Master's Thesis

Economic impacts from PM2.5 pollution-related health effects in China's industry sector: A provincial-level analysis

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Abstract:

The health and economic impacts of PM2.5 from the industry sector at the provincial level in China have not been investigated. This study evaluates the PM2.5 pollution-related health impacts of the industry sector on China's economy at both national and provincial levels in 2030 under different scenarios. This study combines the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model, the health model and the computable general equilibrium (CGE) model. The results show that at a national level, the industry sector led to 117.57 thousand deaths, 0.0022 case/capita of PM2.5 pollution-related cases, the additional medical expenditures of 0.28 billion USD in 2015. Other impacts include 67.35 billion USD of VSL loss and 0.07 day/capita of work time loss. Without additional control measures in 2030, air pollution related to the industry sector will cause 131.49 thousands deaths, the number of sick case would increase to 0.0024 case/capita, the additional medical expenditures would increase to 0.52 billion USD, VSL loss would increase to 124.86 billion USD, and work time loss would increase to 0.23 day/capita. Based on the models, implementing control strategy scenario would decrease 48.67 thousand deaths in 2030. The morbidity would decrease by 0.0009 case/capita. Total additional medical expenditures would be reduced by 0.19 billion USD. VSL loss would be reduced by 46.21 billion USD. Work time loss would be reduced by 0.06 day/capita, comparing with the no control measure scenario. In addition, PM2.5 pollution from the industry sector will cause 1.09% GDP loss and 1.68% Welfare loss in 2030. Provinces which suffer more health impacts from the industry sector (such as Shandong and Hunan) would gain more benefits after the implementation of control PM2.5 pollution, which further shows that control measures will have functions in these provinces.

Keywords: Air pollution, PM2.5 concentration, health, economy, national, provincial

Contents

1. Induction

1.1 Background

Outdoor air pollution kills more than 3 million people across the world every year, and causes health problems from asthma to heart disease for many more (OECD, 2014). Air pollution represents the biggest environmental risk to health (WHO, 2016). With China's rapid economic growth and rapid industrialization and urbanization, environmental problems are increasingly prominent. China is facing serious pollution of particulate matter (PM), such as PM2.5 that have a diameter of less than 2.5 micrometers (Chen *et al.*, 2018). In 2015, for instance, PM2.5 concentration in 30 Chinese provinces were 28–81μg/m^3, with a mean of 52μg/m^3 (China Environmental State Bulletin, 2015), exceeding the World Health Organization (WHO) guideline level of 10μg/m^3 (WHO, 2016), which poses a significant impact to human health (van Zelm et al., 2016). (Yang et al., 2013) used positive matrix factorization to identify the types of PM2.5 sources and corresponding mass contributions to PM2.5 mass concentrations using PM2.5 measurements obtained from Dec. 2007 to Oct. 2008 in Jinan, showing that the reconstructed mass concentrations from six sources matched the observations, and the resolved sources constituted 98.91% of the PM2.5 mass concentrations. Secondary sources, the major source contributor, accounted for 55.15% of PM2.5 mass concentration, while several other sources, including coal burning (20.98%), soil dust (9.30%), motor vehicles (6.06%), biomass burning (4.55%), and industry (2.87%), contributed a total of 43.76%. SO_2, NO_x, Soot and Dust emissions are main sources of PM2.5 (Hodan and Barnard, 2004). PM2.5 concentration is greatly affected by secondary generation. Therefore, while controlling PM2.5 pollution, it is necessary to consider the impact of other pollutants on PM2.5 concentration. The added value of China's manufacturing industry surpassed that of the United States to become the world's number one manufacturing country in 2010 (L. Liu et al., 2018). Although the proportion of the added value of tertiary industry (46.1%) in China has exceeded that of second industry (43.9%) in 2013, the industry sector still holds the largest share (approximately 70%) in the energy consumption structure and remains the biggest contributor in terms of air pollutants emissions (Zheng et al., 2016). Industry is the largest contributor of emissions of sulfur dioxide (SO_2), nitrogen oxide (NO_x), carbon monoxide (CO), and PM2.5, the proportion is 57%, 34%, 44%, and 50%, respectively in 2010. Meanwhile, it contributes over 34% of the total emissions of PM10 and BC in China in 2010 (Li *et al.*, 2017). Moreover, exposure to PM2.5 and NO_X from industry was associated with decreased lung function (Bergstra, Brunekreef and Burdorf, 2018).

China is a country with significant regional differences, such as economic development, technology, and energy structure (Feng *et al.*, 2013). The air pollutant emission also differs by province. Provinces with high production of industrial boilers usually have high PM2.5 concentrations. Industrial boilers are usually heavy and not convenient for long-range transportation, so most of the produced boilers are likely to be installed and used locally, leading to this phenomenon (Zhang *et al.*, 2018). Consequently, the situation of regional air pollutant emissions in China is of great significance for air pollution control.

1.2 Literature review

Many studies have shown the effects of air pollution on human health. For instance, at the global level, (Lelieveld *et al.*, 2015) based on the method of the Global Burden of Disease 2010 to calculate that outdoor air pollution, mostly by PM2.5, leads to 3.3 million premature deaths per year worldwide, predominantly in Asia (Apte *et al.*, 2015) used cause-specific integrated exposure-response functions developed for the Global Burden of Disease 2010 to assess how regional and global improvements in ambient air quality could reduce attributable mortality from PM2.5, showing that an aggressive global program of PM2.5 mitigation in line with WHO interim guidelines could avoid 750 000 (23%) of the 3.2 million deaths per year currently (ca. 2010) attributable to ambient PM2.5. At the national level, (Latif *et al.*, 2018) found that haze episodes have contributed to increasing hospital visits for treatments related to chronic obstructive pulmonary diseases, upper respiratory infections, asthma and rhinitis. In addition, respiratory mortality increased 19% due to haze episodes, and children and senior citizens are more likely to suffer the health impacts of haze. (Song *et al.*, 2017) suggested the PM2.5 in 2015 contributed as much as 40.3% to total stroke deaths, 33.1% to acute lower respiratory infection (ALRI, <5yr) deaths, 26.8% to ischemic heart disease (IHD) deaths, 23.9% to lung cancer (LC) deaths, 18.7% to chronic obstructive pulmonary disease (COPD) deaths, 30.2% to total deaths combining IHD, stroke, COPD, and LC, 15.5% to all-cause deaths in China. At the sub-national level, (Xie *et al.*, 2011) found that in Pearl River Delta, if the PM2.5 concentrations were reduced to below the WHO guideline value, the annual avoidable deaths would be 40000. At the city level, (Bayat *et al.*, 2019) used the concentration response function of the Global Exposure Mortality Model, they estimated a total of 7146 adult deaths attributable to PM2.5 in Tehran in 2017. In addition, the leading causes of death were ischemic heart disease, stroke, lower respiratory infections, chronic obstructive pulmonary disease, and lung cancer. (Bai *et al.*, 2019) estimated that among 145,200 students in colleges and universities in Changchun, the northeast of China, 109–134 died prematurely due to PM2.5 pollution, 71–75 of which were attributed to indoor PM2.5 pollution. Indoor and outdoor PM2.5 pollution resulted in 42 chronic bronchitis, 2565 medical outpatient visits, 19 cardiovascular diseases, and 5 respiratory diseases. At the sectoral level, (Giannadaki *et al.*, 2018) indicated that a 50% reduction in agricultural emissions could prevent > 200 thousand deaths per year, notably in China, accompanied with economic benefits of many billion US$. A cost-benefit assessment of ammonia emission abatement options for the EU indicates that the reduction of agricultural emissions generates net financial and social benefits. (Tian *et al.*, 2018)showed that the road transport sector leads to 163.64 thousand deaths per year in China. Meanwhile, implement control strategies to reduce PM2.5 pollution in the road transport sector could bring positive benefits in half of the Chinese provinces especially in provinces that suffer greater health impacts from the road transport sector. It can be seen that studies at the sectoral level can provide useful insights for the formulation of air pollution policies.

