Methods:

We adopt an integrated interdisciplinary analysis framework that links a multi-regional input-output model, a GEOS-Chem chemical transport model, a population exposure model, and an exposure-response model.

Results:

From a production perspective, China's contributions to population-weighted mean $PM_{2.5}$ concentrations in South Korea and Japan are considerable, while the contributions of South Korea and Japan to China are negligible. However, the contributions from South Korea and Japan to $PM_{2.5}$ population exposure and associated premature deaths in China are nonnegligible from both production and consumption perspectives. From a consumption perspective, the contributions of South Korea and Japan to $PM_{2.5}$-related premature deaths in China amount to 6.96 [95% confidence interval (CI): 6.36, 7.56] and 9.79 (95% CI: 8.93, 10.64) thousand deaths in 2015, respectively, and 5.03 (95% CI: 4.55, 5.49) and 7.75 (95% CI: 7.02, 8.47) in 2017, respectively. These figures are larger than China's contributions to $PM_{2.5}$-related premature deaths in South Korea and Japan, which measure 4.63 (95% CI: 3.97, 5.28) and 3.91 (95% CI: 2.78, 5.01) thousand deaths in 2015, respectively, and 4.43 (95% CI: 3.75, 5.1) and 3.69 (95% CI: 2.57, 4.79) in 2017, respectively.

Discussion:

Our findings show that mutual contributions of $PM_{2.5}$ pollution and associated health impacts among the three countries vary considerably when different metrics and accounting perspectives are applied. A consumption perspective reveals narrower gaps in mutual contributions than a production perspective. Our findings could help policy makers, scholars, and the general public in China, South Korea, and Japan understand the intricacies involved in assigning environmental responsibilities and achieving environmental justice with respect to transboundary $PM_{2.5}$ pollution.

Keywords

Transboundary $PM_{2.5}$ pollution; Source-receptor relationship; Trade; Premature deaths; $PM_{2.5}$ population exposure; Northeast Asia.

1. Introduction

Transboundary fine particulate matter ($PM_{2.5}$) pollution has become an increasingly significant and sensitive environmental issue in China, South Korea, and Japan due to its adverse impacts on human health. This has led to a proliferation of studies focusing on the source–receptor relationship (SRR) of $PM_{2.5}$ pollution among these countries in recent years.[1,2] These studies allow for an understanding of the source areas of transboundary $PM_{2.5}$ pollution in Northeast Asia (NEA) and their source contributions to receptor countries via atmospheric transport.[3-7] However, most of these studies attribute the pollution to a country only by evaluating the direct air pollutant emissions produced in that country, but overlook the indirect air pollutant emissions embodied in cross-border trade caused by consumption in other countries. A typical anthropogenic emission process of air pollutants is not only executed by producers, but also stimulated by consumers,[8] which raises a critical question about to which extent the consumer countries that have benefited from the emission process should be accountable for the emission and the consequent air pollution. Therefore, it is recommended that future studies on the SRR of $PM_{2.5}$ pollution in NEA should consider both production and consumption perspectives.[1]

A production perspective views all emissions produced in a country as the responsibility of that country. Clearly, only the impact of atmospheric transport on the air quality in downwind countries will be considered when examining the SRR of $PM_{2.5}$ pollution from this perspective. By contrast, a consumption perspective regards all emissions induced by the consumption of a country via the trade of goods and services to be the responsibility of that country, irrespective of the countries where the emissions are produced.[9-12] In this sense, not only atmospheric transport relocates $PM_{2.5}$ pollution between countries, but also trade displaces $PM_{2.5}$ pollution by physically separating the production and consumption activities. The consumption perspective has been explored in air pollution studies both internationally[11,13] and nationally[14-16]; however, it has not been used to examine the SRR of $PM_{2.5}$ pollution in NEA especially on the country level that is required to guide local actions. A related study examines the consumption-based health burdens of black and organic carbon in Asia,[17] but it neither investigates the lumped $PM_{2.5}$, nor provides a production-based analysis of concentrations of black and organic carbon or the associated health impacts. Therefore, the SRR of $PM_{2.5}$ pollution in NEA from a consumption perspective and their differences from those of a production perspective remain unknown.

Here, we adopt an integrated analysis framework, consisting of a multi-regional input-output (MRIO) model, a GEOS-Chem chemical transport model, a population exposure model, and an exposure-response model, to provide a contemporary, comprehensive, and quantitative analysis of the SRR of $PM_{2.5}$ pollution and associated health impacts among China, South Korea, and Japan in 2015 and 2017. For modelling purposes, we use the latest detailed sectoral emission dataset, the Emissions Database for Global Atmospheric Research v6.1 (EDGARv6.1).[18] EDGARv6.1 incorporates China's substantial emission reductions since 2013 due to its five-year clean air actions.[19] This allows us to capture possible changes over time in China's contributions to $PM_{2.5}$ pollution and associated health impacts in South Korea and Japan, which was not possible in prior studies due to data unavailability.[13,17] Our experimental design enables us to quantify the extent to which transboundary $PM_{2.5}$ pollution and associated health impacts are mutual among nations in NEA.

2. Methods

We adopt an integrated analysis framework that consists of four steps (Figure S1). First, we use a MRIO model to develop the consumption-based emission inventories based on China's MRIO tables [20], the Organization for Economic Cooperation and Development (OECD) inter-country input–output (ICIO) tables,[21] and the production-based emission inventory EDGARv6.1.[18] Second, we use the GEOS-Chem chemical transport model to simulate the surface $PM_{2.5}$ concentrations in China, South Korea, and Japan under a baseline and nine emission-reduction scenarios (Table 1). The simulation results of the nine emission-reduction scenarios are compared with that of the baseline scenario to determine the grid-level fractional contributions to $PM_{2.5}$ pollution from production- and consumption-based emissions in NEA countries. In the third and fourth steps, we use the fractional contributions, satellite-based $PM_{2.5}$ data, and other auxiliary data in an exposure model and an exposure-response model to calculate the population-weighted mean (PWM) $PM_{2.5}$ concentrations, $PM_{2.5}$ population exposure, $PM_{2.5}$-related premature deaths, and contributions from source countries to these metrics in receptor countries. Additional details on each step are as follows.

2.1. Multi-regional input-output model for deriving consumption-based emissions

We calculate the consumption-based emissions via an input–output analysis of the economic output in monetary unit required to produce goods and services for consumption in a region, multiplied by emission intensities. We perform the input-output analysis on a sector and region basis using a MRIO model that combines China's MRIO tables obtained from the Carbon Emission Accounts & Datasets with the OECD ICIO tables.[21] The MRIO model describes the transactions of products within and among China, South Korea, Japan, and other regions. By capturing the economic processes among sectors and regions, the model enables the tracing of the consumption in a region to its source region of production.[9]

The MRIO model consists of 95 regions, including 31 provinces of mainland China and 64 OECD countries/regions including South Korea and Japan (Table S1). The MRIO model begins with the following equation for monetary flows:

$$\begin{pmatrix} x_1 \\ \vdots \\ x_r \\ \vdots \\ x_{95} \end{pmatrix} = \begin{pmatrix} A_{1,1} & \dots & A_{1,s} & \dots & A_{1,95} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ A_{r,1} & \cdots & A_{r,s} & \cdots & A_{r,95} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ A_{95,1} & & A_{95,s} & & A_{95,95} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_r \\ \vdots \\ x_{95} \end{pmatrix} + \begin{pmatrix} \sum_s \sum_t y_{1,s}^t \\ \vdots \\ \sum_s \sum_t y_{r,s}^t \\ \vdots \\ \sum_s \sum_t y_{95,s}^t \end{pmatrix} \quad [1]$$

where x_r ($r = 1, 2, \ldots, 95$) is a vector of the total economic output for each sector in region *r*. The subscripts ranging from 1 to 31 indicate the 31 provinces of mainland China, and the subscripts ranging from 32 to 95 indicate the 64 OECD countries/regions. $A_{r,s}$ ($r = 1, 2, \ldots, 95$, $s = 1, 2, \ldots, 95$) represents the matrix of direct consumption coefficients in which the columns represent the amount of input from the sectors in region *r* required for one unit of output to be produced by each sector in region *s*. $y_{r,s}^t$ is the final demand in region *s*, which is satisfied by the goods produced in region *r*. *t* refers to different types of final demand, including consumption by rural and urban residents, government investment, fixed asset investment, and others. A simplified version of Equation [1] is as follows:

$$\boldsymbol{x} = A\boldsymbol{x} + \boldsymbol{y} \quad [2]$$

where $\boldsymbol{x}$ is the matrix of the total economic output, A is the matrix of direct consumption coefficients, and $\boldsymbol{y}$ is the matrix of final demand.

If Equation [2] is solved for the total economic output, then it can be expressed as:

$$\boldsymbol{x} = (I - A)^{-1}\boldsymbol{y} \quad [3]$$

where I is the identity matrix and $(I - A)^{-1}$ denotes the Leontief inverse matrix. By multiplying the economic output with the emission intensity, the emissions produced in one region for consumption in a different region can be calculated as:

$$\boldsymbol{E} = \hat{f}(I - A)^{-1}\boldsymbol{y} \quad [4]$$

where $\boldsymbol{E}$ represents the emissions of air pollutants induced by consumption, $\hat{f}$ is a diagonal matrix of the region- and sector-specific emission intensities (pollutant emissions per unit of economic output).

To facilitate the MRIO analysis, we combine and match the sectors in the China's MRIO tables, OECD ICIO tables, and EDGARv6.1 dataset through a mapping process (Tables S2, S3, and S4) adapted from previous consumption-based studies.[15] In addition, we assume that the consumption-based emission inventory has the same spatial distribution as the production-based emission inventory for each sector. Therefore, we use the latter as the spatial proxy to distribute the former from regional to grid level to facilitate the GEOS-Chem chemical transport model simulations.

2.2. GEOS-Chem chemical transport model for simulating $PM_{2.5}$ concentrations

We run v12.9.3 of GEOS-Chem tropospheric chemistry ("tropchem") mechanism to provide surface $PM_{2.5}$ concentrations at a horizontal resolution of 0.5° latitude and 0.625° longitude for the months of January through December in 2015 and 2017 within a self-defined study domain (Figure S2). The study domain covers China, South Korea, and Japan, as well as potential source areas of $PM_{2.5}$ pollution in Northeast Asia (NEA) such as South and Central Asia. We perform two self-consistent global runs using GEOS-Chem to provide initial and time-dependent lateral boundary conditions at a horizontal resolution of 2° latitude and 2.5° longitude that are necessary for regional runs. These two global runs cover the periods of July 2014 to December 2015 for the 2015 simulation and July 2016 to December 2017 for the 2017 simulation. The first six months of each run serve as the model spin-up. Both global and regional runs are driven by the meteorology from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2).[22] We employ EDGARv6.1 anthropogenic emissions and other GEOS-Chem default emissions (Table S5). We turn off emissions in the latter that exist in the former, which include emissions from anthropogenic activities, agricultural soil nitrogen oxides (NOx), agricultural waste burning, aviation, and shipping, to avoid double counting. In practice, we initially have an insufficiently high model performance for black carbon. We improve its simulation by re-distributing its emissions in EDGARv6.1 to the spatial profile of black carbon emissions in MIX Asian emission inventory[23] that can better represent regional characteristics.

We evaluate the model performance using hourly $PM_{2.5}$ concentration measurements collected from 1) China National Environmental Monitoring Center (CNEMC); 2) AirKorea of the Korean Ministry of Environment; 3) Atmospheric Environmental Regional Observation System (AEROS), the Ministry of the Environment Government of Japan; and 4) Acid Deposition Monitoring Network in East Asia (EANET). In addition, we evaluate the model performance using ground measurements of $PM_{2.5}$ chemical components (sulfate, nitrate, ammonium, organic carbon (OC), and black carbon (BC)) collected from a variety of sources.[24]

To ensure the accuracy of the evaluation of the model performance, we perform a comprehensive data quality check of the hourly $PM_{2.5}$ concentration measurements. This involves removing any problematic data points using data quality control procedures that have been established in previous studies[25,26]:

1. Convert the timestamps of all hourly observation data to the Universal Coordinated Time (UTC).

   The air quality monitoring systems in different countries record hourly observation data using different time zone settings. For example, CNEMC records hourly $PM_{2.5}$ concentration measurements using China Standard Time (UTC+8:00), while AirKorea and AEROS use Korean Standard Time and Japan Standard Time (UTC+9:00), respectively. To facilitate the comparison between observed and modelled data, we convert the timestamps of all hourly observation data to UTC.

2. Set lower and upper limits of hourly $PM_{2.5}$ concentration measurements to [0, 3000] μg/m^3.

   We consider hourly $PM_{2.5}$ concentration measurements less than 0 μg/m^3 or exceeding 3000 μg/m^3 as potential instrumental failures and therefore remove them from further analysis by setting their values to NaN (Not a Number).

3. Remove $PM_{2.5}$ concentration measurements that exceed concurrently co-located PM_{10} concentration measurements.

   $PM_{2.5}$ concentration measurements are the mass of particles with an aerodynamic diameter less than 2.5 μm per unit volume of air, while PM_{10} concentration measurements are the mass of particles with an aerodynamic diameter less than 10 μm per unit volume of air. It is clear that at any given time and location, the $PM_{2.5}$ concentration measurements should never exceed those of PM_{10}.[25] Therefore, we consider $PM_{2.5}$ concentration measurements that exceed concurrently co-located PM_{10} concentration measurements as problematic measurements, and subsequently remove them from further analysis by setting their values to NaN.

4. Eliminate any series of five consecutive hourly $PM_{2.5}$ concentration measurements that are identical in value.

   $PM_{2.5}$ measurements are typically volatile, so it is highly unlikely for air quality monitoring instrument to record the same value for five consecutive hours.[25] As a result, we consider any such repeated measurements to be potential instrumental errors and mark them as invalid by setting their values to NaN.

5. Remove any extreme jumps in hourly $PM_{2.5}$ concentration measurements.

   Occasionally, meteorological events such as strong winds can cause dramatic changes in $PM_{2.5}$ concentration measurements. However, these events are usually accompanied by sustained high $PM_{2.5}$ concentrations either before or after their occurrence. As a result, it is unlikely for $PM_{2.5}$ concentrations to change abruptly without any connection to the measurements before or after.[26] To identify problematic abrupt changes in $PM_{2.5}$ concentration measurements, we adopt the method proposed by Jiang, Jolleys[26]. This involves two steps: first, if the hourly change in $PM_{2.5}$ concentration at a given hour (t), relative to t-1 and t+1, is greater than 15 times the hourly change in $PM_{2.5}$ concentration at t-1 relative to t-2, and greater than 15 times the hourly change in $PM_{2.5}$ concentration at t+1 relative to t+2, then the $PM_{2.5}$ concentration at t is considered invalid and set to NaN. Second, if the hourly change in $PM_{2.5}$ concentration at a given hour (t) relative to t-1 is greater 20 times the hourly change in $PM_{2.5}$ concentration at t-1 relative to t-2, and the $PM_{2.5}$ concentration at t+1 is invalid, then the $PM_{2.5}$ concentration at t is considered invalid and set to NaN.

6. Check the continuity of hourly $PM_{2.5}$ concentration measurements at each air quality monitoring site.

   If more than 10% of the hourly measurements at an air quality monitoring site in a given year are missing or marked as invalid after applying the quality control steps described above, we remove that site's data from our analysis for that year.

