Supporting Information for

Mismatched social welfare allocation and PM2.5-related health damage along value chains within China

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Supporting Information Text

Uncertainty analysis on health impact assessment

An uncertainty analysis of PM2.5-related mortality and morbidity was conducted in this study. Limited to the available data, we referred to two different studies $1,2$ with slightly different calculation functions to calculate the PM2.5-related mortality and morbidity separately. The parameters of exposure-response coefficient and baseline concentration setting were the focus of uncertainty analysis here.

For the estimation of $PM_{2.5}$ -related mortality, the updated integrated exposure– response functions¹ were applied, and the impact could be calculated as follows,

$$
Y = Y_0 \left(1 - \frac{1}{RR} \right) Pop \tag{1}
$$

$$
RR(z) = 1 + \alpha \left(1 - e^{\beta (z - z_{cf})^{\gamma}}\right)
$$
 (2)

where Y_0 is the baseline incidence rate, Pop means the exposed population, RR denotes the relative risk for specific health endpoint, z and z_{cf} represent the concentration of PM_{2.5} and theoretical minimum risk exposure level, and α , β , and γ are parameters. β is the ratio of the integrated exposure–response functions at low to high concentrations. β was provided for every interval of PM_{2.5} concentration levels from 0 to infinity. The data sources remain the same with previous work³. Referring to the posterior distributions of parameters from Cohen et al.¹, we applied the Monte Carlo method to repeat 10000 times calculations, obtaining the possibility distribution of mortality triggered by $PM_{2.5}$ exposure and confidence intervals of results (Fig. S1a).

For the estimation of PM2.5-related morbidity, we applied a log-linear exposureresponse function² to estimate four health endpoints of morbidity as follow,

$$
HI = Pop \times (Y - Y_0)
$$
 (3)

$$
Y = Y_0 \times e^{\beta (C - C_0)} \tag{4}
$$

where HI represents the morbidity under $PM_{2.5}$ concentration level C, Y_0 is the baseline incidence rate, β is the exposure-response coefficients denoting the incidence change of certain health impact per μg m⁻³ PM_{2.5} increment; C₀ is the baseline PM_{2.5} concentration. Obviously, the formula for morbidity estimation is cruder compared to the calculation of mortality, and β is set singularly for each health ending, without specific values for the different concentration intervals. Similarly, we obtained the confidence intervals (Table. S1) of β from Hao et al.² and conducted Monte Carlo method by simulating 10,000 cases with randomly chosen parameter (Fig. S1b).

According to the uncertainty analysis of exposure-response coefficient, national value chain induced 146.9—197.7 thousand people of mortality (95% confidence interval), 3.6—17.9 million people of morbidity (95% confidence interval) of mainland China in 2017, and a total health economic loss of 663.7 billion–886.7 billion CNY (95% confidence interval) (Fig. S1). Uncertainty analysis of health damage at a provincial scale are presented in Fig. S2 and S3.

For the baseline $PM_{2.5}$ concentration C_0 , we considered WHO recommendation and China national standard for air quality. WHO decreased the recommended annual PM2.5 concentration level from 10 μ g m⁻³ in Air Quality Guidelines 2005⁴ to 5 μ g m-3 in Air Quality Guidelines 2021⁵. The recommendation is made in the interests of health, but it is difficult to reach for some countries, especially for certain developing countries. Regarding China, national class I and II standard for annual PM2.5 concentration level⁶ is 15 μ g m⁻³ and 35 μ g m⁻³. However, most of areas in China are far from meeting the class I standard. According to official statistics, the annual average PM2.5 concentration level remained 30~43 μg m-3 during 2017-2021 period, and only 6.2% of cities reached the class I standard in 2021 according to the annual reports on the state of the ecology and environment published by Ministry of Ecology and Environment of the People's Republic of China. Here, this study estimated the $PM_{2.5}$ exposure related morbidity based on varying levels of the baseline $PM_{2.5}$ concentration: 5, 10, 15 μ g m⁻³. The results showed that the baseline PM_{2.5} concentration make little sense to the final conclusion (Table S2), that the upper and lower settings brought about less than $\pm 5\%$ of change in morbidity estimation and $\pm 1\%$ of change in health economic loss. Hence, for simplicity and the minor influence of it, only the results under 10μ g m⁻³ baseline PM_{2.5} concentration level were presented in the main text.

Uncertainty analysis on value of statistical life

In this study, we applied the value of statistical life (VSL) to evaluate $PM_{2.5}$ exposure-related health economic loss. Measured by willingness to pay, VSL considers human subjective feelings on the impact of air pollution on health, presenting spatial and temporal disparities, as well as distinctions among different groups of people. It is another source of uncertainty in this study. In Table S3, we present existing VSL original data for mainland China, which has been widely applied in previous studies to quantify the external cost of air pollutant emissions or the health benefit of emission reduction.

To better compare data from different sources, we unified data into the same year and currency as follows⁷:

$$
VSL_t = VSL_0 \left(\frac{\text{Income}_t}{\text{Income}_0}\right)^e \tag{5}
$$

where VSL_t denotes the VSL of year t, $VSL₀$ means the VSL of the base year, Incomet represents the residential disposable income of year t , Income $₀$ means the residential</sub> disposable income of the base year, and e means income elasticity.

After the year transfer, significant differences among various VSL data were observed, with high values 26 to 50 times the low values (see Table S4). The VSL of Anqing ⁸ served as the bottom, while the VSL of Jingzhong ⁹ and Shanghai/Jiujiang/Nanning 10 was the ceiling when income elasticity was 0.8–1.0 and 1.2-1.6, respectively. Because these data were published for a longer time and great variations were observed in the VSL of one city during the period from 2005 to 2016 11 , we used the most recent results from Cao C et al. ⁹, which covered six cities across mainland China in this study. We used the average values of these of six cities to evaluate health economic loss.