Air pollution not only has negative effects on human health, but also has a negative impact on the economy. For instance, (Lanzi, Dellink and Chateau, 2018) showed that the global economic costs of outdoor air pollution gradually increase to 1% of global GDP by 2060, with highest GDP losses in China. (Thompson *et al.*, 2014) found that monetized human health benefits associated with air quality improvements can offset 26–1,050% of the cost of US carbon policies. More flexible policies that minimize costs, such as cap-and-trade standards, have larger net co-benefits than policies that target specific sectors. (Stewart *et al.*, 2003) showed that health-related loss of productive time costs employers UDS225.5 billion per year in the USA. (Xie *et al.*, 2016) estimated that China experiences a 2.00% GDP loss and 25.2 billion USD in health expenditure from PM2.5 pollution in 2030 without PM2.5 pollution control policy. (Wang *et al.*, 2015) showed that in the Yangtze River Delta in China, the economic loss is 22.1 billion Chinese Yuan in 2010. The industrial and residential sectors contributed the most, accounting for more than 50% of the total economic loss. (Wu *et al.*, 2017) showed that with the application of multiregional integrated control strategies neighboring provinces would be the most effective in reducing PM2.5 concentration in Shanghai, leading to only 0.34% of GDP loss, and labor-intensive sectors suffer more output loss from PM2.5 pollution. Implement control strategies to reduce PM2.5 pollution may have certain economic impact on some sectors and regions.

1.3 Research objectives

To the best of our knowledge, studies on the industry-related air pollution on health and economic effects are rare. Furthermore, the health and economic impacts of PM2.5 from the industry sector at the provincial level in China have not been investigated. Therefore, it is essential to have a study to provide valuable policy insights to these decision makers. This study aims to evaluate the health and economic impacts caused by PM2.5 pollution from the industry sector in 30 Chinese provinces in 2030. Three research questions will be addressed in this study.

1) What will be the trends of air pollutants from the industry sector in 30 Chinese provinces towards 2030?
2) What are the health and economic impacts of PM2.5 pollution from the industry sector in 30 Chinese provinces?
3) What are the benefits of improving PM2.5 pollution in the industry sector?

2. Methodology Framework

This study evaluates the PM2.5 pollution-related health impacts caused by the industry sector on China's economy at both national and provincial levels in 2030 under different scenarios, using the combination of the GAINS (Greenhouse Gas and Air Pollution Interactions and Synergies) model, the IMED/HEL (Integrated Model of Energy, Environment and economy for Sustainable Development/Health) model, and the IMED/CGE (Computable General Equilibrium) model. Because of data availability, all three models cover 30 Chinese provinces, except for Hong Kong and Macau.

2.1 Overview of methodology

As shown in Figure 1. Firstly, the GAINS-China model calculates the air pollutants primary emissions and provides annual average PM2.5 concentration in 30 provinces of China in the future. With the annual average PM2.5 concentration from the GAINS model, the health assessment model, the IMED/HEL can quantify the impact of air pollution on health, including mortality, morbidity, work time loss, and additional health expenditure. Finally, the CGE model, the IMED/CGE, is used to evaluate the impact of PM2.5 on economy.

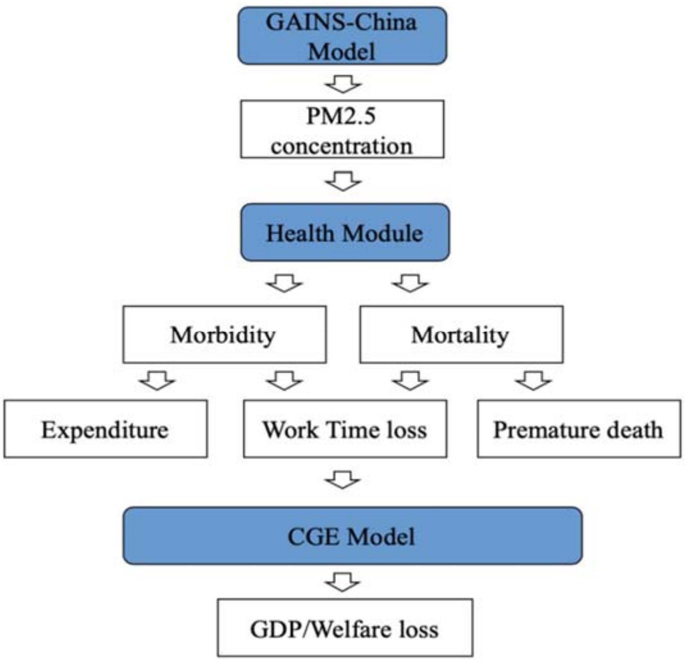

Figure 1 Research Framework

2.2 The GAINS model

GAINS model[1] is an integrated assessment model dealing with costs and potentials for air pollution control and greenhouse gas (GHG) mitigation and assesses interactions between policies (Amann *et al.*, 2008). GAINS model was developed by the International Institute for Applied Systems Analysis (IIASA) in Austria, originally as the Regional Air pollution Information and Simulation (RAINS) model to estimate air pollutant emissions and design abatement strategies in Europe. It provides a consistent framework for estimating emissions, mitigation potentials, and costs for air pollutants, such as SO_2, NOx, PM, NH3, NMVOC, and greenhouse gases included in the Kyoto protocol (Amann *et al.*, 2011; Amann, Klimont and Wagner, 2013). The GAINS-China is an application of the GAINS model for East Asia. Documentation on the model and access to principal data, assumptions, and results are freely available online. Various air-pollutant-mitigation technologies are considered in the GAINS-China model. (Wu *et al.*, 2017; Tian *et al.*, 2018; Xie *et al.*, 2019)

The basic principle of calculating air pollutant and GHG emissions, and emission control costs in the model is presented in Eqs.1 and 2.

$$Emissions = \sum_i Activity_i \times F \times (1-r) \times C \tag{1}$$

$$Costs = \sum_i Activity_i \times U \times C \tag{2}$$

Components appearing on the right side of the equations are organized into three different data categories: activity pathways, emission vectors, and control strategies. Each emission scenario in the GAINS model is created through a combination of these three components. Emissions-generating economic activities (*Activity)* are organized into activity pathways which are divided into five groups: Agriculture, Energy, Mobile, Process, and VOC sources. This study mainly focuses on Energy sources activity. *F* (emission factors of activities), *r* (removal efficiencies of control technologies), *U* (unit cost

[1] The details of the model can be found in https://www.iiasa.ac.at/web/home/research/researchPrograms/air/GAINS-tutorial.pdf.

of control technologies), together with all background information, form the so-called emission vectors. Finally, *C* (control technologies) for each activity are specified in control strategies. Emissions and control costs of each emission scenario are the sum of all *i* activities.