After performing the data quality check, we compare *in situ* observations and model simulations of lumped $PM_{2.5}$ on a yearly scale. For $PM_{2.5}$ chemical components (sulfate, nitrate, ammonium, OC, and BC), we compile the modelled values according to the monitoring period for each observation of $PM_{2.5}$ chemical components, as the monitoring periods for observation data of $PM_{2.5}$ chemical components can vary from several days to months.[24]

To describe the comparisons between *in situ* observations and model simulations, we use the Pearson correlation coefficients (R), normalized mean bias (NMB), normalized mean error (NME), mean fractional bias (MFB), and mean fractional error (MFE)[27]:

$$R = \frac{\sum_1^N (M-\bar{M})(O-\bar{O})}{\sqrt{\sum_1^N (M-\bar{M})^2 \sum_1^N (O-\bar{O})^2}} \quad [5]$$

$$NMB = \frac{\sum_1^N (M-O)}{\sum_1^N O} \quad [6]$$

$$NME = \frac{\sum_1^N |M-O|}{\sum_1^N O} \quad [7]$$

$$MFB = \frac{1}{N}\sum_1^N \left(\frac{M-O}{O+M/2}\right) \quad [8]$$

$$MFE = \frac{1}{N}\sum_1^N \left|\frac{M-O}{O+M/2}\right| \quad [9]$$

Where M and O refer to modelled and observed values, respectively; $\bar{M}$ and $\bar{O}$ are the respective means of M and O, and N denotes the number of comparison points.

Table S6 shows the evaluation of concentrations of simulated $PM_{2.5}$ and its chemical components against ground measurements data. For the lumped $PM_{2.5}$, the Pearson correlation coefficients, NMB, NME, MFB and MFE between modelled and observed values for the years of 2015 and 2017 are 0.71 and 0.75, 39.0% and 39.9%, 49.0% and 49.4%, 20.2% and 21.9%, 28.7% and 29.1%, respectively. For model evalution of concentrations of $PM_{2.5}$ chemical components in 2015, the Pearson correlation coefficients, NMB, NME, MFB and MFE between modelled and observed values range from 0.48 to 0.69, -12.7% to 34.6%, 30.5% to 58.8%, -1.2% to 29.1%, 23.9% to 44.2%, respectively. For model evalution of concentrations of $PM_{2.5}$ chemical components in 2017, the Pearson correlation coefficients, NMB, NME, MFB and MFE between modelled and observed values range from 0.14 to 0.8, -9.0% to 46.7%, 27.0% to 79.6%, -3.8% to 38.6%, 19.9% to 42.3%, respectively.

The above statistics show that our model performs reasonably well in simulating lumped $PM_{2.5}$ concentrations, but has a common issue with currently available global emission inventories: overestimates in the east of model domain and underestimates in the west (Figure S3).[28] To address this issue, we follow an approach commonly adopted in the field [13] that uses the model output to calculate the fractional contributions of production- and consumption-based emission to surface $PM_{2.5}$ concentration (Equation [10]).

We define a total of ten emission scenarios (Table 1) to estimate the contributions of each country to $PM_{2.5}$ concentrations in NEA from both production and consumption perspectives. In Scenario 1, we use the production-based emission inventory (EDGAR v6.1) to simulate the baseline $PM_{2.5}$ concentrations. Suppose we define C_{s1} as the baseline $PM_{2.5}$ concentrations simulated under the baseline scenario (Scenario 1) in which no emissions are excluded, C_{s2} as the simulated $PM_{2.5}$ concentration under the Scenario 2 in which the emissions in China are excluded. Therefore, the difference in simulated $PM_{2.5}$ concentrations between Scenario 1 and Scenario 2 ($C_{s1} - C_{s2}$) measures the contribution of production-based emissions in China to $PM_{2.5}$ concentrations in NEA. Similarly, Scenarios 3 and 4 set the production-based emissions in South Korea and Japan, respectively, to zero to derive the contributions of production-based emissions in South Korea ($C_{s1} - C_{s3}$) and Japan ($C_{s1} - C_{s4}$), respectively, to $PM_{2.5}$ concentrations in NEA. Scenarios 5, 6, and 7 set the consumption-based emissions induced by the consumption in China, South Korea, and Japan, respectively, to zero to derive the contributions of the consumption-based emissions in China ($C_{s1} - C_{s5}$), South Korea ($C_{s1} - C_{s6}$), and Japan ($C_{s1} - C_{s7}$), respectively, to $PM_{2.5}$ concentrations in NEA. Scenarios 8, 9, and 10 are additionally designed to decompose the contributions from China's production-based emissions to $PM_{2.5}$ concentrations in South Korea and Japan into parts induced by the consumption in South Korea, Japan, and other countries. The part of transboundary contributions from emissions produced in China but induced by consumption in South Korea is calculated as the difference between baseline $PM_{2.5}$ concentrations and simulated $PM_{2.5}$ concentrations under scenario 8: $C_{s1} - C_{s8}$. Similarly, the part induced by consumption in Japan is calculated as $C_{s1} - C_{s9}$. The part induced by consumption outside China is calculated as $C_{s1} - C_{s10}$. Therefore, the part induced by consumption in China is calculated as $(C_{s1} - C_{s2}) - (C_{s1} - C_{s10}) = (C_{s10} - C_{s2})$. Finally, the part induced by consumption outside China, South Korea, and Japan is calculated indirectly as $(C_{s1} - C_{s2}) - (C_{s1} - C_{s8}) - (C_{s1} - C_{s9}) - (C_{s10} - C_{s2}) = (C_{s1} - C_{s10}) - (C_{s1} - C_{s8}) - (C_{s1} - C_{s9})$.

The fractional contributions associated with the i^{th} emission-reduction scenario at the grid level are calculated as:

$$F^i = (C_{s1} - C_{si})/C_{s1}, \quad [10]$$

where F^i (i = 2, 3, …, 10) refers to the gridded fractional contributions attributable to the i^{th} emission source associated with the i^{th} emission-reduction scenario of which the gridded $PM_{2.5}$ concentrations are termed C_{si}. All the calculations are aggregated to the annual level.

2.3. Exposure model for calculating $PM_{2.5}$ population exposure

Exposure to $PM_{2.5}$ pollution is associated with multiple health endpoints and is one of the leading risk factors contributing to disease burden worldwide.[29] We define the $PM_{2.5}$ population exposure in a country as the total doses of $PM_{2.5}$ mass inhaled per day by the entire population in that country. To calculate the exposure, we use an exposure model that takes into account the time activity patterns, indoor/outdoor air quality, and human inhalation rates. More specifically, we compute the baseline $PM_{2.5}$ population exposure in a country by summing the product of population, inhalation rate, outdoor/indoor $PM_{2.5}$ concentrations, and outdoor/indoor time fractions for all grid cells covering that country:

$$Baseline\ PE = \sum_g (P_g \times IR \times (PM_{out_g} \times T_{out} + PM_{in_g} \times T_{in}))\ /10^9 \quad [11]$$

$$PM_{in_g} = PM_{out_g} \times IF \quad [12]$$

where $Baseline\ PE$ refers to the baseline $PM_{2.5}$ population exposure with a unit of kg per day, P_g refers to the population count at the g^{th} grid cell, which is obtained from the Worldpop high-resolution population distribution datasets.[30] PM_{out_g} refers to the outdoor ambient $PM_{2.5}$ concentration at the g^{th} grid cell, which is obtained from a newly available high-resolution (1 km × 1 km) satellite-derived $PM_{2.5}$ concentration dataset.[31] IR refers to the inhalation rate that measures the amount of air inhaled per day (m^3 per day) by people in that country or its different regions. T_{out} and T_{in} refer to the time fractions that people in that country or its different regions spend in outdoor and indoor environments, respectively. IR, T_{out} and T_{in} are obtained from the Chinese exposure factor handbook,[32] updated exposure factors study in South Korea,[33] and Japan exposure factor handbook,[34] respectively. They are listed in Table S7 and S8. PM_{in_g} refers to the indoor $PM_{2.5}$ concentration at the g^{th} grid cell. IF refers to the infiltration factors, which measure the equilibrium fractions of outdoor particles penetrating indoors and remaining suspended.[35] IF are obtained from the literature[36-38] and are listed in Table S9. The sum of all the combinations of these terms is expressed in μg because the unit of PM_{out_g} is $\mu g/m^3$. To obtain a unit of kg, we divide the sum by 10^9.

We compute the $PM_{2.5}$ population exposure in a receptor country contributed by the i^{th} emission source by summing the product of population, inhalation rates, gridded fractional contribution calculated from Equation [10], outdoor/indoor $PM_{2.5}$ concentrations, and outdoor/indoor time fractions for all grid cells covering that receptor country:

$$Source\ PE^i = \sum_g (P_g \times IR \times F_g^i \times (PM_{out_g} \times T_{out} + PM_{in_g} \times T_{in}))/10^9 \quad [13]$$

The baseline PWM ambient $PM_{2.5}$ concentration in a country is calculated as:

$$Baseline\ PWM = \sum_g (P_g \times PM_{out_g}) / \sum_g (P_g) \quad [14]$$

The PWM ambient $PM_{2.5}$ concentration in a receptor country contributed by the i^{th} emission source is then calculated as:

$$Source\ PWM^i = \sum_g (P_g \times F_g^i \times PM_{out_g}) / \sum_g (P_g) \quad [15]$$

With baseline and source PE and PWM, we quantify the relative contributions of $PM_{2.5}$ concentrations and associated population exposure in a receptor country attributable to the i^{th} emission source as:

$$RC1^i = Source\ PWM^i / Baseline\ PWM \quad [16]$$

$$RC2^i = Source\ PE^i / Baseline\ PE \quad [17]$$

2.4. Exposure-response model for estimating $PM_{2.5}$-related premature deaths

We use the Meta Regression-Bayesian, Regularized, Trimmed (MR-BRT) model, as developed in the GBD-2019 study,[39] to estimate $PM_{2.5}$-related premature deaths. The MR-BRT model characterizes the exposure-response relationship across a wide range of ambient $PM_{2.5}$ concentrations.[39] It is particularly well-suited for studies focusing on Asia, as it incorporates additional data from cohort studies conducted in high-pollution, low-income countries such as China. In this study, we estimate the number of premature deaths attributable to $PM_{2.5}$ pollution resulting from adult (25 years and older) ischemic heart disease, stroke, chronic obstructive pulmonary disease, type II diabetes, lung cancer, and childhood (younger than 5 years) and adult (25 years and older) acute lower respiratory infection. Additionally, we calculate the 95% Confidential Intervals (CIs) for our estimates of attributable premature deaths.

We estimate the number of premature deaths related to $PM_{2.5}$ pollution resulting from adult (25 years and older) ischemic heart disease, stroke, chronic obstructive pulmonary disease, type II diabetes, lung cancer, and childhood (younger than 5 years) and adult (25 years and older) acute lower respiratory infection, using the following equations:

$$M = \sum_g \sum_d \sum_a M_{a,g}^d \quad [18]$$

$$M_{a,g}^d = AF_{a,g}^d \times B_a^d \times P_{a,g} \quad [19]$$

$$AF_{a,g}^d = (RR_a^d\left(PM_{out_g}\right) - 1)/RR_a^d(PM_{out_g}) \quad [20]$$

where M is the total $PM_{2.5}$-related premature deaths in a receptor country, $M_{a,g}^d$ is the $PM_{2.5}$-related premature deaths for the a^{th} age group due to the d^{th} disease at the g^{th} grid cell in that receptor country, and $AF_{a,g}^d$ is the attributable fraction to $PM_{2.5}$ pollution for the a^{th} age group and the d^{th} disease at the g^{th} grid cell in that receptor country; B_a^d is the baseline death incidence due to the d^{th} disease for the a^{th} age group in that receptor country, with its values derived from the national average data in the Global Burden of Disease Study 2019 (GBD 2019) database.[40] $RR_a^d\left(PM_{out_g}\right)$ is the relative risk (RR) for the a^{th} age group and the d^{th} disease due to exposure to ambient $PM_{2.5}$ pollution at the g^{th} grid cell in that receptor country, which is further calculated using the MR-BRT model developed in the GBD 2019 study.[39]

The MR-BRT model describes the exposure-response relationship for a wide range of ambient $PM_{2.5}$ concentrations.[39] The relative risk at the g^{th} grid cell for the a^{th} age group and the d^{th} disease is calculated as:

$$RR_a^d\left(PM_{out_g}\right) = \begin{cases} MRBRT(PM_{out_g})/MRBRT(tmrel), & PM_{out_g} > tmrel \\ 1, & PM_{out_g} < tmrel \end{cases} \quad [21]$$

where $tmrel$ is the theoretical minimum risk exposure level (TMREL), $MRBRT(PM_{out_g})$ and $MRBRT(tmrel)$ refer to the estimates of risks when exposed to $PM_{2.5}$ concentrations of PM_{out_g} and tmrel, respectively. The GBD 2019 study generates 1000 samples of TMREL estimates with a uniform distribution from 2.4 to 5.9 μg/m^3, and 1000 risk estimates for each $PM_{2.5}$ exposure interval level and each disease. These estimates, which are provided in the format of look-up tables,[41] enable us to calculate the 95% confidential intervals (CIs) of $PM_{2.5}$-related premature deaths.

To determine the number of premature deaths attributable to the ith emission source, we follow previous studies[14,42-44] and adopt the direct proportion approach, which assumes a linear relationship between the proportions of $PM_{2.5}$ concentration to the proportion of total $PM_{2.5}$-related premature deaths:

$$Source\ M^i = \sum_g \sum_d \sum_a (M_{a,g}^d \times F_g^i) \quad [22]$$

where $Source\ M^i$ is the number of $PM_{2.5}$-related premature deaths in a receptor country attributable to the ith emission source.

With total $PM_{2.5}$-related premature deaths M and $PM_{2.5}$-related premature deaths attributable to the ith emission source $Source\ M^i$, we calculate the relative contribution of $PM_{2.5}$-related premature deaths in a receptor country attributable to the ith emission source as:

$$RC3^i = Source\ M^i / M \quad [23]$$

In addition, in order to verify whether there are statistically significant differences between these consumption-based estimates and production-based estimates, we calculate monthly-scale values for PWM $PM_{2.5}$ concentration and $PM_{2.5}$ population exposure from both production and consumption perspectives, and use these results to conduct paired Student t-tests. We do not calculate monthly-scale $PM_{2.5}$-related premature deaths because the monthly baseline death incidence data are not available. Therefore, we do not conduct statistical tests for comparing the consumption-based $PM_{2.5}$-related premature deaths and production-based $PM_{2.5}$-related premature deaths.

3. Results

3.1. Local and transboundary contributions to $PM_{2.5}$ concentrations between China, South Korea, and Japan

Figure 1 shows the gridded fractional contributions to $PM_{2.5}$ concentrations from production- and consumption-based emissions in NEA countries in 2017. Results from 2015 are pretty similar and have therefore been omitted for brevity. The fractional contributions are defined as the ratios of the differences between the baseline and non-baseline (Table 1) $PM_{2.5}$ concentrations to the baseline $PM_{2.5}$ concentrations. We identify three interesting spatial patterns. First, the impacts of emissions from China, South Korea, and Japan on $PM_{2.5}$ concentrations are primarily constrained within their own borders, regardless of whether viewed from a perspective of production or consumption. Second, the impacts of production-based (Figure 1A) emissions from upwind countries on $PM_{2.5}$ concentrations in downwind countries due to atmospheric transport are evident. Third, the footprint of the impacts on $PM_{2.5}$ concentrations attributable to consumption-based emissions is more widely distributed than that attributed to production-based emissions (Figures 1E and 1F versus Figures 1B and 1C). This suggests that trade expands the extent to which atmospheric transport relocates $PM_{2.5}$ pollution among countries by separating production and consumption activities and allowing the production of emissions to occur far from where the goods are consumed.

Table 2 shows the contributions from source to receptor countries' PWM $PM_{2.5}$ concentrations in NEA in 2015 and 2017. The production perspective shows that the largest contributors to PWM $PM_{2.5}$ concentrations in China, South Korea, and Japan in 2015 are themselves with local contributions of 72.2%, 38.9%, and 38.7%, respectively. This pattern persists in 2017 with slightly decreased values of 70.7%, 37.3%, and 37.7% for China, South

Korea, Japan, respectively. The consumption perspective suggests that the results for China are similar as the largest contributor is China itself, but the largest proportions of PWM $PM_{2.5}$ concentrations in South Korea and Japan are contributed by the emissions driven by the consumption in other countries and natural sources of $PM_{2.5}$ (e.g., dust, sea salt, etc.).