In addition, income elasticity was used to transfer estimates of VSL between different years, different regions or different income populations. According to Table S4, we find that income elasticity will greatly affect VSL estimates. Here, we conducted a reliability analysis on data from Cao C, et al. 9 to determine the suitable income elasticity, and results show in Table S5 and S6. VSL reflects the present value of the total value of an individual's expected remaining life years. According to Hammitt J. and Robinson L.⁷, VSL should be greater than the current value of expected income in the remaining years of life because the utility of life will be greater than the utility of income. When income elasticity > 1.4 , VSL was observed lower than expected income in Table S5 (highlighted in red). Therefore, we determined income elasticity to be 1.4 to calculate VSL in 2017, which is also consistent with previous studies 12,13 .

A supplementary analysis on health impact assessment under supply chain variation based on hypothetical extraction method (HEM)

This study implemented a comprehensive analysis framework with a combination of input-output model, value chain method, the extended response surface model (ERSM) with polynomial functions, and exposure–response functions to explore the regional health impacts in the participation in domestic value chain. In the first module, with aid of input-output model and value chain method, we decomposed the total pollutants emissions into sectoral level across provincial regions along the domestic value chain. In the second module, the pollutants emissions are further incorporated into ERSM and exposure–response functions to estimate the PM2.5 exposure related mortality and morbidity. To be specific, the second module calculated the health effects for both the realistic case or baseline case (all pollutants are emitted as was) and the counterfactual case (pollutant emissions due to a trade activity were removed). Then, the health impact of certain trade activity was obtained through subtracting the certain counterfactual case by baseline case. Finally, gathering the impact of every region or sector, we derived the overall uneven distribution of losses and gains across all the regions or sectors along value chain.

Here we used counterfactual to get the difference, so as to evaluate the contribution (or possible proportion) of every region/sector in the value chain. It is equivalent to assuming that, the emissions due to the absence of one region's producing activity is directly removed, and ignores the dynamicity of production network. However, for policy makers of every provincial region, the assumption may bring about overestimation or underestimation on the gains and losses of the region in the participation in production division of labor. For example, some other regions may replace the position of the original one to maintain the normal operation of supply chain, while the partial pollutants may float back to the original region under atmospheric transport.

To improve our original finding and provide a more realistic reference for policy makers, this study attempted to quantitively measure the health impact assessment under a dynamic production network, and compared the results. Based on input-output table, hypothetical extraction method (HEM) is adopted here to single out the entire impact of a certain activity by deleting it in the tables and replacing the extracted one with the others¹⁴. Specifically speaking, to obtain the impacts of one provincial region when it supplies intermediate or final products in domestic value chain, we deleted the intermediate inputs and final products of it in the intra-regional trade; meanwhile, the deleted intermediate inputs and final products of it were allocated to the corresponding industries of other regions. Obviously, there are two factors determining the variation of the results of HEM and the original one:

1) First, when one region's intermediate inputs coefficients become zero in domestic outflows, its total amount of international export will decrease as well. Thus, its pollutants emission will be lower in such a counterfactual case enlarging the gap with baseline case. Consequently, the health impact assessed by HEM will be higher than the original one.

2) Second, when the replacement exists in the production network, other provincial regions will undertake more productions and thus emit more pollutants. Under atmospheric transport, the rising emission from others will also induce higher pollution concentration for the target region, shrinking the gap with baseline case. As a result, the health impact assessed by HEM will be lower than the original one.

Results showed that the results by HEM is -19%~7% of the estimates from traditional method (Table S7). It means our original results may underestimate the health impacts by no more than 19% and overestimate by no more than 7%. Herein, if we only consider the second factor (i.e., the replacement effect and the resulting other regions' rising emission), our original results may overestimate the health impacts of every region in its participation in domestic value chain by 0%~23%.

Given to the difficulty to integrate with value chain method and the accompanied more uncertainties of the dynamic system, we remained the current ways to investigate regional health damage in the domestic value chain with supplementing the above analysis as an uncertainty analysis of our results.

Supporting Information Figures and Tables

Figure. S1. Uncertainty analysis of PM2.5 exposure-related health damage

Figure. S1. Uncertainty analysis of PM_{2.5} exposure-related health damage in the national value chain in 2017. a. Total mortality, people; b. Total morbidity, people; c. Total health economic loss, CNY. Note that the morbidity presented here is estimated based on $C_0 = 10 \,\mu g \,\text{m}^{-3}$.

Figure. S2. Uncertainty analysis of PM2.5 exposure-related mortality

Figure. S2. Uncertainty analysis of PM_{2.5} exposure-related mortality at a provincial scale. The boxplot shows the highest value, 3/4 quartile, average (marked with a cross), 1/2 quartile, 1/4 quartile, and lowest value. Note that the morbidity presented here is estimated based on $C_0 = 10 \mu g m^{-3}$.

Figure. S3. Uncertainty analysis of PM2.5 exposure-related morbidity

Figure. S3. Uncertainty analysis of PM_{2.5} exposure-related morbidity at a provincial scale. The boxplot shows the highest value, 3/4 quartile, average (marked with a cross), 1/2 quartile, 1/4 quartile, and lowest value. Note that the morbidity presented here is estimated based on $C_0 = 10 \mu g m^{-3}$.

Figure. S4. The impacts of inter-regional trade on PM2.5 concentration variation

Figure. S4. The impacts of inter-regional trade on $PM_{2.5}$ concentration variations. PM_{2.5} concentration variations mean the differences in PM_{2.5} concentration between basic scenario (the $PM_{2.5}$ concentration of real world) and the others based on hypothesis extraction method (such as the simulated $PM_{2.5}$ concentration when removing emissions of certain activity of one provincial region). The variations to some extend reflect the impacts of certain activity to the PM_{2.5} concentration. Each figure is the influence of one provincial region's emission on the change in $PM_{2.5}$ concentration. Tibet and Qinghai are not presented here, the maximum influences of which were less than $2 \mu g m^{-3}$.

Figure. S5. Contributions to resource product exports in the national value chain. a. Intermediate products of mining industry. b. Intermediate products of the resource processing industry. Provinces in North Central are highlighted by black borders.