Based on the detailed spatial and sectoral GAINS emission inventory, GAINS computes fields of ambient concentrations of PM2.5 with the help of source-receptor relationships derived from an atmospheric chemistry-transport model named the TM5 model. The model computed contributions from (i) primary particulate matter released from anthropogenic sources, (ii) secondary inorganic aerosols formed from anthropogenic emissions of SO_2, NO_x and NH_3, (iii) particulate matter from natural sources (soil dust, sea salt, biogenic sources).

2.3 The IMED/HEL model

The IMED/HEL model[2] is applied to quantify the health impacts of PM2.5 concentration.

2.3.1 Health endpoint

All results are given by region *r*, year y, scenario s. For simplification, they are omitted in the following description. Exposure to incremental PM2.5 pollutant leads to health problems called health endpoints, which are categorized into morbidity and chronic mortality (Table 1). As showed in Eqs.3 and 4, this study based on linear exposure-response functions (ERFs) from reference (Cao *et al.*, 2011) and (Apte *et al.*, 2015). When the concentration is lower than or equal to the threshold of 10μg/m^3, RR is 1, which causes no health impacts. The number of health endpoints is estimated by multiplying RR with population and reported cause-specific mortality rate.

$$RR_{p,r,s,y,m,e,g}(C) = \begin{cases} 1, & \text{if } C_{p,r,s,y} \leq C0_p \\ 1 + CRF_{m,e,g} \times (C_{p,r,s,y} - C0_p), \quad \text{linear function}, & \text{if } C_{p,r,s,y} > C0_p \end{cases} \tag{3}$$

[2] The details of the model can be found in http://scholar.pku.edu.cn/hanchengdai/imedhel.

$$EP_{p,r,s,y,m,e,g}(C) = \begin{cases} P_{r,y,m} \times (RR_{p,r,s,y,m,e,g}(C) - 1), & \text{for linear morbidity function} \\ P_{r,y,m} \times (RR_{p,r,s,y,m,e,g}(C) - 1) \times I_{r,\text{"all cause"}}, & \text{for linear mortality function} \end{cases} \quad (4)$$

where $RR(C)$ is the relative risk for the end point at concentration C (case/person/year or day/person/year), EP is the health end point (case/year or day/year), C is the concentration level of the pollutant, $C0$ is the threshold concentration that causes health impacts (10μg/m^3 for PM2.5), CRF is the concentration−response function, P is the population, ages 15−65 for work loss day, ages 25−65 for ischemic heart disease and stroke, and entire cohort for other endpoints. $I_{r,\text{“all cause”}}$ is the reported average annual natural death rate for end point, and suffixes p, r, s, y, m, e, and g represent pollutant (PM2.5), region, scenario, year, end point category (morbidity or mortality), end point, and value range (medium, low, and high), respectively.

Table 1 Exposure-Response Functions for health endpoints

Category	Endpoint	Unit	Medium	C.I. (95%) Low	C.I. (95%) High
Morbidity	Work loss day	day/person	2.07E-02	1.76E-02	2.38E-02
	Respiratory hospital admissions	/μg-m^3/year	1.17E-05	6.38E-06	1.72E-05
	Cerebrovascular hospital admission	case/person	8.40E-06	6.47E-07	1.16E-05
	Cardiovascular hospital admissions	/μg-m^3/year	7.23E-06	3.62E-06	1.09E-05
	Chronic bronchitis		4.42E-05	-1.82E-06	9.02E-05
	Asthma attacks		1.22E-04	4.33E-05	1.21E-03
	Respiratory symptoms days		2.50E-02	2.17E-01	4.05E-01
Chronic	All-cause (International)		0.004	0.0003	0.008
mortality	All-cause (China-specific)		0.0009	-0.0003	0.0018

Source: (Cao *et al.*, 2011; Apte *et al.*, 2015)

2.3.2 Annual per capita work loss rate

The annual total work loss day (*WLD*) of a region is a summation of work loss day from morbidity and cumulative work loss day from chronic mortality aged from 15 to 65 years old (Eq.5). Based on the death rates for different age group and cause-specific mortality from China health statistics, we assume 4% of total chronic mortality is aged between 14 and 65 years old. The annual per capita work loss rate (*WLR*) is obtained by dividing *WLD* with working population times annual working days (Eq.6). In the CGE model, *WLR* is used to calculate the actual labor force after subtracting the work loss (Eq.7).

$$WLD_{p,r,s,y,g} = \sum_{m}(EP_{p,r,s,y,m,\text{"wld"},g}) + \sum_{e,y\prime<y}(EP_{p,r,s,y\prime,\text{"mt"},e,g}) \times SHR_{r,\text{"15−65"}} \times DPY \qquad (5)$$

$$WLR_{p,r,s,y,g} = \frac{WLD_{p,r,s,y,g}}{DPY \times P_{r,y,\text{"15−65"}}} \qquad (6)$$

$$LAB_{p,r,s,y,g} = LAB0_{r,\text{"ref"},y} \times (1 - WLR_{p,rs,y,v}) \qquad (7)$$

where *WLD* is the annual work loss day (day/year), WLR is the annual per capita work loss rate, wld is the subset “work loss day” of e, mt is the subset “chronic mortality” of m, *LAB* is the labor force after considering work loss, *LAB0* is the labor force in the reference scenario, and *DPY* is the per capita annual working days (5 days/week × 52 weeks/year = 260 days/year).

2.3.3 Health expenditure

Additional health expenditure is obtained by multiplying outpatient and hospital admission price with total endpoints (Eq.8). The price is a function of per capita GDP of each province (Eq.9), and the parameters β and θ were estimated through regression analysis of statistical price by disease and GDP of each province from 2003 to 2012. Additional medical expenditure is regarded as household expenditure pattern change, which means that as more money is spent on medical services, less is available on other commodities.

$$HE_{p,r,s,y,g} = PR_{r,s,y,e,g} \times EP_{p,r,s,y,m,e,g} \quad (8)$$

$$PR_{r,s,y,e} = \beta \times GDPPC_{r,s,y} + \theta_{r,e} \quad (9)$$

where *HE* is the total additional health expenditure (billion USD/year), PR is the price of the medical service (USD/case), *GDPPC* is the per capita gross domestic production from the CGE model, and β and θ are the parameters derived from regression analysis of the medical service price.

2.4 The IMED/CGE model

2.4.1 An overview

The CGE model could capture the full range of interaction and feedback effects between different agents in the economic system. It has been widely used to assess the economic and environmental impacts of different climate policies at global (Bohringer and Loschel, 2005; Fujimori, Masui and Matsuoka, 2014, 2015) and national (Zhang, 1998; Wang, Wang and Chen, 2009) levels. This study evaluates the economic loss caused by air pollution through the CGE model.

The IMED|CGE model applied in this study can be classified as a global multi-sector and multi-region recursive dynamic CGE model.[3] Depending on the specific research objectives, the regional or sectoral classification of the model is flexible. This IMED|CGE model is solved by Mathematical Programming System for General Equilibrium under General Algebraic Modeling System (GAMS/MPSGE) (Rutherford, 1999) at a one-year time step. The IMED|CGE model includes a production block, a market block with domestic and international transactions, as well as government and household incomes and expenditures blocks. Activity output for each sector follows a nested constant elasticity of substitution (CES) production function. Inputs are categorized into material commodities, energy commodities, labor, capital, and resources.

[3] The details of the model can be found in http://scholar.pku.edu.cn/hanchengdai/imedcge.