With respect to transboundary contributions, we find that, in 2015, the emissions produced (induced by consumption) in China contribute 35.0% (26.9%) and 22.1% (17.6%) to PWM $PM_{2.5}$ concentrations in South Korea and Japan, respectively. Contributions of the emissions produced (induced by consumption) in South Korea to PWM $PM_{2.5}$ concentrations in China and Japan are relatively low at 0.4% (0.5%) and 3.6% (2.5%), respectively. Contributions of Japan's production-based (consumption-based) emissions to PWM $PM_{2.5}$ concentrations in China and South Korea are even lower at 0.1% (0.7%) and 0.9% (1.6%), respectively. From 2015 to 2017, there are only minor changes in these values, suggesting that the results are fairly consistent despite any differences in emissions, meteorology, and other factors during the two years.

We find that the consumption-based PWM $PM_{2.5}$ concentrations and production-based PWM $PM_{2.5}$ concentrations are significantly different (Table S10). We also find that consumption-related contributions from upwind countries to downwind countries (from China to South Korea and Japan, and from South Korea to Japan) are lower than the corresponding production-related contributions. Conversely, consumption-related contributions from downwind countries to upwind countries (from Japan to South Korea and China, and from South Korea to China) are higher than the corresponding production-related contributions. This suggests that trade narrows the gaps in mutual contributions of PWM $PM_{2.5}$ concentrations among China, South Korea, and Japan, which becomes even more noticeable when we observe the $PM_{2.5}$ population exposure and associated premature deaths below.

3.2. Transboundary contributions to $PM_{2.5}$ population exposure between China, South Korea, and Japan

Table 3 shows the SRR of $PM_{2.5}$ population exposure among China, South Korea, and Japan. From a production perspective, China's contributions to $PM_{2.5}$ population exposure in South Korea (3.79 and 3.72 kg/d) are 1.3 and 2.8 times those of South Korea to China (2.93 and 1.32 kg/d) in 2015 and 2017, respectively. China's contributions to $PM_{2.5}$ population exposure in Japan (2.11 and 2.07 kg/d) are 4.4 and 14.8 times those of Japan to China (0.48 and 0.14 kg/d) in 2015 and 2017, respectively. South Korea's contributions to $PM_{2.5}$ population exposure in Japan (0.34 and 0.37 kg/d) are 3.4 and 6.2 times those of Japan to South Korea (0.1 and 0.06 kg/d) in 2015 and 2017, respectively.

The results calculated from a consumption perspective show a different pattern. Particularly, China's contributions to $PM_{2.5}$ population exposure in South Korea (2.92 and 2.88 kg/d) are 0.7 and 1.1 times those of South Korea to China (3.9 and 2.74 kg/d) in 2015 and 2017, respectively. China's contributions to $PM_{2.5}$ population exposure in Japan (1.68 and 1.68 kg/d) are approximately 31% and 39% those of Japan to China (5.48 and 4.26 kg/d) in 2015 and 2017, respectively. South Korea's contributions to $PM_{2.5}$ population exposure in Japan (0.24 and 0.27 kg/d) are approximately 1.4 and 1.9 times those of Japan to South Korea (0.17 and 0.14 kg/d) in 2015 and 2017, respectively. In addition, from a consumption perspective, the largest contributor to $PM_{2.5}$ population exposure in South Korea and Japan are not themselves but the emissions driven by the consumption in the other countries and natural sources of $PM_{2.5}$.

Once again, we find that there are significant differences between the consumption-based $PM_{2.5}$ population exposure and production-based $PM_{2.5}$ population exposure (Table S11). We generally find narrower gaps in mutual contributions of $PM_{2.5}$ population exposure among China, South Korea, and Japan from a perspective of consumption than production in both years of 2015 and 2017. In addition, Table 3 shows that South Korea and Japan's contributions to $PM_{2.5}$ population exposure in China become larger than or comparable to that of China to South Korea and Japan when switching from a perspective of production to consumption.

3.3. Transboundary contributions to $PM_{2.5}$-related premature deaths between China, South Korea, and Japan

The SRR of $PM_{2.5}$-related premature deaths among China, South Korea, and Japan (Table 4) largely follows the pattern of $PM_{2.5}$ population exposure. For brevity, we report that in 2015 and 2017, the ratios of China's contributions to $PM_{2.5}$-related premature deaths in South Korea and vice versa are 1.2 (6.02 versus 5.22 thousand premature deaths) and 2.3 (5.73 versus 2.47 thousand premature deaths) from a production perspective, and 0.7 (4.63 versus 6.96 thousand premature deaths) and 0.9 (4.43 versus 5.03 thousand premature deaths) from a consumption perspective. The ratios of China's contributions to $PM_{2.5}$-related premature deaths in Japan and vice versa in 2015 and 2017 are 5.7 (4.92 versus 0.87 thousand premature deaths) and 15.7 (4.56 and 0.29 thousand premature deaths) from a production perspective, and 0.4 (3.91 versus 9.79 thousand premature deaths) and 0.5 (3.69 versus 7.75 thousand premature deaths) from a consumption perspective. The ratios of South Korea's contributions to $PM_{2.5}$-related premature deaths in Japan and vice versa in 2015 and 2017 are 5.3 (0.8 versus 0.15 thousand premature deaths) and 9.3 (0.84 versus 0.09 thousand premature deaths) from a production perspective, and 2.1 (0.56 versus 0.27 thousand premature deaths) and 2.9 (0.61 versus 0.21 thousand premature deaths) from a consumption perspective. In addition, the consumption perspective suggests that the $PM_{2.5}$-related premature deaths in China, South Korea, and Japan are also highly influenced by emissions driven by the consumption in other countries and natural sources of $PM_{2.5}$.

4. Discussion

We provide a contemporary, comprehensive, and quantitative assessment of the SRR of $PM_{2.5}$ pollution and associated health impacts among China, South Korea, and Japan in 2015 and 2017. We find that China is the major contributing source country for transboundary PWM $PM_{2.5}$ concentrations in South Korea and Japan, while the contributions of South Korea and Japan to PWM $PM_{2.5}$ concentrations in China are negligible. This is consistent from both production and consumption perspectives, with the latter showing narrower gaps in mutual contributions than the former. However, the contributions from South Korea and Japan to $PM_{2.5}$ population exposure and associated premature deaths in China are non-negligible from both production and consumption perspectives. From a consumption perspective, South Korea and Japan contribute to $PM_{2.5}$ population exposure and associated premature deaths in China at levels that are generally larger than China's contributions to South Korea and Japan. This reverses the relationship in mutual contributions of $PM_{2.5}$ population exposure and associated premature deaths when viewed from a production perspective. This reversed relationship primarily stems from the differences between the consumption-based emission inventory and production-based emission inventory, as well as the differences in population size between countries. From a production perspective, the emissions produced in China are all China's responsibility. But, from a consumption perspective, Japan and South Korea are responsible for part of the emissions produced in China because that part of emissions are produced to meet the demand driven by the consumption in Japan and South Korea (see Table S12 on the contributions from source to receptor countries' nitrogen oxides (NOx) emissions in Northeast Asia in 2015 for an illustration). Although this part of emissions may only contribute a small fraction to PWM $PM_{2.5}$ concentration in China, due to China's large population size, the total health impacts caused to China are non-negligible and larger than China's contribution to Japan and South Korea.

4.1. Comparisons to prior studies

Comparisons with prior analyses are limited by differences in study areas and periods as well as differences in data and models adopted. There have been quantifications of the SRR of $PM_{2.5}$ pollution and associated health impacts in Asia.[13,17] However, these analyses use coarse resolution models that have not been informed by local measurements and have not revealed country-to-country relationships, making them inadequate to guide local actions. In contrast to previous studies, we have employed regional models, which are informed by local measurements, to disclose the SRR of the $PM_{2.5}$ concentrations and associated population exposure and premature deaths among China, South Korea, and Japan in more details. This represents a significant improvement and will benefit local policymaking.

4.2. Decrease in China's contributions to $PM_{2.5}$ pollution in South Korea and Japan

Nonetheless, we select and compare production-based studies (Tables S13 and S14) that have explicitly quantified China's contributions to $PM_{2.5}$ pollution in South Korea and Japan over a period no less than one year. Figure 2 shows reductions in China's contributions to $PM_{2.5}$ pollution in South Korea and Japan from 2008 to 2017, which roughly coincides with the decreasing emission trend in China from 2010 to 2017, suggesting the co-benefits of China's clean air actions for neighboring countries' air quality.

However, China's clean air actions mainly rely on the end-of-pipe pollution control measures of which the benefits will become mostly exhausted by 2030.[45] While China's ambitious carbon neutrality goals will continuously improve its own and likely surrounding countries' air quality in the next couples of decades by entailing systematic changes in energy sources and industrial transformation,[46,47] consumption-side efforts can help boost the process. For instance, the implementation of the Regional Comprehensive Economic Partnership (RCEP) free trade agreement in January 2022 presents an opportunity for China, South Korea, and Japan to jointly develop effective $PM_{2.5}$ mitigation strategies, particularly from a consumption side.

4.3. Contributions driven by the consumption in other countries outside Northeast Asia to $PM_{2.5}$ pollution and associated health impacts in China, South Korea, and Japan

More importantly, the results for all three metrics from a consumption perspective consistently show that the $PM_{2.5}$ pollution and associated health impacts in all three countries are highly influenced by the consumption in other countries outside Northeast Asia and the natural sources of $PM_{2.5}$. Taking South Korea and Japan as an illustration, the consumption perspective shows that the largest proportion of $PM_{2.5}$ pollution and associated health impacts are from the emissions driven by the consumption in other countries and the natural sources of $PM_{2.5}$. Previous studies have shown that the contribution of the natural sources for $PM_{2.5}$ concentrations in China, South Korea, and Japan are approximately 10%~24%, 9.9%~10%, and 16.1%~42%, respectively.[48,49] We can infer that, after deducting the contributions from natural sources, other countries outside Northeast Asia may have played a non-negligible role in contributing to the $PM_{2.5}$ pollution and associated health impacts in Northeast Asia from a consumption perspective. Moreover, as shown in Tables 2-4, when shifting the perspective from production to consumption, the contribution from China decreases while the contribution in the "Others" category from other countries and natural sources of $PM_{2.5}$ increases. The changes in the "Others" category in Tables 2-4 from the production to the consumption perspective reflect the changes in other countries' contributions from production to consumption, as the contributions from natural sources of $PM_{2.5}$ are identical in both scenarios and hence are cancelled out when we calculate the changes. Therefore, the general public, the media, and the governments in Northeast Asia should really look beyond this region but focus on the rest of the world, especially those affluent countries with high consumption.[13,50]

In addition, in order to examine to which extent the consumption in China, South Korea, Japan, and other countries are responsible for the transboundary $PM_{2.5}$ pollution and associated health impacts transported from China to South Korea and Japan, we construct Scenarios 8, 9, and 10 (Table 1) which subtract the emissions in China induced by the consumption in South Korea, Japan, and all other countries except China, respectively. These additional scenarios help to decompose the contributions from China's production-based emissions to $PM_{2.5}$ pollution and associated health impacts in South Korea and Japan into parts induced by the consumption in South Korea, Japan, and other countries. Table 5 shows the partition of transboundary contributions from China to $PM_{2.5}$ pollution and associated population exposure and premature deaths in South Korea and Japan. While the consumption in China contributes mostly to transboundary $PM_{2.5}$ pollution and associated population exposure and premature deaths transported from China to South Korea and Japan, the roles played by the consumption in other countries are non-negligible. The emissions produced in China but induced by consumption in other countries outside Northeast Asia in 2015 contribute 23.4% and 23.3% to $PM_{2.5}$ pollution and associated population exposure and premature deaths in South Korea and Japan, respectively. The corresponding values for South Korea and Japan in 2017 are slightly lower but still non-negligible at 22.1% and 21.5%. Once again, this highlights that an improved regional air quality requires joint efforts from all relevant countries.

4.4. Limitations and uncertainties

Our work has several sources of uncertainties. First, the preparation of consumption-based emission inventories relies on the production-based emission inventory EDGARv6.1 and the input–output tables in the MRIO model, so errors in these datasets may propagate to our results. The uncertainties in the EDGARv6.1 derive from the incomplete knowledge and inaccurate estimation of anthropogenic activities and emission factors. Studies have shown that the uncertainties of sulfur dioxide (SO_2), NO_X, carbon monoxide (CO), non-methane volatile organic compound (NMVOC), ammonia (NH_3), BC, and OC in EDGARv4.3.2 are estimated as 14.4%~47.6%, 17.2%~69.4%, 25.9%~64.6%, 32.7%~73.6%, 186%~294.4%, 46.8%~92%, and 88.7%~153.2%, respectively.[52] EDGARv6.1 likely have a similar but narrower range. The input-output tables are compiled based on national statistics on GDP, trade and survey data, but the quality of these data vary across countries and years. Trade data, for example, often have asymmetries and imbalances, where the sum of exports exceeds the sum of imports.[53] Therefore, a harmonization calculation process is usually performed to compile the input-output tables. Several global input-output databases are available, each using different data sources and harmonization and consolidation procedures, including Eora,[54] GTAP,[55] EXIOBASE,[56] WIOD,[57] and OECD ICIO.[21] Among these databases, the OECD ICIO database is compiled by OECD, while all other global input-output databases are compiled by academic researchers.[53] Therefore, OECD ICIO is regarded as the most authoritative, credible, and robust global input-output database currently available.[58] In addition, our study has combined the global OECD ICIO dataset with China's MRIO tables with details on 31 provinces of China, which provides more reliable estimations of the consumption-based emission inventory.

Second, the simulated surface $PM_{2.5}$ concentrations are affected by uncertainties in emission inventories and limitations in air quality modelling. The uncertainties in emission inventories are described above. The limitations in air quality modelling here refer to the imperfect representation of atmospheric chemistry and meteorological processes in the GEOS-Chem model. Our current understanding of many physicochemical mechanisms, such as the formation of secondary organic aerosols, deposition and scavenging, remains to be improved. Due to the computational intensity of the GEOS-Chem model, it is not feasible to estimate the uncertainties through sensitivity analyses.[43] Instead, the impact of uncertainties in emission inventories and limitations in air quality modelling can be evaluated by comparing the simulated $PM_{2.5}$ concentrations against the ground measurements. As shown in the model performance evaluation, the simulated $PM_{2.5}$ concentrations generally agree well with the ground observations, with R values ranging from 0.71 to 0.75 and NMB values ranging from 39.0% to 39.9% over different years. To further reduce the error from the simulation process, the GEOS-Chem model output is only used to estimate the fractional contributions of production- and consumption-based emissions to the baseline simulated $PM_{2.5}$ concentrations. Then, by multiplying the fractional contributions and a high-resolution satellite-derived $PM_{2.5}$ concentration dataset with relatively small uncertainty [31], we can obtain a more accurate estimation of the fractional $PM_{2.5}$ concentrations contributed by an emission source.

Third, the estimates of $PM_{2.5}$ population exposure is affected by uncertainties in the data on time activity patterns, inhalation rates, and infitration factors. These data are derived from the surveys provided in the exposure factor handbooks in China,[32] South Korea,[33] and Japan.[34] Unfortunately, these exposure handbooks did not provide sufficient information on uncertainties of these data. The exposure factor handbook in Japan,[34] for example, only provides a short summary in Japanese and English that presents a single value for outdoor time and inhalation rate. One study focusing on China assumes a coefficient of variation of 5% for the time activity patterns of Chinese residents,[36] but we have not found uncertainty information for Japan and South Korea.