Table S1. PM2.5 exposure-response coefficients for each health endpoint

Table S1. PM_{2.5} exposure-response coefficients for each health endpoint²

Table S2. The health damage of inter-regional trade estimated under varying baseline concentration levels

Table S2. The health damage of inter-regional trade estimated under varying baseline

concentration levels

Table S3. Original source and data of VSL

Table S3. Original source and data of VSL

Table S4. Data of VSL

Income elasticity VSL	0.8		$\begin{array}{ccc} \end{array}$ 1.2	14	1.6
Min	117331	162359	224668	310890	430202
Max					5783052 5647186 6944089 8964704 11573284
Average	2526004			2945811 3499399 4233482 5212342	

Table S4. Data of VSL (2017 RMB)

Table S5. Reliability analysis minimum value of VSL

Year	Current value of	VSL in different income elasticity						
	Expected income	0.8		1.2	1.4	1.6		
2017	973627	3446190	3365226	3286164	3208959	3133569		
2015	789192	3101016	2949309	2805023	2667796	2537283		
2012	651416	2604130	2370929	2158611	1965307	1789312		
2010	592826	2206135	1926994	1683172	1470201	1284177		
2007	509043	1740597	1432891	1179581	971052	799388		
2005	424554	1442462	1132976	889891	698962	548997		
1995	188153	739985	491891	326975	217350	144480		

Table S5. Reliability analysis minimum value of VSL (of data from Cao C, et al. 2021)

Table S6. Reliability analysis maximum value of VSL

Table S6. Reliability analysis maximum value of VSL (of data from Cao C, et al. 2021)

Table S7. Social welfare allocation and health damage data for Figure 2

Table S7. The provincial ranking based on social welfare allocation and health damage

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^a It's sort by ascending order. The above lists are corresponding to Figure 2a-d. the provincial name and abbreviations can be found in Figure 1.

Table S8. Comparison in the results of health damage assessment based on HEM

Table S8. Comparison in the results of health damage assessment^a

^a The figures are calculated by: (original results-HEM results)/HEM results

SI References

- (1) Cohen, A. J.; Brauer, M.; Burnett, R.; Anderson, H. R.; Frostad, J.; Estep, K.; Balakrishnan, K.; Brunekreef, B.; Dandona, L.; Dandona, R.; Feigin, V.; Freedman, G.; Hubbell, B.; Jobling, A.; Kan, H.; Knibbs, L.; Liu, Y.; Martin, R.; Morawska, L.; Pope, C. A.; Shin, H.; Straif, K.; Shaddick, G.; Thomas, M.; van Dingenen, R.; van Donkelaar, A.; Vos, T.; Murray, C. J. L.; Forouzanfar, M. H. Estimates and 25-Year Trends of the Global Burden of Disease Attributable to Ambient Air Pollution: An Analysis of Data from the Global Burden of Diseases Study 2015. *The Lancet* **2017**, *389* (10082), 1907–1918. https://doi.org/10.1016/S0140-6736(17)30505-6.
- (2) Yin, H.; Pizzol, M.; Xu, L. External Costs of PM2.5 Pollution in Beijing, China: Uncertainty Analysis of Multiple Health Impacts and Costs. *Environmental Pollution* **2017**, *226*, 356–369. https://doi.org/10.1016/j.envpol.2017.02.029.
- (3) Zheng, H.; Zhao, B.; Wang, S.; Wang, T.; Ding, D.; Chang, X.; Liu, K.; Xing, J.; Dong, Z.; Aunan, K.; Liu, T.; Wu, X.; Zhang, S.; Wu, Y. Transition in Source Contributions of PM2.5 Exposure and Associated Premature Mortality in China during 2005–2015. *Environ Int* **2019**, *132*. https://doi.org/10.1016/j.envint.2019.105111.
- (4) World Health Organization. *Air Quality Guidelines Global Update 2005: Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide*; 2005. https://www.who.int/publications/i/item/WHO-SDE-PHE-OEH-06.02.
- (5) World Health Organization. *WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*; 2021. https://apps.who.int/iris/handle/10665/345329.
- (6) *Ambient Air Quality Standards of the People's Republic of China*; 2016. https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/dqhjbh/dqhjzlbz/201203/t20120302_ 224165.shtml.
- (7) Hammitt, J. K.; Robinson, L. A. The Income Elasticity of the Value per Statistical Life: Transferring Estimates between High and Low Income Populations. *J Benefit Cost Anal* **2011**, *2* (1). https://doi.org/10.2202/2152-2812.1009.
- (8) Hammitt, J. K.; Zhou, Y. The Economic Value of Air-Pollution-Related Health Risks in China: A Contingent Valuation Study. In *Environmental and Resource Economics*; 2006; Vol. 33, pp 399–423. https://doi.org/10.1007/s10640-005-3606- 0.
- (9) Cao, C.; Song, X.; Cai, W.; Li, Y.; Cong, J.; Yu, X.; Niu, X.; Gao, M.; Wang, C. Estimating the Value of Statistical Life in China: A Contingent Valuation Study in Six Representative Cities. **2021**. https://doi.org/10.21203/rs.3.rs-199197/v1.
- (10) Cropper, M. L. *Measuring the Costs of Air Pollution and Health in China*; Washington DC, 2009. https://www.resources.org/archives/measuring-the-costsof-air-pollution-and-health-in-china/.
- (11) Hammitt, J. K.; Geng, F.; Guo, X.; Nielsen, C. P. Valuing Mortality Risk in China: Comparing Stated-Preference Estimates from 2005 and 2016. *J Risk Uncertain* **2019**, *58* (2–3), 167–186. https://doi.org/10.1007/s11166-019-09305-5.
- (12) Wang, H.; Mullahy, J. Willingness to Pay for Reducing Fatal Risk by Improving Air Quality: A Contingent Valuation Study in Chongqing, China. *Science of the Total Environment* **2006**, *367* (1), 50–57. https://doi.org/10.1016/j.scitotenv.2006.02.049.
- (13) Mu, Q.; Zhang, S. Assessment of the Trend of Heavy PM2.5 Pollution Days and Economic Loss of Health Effects during 2001-2013. *Beijing Daxue Xuebao (Ziran Kexue Ban)/Acta Scientiarum Naturalium Universitatis Pekinensis* **2015**, *51* (4), 694–706. https://doi.org/10.13209/j.0479-8023.2015.074.
- (14) Dietzenbacher, E.; van Burken, B.; Kondo, Y. Hypothetical Extractions from a Global Perspective. *Economic Systems Research* **2019**, *31* (4), 505–519. https://doi.org/10.1080/09535314.2018.1564135.
- (15) World Bank Group. *Clear Water, Blue Skies: China's Environment in the New Century*; Washington, DC, 1997. https://www.osti.gov/biblio/565495.
- (16) Zhang, X. Valuing Mortality Risk Reductions Using the Contingent Valuation Method: Evidence from A Survey of Beijing Residents in 1999. In *Second World Congress of Environmental and Resource Economists*; California, 2002.
- (17) Deng, X. Economic Costs of Motor Vehicle Emissions in China: A Case Study. *Transp Res D Transp Environ* **2006**, *11* (3), 216–226. https://doi.org/10.1016/j.trd.2006.02.004.
- (18) Kan, H.; Chen, B. Particulate Air Pollution in Urban Areas of Shanghai, China: Health-Based Economic Assessment. *Science of the Total Environment* **2004**, *322* (1–3), 71–79. https://doi.org/10.1016/j.scitotenv.2003.09.010.
- (19) Guo, X.; Haab, T. C.; Hammitt, J. K. Contigent Valuation and the Economic Value of Air Pollution Related Health Risks in China. In *American Agricultural Economics Association Annual Meeting*; California, 2006.
- (20) Krupnick, A.; Zeng, X.; Qin, P. The Willingness to Pay for Mortality Risk Reductions in China. In *World Congress of Environmental and Resource Economists*; 2010.
- (21) Chen, Y. Theory and Application of Environmental Economic Loss Assessment, Fudan University, 2008. https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CDFD&dbname=CDFD1214 &filename=2009017644.nh&uniplatform=NZKPT&v=T2iGp7V_xPZS1XW7eRs NKlnLb_kMizHsWTMqm8l0Q6xCY6Sn42IC1NJhSYKDa52_.
- (22) Zeng, X.; Jiang, Y. Evaluation of Value of Statistical Life in Health Costs Attributable to Air Pollution. *China Environ Sci* **2010**, *30* (2), 284–288.
- (23) Xie, X. The Value of Health: Environmental Benefit Assessment Methods and Urban Air Pollution Control Strategy, Peking University, 2010.
- (24) Gao, T.; Li, G.; Xu, M.; Liang, F.; Zeng, Q.; Pan, X. Evaluation of Atmospheric PM2.5 Health Economics Loss Based on Willingness to Pay. *J Environ Health* **2015**, *32* (8), 697–700. https://doi.org/10.16241/j.cnki.1001-5914.2015.08.011.