Table 2 Socio-economic assumptions for 30 provinces of China

	Population (million)					Per capita GDP (USD/capita)				
	2010	2015	2020	2025	2030	2010	2015	2020	2025	2030
China	1325.3	1347.19	1362.83	1368.70	1364.29	2683.0	3983.7	5836.4	7691.2	9540.0
Beijing	14.84	15.09	15.26	15.33	15.28	8231.8	11638.4	16932.6	21579.4	26386.1
Tianjin	10.50	10.68	10.80	10.85	10.81	6561.6	9584.1	13499.1	16900.4	20229.8
Hebei	70.26	71.41	72.24	72.55	72.32	2400.4	3470.7	5130.9	6761.8	8434.1
Shanxi	34.36	34.93	35.33	35.49	35.37	1889.9	2718.1	3798.4	4766.9	5461.3
Inner Mong	24.87	25.28	25.57	25.68	25.60	3040.6	4938.9	7422.4	10169.8	13013.5
Liaoning	43.84	44.57	45.08	45.28	45.13	3798.7	5523.9	8152.7	10248.4	12479.7
Jilin	28.15	28.62	28.95	29.08	28.98	2474.0	3598.2	4973.2	6431.5	7678.8
Heilongjiang	39.77	40.43	40.90	41.08	40.94	2255.7	3219.1	4459.3	5705.4	6757.2
Shanghai	17.87	18.16	18.37	18.45	18.39	8889.6	12385.8	17937.1	22921.3	28039.6
Jiangsu	77.26	78.53	79.44	79.78	79.53	4340.4	6514.4	9599.0	12579.9	15546.8
Zhejiang	49.82	50.65	51.23	51.46	51.29	5054.5	7501.7	11387.7	15111.9	18796.5
Anhui	64.09	65.15	65.90	66.19	65.97	1504.5	2418.8	3743.6	5325.6	6891.3
Fujian	36.26	36.86	37.29	37.45	37.33	3768.1	5661.8	8571.7	11288.7	14059.6
Jiangxi	44.04	44.77	45.29	45.48	45.34	1494.7	2182.0	3074.7	3989.4	4785.6
Shandong	94.74	96.30	97.42	97.84	97.52	3223.4	4623.3	6556.3	8412.4	10339.8
Henan	100.28	101.93	103.11	103.56	103.23	2144.4	3639.4	5812.8	8501.2	11194.9
Hubei	59.17	60.14	60.84	61.10	60.91	1937.1	2811.8	3915.4	5023.1	5953.3
Hunan	69.15	70.29	71.11	71.41	71.18	1629.3	2367.5	3314.4	4284.3	5142.0
Guangdong	92.24	93.76	94.84	95.25	94.95	4533.8	6549.5	9591.5	12186.5	14762.2
Guangxi	50.30	51.13	51.72	51.95	51.78	1451.5	2209.4	3177.6	4189.6	5197.4
Hainan	8.38	8.51	8.61	8.65	8.62	2070.8	3017.1	4457.2	5877.3	7425.8
Chongqing	29.36	29.84	30.19	30.32	30.22	1857.2	2912.3	4328.5	6031.6	7906.1
Sichuan	84.60	85.99	86.99	87.37	87.09	1513.0	2282.4	3268.6	4346.6	5457.7
Guizhou	40.03	40.69	41.16	41.34	41.20	847.2	1238.7	1721.6	2283.7	2863.5
Yunnan	45.20	45.94	46.48	46.68	46.53	1333.3	2040.4	2958.9	3996.6	5037.8
Shaanxi	38.20	38.83	39.28	39.45	39.33	1624.3	2451.3	3481.3	4717.7	5971.8
Gansu	26.40	26.83	27.15	27.26	27.18	1165.7	1723.5	2450.3	3311.7	4281.1
Qinghai	5.52	5.61	5.67	5.70	5.68	1669.3	2497.6	3617.5	4852.3	6087.1
Ningxia	5.97	6.07	6.14	6.16	6.14	1638.5	2405.9	3443.1	4633.8	5961.7
Xinjiang	19.87	20.20	20.43	20.52	20.46	2010.4	2951.4	4267.6	6032.9	8103.2

Technical descriptions have been introduced in (Dai *et al.*, 2016; Xie *et al.*, 2016). It has been applied systematically to analyze air pollution reduction, human health, resource efficiency, energy and climate mitigation policies of China at the national and provincial levels (Tian *et al.*, 2018). The IMED|CGE model has been configured extensively to reflect the historical and future pathway of China in reference (Dong *et al.*, 2015). For instance, we adjusted the IMED|CGE model assumptions to match the historical statistics of population growth, GDP growth rate, energy use, and air pollutant emissions in each province as much as possible. As for the future, China's GDP growth and demographic evolution follows SSP2 (Shared Socioeconomic Pathway) scenario (O'Neill *et al.*, 2014), which is characterized by moderate economic growth, fairly rapid growing population and lessened inequalities between west, central, and east China. Table 2 shows the socioeconomic assumptions for 30 provinces of China.

2.4.2 Technical Introduction to IMED|CGE model

1) Production

For each sector (j) in region (r), gross output $Q_{r,j}$ is produced using inputs of labor ($L_{r,j}$), capital ($K_{r,j}$), energy ($E_{r,j}$ is $coal_{r,j}$, $Coil_{r,j}, Cgas_{r,j}$ and $Cele_{r,j}$, and non-energy material ($M_{r,j}$). In some sectors (Agriculture, Coal, Crude oil, Mining), resource ($R_{r,j}$) is also input. A five-level nested function is used to characterize the production technologies as showed in Figure 2a and Eq.11 below. The producer maximizes its profit by choosing its output level and inputs use, depending on their relative prices (Eq.10) subject to its technology (Eq.11).

$$max\colon \pi_{r,j} = p_{r,j} \cdot Q_{r,j} - \left(\sum_{i=1}^{N} p_{r,i} \cdot X_{r,i,j} + \sum_{v=1}^{V} w_{r,v} \cdot V_{r,v,j} \right) - T^{z}_{r,j} \tag{10}$$

Subject to the production technology:

$$Q_{r,j} = LEO_{1rj} \left\{ \begin{matrix} M_{r,j}, R_{r,j}, CES_{2vae} \\ \left[CES_{3va}\left(K_{r,j}, L_{r,j}\right), CES_{3re}\left(ele_{r,j}, CES_{4fos}\langle coal_{r,j}, gas_{r,j}, oil_{r,j}\rangle\right)\right] \end{matrix} \right\} \tag{11}$$

where $\pi_{r,j}$ is profit of j-th producers in region r, $Q_{r,j}$ is output of j-th sector in region r, $X_{r,i,j}$ is intermediate inputs of i-th goods[4] in j-th sector in region r, $X_{r,i,j}$ includes $M_{r,i,j}$ (non-energy

[4] Goods include services.

material), $ele_{r,j}$ (electricity), $coal_{r,j}$ (coal), $gas_{r,j}$ (natural gas or manufactured gas), $oil_{r,j}$ (crude oil), $pet_{r,j}$ (refined oil) and $RES_{r,j}$ (resource which is originated from the natural resource endowment), $V_{r,v,j}$ is v-th primary factor inputs in j-th sector in region r, $p_{r,i}$ is price of the j-th composite commodity, $w_{r,v}$ is v-th factor price in region r, CES_{krj} is the CES function at the k-th nesting level, the first level, LEO_{1rj}, is Leontief function, the second level CES_{2vae} is aggregation of value added and energy composite, the third level CES_{3va} is aggregation of value added, and CES_{3e} is aggregation of energy composite, the fourth level CES_{4j} is aggregation of fossil energy inputs.