Lastly, the MR-BRT model may introduce additional uncertainties to our results. The MR-BRT model developed in the GBD 2019 study is built based on cohort studies from various countries.[39] However, very few cohort studies have examined the health outcomes of $PM_{2.5}$ pollution in China, South Korea and Japan. The database of cohort studies in the GBD-2019 is still predominantly composed of western cohort studies. Nonetheless, the MR-BRT model is the most recent and widely used method for estimating health impacts of ambient air pollution. Compared with the previous Integrated Exposure Response (IER) model[59] and the Global Exposure Mortality Model (GEMM) model,[60] the MR-BRT model in the GBD-2019 study incorporates more recent cohort studies, including those in China and India, which provide more data at high $PM_{2.5}$ levels. In addition, existing concentration-response models generally assume that the composition of $PM_{2.5}$ pollution does not vary with countries and that the toxicity of $PM_{2.5}$ pollution at a given concentration level is equivalent across different components (sulfate, nitrate, ammonium, OC, and BC). However, the health impacts of $PM_{2.5}$ pollution in a region may differ from those in other regions due to variations in the toxicity of $PM_{2.5}$ sources.[61,62] This points to a need for future studies that take into account the varying toxicity of different $PM_{2.5}$ components.

References

1. Liu J, Li J, Yao F. Source-receptor relationship of transboundary particulate matter pollution between China, South Korea and Japan: approaches, current understanding and limitations. *Crit Rev Environ Sci Technol* 2022; **52**(21): 3896-920. doi:10.1080/10643389.2021.1964308.
2. Shapiro MA, Yarime M. Effects of national affiliations and international collaboration on scientific findings: The case of transboundary air pollution in Northeast Asia. *Environ Sci Policy* 2021; **118**: 71-85. doi:10.1016/j.envsci.2021.01.005.
3. Yim SHL, Gu YF, Shapiro M, Stephens B. Air quality and acid deposition impacts of local emissions and transboundary air pollution in Japan and South Korea. *Atmospheric Chemistry and Physics* 2019; **19**(20): 13309-23. doi:10.5194/acp-19-13309-2019.
4. Oh HR, Ho CH, Koo YS, et al. Impact of Chinese air pollutants on a record-breaking PMs episode in the Republic of Korea for 11-15 January 2019. *Atmospheric Environment* 2020; **223**: 117262. doi:10.1016/j.atmosenv.2020.117262.
5. Han X, Cai JZ, Zhang MG, Wang XF. Numerical simulation of interannual variation in transboundary contributions from Chinese emissions to $PM_{2.5}$ mass burden in South Korea. *Atmospheric Environment* 2021; **256**: 118440. doi:10.1016/j.atmosenv.2021.118440.
6. Ikeda K, Yamaji K, Kanaya Y, et al. Source region attribution of $PM_{2.5}$ mass concentrations over Japan. *Geochemical Journal* 2015; **49**(2): 185-94. doi:10.2343/geochemj.2.0344.
7. Choi J, Park RJ, Lee H-M, et al. Impacts of local vs. trans-boundary emissions from different sectors on $PM_{2.5}$ exposure in South Korea during the KORUS-AQ campaign. *Atmospheric Environment* 2019; **203**: 196-205. doi:10.1016/j.atmosenv.2019.02.008.
8. Meng J, Liu J, Xu Y, et al. Globalization and pollution: tele-connecting local primary $PM_{2.5}$ emissions to global consumption. *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences* 2016; **472**(2195): 20160380. doi:10.1098/rspa.2016.0380.
9. Liang S, Qu S, Zhu Z, Guan D, Xu M. Income-Based Greenhouse Gas Emissions of Nations. *Environmental Science & Technology* 2017; **51**(1): 346-55. doi:10.1021/acs.est.6b02510.
10. Liang S, Stylianou KS, Jolliet O, et al. Consumption-based human health impacts of primary $PM_{2.5}$: The hidden burden of international trade. *Journal of Cleaner Production* 2017; **167**: 133-9. doi:10.1016/j.jclepro.2017.08.139.
11. Lin J, Pan D, Davis SJ, et al. China's international trade and air pollution in the United States. *Proceedings of the National Academy of Sciences* 2014; **111**(5): 1736-41. doi:10.1073/pnas.1312860111.
12. Meng J, Yang H, Yi K, et al. The Slowdown in Global Air-Pollutant Emission Growth and Driving Factors. *One Earth* 2019; **1**(1): 138-48. doi:10.1016/j.oneear.2019.08.013.
13. Zhang Q, Jiang X, Tong D, et al. Transboundary health impacts of transported global air pollution and international trade. *Nature* 2017; **543**(7647): 705-9. doi:10.1038/nature21712.
14. Jiang X, Zhang Q, Zhao H, et al. Revealing the hidden health costs embodied in Chinese exports. *Environmental science & technology* 2015; **49**(7): 4381-8. doi:10.1021/es506121s.
15. Wang H, Zhang Y, Zhao H, et al. Trade-driven relocation of air pollution and health impacts in China. *Nature Communications* 2017; **8**(1): 738. doi:10.1038/s41467-017-00918-5.
16. Ou J, Huang Z, Klimont Z, et al. Role of export industries on ozone pollution and its precursors in China. *Nature Communications* 2020; **11**(1): 5492. doi:10.1038/s41467-020-19035-x.
17. Takahashi K, Nansai K, Tohno S, Nishizawa M, Kurokawa J-i, Ohara T. Production-based emissions, consumption-based emissions and consumption-based health impacts of $PM_{2.5}$ carbonaceous aerosols in Asia. *Atmospheric Environment* 2014; **97**: 406-15. doi:10.1016/j.atmosenv.2014.04.028.
18. Monforti Ferrario F, Crippa M, Guizzardi D, et al. EDGAR v6.1 Global Air Pollutant Emissions. European Commission, Joint Research Centre (JRC). 2022. http://data.europa.eu/89h/df521e05-6a3b-461c-965a-b703fb62313e.

19. Zheng B, Tong D, Li M, et al. Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions. *Atmospheric Chemistry and Physics* 2018; **18**(19): 14095-111. doi:10.5194/acp-18-14095-2018.
20. Zheng H, Bai Y, Wei W, et al. Chinese provincial multi-regional input-output database for 2012, 2015, and 2017. *Scientific Data* 2021; **8**(1): 244. doi:10.1038/s41597-021-01023-5.
21. OECD. OECD Inter-Country Input–Output (ICIO) Tables, 2018 edition. Organisation for Economic Co-operation and Development. 2018. https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm.
22. Gelaro R, McCarty W, Suárez MJ, et al. The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *Journal of Climate* 2017; **30**(14): 5419-54. doi:10.1175/JCLI-D-16-0758.1.
23. Li M, Zhang Q, Kurokawa JI, et al. MIX: a mosaic Asian anthropogenic emission inventory under the international collaboration framework of the MICS-Asia and HTAP. *Atmospheric Chemistry and Physics* 2017; **17**(2): 935-63. doi:10.5194/acp-17-935-2017.
24. Zhang Q, Zheng Y, Tong D, et al. Drivers of improved $PM_{2.5}$ air quality in China from 2013 to 2017. *Proceedings of the National Academy of Sciences* 2019; **116**(49): 24463-9. doi:10.1073/pnas.1907956116.
25. Liu J, Li W, Li J. Quality screening for air quality monitoring data in China. *Environ Pollut* 2016; **216**: 720-3. doi:10.1016/j.envpol.2016.06.037.
26. Jiang Z, Jolleys MD, Fu T-M, et al. Spatiotemporal and probability variations of surface $PM_{2.5}$ over China between 2013 and 2019 and the associated changes in health risks: An integrative observation and model analysis. *Science of The Total Environment* 2020; **723**: 137896. doi:10.1016/j.scitotenv.2020.137896.
27. Boylan JW, Russell AG. PM and light extinction model performance metrics, goals, and criteria for three-dimensional air quality models. *Atmospheric Environment* 2006; **40**(26): 4946-59. doi:10.1016/j.atmosenv.2005.09.087.
28. Yao F, Palmer PI. Source Sector Mitigation of Solar Energy Generation Losses Attributable to Particulate Matter Pollution. *Environmental Science & Technology* 2022; **56**(12): 8619-28. doi:10.1021/acs.est.2c01175.
29. Hänninen O, Knol AB, Jantunen M, et al. Environmental Burden of Disease in Europe: Assessing Nine Risk Factors in Six Countries. *Environmental Health Perspectives* 2014; **122**(5): 439-46. doi:doi:10.1289/ehp.1206154.
30. Lloyd CT, Chamberlain H, Kerr D, et al. Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. *Big Earth Data* 2019; **3**(2): 108-39. doi:10.1080/20964471.2019.1625151.
31. van Donkelaar A, Hammer MS, Bindle L, et al. Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty. *Environmental Science & Technology* 2021; **55**(22): 15287-300. doi:10.1021/acs.est.1c05309.
32. Ministry of Environmental Protection. Highlights of the Chinese exposure factors handbook (Adults). Beijing, China: China Environmental Science Press; 2014.
33. Yoon H, Seo J, Yoo S-K, et al. Updated general exposure factors for risk assessment in the Korean population. *Journal of Exposure Science & Environmental Epidemiology* 2022. doi:10.1038/s41370-022-00437-6.
34. AIST Research Center for CRM. Japanese Exposure Factors Handbook. National Institute of Advanced Industrial Science and Technology. 2007. https://unit.aist.go.jp/riss/crm/exposurefactors/english_summary.html.
35. Xiang J, Weschler CJ, Wang Q, et al. Reducing Indoor Levels of "Outdoor $PM_{2.5}$" in Urban China: Impact on Mortalities. *Environmental Science & Technology* 2019; **53**(6): 3119-27. doi:10.1021/acs.est.8b06878.

36. Zhang W, Yun X, Meng W, et al. Urban residential energy switching in China between 1980 and 2014 prevents 2.2 million premature deaths. *One Earth* 2021; **4**(11): 1602-13. doi:10.1016/j.oneear.2021.10.013.
37. Funasaka K, Furuichi Y, Sakai M. Intrusion of the atmospheric aerosol to indoor air by the difference in house structure and reference to measures approach from microchemical analysis. *Journal of the Housing Research Foundation "JUSOKEN"* 2018; **44**: 97-107. doi:10.20803/jusokenronbunjisen.44.0_97.
38. Choi DH, Kang DH. Infiltration of Ambient $PM_{2.5}$ through Building Envelope in Apartment Housing Units in Korea. *Aerosol and Air Quality Research* 2017; **17**(2): 598-607. doi:10.4209/aaqr.2016.06.0287.
39. Murray CJL, Aravkin AY, Zheng P, et al. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet* 2020; **396**(10258): 1223-49. doi:10.1016/S0140-6736(20)30752-2.
40. Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2019 (GBD 2019) Results. Institute for Health Metrics and Evaluation (IHME). 2020. https://vizhub.healthdata.org/gbd-results/.
41. Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2019 (GBD 2019) Particulate Matter Risk Curves. Institute for Health Metrics and Evaluation (IHME). 2021. https://doi.org/10.6069/KHWH-2703.
42. Zhao H, Geng G, Zhang Q, et al. Inequality of household consumption and air pollution-related deaths in China. *Nature Communications* 2019; **10**(1): 4337. doi:10.1038/s41467-019-12254-x.
43. Zhao H, Li X, Zhang Q, et al. Effects of atmospheric transport and trade on air pollution mortality in China. *Atmospheric Chemistry and Physics* 2017; **17**(17): 10367-81. doi:10.5194/acp-17-10367-2017.
44. Chafe Zoë A, Brauer M, Klimont Z, et al. Household Cooking with Solid Fuels Contributes to Ambient $PM_{2.5}$ Air Pollution and the Burden of Disease. *Environmental Health Perspectives* 2014; **122**(12): 1314-20. doi:10.1289/ehp.1206340.
45. Cheng J, Tong D, Zhang Q, et al. Pathways of China's $PM_{2.5}$ air quality 2015–2060 in the context of carbon neutrality. *National Science Review* 2021; **8**(12): nwab078. doi:10.1093/nsr/nwab078.
46. Shi X, Zheng Y, Lei Y, et al. Air quality benefits of achieving carbon neutrality in China. *Science of The Total Environment* 2021; **795**: 148784. doi:10.1016/j.scitotenv.2021.148784.
47. Tang R, Zhao J, Liu Y, et al. Air quality and health co-benefits of China's carbon dioxide emissions peaking before 2030. *Nature Communications* 2022; **13**(1): 1008. doi:10.1038/s41467-022-28672-3.
48. Karagulian F, Belis CA, Dora CFC, et al. Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. *Atmospheric Environment* 2015; **120**: 475-83. doi:10.1016/j.atmosenv.2015.08.087.
49. McDuffie EE, Martin RV, Spadaro JV, et al. Source sector and fuel contributions to ambient PM2.5 and attributable mortality across multiple spatial scales. *Nature Communications* 2021; **12**(1): 3594. doi:10.1038/s41467-021-23853-y.
50. Nansai K, Tohno S, Chatani S, et al. Affluent countries inflict inequitable mortality and economic loss on Asia via PM2.5 emissions. *Environ Int* 2020; **134**: 10. doi:10.1016/j.envint.2019.105238.
51. National Institute of Environmental Research (NIER). Summary Report of the 4th stage (2013–2017) LTP Project, 2019. https://nier.go.kr/NIER/cmm/fms/NoLoginFileDown.do;jsessionid=C1A37B9309AC438907222958C0680EF9?atchFileId=FILE_000000000029154&fileSn=0

52. Crippa M, Guizzardi D, Muntean M, et al. Gridded emissions of air pollutants for the period 1970–2012 within EDGAR v4.3.2. *Earth Syst Sci Data* 2018; **10**(4): 1987-2013. doi:10.5194/essd-10-1987-2018.
53. Tukker A, de Koning A, Owen A, et al. Towards Robust, Authoritative Assessments of Environmental Impacts Embodied in Trade: Current State and Recommendations. *J Ind Ecol* 2018; **22**(3): 585-98. doi:10.1111/jiec.12716.
54. Lenzen M, Kanemoto K, Moran D, Geschke A. Mapping the Structure of the World Economy. *Environmental Science & Technology* 2012; **46**(15): 8374-81. doi:10.1021/es300171x.
55. Peters GP, Minx JC, Weber CL, Edenhofer O. Growth in emission transfers via international trade from 1990 to 2008. *Proceedings of the National Academy of Sciences* 2011; **108**(21): 8903-8. doi:doi:10.1073/pnas.1006388108.
56. Tukker A, Poliakov E, Heijungs R, et al. Towards a global multi-regional environmentally extended input–output database. *Ecological Economics* 2009; **68**(7): 1928-37. doi:10.1016/j.ecolecon.2008.11.010.
57. Dietzenbacher E, Los B, Stehrer R, Timmer M, de Vries G. The Construction of World Input–Output Tables in the WIOD Project. *Economic Systems Research* 2013; **25**(1): 71-98. doi:10.1080/09535314.2012.761180.
58. Giljum S, Wieland H, Lutter S, Eisenmenger N, Schandl H, Owen A. The impacts of data deviations between MRIO models on material footprints: A comparison of EXIOBASE, Eora, and ICIO. *J Ind Ecol* 2019; **23**(4): 946-58. doi:10.1111/jiec.12833.
59. Burnett RT, Pope CA, Ezzati M, et al. An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental health perspectives* 2014; **122**(4): 397-403. doi:10.1289/ehp.1307049.
60. Burnett R, Chen H, Szyszkowicz M, et al. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences* 2018; **115**(38): 9592-7. doi:doi:10.1073/pnas.1803222115.
61. Bell ML, Ebisu K. Environmental Inequality in Exposures to Airborne Particulate Matter Components in the United States. *Environmental Health Perspectives* 2012; **120**(12): 1699-704. doi:10.1289/ehp.1205201.
62. Zou YJ, Jin CY, Su Y, Li JR, Zhu BS. Water soluble and insoluble components of urban PM2.5 and their cytotoxic effects on epithelial cells (A549) in vitro. *Environ Pollut* 2016; **212**: 627-35. doi:10.1016/j.envpol.2016.03.022.

Tables

Table 1. Definitions of emission scenarios in this study.