Code

Code for value chain decomposition

#this code is for value chain decomposition based on R language

```
sector = 42region = 31final.demand = 5
```

```
#inputmrio
options(digits = 22)mrio <- read.delim("210520-MRIO17.txt", header=FALSE)
mrio<-as.matrix(mrio)
```

```
df.T<-mrio[1:(sector*region),1:(sector*region)]
FD<-mrio[1:(sector*region),(sector*region+1):(sector*region+region*final.demand)]
df.EX<-mrio[1:(sector*region),(sector*region+region*final.demand+1)]
df.Other<-mrio[1:(sector*region),(sector*region+region*final.demand+2)]
df.IM<-mrio[(region*sector+1),]
```
df.T $[(df.T < 0.0001) \& (df.T > -0.0001)] < -0$ FD[(FD<0.0001)&(FD>-0.0001)]<-0 df.EX[(df.EX<0.0001)&(df.EX>-0.0001)]<-0 df.Other $[(df.Other \le 0.0001)\& (df.Other \ge 0.0001)] \le 0$ df.IM[(df.IM<0.0001)&(df.IM>-0.0001)]<-0

df.TO<-rowSums(df.T)+rowSums(as.matrix(FD))+df.EX+df.Other

#input satellite data setwd("D:/B/GVC/H/20230610HEM/ori calculate 17 SI-EM-AP/data") Qa<-read.csv("AIR SI EM-2017-42-ceads-210520.csv",sep=',',head=FALSE)

 $\# 1$ so2; 2 nox; 3 pm2.5; 4 voc; 5 nh3; 6 social income; 7 employment for(select AP in 1:7) $\{$

 labelAP<-c("so2","nox","pm2.5","nmvoc","nh3","si","em") print(labelAP[select_AP])