The following conditions apply in this regard:

a) Land inputs are considered only for agriculture sector (Cagr), other resources are considered for crude oil and natural gas extraction (Coil), coal mining (Coal) and other mining (Cmin) sectors.

b) Within energy transformation sectors such as oil refining (Cpet) and gas manufacturing (Cgas), primary energy commodities are considered as material inputs.

c) The power sector is modelled by three thermal power (coal, gas and oil) and five non-thermal power (nuclear, hydro, wind, solar and biomass) technologies (Fig.2b). The energy bundle is not combined with capital for thermal power technologies, but linked directly to activity output. This means that electricity output is in a linear relationship with energy inputs.

d) Labor is assumed to be fully mobile across industries within a region but immobile across regions. The mobility feature of capital follows a putty-clay approach, which means that vintage capital is immobile across either regions or industries while new investment is fully mobile across industries within a region.

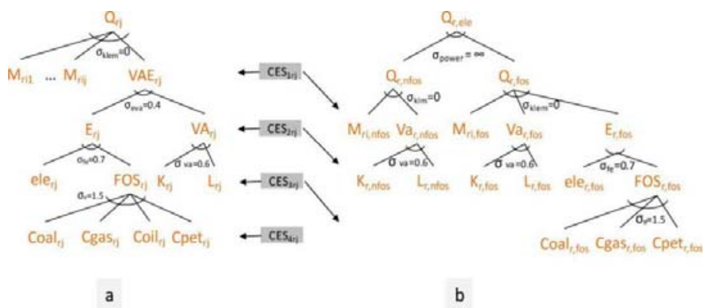

Figure 2 Nesting of production structure: (a) sectors other than electricity sector; and (b) electricity sector

σ is elasticity of substitution for inputs. $VAE_{r,j}$, $VA_{r,j}$, $E_{r,j}$, $FOS_{r,j}$ are CES composites of value added energy, value added, energy and fossil energy, respectively.

2) Final demand

Household and government sectors are represented as two different final consumers. As Eq.12 shows, the representative household receives income from the rental of primary factors ($\sum_{v=1}^{V}\left(w_{r,v} \cdot V_{r,v}\right) + \sum_{j}\left(pld_r \cdot QLAND_{r,j}\right) + \sum_{s,j}(p_{r,s}^{s} \cdot QRES_{r,j,S})$) and lump-sum transfer from the government. The income net of direct tax (T_r^d) is used for either investment (or saving, S_r^p) or final consumption ($\sum_i p_{r,i} \cdot X_{r,i}^{p}$,). Households maximize their utility by choosing the levels of final consumption of commodities, subject to their income and commodity prices (see the income balance in Eq.12 below). Total investment is assumed exogenously by Eq.21. On the other hand, the government collects taxes ($T_r^d + \sum_j T_{r,j}^{z} + \sum_j T_{r,j}^{m}$) and spends the tax revenue for its expenditure ($p_{r,i} \cdot X_{r,i}^{g}$) as explained in Eq.13. Although carbon tax (T_r^{cab}) is collected by the government, the IMED|CGE model assumes that the revenue from carbon tax is recycled to the household sector as a lump-sum transfer. The demands (DEM_r^d) of household consumption, investment goods and government are specified using Cobb-Douglas utility or demand functions (see Eq.14 below).

Income balance of the representative household

$$\begin{aligned}\sum_{v=1}^{V}(\omega_{r,v} \cdot V_{r,v}) + \sum_{j}(pld_r \cdot QLAND_{r,j}) \;\; + \sum_{s,j}(p_{r,j}^{s} \cdot QRES_{r,j,s}) + T_r^{cab} - T_r^d \\ = \sum_i p_{r,i} \cdot X_{r,i}^{p} + S_r^p\end{aligned} \tag{12}$$

Income balance of the government

$$T_r^d + \sum_j T_{r,j}^{z} + \sum_j T_{r,j}^{m} = \sum_i p_{r,i} \cdot X_{r,i}^{g} + S_r^g \tag{13}$$

Cobb-Douglas representation of demand of household, investment and government

$$DEM_r^d = A_r^d \cdot \prod_i^N (X_{r,i}^d)^{\alpha_{r,i}^d}, d \in (household, investment\ \ and\ \ government) \tag{14}$$

The first-order conditions for the optimality of the above problem imply the following demand functions for household, government and investment, respectively:

Demand function for household

$$X_{r,i}^p = \frac{\alpha_{r,i}^p}{p_{r,i}} \cdot (\sum\nolimits_{v=1}^V (w_{r,v} \cdot V_{r,v}) + \sum\nolimits_j (pld_r \cdot QLAND_{r,j}) + \sum\nolimits_{s,j} (p_{r,s}^s \cdot QRES_{r,j,S}) - S_r^p - T_r^d) \tag{15}$$

Demand function for government

$$X_{r,i}^g = \frac{\alpha_{r,i}^g}{p_{r,i}} \cdot (T_r^d + \sum_j T_{r,j}^z + \sum_j T_{r,j}^m - S_r^g) \tag{16}$$

Demand function for investment

$$X_{r,i}^n = \frac{\alpha_{r,i}^n}{p_{r,i}} \cdot (S_r^p + S_r^g + \varepsilon \cdot S_r^f) \tag{17}$$

where DEM_r^d is final demand of households - p, investment - n and government – g, $\omega_{r,v}$ is price of the v-th primary factor, $V_{r,v}$ is v-th primary factor endowment by household, pld_r is land price, $QLAND_{r,j}$ is land in sector j, $p_{r,j}^s$is price of resources, $QRES_{r,j,S}$ is is quantity of resource s in sector j, T_r^{cab} is carbon emission tax revenue, T_r^d is direct tax, S_r^p is household savings, $T_{r,j}^z$ is production tax in sector j, $T_{r,j}^m$ is import tariff of commodity j, S_r^g is government savings, S_r^f is current account deficits in foreign currency terms (or alternatively foreign savings), ε is foreign exchange rate, $p_{r,i}$ is commodity price, $X_{r,i}^p$, $X_{r,i}^g$, $X_{r,i}^n$ are commodity final consumption by households, government and investment, respectively, A_r^d is the scaling parameter in Cobb-Douglas function by agent d, and $\alpha_{r,i}^d$ is the share parameter in Cobb-Douglas function by agent d.

3) Commodity supply and inter-regional trade

Supply of commodity adopts the Armington assumption (Armington, 1969), assuming that goods produced from other provinces and abroad are imperfectly substitutable for domestically and locally produced goods. This approach is shown in Fig.3 and Eqs.18 and 19 below.

Supply to international regions (*f*):

Armington representation of domestically produced and imported commodity

$$X_{f,i} = CES_{s1}\{D_{f,f,i}, CES_{s2}[F_{1,f,i}, \dots, F_{f',f,i}, CES_{s3}(P_{1,f,i}, \dots, P_{p,f,i})]\} \tag{18}$$

Supply to China province (*p*):

Representation of commodity produced locally and produced in other provinces

$$X_{p,i} = CES_{s1}\{F_{1,p,i}, \dots, F_{f,p,i}, CES_{s2}[D_{p,p,i}, CES_{s3}(P_{1,p,i}, \dots, P_{p',p,i})]\} \tag{19}$$

Where $D_{f,f,i}$ is commodity produced in the rest of world, $P_{p,f,i}$ is commodity produced in China's provinces and exported to the rest of world, $F_{f,p,i}$ is commodity produced in the rest of world and imported by China's province, $D_{p,p,i}$ is commodity produced in the province and supplied to the same province, $P_{p',p,i}$ is commodity produced in the other provinces.