Categories	Scenarios	Definition
Base scenario	Scenario 1 (S1)	Baseline scenario in which production-based emissions from EDGARv6.1 is used and no emissions are excluded
Production-based scenarios	Scenario 2 (S2)	A scenario in which emissions produced in China are excluded
	Scenario 3 (S3)	A scenario in which emissions produced in South Korea are excluded
	Scenario 4 (S4)	A scenario in which emissions produced in Japan are excluded
Consumption-based scenarios	Scenario 5 (S5)	A scenario in which emissions induced by final consumption in China are excluded
	Scenario 6 (S6)	A scenario in which emissions induced by final consumption in South Korea are excluded
	Scenario 7 (S7)	A scenario in which emissions induced by final consumption in Japan are excluded
Additional scenarios	Scenario 8 (S8)	A scenario in which emissions in China induced by final consumption in South Korea are excluded
	Scenario 9 (S9)	A scenario in which emissions in China induced by final consumption in Japan are excluded
	Scenario 10 (S10)	A scenario in which emissions in China induced by final consumption in all other countries except China are excluded

Note: EDGARv6.1, the Emissions Database for Global Atmospheric Research v6.1.

Table 2. Contributions from source to receptor countries' population-weighted mean $PM_{2.5}$ concentrations in Northeast Asia.

Year	Receptor country / Source country		China ($\mu g/m^3$, %)		South Korea ($\mu g/m^3$, %)		Japan ($\mu g/m^3$, %)	
2015	Baseline PWM $PM_{2.5}$ concentration		49.86	100%	24.92	100%	12.24	100%
	Source country where pollution is emitted	China	36.01	72.2%	8.73	35.0%	2.71	22.1%
		South Korea	0.19	0.4%	9.69	38.9%	0.44	3.6%
		Japan	0.03	0.1%	0.22	0.9%	4.74	38.7%
		Others	13.63	27.3%	6.28	25.2%	4.35	35.6%
	Source country where goods are consumed	China	25.88	51.9%	6.71	26.9%	2.15	17.6%
		South Korea	0.25	0.5%	6.06	24.3%	0.31	2.5%
		Japan	0.35	0.7%	0.39	1.6%	3.79	31.0%
		Others	23.38	46.9%	11.76	47.2%	5.99	48.9%
2017	Baseline PWM $PM_{2.5}$ concentration		43.38	100%	22.62	100%	11.56	100%
	Source country where pollution is emitted	China	30.68	70.7%	8.39	37.1%	2.64	22.9%
		South Korea	0.08	0.2%	8.44	37.3%	0.48	4.1%
		Japan	0.01	0.0%	0.13	0.6%	4.35	37.7%
		Others	12.61	29.1%	5.66	25.0%	4.09	35.3%
	Source country where goods are consumed	China	22.13	51.0%	6.49	28.7%	2.14	18.5%
		South Korea	0.17	0.4%	5.68	25.1%	0.35	3.0%
		Japan	0.27	0.6%	0.31	1.3%	3.45	29.9%
		Others	20.81	48.0%	10.14	44.9%	5.62	48.6%

Note that the values in the rows of "Others" are residuals after deducting Chinese, South Korean and Japanese contributions from the baseline. Note: $PM_{2.5}$, fine particulate matter; PWM, population weighted mean.

Table 3. Contributions from source to receptor countries' $PM_{2.5}$ population exposure in Northeast Asia.

Year	Receptor country / Source country		China (kg/d, %)		South Korea (kg/d, %)		Japan (kg/d, %)	
2015	Baseline $PM_{2.5}$ population exposure		768.24	100%	10.83	100%	9.56	100%
	Source country where pollution is emitted	China	557.61	72.6%	3.79	35.0%	2.11	22.1%
		South Korea	2.93	0.4%	4.21	38.9%	0.34	3.6%
		Japan	0.48	0.1%	0.1	0.9%	3.7	38.7%
		Others	207.22	26.9%	2.72	25.2%	3.4	35.6%
	Source country where goods are consumed	China	400.7	52.2%	2.92	26.9%	1.68	17.6%
		South Korea	3.9	0.5%	2.64	24.3%	0.24	2.5%
		Japan	5.48	0.7%	0.17	1.6%	2.96	31.0%
		Others	358.16	46.6%	5.10	47.2%	4.68	48.9%
2017	Baseline $PM_{2.5}$ population exposure		680.65	100%	10.04	100%	9.04	100%
	Source country where pollution is emitted	China	484.9	71.2%	3.72	37.1%	2.07	22.9%
		South Korea	1.32	0.2%	3.75	37.3%	0.37	4.1%
		Japan	0.14	0.0%	0.06	0.6%	3.4	37.7%
		Others	194.29	28.6%	2.51	25.0%	3.2	35.3%
	Source country where goods are consumed	China	349.43	51.3%	2.88	28.7%	1.68	18.5%
		South Korea	2.74	0.4%	2.52	25.1%	0.27	3.0%
		Japan	4.26	0.6%	0.14	1.3%	2.7	29.9%
		Others	324.22	47.7%	4.5	44.9%	4.39	48.6%

Note that the values in the rows of "Others" are residuals after deducting Chinese, South Korean and Japanese contributions from the baseline. Note: $PM_{2.5}$, fine particulate matter.

841 **Table 4. Contributions from source to receptor countries' $PM_{2.5}$-related premature deaths in Northeast Asia.**

Year	Source country \ Receptor country		China (thousand premature deaths with 95% CI, %)		South Korea (thousand premature deaths, 95% CI, %)		Japan (thousand premature deaths, 95% CI, %)	
2015	Total $PM_{2.5}$-related premature deaths		1386.51 (1263.53, 1507.49)	100%	17.19 (14.74, 19.62)	100%	22.32 (15.89, 28.66)	100%
	Source country where pollution is emitted	China	995.47 (908.63, 1081.18)	71.8%	6.02 (5.16, 6.87)	35.0%	4.92 (3.5, 6.32)	22.0%
		South Korea	5.22 (4.78, 5.66)	0.4%	6.69 (5.74, 7.64)	38.9%	0.8 (0.58, 1.02)	3.6%
		Japan	0.87 (0.79, 0.95)	0.1%	0.15 (0.13, 0.18)	0.9%	8.72 (6.25, 11.17)	39.1%
		Others	384.95 (349.34, 419.7)	27.7%	4.33 (3.71, 4.93)	25.2%	7.88 (5.56, 10.16)	35.3%
	Source country where goods are consumed	China	717.01 (654.28, 778.89)	51.7%	4.63 (3.97, 5.28)	26.9%	3.91 (2.78, 5.01)	17.5%
		South Korea	6.96 (6.36, 7.56)	0.5%	4.19 (3.59, 4.78)	24.4%	0.56 (0.41, 0.72)	2.5%
		Japan	9.79 (8.93, 10.64)	0.7%	0.27 (0.23, 0.31)	1.6%	6.96 (4.98, 8.93)	31.2%
		Others	652.75 (593.96, 710.4)	47.1%	8.10 (6.95, 9.25)	47.1%	10.89 (7.72, 14.01)	48.8%
2017	Total $PM_{2.5}$-related premature deaths		1247.62 (1129.81, 1363.44)	100%	15.44 (13.07, 17.78)	100%	19.86 (13.75, 25.85)	100%
	Source country where pollution is emitted	China	881.06 (799.07, 961.94)	70.6%	5.73 (4.84, 6.59)	37.1%	4.56 (3.17, 5.91)	22.9%
		South Korea	2.47 (2.24, 2.7)	0.2%	5.78 (4.89, 6.65)	37.4%	0.84 (0.6, 1.07)	4.2%
		Japan	0.29 (0.26, 0.32)	0.0%	0.09 (0.07, 0.1)	0.6%	7.52 (5.22, 9.78)	37.9%
		Others	363.8 (328.25, 398.48)	29.2%	3.84 (3.26, 4.43)	24.9%	6.94 (4.76, 9.09)	35.0%
	Source country where goods are consumed	China	636.64 (577.24, 695.2)	51.0%	4.43 (3.75, 5.1)	28.7%	3.69 (2.57, 4.79)	18.6%
		South Korea	5.03 (4.55, 5.49)	0.4%	3.89 (3.29, 4.48)	25.2%	0.61 (0.43, 0.78)	3.1%
		Japan	7.75 (7.02, 8.47)	0.6%	0.21 (0.18, 0.24)	1.4%	5.95 (4.13, 7.75)	30.0%
		Others	598.2 (540.99, 654.28)	48.0%	6.91 (5.85, 7.96)	44.7%	9.61 (6.63, 12.53)	48.3%

842 Note that the values in the rows of "Others" are residuals after deducting Chinese, South Korean and Japanese contributions from the baseline.
843 Note: $PM_{2.5}$, fine particulate matter; CI, confidential interval.

Table 5. Partition of China' transboundary contributions to $PM_{2.5}$ pollution and associated population exposure and premature deaths in South Korea and Japan.

Year	Receptor country / Source country	South Korea: Concentration (μg/m³, %)	South Korea: Population exposure (kg/d, %)	South Korea: Premature death (thousand premature deaths with 95% CI, %)	Japan: Concentration (μg/m³, %)	Japan: Population exposure (kg/d, %)	Japan: Premature death (thousand premature deaths with 95% CI, %)
2015	China's contribution from production perspective	8.73, 100%	3.79, 100%	6.02 (5.16, 6.87), 100%	2.71, 100%	2.11, 100%	4.92 (3.5, 6.32), 100%
	- part induced by China's consumption	6.56, 75.1%	2.85, 75.1%	4.52 (3.88, 5.16), 75.1%	2.04, 75.2%	1.59, 75.2%	3.7 (2.63, 4.75), 75.2%
	- part induced by South Korea's consumption	0.04, 0.5%	0.02, 0.5%	0.03 (0.02, 0.03), 0.5%	0.01, 0.5%	0.01, 0.5%	0.02 (0.02, 0.03), 0.5%
	- part induced by Japan's consumption	0.09, 1.0%	0.04, 1.0%	0.06 (0.05, 0.07), 1.0%	0.03, 1.0%	0.02, 1.0%	0.05 (0.04, 0.06), 1.0%
	- part induced by others' consumption	2.04, 23.4%	0.89, 23.4%	1.41 (1.21, 1.61), 23.4%	0.63, 23.3%	0.49, 23.3%	1.15 (0.82, 1.47), 23.3%
2017	China's contribution from production perspective	8.39, 100%	3.72, 100%	5.73 (4.84, 6.59), 100%	2.64, 100.0%	2.07, 100%	4.56 (3.17, 5.91), 100%
	- part induced by China's consumption	6.42, 76.5%	2.85, 76.5%	4.38 (3.7, 5.04), 76.5%	2.04, 77.1%	1.59, 77.1%	3.51 (2.44, 4.55), 77.1%
	- part induced by South Korea's consumption	0.04, 0.5%	0.02, 0.5%	0.03 (0.02, 0.03), 0.5%	0.01, 0.5%	0.01, 0.5%	0.02 (0.01, 0.03), 0.5%
	- part induced by Japan's consumption	0.08, 0.9%	0.03, 0.9%	0.05 (0.04, 0.06), 0.9%	0.02, 0.9%	0.02, 0.9%	0.04 (0.03, 0.05), 0.9%
	- part induced by others' consumption	1.85, 22.1%	0.82, 22.1%	1.27 (1.07, 1.46), 22.1%	0.57, 21.5%	0.45, 21.5%	0.98 (0.69, 1.27), 21.5%

Note that the percentages for concentration, population exposure, and premature deaths are slightly different but become identical after rounding. Note: $PM_{2.5}$, fine particulate matter; CI, confidential interval.

Figures captions

Fig. 1. Annual gridded fractional contributions to $PM_{2.5}$ concentrations in 2017 in Northeast Asia from production-based emissions in China (A), South Korea (B), Japan (C), and consumption-based emissions induced by the consumption in China (D), South Korea (E), and Japan (F). Note: $PM_{2.5}$, fine particulate matter.

Fig. 2. The estimated $PM_{2.5}$ concentrations contributed by China to South Korea (A) and Japan (B) from 2008 to 2017 and the primary $PM_{2.5}$ emission trend in China from 2010 to 2017. Each blue triangle represents an estimation of China's contribution to $PM_{2.5}$ concentrations in South Korea from the literature and this study. Each blue diamond represents an estimation of China's contribution to $PM_{2.5}$ concentrations in Japan from the literature and this study. The blue dash lines refer to the trend lines of China's contributions to $PM_{2.5}$ concentrations in South Korea and Japan. The orange line refers to the primary $PM_{2.5}$ emission trend in China from 2010 to 2017 based on data obtained from the study by Zheng, Tong[19]. Numeric data can be found in Table S13, Table S14, and Excel Table S1 in the Supplemental Excel File. Note: $PM_{2.5}$, fine particulate matter.

Fig. 1.