Qa_select<-Qa[,((select_AP-1)*region+1):(select_AP*region)] $df.Qa<-as.vector(t(t(Qa,select)))$

```
 selFD<-array(0,dim=c((sector*region),region,(final.demand+2)))
 for(i in 1:final.demand)\{for(j in 1:region)\{selfD[j,i] < FD[j(i-1)*final.demand+i)] selFD[,j,(final.demand+1)]<-apply(FD[,((j-
1)*final.demand+1):(j*final.demand)],1,sum)
    selFD[,j,(final.demand+2)]<-apply(FD[,((j-1)*final.demand+1):(j*final.demand-
1)],1,sum)
   }
  }
```

```
 df.FD<-selFD[,,(final.demand+1)]############## do not consider different final 
demand categories (just analysis the gross)
  df.FD<-as.matrix(df.FD)
```

```
df.T <- as.matrix(df.T)df.Q <-as.matrix(t(df.Q)) df.EX<-as.matrix(df.EX)
```
total.output <- rowSums(df.T)+rowSums(as.matrix(selFD[,,(final.demand+1)]))+df.EX

```
 #calculate intensity and A
  intensity <- 1:(sector*region)
 intensity| <- 0
 for(i in 1:(sector*region))\{if(total.output[i] > 0.0000001 }
    intensity[i] <- df.Q[i]/total.output[i]
   }
   else
   intensity[i] \leq 0
 }
  intensity <-as.matrix(t(intensity))
 A \leq matrix(0,nrow = (sector*region),ncol = (sector*region))
  for(i in 1:(sector*region)){
  for(j in 1:(sector*region))\{if(total.output[j] > 0.0000001){
    A[i,j] \leq df.T[i,j]/total.output[i] }
    else
```

```
A[i,j] < 0 }
 }
```
 #original: no HEM $A0<-A$ df.FD0<-df.FD $B0 \leq solve(diag(1, nrow(A0)) - A0);$

```
 #functions----------------------------------- 
 sd<-1#select one as domestic(sample.d)
 sb<-2#select the other in a bilateral relationship with sample.d(sample.b)
```

```
 F.F<-function(sd){
    return(intensity[((sd-1)*sector+1):(sd*sector)])
   }
   F.A<-function(sd,sb){
    return(A0[((sd-1)*sector+1):(sd*sector),((sb-1)*sector+1):(sb*sector)])
   }
   F.B<-function(sd,sb){
   return(B0[((sd-1)*sector+1):(sd*sector),((sb-1)*sector+1):(sb*sector)])
   }
   F.YY<-function(sd,sb){
    return(df.FD0[((sd-1)*sector+1):(sd*sector),sb])
   }
   F.EX<-function(sd){###international export
    return(df.EX[((sd-1)*sector+1):(sd*sector),1])
   }
  F.L \leq function(sd) l<-solve(diag(1, sector) - A0[((sd-1)*sector+1):(sd*sector),((sd-
1)*sector+1):(sd*sector)])
    return(l)
   }
   #functions----END
```

```
 #result1: decompose the gross emission of every region. 
   DDTOTAL<-matrix(0,region,6)
   ex.region<-matrix(0,region,region)
   B0<-as.matrix(B0)
   df.EX<-as.vector(df.EX)
  for(i in 1: region)\{for(j in 1: region)\{ex.region[i,j] <- intensity[(i-1)*sector+1):(i*sector)]%*%B0[(i-1)1)*sector+1):(i*sector);(i*)*sector),((i-1)*sector):(i*sector)]%*%df.EX[(i-1)*`1)*sector+1):(i*sector)]
    }
   }
   DDTOTAL[,1]<-apply(ex.region,1,sum)
   #part.1 FssLssYss, corresponding to equation(3) first term in manuscript
   DD1<-matrix(0,region,1)
  for(sd in 1: region)\{c1 < -c(1:region) ###whole 31 provinces
   d <-which(c1==sd)
    c2<-c1[-d] ###31 provinces without selected domestic one
   DD1[sd,1] < F.F(sd) \%^* \% F.L(sd) \%^* \% F.YY(sd,sd) } 
   DDTOTAL[,2]<-DD1
```
 #part.2 export and then import to return, corresponding to equation(3) second term in manuscript

```
 DD2<-matrix(0,region,1)
   for(sd in 1:region){
    c1<-c(1:region) ###whole 31 provinces
   d <-which(c1 == sd)
   c2 < -c1[-d]part2<0for(i in c2)\{for(i in c1)\{ part2<-part2+F.F(sd)%*%F.L(sd)%*%F.A(sd,i)%*%F.B(i,j)%*%F.YY(j,sd)
     }
 }
    DD2[sd,1]<-part2
 }
   DDTOTAL[,3]<-DD2
```
#part.3 Fs Bss Ysr, corresponding to equation(3) third term in manuscript DD3<-matrix(0,region,region) for(sd in 1: region) {

```
 c1<-c(1:region) ###whole 31 provinces
   d <-which(c1==sd)
   c2 < -c1[-d]for(i in c2)\{DD3[sd,i]<-F.F(sd)%*%F.B(sd,sd)%*%F.YY(sd,i)
    }
 }
   DDTOTAL[,4]<-apply(DD3,1,sum)
```

```
 #part.4 Fs Bsr Yrr, part4+part5 corresponding to equation(3) fourth term in 
manuscript
   DD4<-matrix(0,region,region)
   for(sd in 1:region){
   c1 \leq c(1:\text{region}) ###whole 31 provinces
   d <-which(c1 = sd)
   c2 < -c1[-d]for(i in c2)\{ DD4[sd,i]<-F.F(sd)%*%F.B(sd,i)%*%F.YY(i,i)
    }
   }
   DDTOTAL[,5]<-apply(DD4,1,sum)
```

```
 #part.5 Fs Bst Ytr, part4+part5 corresponding to equation(3) fourth term in manuscript
   DD5<-matrix(0,region,region)
  for(sd in 1:region)\{ c1<-c(1:region) ###whole 31 provinces
   d <-which(c1 = sd)
   c2 < -c1[-d]for(i in c2)\{dl <-which(c2==i)
    c3 < -c2[-d1]part5<0for(t in c3)\{part5<-part5+F.F(sd)%*%F.B(sd,t)%*%F.YY(t,i)
 }
    DD5[sd,i] <-part5
    }
   }
   DDTOTAL[,6]<-apply(DD5,1,sum)
   write.csv(DDTOTAL,paste0("DDTOTAL-",labelAP[select_AP],"-2017.csv"))
```
 #result2: local and upstream sectoal decomposition, corresponding to equation(4,5) in manuscript

```
 EEXs<-array(0,dim=c((region*sector),(region*3+2)))
```
EEX<-array(0,dim=c(region,(region*3+2)))

```
c1 < -c(1: region) ###c1 includes all the countries
for(sd in c1)\{dl <-which(c1==sd)
```
 $c2 < -c1[-d1]$ ###c2 includes all the countries except local (sd), and then select partner

for(sb in c2) $\{$ $d2$ <- which $(c2 == sb)$

 $c3 < -c2[-d2]$ ### $c3$ includes all the countries except local (sd) and its trade partner (sb), and then select the third

```
 EEX1<-sweep(t(F.F(sd)%*%F.B(sd,sd)),1,F.YY(sd,sb),"*")#EEX1, corresponding 
to equation(4) first term
```
EEX2<-