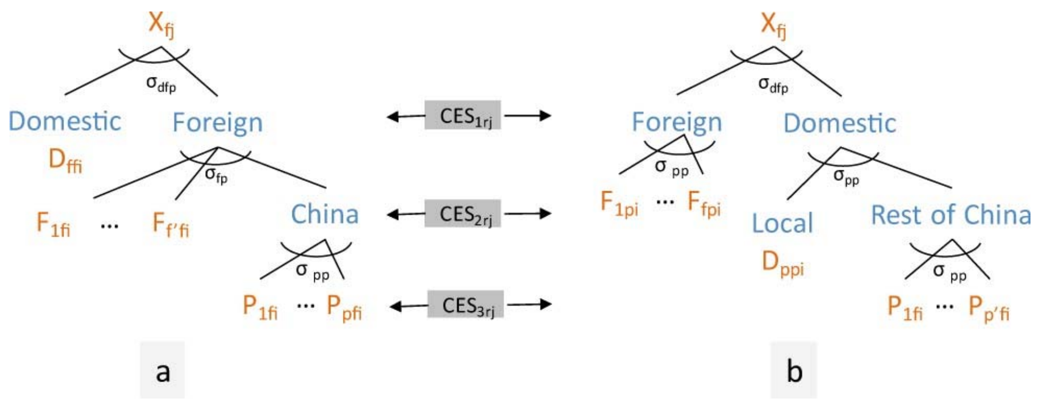

Figure 3 Aggregation of local, domestic and foreign varieties of good for: a, international regions; b, China provinces. σ is elasticity of substitution for inputs

Two types of price variables are distinguished. One is prices in terms of the domestic currency p_i^e and p_i^m; the other is prices in terms of the foreign currency p_i^{We} and p_i^{Wm}. They are linked with each other as follows:

$$p_i^e = \varepsilon \cdot p_i^{We} \tag{20}$$

$$p_i^m = \varepsilon \cdot p_i^{Wm} \tag{21}$$

Furthermore, it is assumed that the economy faces balance of payments constraints, which is described with export and import prices in foreign currency terms:

$$\sum_i p_i^{We} \cdot E_{r,i} + S_r^f = \sum_i p_i^{Wm} \cdot M_i \tag{22}$$

Where $E_{r,i}$ is export of i-th commodity in region r, $M_{r,i}$ is import of i-th commodity in region r, p_i^{We} is export price in terms of foreign currency, p_i^e is export price in terms of domestic currency, p_i^{Wm} is import price in terms of foreign currency, p_i^m is import price in terms of domestic currency.

4) Market clearance

The market-clearing conditions hold for both commodity and factor markets. For the commodity markets described in Eq.23, output $Q_{r,i}$ in the corresponding sector j (i=j) is equal to the total demand of intermediate inputs, household, investment, and government ($\sum_d X_{r,i}^d$), plus export to other international regions ($\sum_f F_{r,f,i}$) and provinces ($\sum_p P_{r,p,i}$), minus import from other international regions ($\sum_f F_{r,f,i}$) and provinces ($\sum_p P_{p,r,i}$), and plus stock change ($STK_{r,i}$):

Market clearance of commodity and services

$$Q_{r,i} = \sum_d X_{r,i}^d + \sum_f F_{r,f,i} + \sum_p P_{r,p,i} - \sum_f F_{f,r,i} - \sum_p P_{p,r,i} - STK_{r,i} \tag{23}$$

For the factor markets described in Eq.24, supply of total factor ($V_{r,v}$) is equal to factor inputs in all sectors ($v_{r,v,j}$):

Market clearance of production factor

$$V_{r,v} = \sum_j v_{r,v,j} \tag{24}$$

5) Macro closure

In a CGE model, the issue of macro closure is the choice of exogenous variables, including macro closure of investment-saving balance and current account balance. In this CGE model, government savings (S_r^g), total investment, and balanced of payment (S_r^f) are fixed exogenously, and foreign exchange rate (ε) is an endogenous variable.

6) Dynamic process

The IMED|CGE model is solved at one-year time step in a recursive dynamic manner, in which the parameters of capital stock (Eqs.25 and 26), labor force (Eq.27), land, natural resource, efficiency (Eq.28), and extraction cost of fossil fuels are updated based on the modelling of inter-temporal behavior and results of previous periods.

Capital accumulation process:

Total investment demand

$$TI_{r,\mathrm{t+1}} = \sum_j CAPSTK_{r,j,t} \cdot \left[\left(1 + g_{r,t+1}\right)^T - (1 - d_r)^T \right] \tag{25}$$

Capital accumulation process:

$$CAPSTK_{r,j,t} = (1 - d_r)^T \cdot CAPSTK_{r,j,t-1} + T \cdot I_{r,\mathrm{i,t}} \tag{26}$$

where $TI_{r,\mathrm{t}}$ is total investment, $I_{r,\mathrm{j,t}}$ is investment in sector j, $CAPSTK_{r,j,t}$ is capital stock accumulation , d_r is the depreciation rate (5% for all regions), and *T* is time step (1 year).

Supply of total labor, land and resource:

Factor growth pattern

$$\mathrm{V}_{r,v}^{t} = \mathrm{V}_{r,v}^{t-1} \cdot (1 + gr_{r,v}^{t}) \tag{27}$$

where $\mathrm{V}_{r,v}^{t}$ is primary factor (v) of labor force, land and resource, and $gr_{r,v}^{t}$ is the corresponding exogenous growth rate.

Efficiency parameters:

The CGE model distinguishes technological efficiency improvement of new investments from that of existing capital stock. For new investments, sectoral efficiencies of energy, land productivity, and total factor productivity are given as exogenous scenarios, while for existing capital stock, efficiency of par (par is efficiency of energy and capital) in time t ($\mathrm{EFF}_{r,par,j}^{ext,t}$) is the average of capital stock ($\mathrm{EFF}_{r,par,j}^{ext,t-1}$) and new investments ($\mathrm{EFF}_{r,par,j}^{new,t-1}$) in the previous period, as per Eq.28 here:

Updating of efficiency parameters

$$EFF_{r,par,j}^{ext,t} = \frac{\left(\mathrm{EFF}_{r,par,j}^{ext,t-1} \cdot CAPSTK_{r,j,t-1} + \mathrm{EFF}_{r,par,j}^{new,t-1} \cdot I_{r,\mathrm{j},\mathrm{t}-1}\right) \cdot (1-d_r)^T}{CAPSTK_{r,j,t}} \tag{28}$$

7) Data

Most of the global data in the IMED|CGE model are based on Global Trade Analysis Project 6 (Dimaranan and McDougall, 2006) and *International Energy Agenc*y (IEA, 2009). China-specific provincial data sources are the inter-regional input-output tables (IOT) (Li, Qi and Xu, 2010) and the Energy Balance Tables (EBT) (National Bureau of Statistics of China, 2003). In addition, carbon emission factors, energy prices for coal, oil and gas, and renewable energy technology costs are also required. All the datasets are currently converted to the base year of 2002. Moreover, it is well known that IOT and EBT are inconsistent when it comes to energy consumption across sectors, and the energy data from EBT is regarded as more reliable than IOT. A novel characteristic of this CGE model is that the IOT of China is consistent with the sectoral energy consumption from China's EBT. In order to achieve this consistency, we used the linear least square method, as described in Eqs.29-32 below.