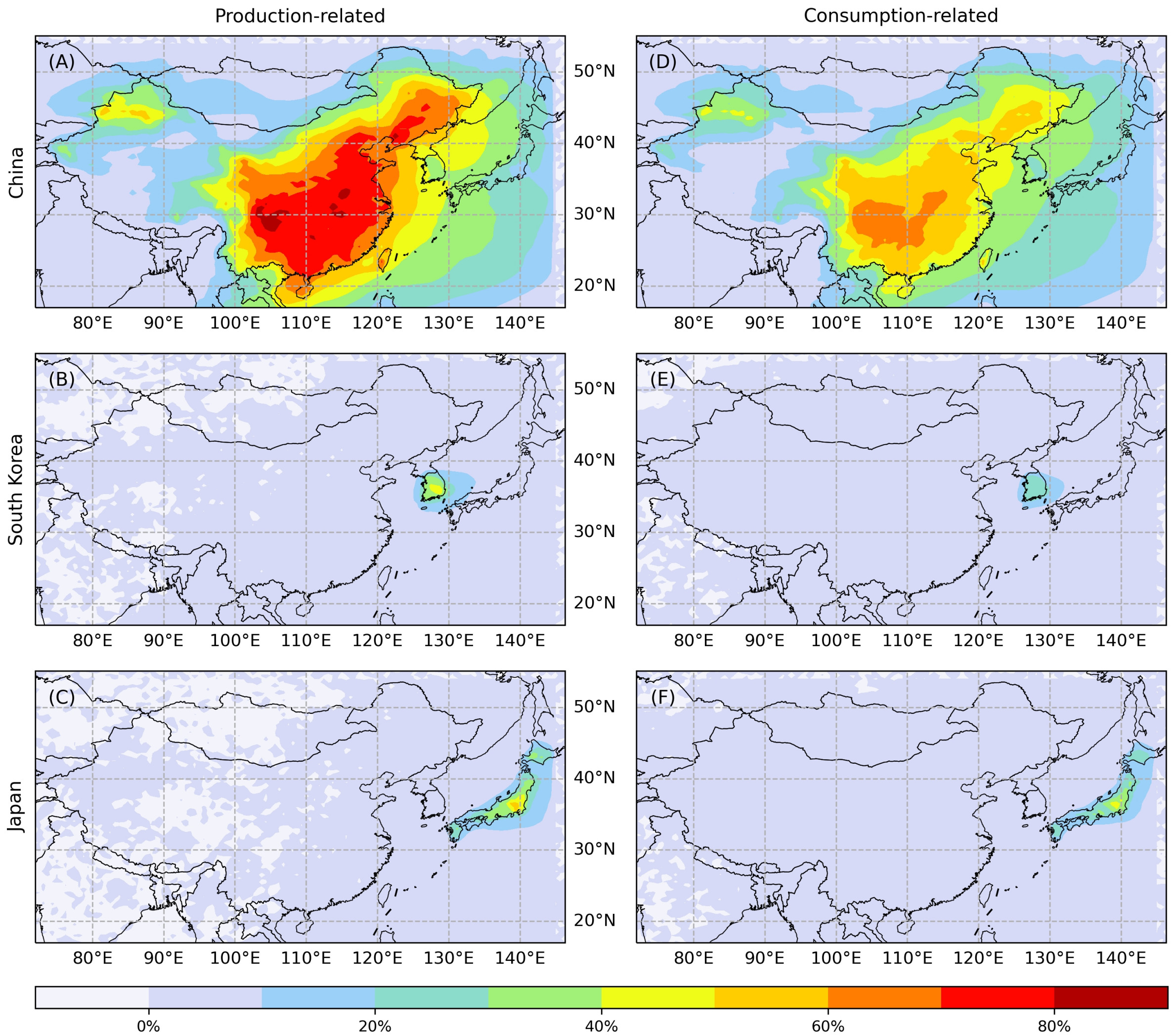
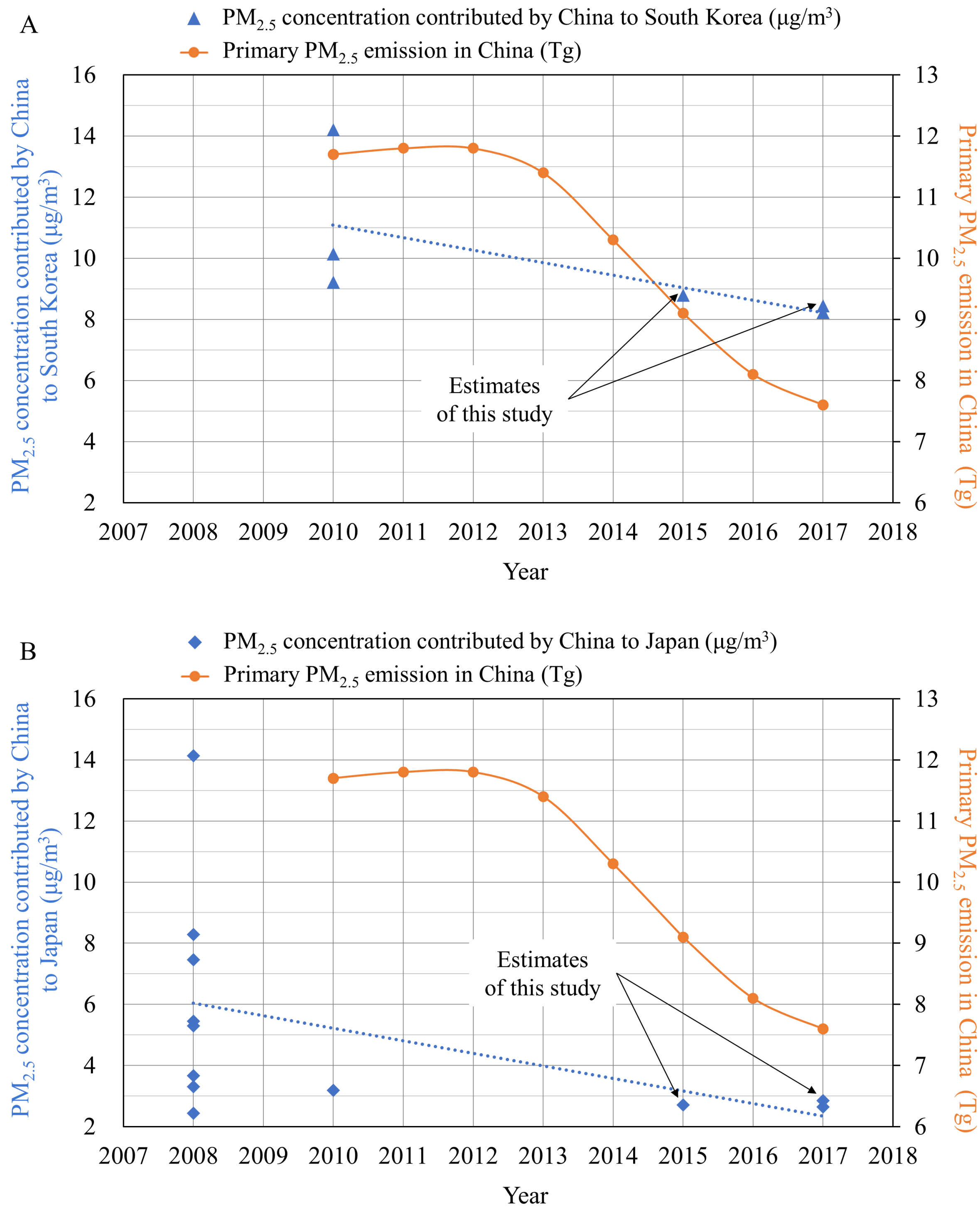

Production-related
Consumption-related
China
South Korea
Japan
(A)
(B)
(C)
(D)
(E)
(F)
50°N
40°N
30°N
20°N
80°E
90°E
100°E
110°E
120°E
130°E
140°E
0%
20%
40%
60%
80%

Fig. 2.


A
PM2.5 concentration contributed by China to South Korea (μg/m3)
Primary PM2.5 emission in China (Tg)
PM2.5 concentration contributed by China to South Korea (μg/m3)
Primary PM2.5 emission in China (Tg)
Estimates of this study
Year
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
2 4 6 8 10 12 14 16
6 7 8 9 10 11 12 13
B
PM2.5 concentration contributed by China to Japan (μg/m3)
Primary PM2.5 emission in China (Tg)
PM2.5 concentration contributed by China to Japan (μg/m3)
Primary PM2.5 emission in China (Tg)
Estimates of this study
Year
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
2 4 6 8 10 12 14 16
6 7 8 9 10 11 12 13

Supplementary material for

Quantifying the mutual contributions of $PM_{2.5}$ pollution and associated population exposure and premature deaths among China, South Korea, and Japan: A dual perspective and an interdisciplinary approach

Table of Contents

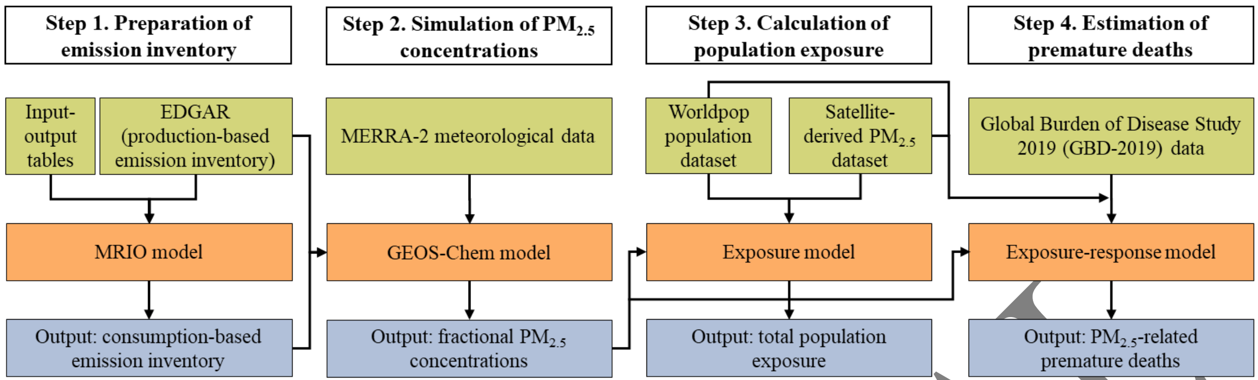


Figure S1. Analysis framework in this study. Each column shows the purpose, input data, model, and output data of each step from top to bottom. Arrows indicate data flow. Note: EDGAR, the Emissions Database for Global Atmospheric Research; MRIO, multi-regional input-output; $PM_{2.5}$, fine particulate matter; MERRA-2, Modern-Era Retrospective analysis for Research and Applications version 2; GBD, global burden of disease.

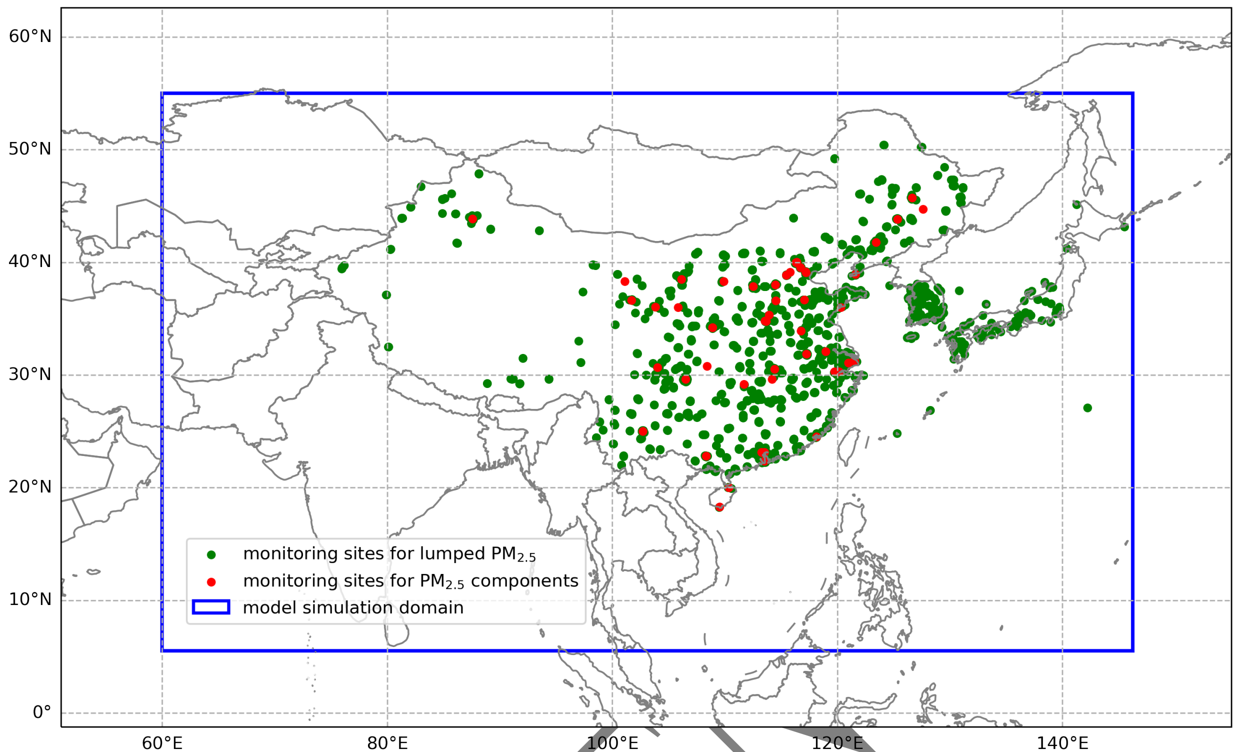


Figure S2. Study domain. Each green dot represents a monitoring site for lumped $PM_{2.5}$. Each red dot represents a monitoring site for $PM_{2.5}$ components. Numeric data can be found in Excel Table S2 in the Supplemental Excel File. Note: $PM_{2.5}$, fine particulate matter.

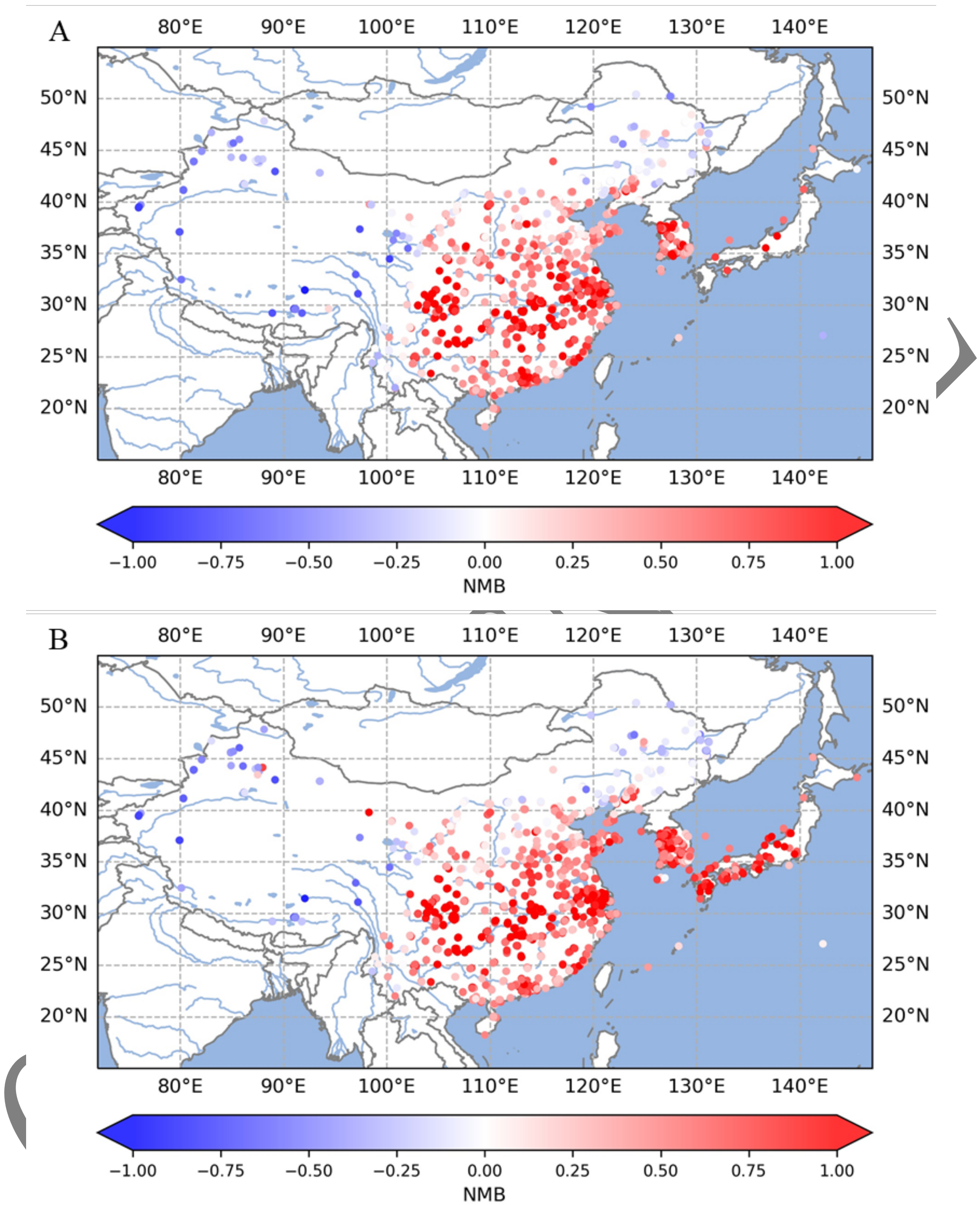


Figure S3. Site-scale evaluation of simulated monthly average $PM_{2.5}$ against ground-level measurements in terms of normalized mean bias (NMB) in 2015 (A) and 2017 (B). Each dot represent a monitoring site. Numeric data can be found in Excel Table S3 in the Supplemental Excel File. Note: $PM_{2.5}$, fine particulate matter; NMB, normalized mean bias.

Table S1. The MRIO model.

			Intermediate demand						Final demand						Total output
			P_1	…	P_{31}	R_1	…	R_{64}	P_1	…	P_{31}	R_1	…	R_{64}	
Intermediate input	Provinces	P_1	(A)			(D)			(B)			(E)			(C)
		P_2													
		…													
		P_{31}													
	Countries	R_1	(F)			(I)			(G)			(J)			(H)
		R_2													
		…													
		R_{64}													

Note that P_m refers to province m in China, and R_n refers to country/region n in this table.