 $sweep(t(F.F(sd)%*%F.L(sd)),1,(F.A(sd,sb)%*%F.B(sb,sb)%*%F.YY(sb,sb)),"**")\#EEX$ 2, EEX2+EEX3 corresponding to equation(4) second term

```
a < -0b < -0c < -0for(i in c3)\{d3 <- which (c2 == i)c4 < -c2[-d3] ###c4 includes all the countries except local (sd) and the selected
third country (i)
       a \leq a + F.A(sd, sb) \% * \% F.B(sb, sb) \% * \% F.YY(sb,i)b < b + F.A(sd, sb) \%*%F.B(sb,i) \%*%F.YY(i,i)for(i in c4)\{c \leq -c + F.A(\text{sd},\text{sb})\% \times \%\text{F.B}(\text{sb},i)\% \times \%\text{F.YY}(i,j) }
```
}

 EEX3<-sweep(t(F.F(sd)%*%F.L(sd)),1,(a+b+c),"*")#EEX3, EEX2+EEX3 corresponding to equation(4) second term

```
 EEX[sd,sb]<-sum(EEX1)
   EEX[sd,(sb+region+1)]<-sum(EEX2)
   EEX[sd,(sb+2*region+2)]<-sum(EEX3)
   EEXs[((sd-1)*sector+1):(sd*sector),sb]<-EEX1
   EEXs[((sd-1)*sector+1):(sd*sector),(sb+region+1)]<-EEX2
  EEXs[(sd-1)*sector+1):(sd*sector),(sb+2*region+2)]<-EEX3 }
 }
```
write.csv(EEX,paste0("EEX-",labelAP[select_AP],".CSV"))

```
 write.csv(EEXs,paste0("EEXs-",labelAP[select_AP],".CSV"))
```

```
 FEEs<-array(0,dim=c((region*sector),(region*4+3)))
   FEE<-array(0,dim=c(region,(region*4+3)))
  c1 < -c(1:region)for(sd in c1)\{ print(sd)
   dl <-which(c1==sd)
   c2 < -c1[-d1]for(sb in c2)\{d2 <-which(c2==sb)
    c3 < -c2[-d2]FEE1<-sweep(t(F.F(sb)%*%F.B(sb,sd)),1,F.YY(sd,sb),"*")
     FEE2<-
sweep(t(F.F(sb)\% * \%F.B(sb,sd)),1,(F.A(sd,sb)\% * \%F.L(sb)\% * \%F.YY(sb,sb)),"a < -0b < -0for(i in c3)\{a \leq a + sweep(t(F.F(i)\% * \%F.B(i, sd)), 1, F.YY(sd, sb), """)h \lt-
b+sweep(t(F.F(i)%*%F.B(i,sd)),1,(F.A(sd,sb)%*%F.L(sb)%*%F.YY(sb,sb)),"*")
     }
     FEE3<-a
     FEE4<-b
     #FEE1+FEE3: corresponding to equation(5) first term
     #FEE2+FEE4: corresponding to equation(5) second term
     FEE[sd,sb]<-sum(FEE1)
     FEE[sd,(sb+region+1)]<-sum(FEE2)
    FEE[sd,(sb+2*region+2)]<\text{sum}(FEE3) FEE[sd,(sb+3*region+3)]<-sum(FEE4)
     FEEs[((sd-1)*sector+1):(sd*sector),sb]<-FEE1
     FEEs[((sd-1)*sector+1):(sd*sector),(sb+region+1)]<-FEE2
     FEEs[((sd-1)*sector+1):(sd*sector),(sb+2*region+2)]<-FEE3
    FEEs[((sd-1)*sector+1):(sd*sector),(sb+3*region+3)]<-FEE4 }
   }
   write.csv(FEE,paste0("FEE-",labelAP[select_AP],".CSV"))
   write.csv(FEEs,paste0("FEEs-",labelAP[select_AP],".CSV"))
```
Code for HEM

#The code for HEM adds a process of A matrix and FD vectors based on Code for value chain decomposition. Here only present the code of processing.

#select local production network

```
HEM outputmerge1<-matrix(0,region,region)#sum up 1-6(so as to see the total change)
 HEM outputmerge2<-matrix(0,region,region)#sum up 2-6(so as to see the domestic
change)(include local)
```
HEM outputmerge3<-matrix(0,region,region)#sum up 3-6(so as to see the intraregional change)

HEM (remove inter-regional outflows of every region)

```
for (exone in 1:p)\{print(paste0("remove province: ",exone))
```

```
 #build new A------
  HEM_A0<-A
    #select exone's local production network
   Aang \leq-matrix(0, nrow = (sector * region), ncol = (sector * region))Aang[((\text{exone-1})^*s+1):(\text{exone}^*s),((\text{exone-1})^*s+1):(\text{exone}^*s)]\leq A[((\text{exone-1})^*s+1):(\text{exone-1})^*s+1]1)*s+1:(exone*s),((exone-1)*s+1):(exone*s)]
```
 #eliminate outflows of exone region HEM $\text{A0}[(\text{exone-1})*s+1):(\text{exone})*s],]<-0$