$$\text{Min } \varepsilon = \sum_{en,i} (Shr_{en,i}^{IOT} - Shr_{en,i}^{EBT})^2 \tag{29}$$

Subject to:

$$Shr_{en,i}^{IOT} = \frac{EN_{en,i}^{IOT}}{TCON_{en}^{IOT}} \tag{30}$$

$$Shr_{en,i}^{EBT} = \frac{EN_{en,i}^{EBT}}{TCON_{en}^{EBT}} \tag{31}$$

$$\sum_i EN_{en,i}^{IOT} \cdot P_{en} = \sum_i EN_{en,i}^{EBT} \quad (32)$$

where ε is error to be minimized, en is energy commodities (coal, gas, oil, electricity), I is sector classification, $Shr_{en,i}^{IOT}$ is share of energy consumption across sectors in IOT (%), $Shr_{en,i}^{EBT}$ is share of energy consumption across sectors in EBT (%), $EN_{en,i}^{IOT}$ is energy consumption of en in sector i in IOT (USD), $EN_{en,i}^{EBT}$ is energy consumption of en in sector i in EBT (PJ), $TCON_{en}^{IOT}$ is total energy consumption of en in IOT (USD), $TCON_{en}^{EBT}$ is total energy consumption of en in EBT (PJ), and P_{en} is price of energy en (USD/PJ).

2.5 Scenarios

Four scenarios are assumed in this study, namely, the BAU, REF, NEID, and TEC scenarios, based on the air pollution control policy. (Table 3)

Table 3 Explanation of four scenarios

Scenarios	Health impact	Air pollution mitigation technologies
BAU	Ignored	No control
REF	Not Ignored	No control
NEID	Not Ignored	Reduction to zero
TEC	Not Ignored	Additional control

The BAU scenario assumes that the health impacts by air pollution are not considered. There is no additional health service cost, premature death, or work time loss from PM2.5 pollution. The scenario simulates an ideal situation that does not exist but can be used to evaluate the negative impacts of pollution and benefits by comparing with the other scenarios. The REF scenario assumes that no air mitigation technology measures are applied in GAINS model. The NEID scenario assumes that there are no emissions from the industry sector. In this instance, the health impacts of air pollutant emissions from the industry sector could be identified by comparing with the REF scenario. The TEC scenario only considers air mitigation technology measures based on China's policies (Wang *et al.*, 2014) used implemented in manufacturing industry sector in the GAINS model, control strategy for PM, NOx, and SO_2 data are changed. The technology related to industry in GAINS model is shown in Table 4.

Table 4 Technology of industry sector in GAINS model

Emission	Type	Technology
NOx	Activity	Natural gas (incl. CNG and derived gases) (GAS)
		Gasoline and other light fractions of oil (includes kerosene and biofuels) (GSL)
		Brown coal/lignite, grade 1 (BC1)
		Brown coal/lignite, grade 2 (BC2)
		Hard coal, grade 1 (HC1)
		Hard coal, grade 2 (HC2)
		Hard coal, grade 3 (HC3)
		Heavy fuel oil (HF)
		Liquefied petroleum gas (LPG)
		Medium distillates (diesel, light fuel oil; includes biofuels) (MD)
	Sector	Industry: other sectors; combustion of fossil fuels other than brown coal/lignite and hard coal (IN_BO_OTH)
		Industry: other sectors; combustion of brown coal/lignite and hard coal in large boilers (>50 MWth) (IN_BO_OTH_L)
		Industry: other sectors; combustion of brown coal/lignite and hard coal in small boilers (< 50 MWth) (IN_BO_OTH_S)
		Industry: other combustion (all sectors) except fuel consumption in mineral products industry (used only for emissions calculations) (IN_OC)
	Technology	Combustion modification on oil and gas industrial boilers and furnaces (IOGCM)
		Combustion modification and selective catalytic reduction on oil and gas industrial boilers and furnaces (IOGCSC)
PM	Activity	Derived coal (coke, briquettes) (DC)
		Heavy fuel oil (HF)
		Medium distillates (diesel, light fuel oil; includes biofuels) (MD)
		Hard coal, grade 1 (HC1)
		Hard coal, grade 2 (HC2)
		Hard coal, grade 3 (HC3)
		Biomass fuels (OS1)
		Other biomass and waste fuels (OS2)
	Sector	Industry: other sectors; combustion of fossil fuels other than brown coal/lignite and hard coal (IN_BO_OTH)
		Industry: other sectors; combustion of brown coal/lignite and hard coal in large boilers (>50 MWth) (IN_BO_OTH_L)
		Industry: other sectors; combustion of brown coal/lignite and hard coal in small boilers (< 50 MWth) (IN_BO_OTH_S)
		Industry: other combustion (all sectors) except fuel consumption in mineral products industry (used only for emissions calculations) (IN_OC)
	Technology	Electrostatic precipitator: 1 field - industrial combustion (IN_ESP1)
		Electrostatic precipitator: 2 fields - industrial combustion (IN_ESP2)
		High efficiency deduster - industrial combustion (IN_HED)
SO_2	Activity	Hard coal, grade 1 (HC1)
		Hard coal, grade 2 (HC2)
		Hard coal, grade 3 (HC3)
	Sector	Industry: other sectors; combustion of brown coal/lignite and hard coal in large boilers (>50 MWth) (IN_BO_OTH_L)
		Industry: other sectors; combustion of brown coal/lignite and hard coal in small boilers (< 50 MWth) (IN_BO_OTH_S)
		Industry: other combustion (all sectors) except fuel consumption in mineral products industry (used only for emissions calculations) (IN_OC)
	Technology	In-furnace control - limestone injection (LINJ)
		Industry - wet flue gases desulphurization (IWFGD)

3. Results

3.1 Air pollutants emissions from industry sector and additional PM2.5 concentration caused by industry sector

This study includes SO_2 and NO_X emissions because SO_2 and NO_X emissions are main sources of PM2.5 concentration (Wang *et al.*, 2019). Figure 4 shows the main air-pollutants emissions of PM2.5, NO_X, and SO_2 from the industry sector at the provincial level and the contribution of the industry sector to PM2.5 concentration in 2015 and 2030, which are obtained by the difference between the REF and NEID scenarios. It is clear that comparing 2030 with 2015, if no additional control measures are implemented under the REF scenario and the NEID scenario, the trend of air pollutants. The national emissions of PM2.5, SO_2 and NO_X from the industry sector will increase to 0.60 million tons (Mt), 10.68 Mt, and 6.21 Mt in 2030, respectively. Most provincial PM2.5 emissions from industry sector are projected to increase by 2030 when compared to the 2015 levels except for Jiangxi, Shanghai, Sichuan. In 2030, the top five provinces of PM2.5 emissions include Hebei (0.065Mt), Shandong (0.051Mt), Liaoning (0.045Mt), Henan (0.0314Mt), and Zhejiang (0.0288Mt). NO_X emissions from industry sector are projected to increase by 2030 over 2015 levels in all provinces except for Jiangxi and Sichuan. In 2030, the top five provinces of NO_X emissions from industry sector include Hebei (0.6608Mt), Shandong (0.5437Mt), Liaoning (0.4446Mt), Jiangsu (0.4332Mt), and Henan (0.3131Mt). SO_2 emissions from industry sector are projected to increase by 2030 over 2015 levels in all provinces except for Chongqing, Jiangxi, Qinghai and Sichuan. The top five provinces of SO_2 emissions from industry sector in 2030 are Shandong (1.1247Mt), Hebei (1.0549Mt), Zhejiang (0.8512Mt), Sichuan (0.7021Mt) and Jiangsu (0.0366Mt). The results show that air pollutant levels vary from province to province. Figure 4 also shows that the top five provinces of PM2.5 concentrations attributable to the industry sector are Chongqing (7.00μg/m^3), Shandong (5.59μg/m^3), Hunan (5.115μg/m^3), Zhejiang (4.470μg/m^3) and Sichuan (3.993μg/m^3) in 2015. In 2030, their respective PM2.5 concentrations would increase to 7.014μg/m^3, 5.977μg/m^3, 5.920μg/m^3, 5.212μg/m^3 and 4.887μg/m^3. In addition, most provinces show higher concentrations in 2030 over 2015 levels except for Anhui, Jiangxi, Qinghai. These results show that most provinces will face higher levels of industrial related air pollution if emissions from the industry sector are not controlled.