Parts (A), (B), and (C) in the above table indicate the intermediate demand matrix, the final demand matrix, and the total output vector in China's MRIO table, respectively. Part (D) and Part (E) in the above table were calculated using the following equations [1] and [2], respectively:

$$Z_{CA}{}_{ij}^{r} = EX\_M_i^r * \frac{Z\_IC_{CA_{ij}}}{\sum_j Z\_IC_{CA_{ij}} + Y\_IC_{CA_{ik}} + \sum_R \sum_j Z\_IC_{CR_{ij}} + \sum_R Y\_IC_{CR_{ik}}} \quad [1]$$

$$Y_{CA}{}_{ik}^{r} = EX\_M_i^r * \frac{Y\_IC_{CA_{ik}}}{\sum_j Z\_IC_{CA_{ij}} + Y\_IC_{CA_{ik}} + \sum_R \sum_j Z\_IC_{CR_{ij}} + \sum_R Y\_IC_{CR_{ik}}} \quad [2]$$

where $Z_{CA}{}_{ij}^{r}$ refers to the result matrix in Part (D), and $Y_{CA}{}_{ik}^{r}$ refers to the result matrix in Part (E). $EX\_M_i^r$ represents the export vector in China's MRIO table. $Z\_IC_{CA_{ij}}$ and $Y\_IC_{CA_{ik}}$ represent, the intermediate demand and final demand matrices of China, respectively, to any other 64 countries (regions) in the OECD ICIO table. $Z\_IC_{CR_{ij}}$ and $Y\_IC_{CR_{ik}}$ represent, the intermediate demand and final demand matrices of China, respectively, to the remaining 63 countries (regions)in the OECD ICIO table. Note that the subscripts of C, A, and R represent China, any other 64 countries (regions), and the remaining 63 countries (regions), respectively. The subscripts of i and j denote the sectors, and k indicates different types of final demand, including consumption by rural and urban residents, government investment, fixed asset investment, and others. The superscript of r represents the provinces in China.

Part (F) and Part (G) in the above table were calculated using the following equations [3] and [4], respectively:

$$Z_{AC}{}_{ij}^{r} = IM\_M_{Z}{}_{j}^{r} * \frac{Z\_IC_{AC_{ij}}}{\sum_i Z\_IC_{AC_{ij}} + \sum_R \sum_i Z\_IC_{RC_{ij}}} \quad [3]$$

$$Y_{AC}{}_{ik}^{r} = IM\_M_{Y}{}_{j}^{r} * \frac{Y\_IC_{AC_{ik}}}{\sum_i Y\_IC_{AC_{ik}} + \sum_R \sum_i Y\_IC_{RC_{ik}}} \quad [4]$$

where $Z_{AC}{}_{ij}^{r}$ refers to the result matrix in Part (F), and $Y_{AC}{}_{ik}^{r}$ refers to the result matrix in Part (G). $IM\_M_{Z}{}_{j}^{r}$ and $IM\_M_{Y}{}_{j}^{r}$ denote the intermediate and final import vectors in China's MRIO table, respectively.

Part (H) in the above table was calculated using the following equation:

$$X_{A_i} = X\_IC_{A_i} * \frac{\sum_r X\_M_i^r}{X\_IC_{C_i}} \quad [5]$$

where X_{A_i} refers to the result matrix in Part (H). $X\_IC_{C_i}$ and $X\_IC_{A_i}$ indicate the output vector of China, and any other 64 countries (regions) in the OECD ICIO table. $X\_M_i^r$ indicate the total output vector in China's MRIO table.

Part (I) and Part (J) in the above table were calculated using the following equations:

$$Z_{AA_{ij}} = (X_{A_i} - \sum_j Z_{AC}{}_{ij}^{r} - Y_{AC}{}_{ik}^{r}) * \frac{Z\_IC_{AA_{ij}}}{\sum_j Z\_IC_{AA_{ij}} + \sum_R \sum_j Z\_IC_{AR_{ij}} + Y\_IC_{AA_{ik}} + \sum_R Y\_IC_{AR_{ik}}} \quad [6]$$

$$Y_{AA_{ij}} = (X_{A_i} - \sum_j Z_{AC}{}_{ij}^{r} - Y_{AC}{}_{ik}^{r}) * \frac{Y\_IC_{AA_{ik}}}{\sum_j Z\_IC_{AA_{ij}} + \sum_R \sum_j Z\_IC_{AR_{ij}} + Y\_IC_{AA_{ik}} + \sum_R Y\_IC_{AR_{ik}}} \quad [7]$$

Note: MRIO, multi-regional input-output; $PM_{2.5}$, fine particulate matter; OECD, the Organization for Economic Cooperation and Development; ICIO, inter-country input–output.

Table S2. Mapping good sectors between China's MRIO table and OECD ICIO table

The MRIO model	China's MRIO table	OECD ICIO table
Agriculture	Agriculture, forestry and fishery products	Agriculture, forestry and fishing
Mining	Coal mining and processing products	Mining and extraction of energy producing products
	Oil and gas mining products	Mining and quarrying of non-energy producing products
	Metal mining and processing products	Mining support service activities
	Non-metallic minerals	
Food and tobacco	Food and tobacco	Food products, beverages and tobacco
Textiles and Clothes	Textile	Textiles, wearing apparel, leather and related products
	Textile clothing, shoes, hats, leather	
Wood and furniture	Wood products and furniture	Wood and products of wood and cork
Paper printing	Paper making, printing, cultural, educational and sports goods	Paper products and printing
Coke and petroleum	Petroleum, coking products and nuclear fuel processing products	Coke and refined petroleum products
Chemicals	Chemical products	Chemicals and pharmaceutical products
		Rubber and plastic products
Non-metallic mineral	Non-metallic mineral products	Other non-metallic mineral products
Metals	Metal smelting products	Basic metals
	Metal products	Fabricated metal products
General equipment	General equipment, special equipment	Machinery and equipment, n.e.c.
Electrical and optical equipment	Electrical machinery and equipment	Computer, electronic and optical products
	Communication equipment, computers and other electronic equipment	Electrical equipment
	Instruments and meters	
Transport equipment	Transportation equipment	Motor vehicles, trailers and semi-trailers
		Other transport equipment
Other manufacturing	Other manufacturing products	Other manufacturing; repair and installation of machinery and equipment
	Scrap	
	Metal products, equipment repair services	
Electricity	Production and supply of electricity	Electricity, gas, water supply, sewerage, waste and remediation services
	Production and supply of heat and gas	
	Production and supply of water	

Note: MRIO, multi-regional input-output; OECD, the Organization for Economic Cooperation and Development; ICIO, inter-country input–output.

Table S3. Mapping construction and service sectors between China's MRIO table and OECD ICIO table

The MRIO model	China's MRIO table	OECD ICIO table
Construction	Construction	Construction
Wholesale and retail trade	Wholesale and retail	Wholesale and retail trade; repair of motor vehicles
Hotels and restaurants	Accommodation and catering	Accommodation and food services
Transport, postage, and warehousing	Transportation, warehousing and post	Transportation and storage
		Telecommunications
Other services	Others	Publishing, audiovisual and broadcasting activities
		IT and other information services
		Financial and insurance activities
		Real estate activities
		Other business sector services
		Public administration and defence; compulsory social security
		Education
		Human health and social work
		Arts, entertainment, recreation and other service activities
		Private households with employed persons

Note: MRIO, multi-regional input-output; OECD, the Organization for Economic Cooperation and Development; ICIO, inter-country input–output.

Table S4. Re-organization of the emission sources in EDGARv6.1 into 20 sectors in the MRIO model. Note that household direct emissions from residential sectors in the EDGARv6.1 are considered to be driven by local direct consumption and are thus not mapped to any MRIO sectors.

The MRIO model	EDGARv6.1
Agriculture	Manure management
	Rice cultivation
	Direct soil emissions
	Manure in pasture/range/paddock
	Other direct soil emissions
	Agricultural waste burning
Mining	Fugitive emissions from solid fuels
	Fugitive emissions from oil and gas
	Fossil fuel fires
	Fugitive emissions from gaseous fuels
	Fugitive emissions from liquid fuels
Food and tobacco	Production of pulp/paper/food/drink
Textiles and Clothes	Manufacturing Industries and Construction
Wood and furniture	Manufacturing Industries and Construction
Paper printing	Production of pulp/paper/food/drink
Coke and petroleum	Other Energy Industries
Chemicals	Soda ash production and use
	Production of chemicals
	Solvent and other product use: degrease
	Solvent and other product use: other
	Solvent and other product use: paint
	Solvent and other product use: chemicals
Non-metallic mineral	Cement production
	Lime production
	Production of other minerals
Metals	Production of metals
General equipment	Manufacturing Industries and Construction
Electrical and optical equipment	Semiconductor/electronics manufacture
	Electrical equipment
Transport equipment	Manufacturing Industries and Construction
Other manufacturing	Solid waste disposal on land
	Waste incineration
	Wastewater handling
	Other waste handling
Electricity	Public electricity and heat production
Construction	Manufacturing Industries and Construction
Transport, postage, and warehousing	Domestic aviation
	Road transportation no resuspension
	Road transportation resuspension
	Rail transportation

	Inland navigation
	Other transportation
Wholesale and retail trade	Residential and other sectors
Hotels and restaurants	
Other services	
Household direct emissions	

Note: EDGARv6.1, the Emissions Database for Global Atmospheric Research v6.1; MRIO, multi-regional input-output; OECD, the Organization for Economic Cooperation and Development; ICIO, inter-country input–output.

Table S5. Other GEOS-Chem default emissions used in this study

Emissions	References
Emissions from aircraft	Stettler, Eastham and Barrett[1]
Emissions from open fires from tropical deforestation, boreal forest, peat, savannah, and temperate forest	van der Werf, Randerson[2]
Emissions from soil	Hudman, Moore[3]
Emissions from lightning	Murray, Jacob[4]
Emissions from nitrogen oxides, biogenic volatile organic compounds	Guenther, Jiang[5]
Emissions from ammonia	Bouwman, Lee[6]
Emissions from volcanic sulfur dioxide	Carn, Yang[7]
Emissions from mineral	Zender, Bian and Newman[8]
Emissions from anthropogenic dust	Philip, Martin[9]
Emissions from oceanic sea salt	Gong[10], Jaeglé, Quinn[11]
Emissions from the remaining emission sources	Riddick, Dragosits[12], Liang, Stolarski[13], Ordóñez, Lamarque[14], Millet, Guenther[15], Johnson[16], Nightingale, Malin[17], Vinken, Boersma[18], Holmes, Prather and Vinken[19], Sherwen, Evans[20]

Table S6. Model evaluation against ground measurements for lumped $PM_{2.5}$ and its components.

Year	Species	N	R	NMB	NME	MFB	MFE
2015	lumped $PM_{2.5}$	486	0.71	39.0%	49.0%	20.2%	28.7%
	sulfate	58	0.49	34.6%	45.9%	22.6%	28.0%
	nitrate	58	0.69	1.5%	30.5%	4.8%	23.9%
	ammonium	58	0.67	33.6%	41.7%	29.1%	32.4%
	organic carbon	57	0.57	-12.7%	43.8%	-1.2%	30.4%
	black carbon	61	0.48	-6.0%	58.8%	7.4%	44.2%
2017	lumped $PM_{2.5}$	537	0.75	39.9%	49.4%	21.9%	29.1%
	sulfate	38	0.24	68.4%	79.6%	38.6%	42.3%
	nitrate	38	0.8	-9.0%	27.0%	-3.8%	19.9%
	ammonium	38	0.58	46.7%	52.3%	35.3%	37.4%
	organic carbon	37	0.14	1.1%	53.7%	6.9%	35.2%
	black carbon	38	0.57	26.2%	41.7%	14.9%	25.6%

Note: $PM_{2.5}$, fine particulate matter; R, pearson correlation coefficient; NMB, normalized mean bias; NME, normalized mean error; MFB, mean fractional bias; MFE, mean fractional error.

Table S7. Inhalation rates used in this study

Region/Country	Inhalation rate (m^3/d)	References
Beijing, China	16.1	
Tianjin, China	16.2	
Hebei, China	16	
Shanxi, China	16.1	
Inner Mongolia, China	16.3	
Liaoning, China	16.3	
Jilin, China	16.2	
Heilongjiang, China	16	
Shanghai, China	15.8	
Jiangsu, China	15.4	
Zhejiang, China	15.6	
Anhui, China	15.4	
Fujian, China	15.5	
Jiangxi, China	15.2	
Shandong, China	16.1	Ministry of Environmental Protection[21]
Henan, China	15.6	
Hubei, China	15.8	
Hunan, China	15.8	
Guangdong, China	15	
Guangxi, China	15.1	
Hainan, China	15.3	
Chongqing, China	14.8	
Sichuan, China	15.4	
Guizhou, China	15.6	
Yunnan, China	15.5	
Tibet, China	15.3	
Shaanxi, China	15.1	
Gansu, China	15.6	
Qinghai, China	16	
Ningxia, China	16	
Xinjiang, China	16.3	
South Korea	14.61	Yoon, Seo[22]
Japan	17.3	AIST Research Center for CRM[23]

101 **Table S8. Time-activity factors used in this study**

Region/Country	Time spent in indoor (h/d)	Time spent in outdoor (h/d)	References
Beijing, China	20.75	3.25	Ministry of Environmental Protection[21]
Tianjin, China	20.87	3.13	
Hebei, China	20.97	3.03	
Shanxi, China	20.25	3.75	
Inner Mongolia, China	19.83	4.17	
Liaoning, China	20.92	3.08	
Jilin, China	21.57	2.43	
Heilongjiang, China	20.5	3.5	
Shanghai, China	21.42	2.58	
Jiangsu, China	21.17	2.83	
Zhejiang, China	20.8	3.2	
Anhui, China	20.57	3.43	
Fujian, China	20.9	3.1	
Jiangxi, China	20.22	3.78	
Shandong, China	21.18	2.82	
Henan, China	19	5	
Hubei, China	19.58	4.42	
Hunan, China	20.5	3.5	
Guangdong, China	20.5	3.5	
Guangxi, China	19.17	4.83	
Hainan, China	18.43	5.57	
Chongqing, China	20.55	3.45	
Sichuan, China	19.85	4.15	
Guizhou, China	20.18	3.82	
Yunnan, China	18.67	5.33	
Tibet, China	18.35	5.65	
Shaanxi, China	19.5	4.5	
Gansu, China	18.5	5.5	
Qinghai, China	21.18	2.82	
Ningxia, China	21.25	2.75	
Xinjiang, China	19.25	4.75	
South Korea	21.82	2.18	Yoon, Seo[22]
Japan	22.8	1.2	AIST Research Center for CRM[23]

102

Table S9. Infiltration factors used in this study.

Region/Country	Infiltration factors	References
Beijing, China	67.3%	
Tianjin, China	60.5%	
Hebei, China	57.5%	
Shanxi, China	56.8%	
Inner Mongolia, China	55.8%	
Liaoning, China	57.8%	
Jilin, China	56.3%	
Heilongjiang, China	57.5%	
Shanghai, China	81.5%	
Jiangsu, China	80.8%	
Zhejiang, China	82.5%	
Anhui, China	81.3%	
Fujian, China	84.8%	
Jiangxi, China	85.3%	
Shandong, China	63.5%	
Henan, China	62.8%	Zhang, Yun[24]
Hubei, China	81.5%	
Hunan, China	83.3%	
Guangdong, China	85.5%	
Guangxi, China	82.8%	
Hainan, China	88.0%	
Chongqing, China	84.0%	
Sichuan, China	82.8%	
Guizhou, China	81.3%	
Yunnan, China	82.0%	
Tibet, China	54.3%	
Shaanxi, China	58.5%	
Gansu, China	58.0%	
Qinghai, China	54.8%	
Ningxia, China	60.0%	
Xinjiang, China	54.5%	
South Korea	65.0%	Choi and Kang[25]
Japan	45.0%	Funasaka, Furuichi and Sakai[26]

Note that the infiltration factor for each province in China is computed by averaging the values of infiltration factors across heating/non-heating seasons and urban/rural areas for that province [24].