#merge the above two: remian the local but remove the inter-regional outflows of exone

```
HEM_A<-HEM_A0+Aang
```

```
 #A gap
sumA < -matrix(0, nrow = (sector), ncol = (sector *region))sumA HEM \leq-matrix(0,nrow = (sector),ncol = (sector*region))for(i in 1:s)\{for(j in 1:p)\{sumA[i,]<-sumA[i,]+A[(i-1)*sector+i),]sumA_HEM[i,]\le-sumA_HEM[i,]+HEM_A[((j-1)*sector+i),]
  }
 }
sumA_gap<-matrix(0,nrow = (sector),ncol = (sector*region))
sumA_gap<-sumA-sumA_HEM
```
}

```
 #A shares for the rest
A_share\leq-matrix(0,nrow = (sector*region),ncol = (sector*region))
for(j in 1:p)\{iv sumA HEM<-sumA HEM\land(-1)
 iv_sumA_HEM[iv_sumA_HEM==Inf]<-0
 A_share[(i-1)*s+1):(i*s),]<-HEM_A[(i-1)*s+1):(i*s),]*iv_sumA_HEM
 }
```

```
A_share[is.na(A_share)]\leq-0
 #colSums(A_share)
```

```
HEM A needreplace \leq-matrix(0,nrow = (sector*region),ncol = (sector*region))
for(j in 1:p)\{HEM_A_needreplace[((j-1)*s+1):(j*s),]<-A_share[((j-1)*s+1):(j*s),]*sumA_gap
 }
```
 #HEM_A include replace HEM2_A<-HEM_A+HEM_A_needreplace

#build new A-------end

 #build new FD------- HEM_FD0<-df.FD #select exone's local production network $FDang \leq-matrix(0, nrow = (sector * region), ncol = (region))$ FDang[((exone-1)*s+1):(exone*s),exone]<-df.FD[((exone-1)*s+1):(exone*s),exone]

 #eliminate export of exone region HEM FD0[((exone-1)*s+1):(exone*s),]<-0

 #merge the above two: remian the local but remove the inter-regional outflow of exone HEM_FD<-HEM_FD0+FDang

```
 #y gap
sumy < -matrix(0, nrow = (sector), ncol = (region))sumy HEM<-matrix(0,nrow = (sector),ncol = (region))
for(i in 1:s)\{for(j in 1:p)\{sumy[i,]<-sumy[i,]+df.FD[((j-1)*sector+i),]sumy HEM[i,]<-sumy HEM[i,]+HEM_FD[((j-1)*sector+i),]
  }
 }
 sumy_gap<-sumy-sumy_HEM
```

```
 #y shares for the rest
y_share\leq-matrix(0,nrow = (sector*region),ncol = (region))
for(j in 1:p)\{iv sumy HEM\le-sumy HEM\le(-1)
 iv_sumy_HEM[iv_sumy_HEM==Inf]<-0
 y_share[((i-1)*s+1):(i*s),]<-HEM_FD[((i-1)*s+1):(i*s),]<sup>*</sup>iv_sumy_HEM
 }
```

```
y share[is.na(y share)]<0 #colSums(y_share)
```

```
HEM y needreplace \leq -\frac{matrix(0, nrow = (sector * region), ncol = (region))}{m}for(j in 1:p)\{HEM y_needreplace[((j-1)*s+1):(j*s),]\leq y\;\text{share}[((j-1)*s+1):(j*s),]\leq y\;\text{sharp} }
```
 #HEM_FD include replace HEM2_FD<-HEM_FD+HEM_y_needreplace

#build new FD-------end

 #ori: no HEM $#AO < A$ #df.FD0<-df.FD

 #HEM $A0$ -HEM A df.FD0<-HEM_FD

Code for health impact assessment

%this code is for health impact assessment based on MATLAB

 $ICONC1s=[1];$ $ICONC2s=[0];$ [POPs,TXT,RAW]=xlsread('file0.xlsx','pop','B3:B42226'); [AGEs,TXT,RAW]=xlsread('file0.xlsx','CRF','J2:J86'); [CRFs,TXT,RAW]=xlsread('file0.xlsx','CRF','D2:F86'); $[INCs, TXT, RAW] = xlsread('file0.xlsx','CRF','I2:186');$ $nendpoint = 5$; STageconcs = $[1, 10, 37, 48, 56]$; EDageconcs = $[9, 36, 47, 55, 85]$;

```
%setting formats
```

```
result re = csvread('file1 dataframe.csv',1,0,[1 0 31 1]); % a dataframe for regional
results of mortality
illresult re = csvread('file1 dataframe.csv',1,0,[1 0 31 1]);
illresult re1 = csvread('file1 dataframe.csv',1,0,[1 0 31 1]);
illresult re2 = csvread('file1 dataframe.csv',1,0,[1 0 31 1]);illresult re3 = csvread('file1 data frame.csv',1,0,[1 0 31 1]);illresult \text{re}4 = \text{csvread}(\text{file1 dataframe.csv}, 1, 0, [1 0 31 1]);result 20 = csvread('file1 dataframe.csv',1,0,[1 0 31 1]);
illresult 20 = csvread('file1 dataframe.csv',1,0,[1 0 31 1]);
```
result $10 =$ csvread('file2 matching table.csv',1,1,[1 1 42224 2]); % a matching table for grids and regions

illresult $10 =$ csvread('file2 matching table.csv',1,1,[1 1 42224 2]);

 $pppppath = "D:\heath";$ $path = dir(pppppath);$

```
ncase = length(path)-2;\text{cont} = 2nrow = 42224 % number of grids
AC_total = zeros(nrow,ncase);
AC \text{illtotal} = \text{zeros}(n \times n \times n \times n \times n);
AC illtotal1 = zeros(nrow,ncase);
AC illtotal2 = zeros(nrow,ncase);AC illtotal3 =zeros(nrow,ncase);
AC illtotal4 =zeros(nrow,ncase);
```
 % Progress bar h=waitbar(0,'Data export in progress……'); $pause(1);$

for icase $= 1:1:$ (ncase)

p=fix(icase/ncase*10000)/100;

str=[' The output is in progress and the current progress is ',num2str(p),' %, finished! ',num2str(icase),'/',num2str(ncase)];

waitbar(icase/ncase,h,str);