Table S10. Testing for the differences between production-based monthly population-weighted mean $PM_{2.5}$ concentration and consumption-based monthly population-weighted mean $PM_{2.5}$ concentration

Year	Source	Receptor	Mean of production-based monthly population-weighted mean $PM_{2.5}$ concentration	Mean of consumption-based monthly population-weighted mean $PM_{2.5}$ concentration	t	p
2015	China	South Korea	8.75	6.73	13.57	< 0.001
2015	China	Japan	2.70	2.14	9.86	< 0.001
2015	South Korea	China	0.17	0.24	-2.31	0.041
2015	South Korea	Japan	0.44	0.31	9.85	< 0.001
2015	Japan	China	0.03	0.35	-9.62	< 0.001
2015	Japan	South Korea	0.22	0.38	-8.29	< 0.001
2015	Others	China	13.49	23.39	-7.53	< 0.001
2015	Others	South Korea	6.25	11.75	-14.38	< 0.001
2015	Others	Japan	4.38	6.01	-29.48	< 0.001
2017	China	South Korea	8.38	6.50	11.24	< 0.001
2017	China	Japan	2.64	2.14	10.74	< 0.001
2017	South Korea	China	0.07	0.16	-5.05	< 0.001
2017	South Korea	Japan	0.48	0.35	9.04	< 0.001
2017	Japan	China	0.01	0.27	-9.41	< 0.001
2017	Japan	South Korea	0.13	0.30	-10.65	< 0.001
2017	Others	China	12.34	20.70	-7.06	< 0.001
2017	Others	South Korea	5.68	10.19	-21.44	< 0.001
2017	Others	Japan	4.07	5.61	-27.58	< 0.001

Paired Student t-tests are used to test for the differences between production-based monthly population-weighted mean $PM_{2.5}$ concentrations (n=12) and consumption-based monthly population-weighted mean $PM_{2.5}$ concentrations (n=12). Note: $PM_{2.5}$, fine particulate matter.

Table S11. Testing for the differences between production-based monthly $PM_{2.5}$ population exposure and consumption-based monthly $PM_{2.5}$ population exposure

Year	Source	Receptor	Mean of production-based monthly $PM_{2.5}$ population exposure	Mean of consumption-based monthly $PM_{2.5}$ population exposure	t	p
2015	China	South Korea	3.80	2.92	13.57	< 0.001
2015	China	Japan	2.11	1.67	9.86	< 0.001
2015	South Korea	China	2.68	3.75	-2.25	0.046
2015	South Korea	Japan	0.34	0.24	9.85	< 0.001
2015	Japan	China	0.45	5.43	-9.65	< 0.001
2015	Japan	South Korea	0.10	0.17	-8.29	< 0.001
2015	Others	China	205.78	358.84	-7.73	< 0.001
2015	Others	South Korea	2.71	5.11	-14.38	< 0.001
2015	Others	Japan	3.42	4.70	-29.48	< 0.001
2017	China	South Korea	3.72	2.89	11.25	< 0.001
2017	China	Japan	2.06	1.67	10.72	< 0.001
2017	South Korea	China	1.10	2.62	-5.02	< 0.001
2017	South Korea	Japan	0.37	0.27	9.03	< 0.001
2017	Japan	China	0.13	4.23	-9.36	< 0.001
2017	Japan	South Korea	0.06	0.14	-10.65	< 0.001
2017	Others	China	191.13	323.61	-7.18	< 0.001
2017	Others	South Korea	2.53	4.53	-21.51	< 0.001
2017	Others	Japan	3.18	4.39	-27.64	< 0.001

Paired Student t-tests are used to test for the differences between production-based monthly $PM_{2.5}$ population exposure (n=12) and consumption-based monthly $PM_{2.5}$ population exposure (n=12). Note: $PM_{2.5}$, fine particulate matter.

Table S12. Contributions from source to receptor countries' nitrogen oxides (NOx) emissions in Northeast Asia in 2015.

Year	Receptor country / Source country		China (Gg, %)		South Korea (Gg, %)		Japan (Gg, %)	
2015	Total NOx emissions of Receptor		24817.49	100%	1260.93	100%	2255.31	100%
	Responsibility allocation from a production perspective	China	24817.49	100%	0	0%	0	0%
		South Korea	0	0%	1260.93	100%	0	0%
		Japan	0	0%	0	0%	2255.31	100%
		Others	0	0%	0	0%	0	0%
	Responsibility allocation from a consumption perspective	China	19413.15	78.2%	118.72	9.4%	89.73	4.0%
		South Korea	150.68	0.6%	736.74	58.4%	14.9	0.7%
		Japan	340.57	1.4%	25.18	2.0%	1728.45	76.6%
		Others	4913.09	19.8%	380.29	30.2%	422.24	18.7%

Note: NOx, nitrogen oxides; Gg, Gigagram.

Table S13. Studies of the source-receptor relationship of transboundary $PM_{2.5}$ pollution with South Korea as the receptor region for an analysis period equal or over one year.

Entry	Year of anthropogenic emission inventory in China	Receptor	China' absolute contribution (μg/m^3)	China' relative contribution (%)
Han, Cai[27]	2017	South Korea	Not available (NA)	15.7%
Han, Cai[27]	2015	South Korea	NA	20.4%
Han, Cai[27]	2010	South Korea	NA	28.0%
Bae, Kim[28]	2010	Seoul, South Korea	14.15	42%
Bae, Kim[29]	2010	South Korea	10.08	56% [a]
National Institute of Environmental Research (NIER)[30]	2017	Seoul, Daejeon and Busan in South Korea	8.17 [b]	32.1%
Yim, Gu[31]	2010	South Korea	9.16	54.2%
This study	2015	South Korea	8.73	35.0%
This study	2017	South Korea	8.39	37.1%

Note: $PM_{2.5}$, fine particulate matter; NA, not available; NIER, National Institute of Environmental Research;

a. Two estimations of China's relative contributions over South Korea are calculated using two different modelling grid resolutions.[29] The relative contribution of 56% is estimated using a higher modelling grid resolution and is believed to be more accurate.[29]

b. The contribution is estimated based data in Figure 2.7 in the report by National Institute of Environmental Research (NIER)[30] using the digitizer tool of OriginPro 2022.

Table S14. Studies of the source-receptor relationship of transboundary $PM_{2.5}$ pollution with Japan as the receptor region for an analysis period equal or over one year.

Entry	Year of anthropogenic emission inventory in China	Receptor	China' absolute contribution (μg/m^3)	China' relative contribution (%)
National Institute of Environmental Research (NIER)[30]	2017	Tokyo, Osaka, Fukuoka in Japan	2.85	24.6%
Yim, Gu[31]	2010	Japan	3.19	53.9%
Ikeda, Yamaji[32]	2008	Kyushu, Japan	5.45 [a]	61%
Ikeda, Yamaji[32]	2008	Chugoku, Japan	Not available (NA)	59%
Ikeda, Yamaji[32]	2008	Shikoku, Japan	NA	60%
Ikeda, Yamaji[32]	2008	Kinki, Japan	3.66 [a]	51%
Ikeda, Yamaji[32]	2008	Hokuriku, Japan	NA	55%
Ikeda, Yamaji[32]	2008	Tokai-Koshin, Japan	NA	45%
Ikeda, Yamaji[32]	2008	Tohoku, Japan	3.30 [a]	59%
Ikeda, Yamaji[32]	2008	Hokkaido, Japan	NA	69%
Ikeda, Yamaji[32]	2008	Kanto, Japan	2.44 [a]	39%
Ikeda, Yamaji[33]	2008	Fukue, Japan	14.13	78.5%
Ikeda, Yamaji[33]	2008	Oki, Japan	8.28	69%
Ikeda, Yamaji[33]	2008	Nonodake, Japan	5.30	46.1%
Ikeda, Yamaji[33]	2008	Rishiri, Japan	7.46	86.7%
This study	2015	Japan	2.71	22.1%
This study	2017	Japan	2.64	22.9%

Note: $PM_{2.5}$, fine particulate matter; NA, not available; NIER, National Institute of Environmental Research;

a. The contribution is estimated based data in Figure 4 in the study by Ikeda, Yamaji[32] using the digitizer tool of OriginPro 2022.

References

1. Stettler MEJ, Eastham S, Barrett SRH. Air quality and public health impacts of UK airports. Part I: Emissions. *Atmospheric Environment* 2011; **45**(31): 5415-24. doi:10.1016/j.atmosenv.2011.07.012.
2. van der Werf GR, Randerson JT, Giglio L, et al. Global fire emissions estimates during 1997–2016. *Earth Syst Sci Data* 2017; **9**(2): 697-720. doi:10.5194/essd-9-697-2017.
3. Hudman RC, Moore NE, Mebust AK, et al. Steps towards a mechanistic model of global soil nitric oxide emissions: implementation and space based-constraints. *Atmos Chem Phys* 2012; **12**(16): 7779-95. doi:10.5194/acp-12-7779-2012.
4. Murray LT, Jacob DJ, Logan JA, Hudman RC, Koshak WJ. Optimized regional and interannual variability of lightning in a global chemical transport model constrained by LIS/OTD satellite data. *Journal of Geophysical Research: Atmospheres* 2012; **117**(D20): D20307. doi:10.1029/2012JD017934.
5. Guenther AB, Jiang X, Heald CL, et al. The Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN2.1): an extended and updated framework for modeling biogenic emissions. *Geosci Model Dev* 2012; **5**(6): 1471-92. doi:10.5194/gmd-5-1471-2012.
6. Bouwman AF, Lee DS, Asman WAH, Dentener FJ, Van Der Hoek KW, Olivier JGJ. A global high-resolution emission inventory for ammonia. *Global Biogeochemical Cycles* 1997; **11**(4): 561-87. doi:10.1029/97GB02266.
7. Carn SA, Yang K, Prata AJ, Krotkov NA. Extending the long-term record of volcanic SO2 emissions with the Ozone Mapping and Profiler Suite nadir mapper. *Geophysical Research Letters* 2015; **42**(3): 925-32. doi:10.1002/2014GL062437.
8. Zender CS, Bian H, Newman D. Mineral Dust Entrainment and Deposition (DEAD) model: Description and 1990s dust climatology. *Journal of Geophysical Research: Atmospheres* 2003; **108**(D14). doi:10.1029/2002JD002775.
9. Philip S, Martin RV, Snider G, et al. Anthropogenic fugitive, combustion and industrial dust is a significant, underrepresented fine particulate matter source in global atmospheric models. *Environmental Research Letters* 2017; **12**(4): 044018. doi:10.1088/1748-9326/aa65a4.
10. Gong SL. A parameterization of sea-salt aerosol source function for sub- and super-micron particles. *Global Biogeochemical Cycles* 2003; **17**(4). doi:10.1029/2003GB002079.
11. Jaeglé L, Quinn PK, Bates TS, Alexander B, Lin JT. Global distribution of sea salt aerosols: new constraints from in situ and remote sensing observations. *Atmos Chem Phys* 2011; **11**(7): 3137-57. doi:10.5194/acp-11-3137-2011.
12. Riddick SN, Dragosits U, Blackall TD, Daunt F, Wanless S, Sutton MA. The global distribution of ammonia emissions from seabird colonies. *Atmospheric Environment* 2012; **55**: 319-27. doi:10.1016/j.atmosenv.2012.02.052.
13. Liang Q, Stolarski RS, Kawa SR, et al. Finding the missing stratospheric Bry: a global modeling study of CHBr3 and CH2Br2. *Atmos Chem Phys* 2010; **10**(5): 2269-86. doi:10.5194/acp-10-2269-2010.
14. Ordóñez C, Lamarque JF, Tilmes S, et al. Bromine and iodine chemistry in a global chemistry-climate model: description and evaluation of very short-lived oceanic sources. *Atmos Chem Phys* 2012; **12**(3): 1423-47. doi:10.5194/acp-12-1423-2012.
15. Millet DB, Guenther A, Siegel DA, et al. Global atmospheric budget of acetaldehyde: 3-D model analysis and constraints from in-situ and satellite observations. *Atmos Chem Phys* 2010; **10**(7): 3405-25. doi:10.5194/acp-10-3405-2010.
16. Johnson MT. A numerical scheme to calculate temperature and salinity dependent air-water transfer velocities for any gas. *Ocean Sci* 2010; **6**(4): 913-32. doi:10.5194/os-6-913-2010.

17. Nightingale PD, Malin G, Law CS, et al. In situ evaluation of air-sea gas exchange parameterizations using novel conservative and volatile tracers. *Global Biogeochemical Cycles* 2000; **14**(1): 373-87. doi:10.1029/1999GB900091.

18. Vinken GCM, Boersma KF, Jacob DJ, Meijer EW. Accounting for non-linear chemistry of ship plumes in the GEOS-Chem global chemistry transport model. *Atmos Chem Phys* 2011; **11**(22): 11707-22. doi:10.5194/acp-11-11707-2011.

19. Holmes CD, Prather MJ, Vinken GCM. The climate impact of ship NOx emissions: an improved estimate accounting for plume chemistry. *Atmos Chem Phys* 2014; **14**(13): 6801-12. doi:10.5194/acp-14-6801-2014.

20. Sherwen T, Evans MJ, Carpenter LJ, et al. Iodine's impact on tropospheric oxidants: a global model study in GEOS-Chem. *Atmos Chem Phys* 2016; **16**(2): 1161-86. doi:10.5194/acp-16-1161-2016.

21. Ministry of Environmental Protection. Highlights of the Chinese exposure factors handbook (Adults). Beijing, China: China Environmental Science Press; 2014.

22. Yoon H, Seo J, Yoo S-K, et al. Updated general exposure factors for risk assessment in the Korean population. *Journal of Exposure Science & Environmental Epidemiology* 2022. doi:10.1038/s41370-022-00437-6.

23. AIST Research Center for CRM. Japanese Exposure Factors Handbook. National Institute of Advanced Industrial Science and Technology. 2007. https://unit.aist.go.jp/riss/crm/exposurefactors/english_summary.html.

24. Zhang W, Yun X, Meng W, et al. Urban residential energy switching in China between 1980 and 2014 prevents 2.2 million premature deaths. *One Earth* 2021; **4**(11): 1602-13. doi:10.1016/j.oneear.2021.10.013.

25. Choi DH, Kang DH. Infiltration of Ambient PM2.5 through Building Envelope in Apartment Housing Units in Korea. *Aerosol and Air Quality Research* 2017; **17**(2): 598-607. doi:10.4209/aaqr.2016.06.0287.

26. Funasaka K, Furuichi Y, Sakai M. Intrusion of the atmospheric aerosol to indoor air by the difference in house structure and reference to measures approach from microchemical analysis. *Journal of the Housing Research Foundation "JUSOKEN"* 2018; **44**: 97-107. doi:10.20803/jusokenronbunjisen.44.0_97.

27. Han X, Cai JZ, Zhang MG, Wang XF. Numerical simulation of interannual variation in transboundary contributions from Chinese emissions to PM2.5 mass burden in South Korea. *Atmospheric Environment* 2021; **256**: 118440. doi:10.1016/j.atmosenv.2021.118440.

28. Bae C, Kim BU, Kim HC, Yoo C, Kim S. Long-Range Transport Influence on Key Chemical Components of PM2.5 in the Seoul Metropolitan Area, South Korea, during the Years 2012-2016. *Atmosphere* 2020; **11**(1): 19. doi:10.3390/atmos11010048.

29. Bae M, Kim B-U, Kim HC, Kim S. A Multiscale Tiered Approach to Quantify Contributions: A Case Study of PM2.5 in South Korea During 2010–2017. *Atmosphere* 2020; **11**(2): 141. doi:10.3390/atmos11020141.

30. National Institute of Environmental Research (NIER). Summary Report of the 4th stage (2013–2017) LTP Project, 2019. https://nier.go.kr/NIER/cmm/fms/NoLoginFileDown.do;jsessionid=C1A37B9309AC438907222958C0680EF9?atchFileId=FILE_000000000029154&fileSn=0

31. Yim SHL, Gu YF, Shapiro M, Stephens B. Air quality and acid deposition impacts of local emissions and transboundary air pollution in Japan and South Korea. *Atmospheric Chemistry and Physics* 2019; **19**(20): 13309-23. doi:10.5194/acp-19-13309-2019.
32. Ikeda K, Yamaji K, Kanaya Y, et al. Source region attribution of PM2.5 mass concentrations over Japan. *Geochemical Journal* 2015; **49**(2): 185-94. doi:10.2343/geochemj.2.0344.
33. Ikeda K, Yamaji K, Kanaya Y, et al. Sensitivity analysis of source regions to PM2.5 concentration at Fukue Island, Japan. *J Air Waste Manage Assoc* 2014; **64**(4): 445-52. doi:10.1080/10962247.2013.845618.