⁰⁄0--------------------------

result $1 =$ result 10; result 2 = result 20;

```
illresult 1 = illresult 10:
illresult 11 = illresult 10;
illresult 12 = illresult 10;
illresult 13 = illresult 10;
illresult 14 = illresult 10;
illresult 2 = illresult 20;
illresult 21 =illresult 20;
illresult 22 = illresult 20;
illresult 23 = illresult 20;
illresult 24 =illresult 20;
```

```
 nameicase=num2str(icase);
fileposition = struct(pppppath," \",nameicase," 201701.csv");
CONCs = \text{csvread}(\text{fileposition}, 2, 11, [2 11 42225 11]); % Scenario Data Import
tmp = size(CONCs);nrow = tmp(1);
```

```
cone2 = zeros(nrow,1);conc1 = CONCs(:,1);pop = POPs(:,1);%unit: 10000 person
age = AGEs(:,1);inc = INCs(:,1);
```
%health end is death

 AC endpoint = zeros(nrow,nendpoint);

for iendpoint $= 1$:nendpoint

```
AC ageconc = zeros(nrow,EDageconcs(iendpoint)-STageconcs(iendpoint)+1);
 for iageconc = STageconcs(iendpoint):EDageconcs(iendpoint)
```

```
 deltaconc=(min(conc1,CRFs(iageconc,2))-
```

```
max(conc2,CRFs(iageconc,1))).*(conc1>conc2).*(conc1>CRFs(iageconc,1)).*(conc2<=
CRFs(iageconc,2))...
```
+(min(conc2,CRFs(iageconc,2))-

```
max(conc1,CRFs(iageconc,1))).*(conc1<=conc2).*(conc2>CRFs(iageconc,1)).*(conc1<
=CRFs(iageconc,2));
```

```
rr=(1-(1./exp(CRFs(iageconc,3)*deltaconc))).*((conc1>conc2)-(conc1<=conc2));
AC ageconc(:,iageconc-
```
STageconcs(iendpoint)+1)=rr.*pop*age(iageconc,1)*inc(iageconc,1)/100/100000*10000

;

 end AC endpoint(:,iendpoint)=sum(AC ageconc,2); end AC_total(:,(icase))=sum(AC_endpoint,2); result $1(:,1) = \text{sum}(AC \text{ endpoint},2);$ %input to match file

```
 %health end is illness
AC \text{ill} = \text{zeros}(n \cdot 4);
 E0 = [0.00694,0.00546,0.0094,0.038];% Baseline incidence
beta = [0.0027, 0.00068, 0.0021, 0.0079];% Exposure-response coefficient mean value
CO = 10; % PM2.5 concentration; here can set as 5, 10, 15 \mug m-3
for ill = 1:4Ei = E0(i11).*exp(beta(i11).*(cone1-C0)).*(cone1 >C0);H I = pop.*(Ei-E0(i11)).*(Ei>E0(i11)).*10000;AC \text{ill}(:,\text{ill}) = \text{H}III;
 end
AC illtotal(:,(icase))=sum(AC ill,2);
AC illtotal1(:,(icase)) = AC ill(:,1);
AC illtotal2(:,(icase)) = AC ill(:,2);
AC illtotal3(:,(icase)) = AC_ill(:,3);
AC illtotal4(:,(icase)) = AC ill(:,4);
illresult 1(:,1) = \text{sum}(AC\text{ ill},2);%input to match file
illresult 11(:,1) = AC ill(:,1);illresult 12(:,1) = AC ill(:,2);
illresult 13(:,1) = AC ill(:,3);
illresult 14(:,1) = AC ill(:,4);
 %combine to 31 provinces
for re = 1:42224if result 1(re,2) \sim= 0for re2 = 1:31if result 1(re,2) == result 2(re2,1)result 2(re2,2) = result 2(re2,2)+result 1(re,1);
          illresult 2(re2,2) =illresult 2(re2,2) +illresult 1(re,1);
          illresult 21(re2,2) =illresult 21(re2,2) +illresult 11(re,1);
          illresult 22(re2,2) =illresult 22(re2,2) +illresult 12(re,1);
          illresult 23(re2,2) =illresult 23(re2,2) +illresult 13(re,1);
          illresult 24(re2,2) =illresult 24(re2,2)+illresult 14(re,1);
        end
      end
   end
 end
result re(1:31,cont) = result 2(1:31,2);illresult re(1:31,cont) = illresult 2(1:31,2);illresult re1(1:31,cont) = illresult 21(1:31,2);illresult re2(1:31,cont) = illresult 22(1:31,2);
```
illresult $re3(1:31,cont) =$ illresult $23(1:31,2);$ illresult re4(1:31,cont) = illresult $24(1:31,2);$

```
result re(32,cont) = strcat(nameicase," 201701");
illresult re(32,cont) = strcat(nameicase," 201701");
illresult rel(32,cont) = struct(nameicase," 201701");
illresult re2(32,cont) = strcat(nameicase," 201701");
illresult re3(32,cont) = strcat(nameicase," 201701");
illresult \text{re}4(32,\text{cont}) = \text{strcat}(\text{nameicase}, "201701");\text{cont} = \text{cont}+1;
```
⁰⁄0--------------------------

end

close(h); msgbox('finished~');

illresult $resep = zeros((32*4),(ncase*4));$ illresult $resep(1:32,1:(ncase+1)) =$ illresult re1; illresult resep(33:64,(ncase+2):(2*ncase+2)) = illresult re2; illresult resep(65:96,(2*ncase+3):(3*ncase+3)) = illresult re3; illresult resep(97:128,(3*ncase+4):(4*ncase+4)) = illresult re4;

format long

```
dlmwrite(strcat(pppppath,"\","deathresult_nocombine.csv"),AC_total,'precision','%.6f');
dlmwrite(strcat(pppppath,"\","deathresult_combine.csv"),result_re,'precision','%.9f');
dlmwrite(strcat(pppppath,"\","total_illresult_nocombine.csv"),AC_illtotal,'precision','%.6
f');
dlmwrite(strcat(pppppath,"\","total_illresult_combine.csv"),illresult_re,'precision','%.9f');
dlmwrite(strcat(pppppath,"\","sep4_illresult_combine.csv"),illresult_resep,'precision','%.
9f');
```
save AC_total; save result re; save AC illtotal; save illresult re; save illresult resep;