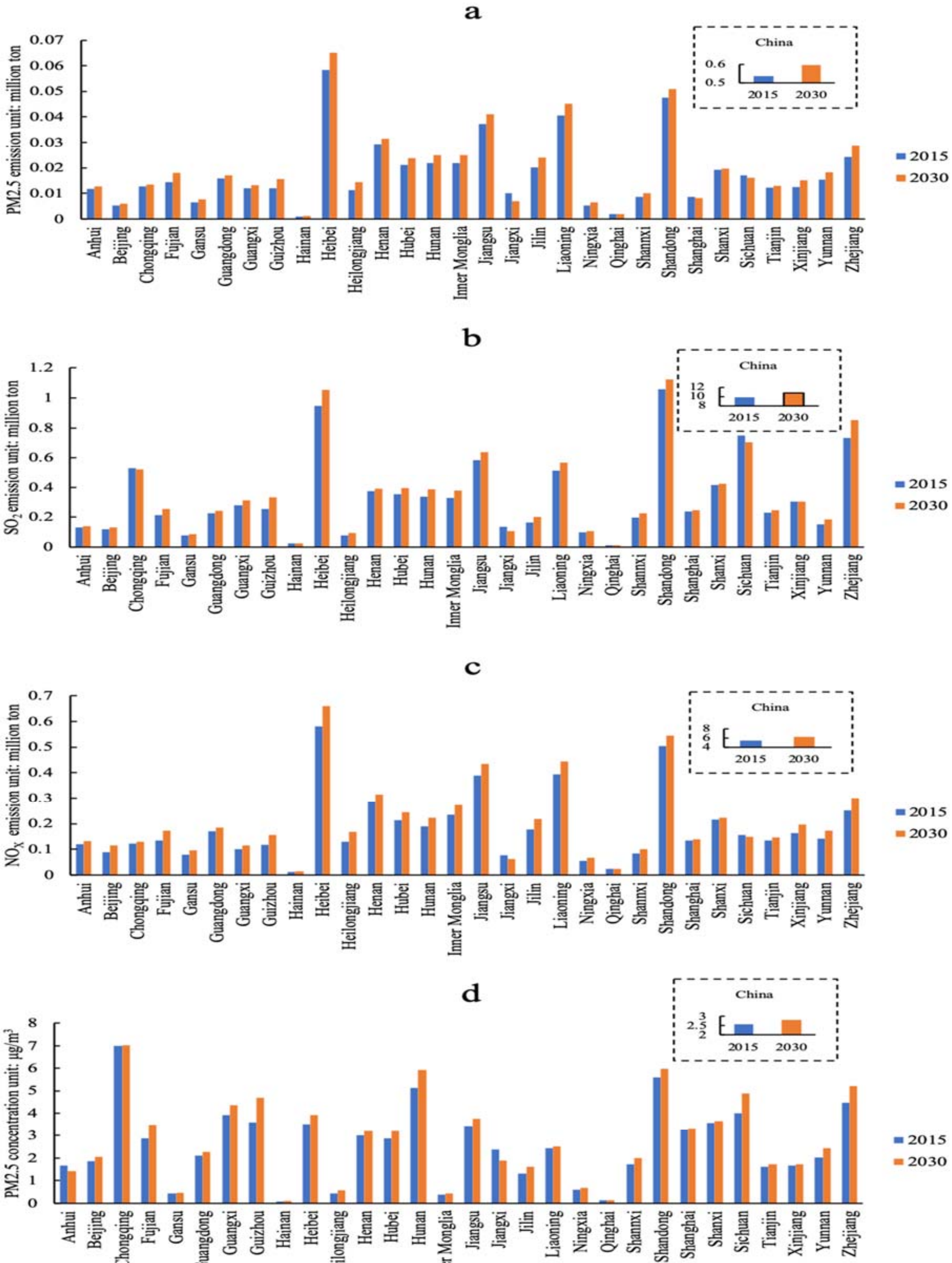

Figure 4 Air pollutant emissions and PM2.5 concentration caused by industry sector in 2015 and 2030

3.2 The health and macroeconomic impacts attributable to industry sector

Figure 5 shows the health impacts attributable to the industry sector, including mortality, morbidity, total additional medical expenditure, VSL (value of statistical life) loss, and work time loss. At the national level, the industry sector led to 117.57 thousand deaths, 0.0022 case per capita of PM2.5 pollution-related health problems, the additional medical expenditures of 0.28 billion USD in 2015. Other impacts include 67.35 billion USD of VSL loss and 0.07 day/capita of work time loss. In 2030, mortality would increase to 131.49 thousands of premature deaths, the number of sick case would increase to 0.0024 case/capita, the additional medical expenditures would increase to 0.52 billion USD, VSL loss would increase to 124.86 billion USD, and work time loss would increase to 0.23 day/capita from the 2015 level.

At the provincial level, the top five provinces of mortality attributed to the industry sector in Shandong (15.40 thousand people), Hunan (10.28 thousand people), Sichuan (9.82 thousand people), Henan (8.81 thousand people) and Jiangsu (7.70 thousand people) in 2015. Mortality are projected to increase in 2030 over 2015 levels in all province except Anhui and Jiangxi. The top five provinces of mortality attributed to air pollution will include Shandong (16.67 thousand people), Sichuan (12.17 thousand people), Hunan (12.05 thousand people), Henan (9.48 thousand people) and Jiangsu (8.56 thousand people) in 2030. However, Hainan, Ningxia, and Gansu had lower mortality than other provinces in 2015 and will have lower mortality in 2030, with figures of 0.02 thousand people, 0.11 thousand people and 0.32 thousand people in 2015, and increased to 0.02 thousand people, 0.12 thousand people and to 0.37 thousand people in 2030, respectively.

Morbidity is projected to increase in all provinces in 2030 over 2015 levels except Anhui and Jiangxi. The top five provinces of morbidity attributed to air pollution include Chongqing, Shandong, Hunan, Zhejiang and Sichuan that will increase from 0.00602 to 0.00603 case/capita, 0.00481 to 0.00514 case/capita, 0.00440 to 0.00509 case/capita, 0.00384 to 0.00448 case/capita and 0.00343 to 0.00420 case/capita from 2015 to 2030, respectively. Anhui and Jiangxi present decreasing trends, where the morbidity will decrease from 0.00143 to 0.00122 case/capita and 0.00206 to 0.00162 from 2015 to 2030, respectively.

The top five provinces of additional medical expenditures include Shandong, Jiangsu, Hunan, Zhejiang and Sichuan, with figures of 0.043 billion USD, 0.027 billion USD, 0.021 billion USD, 0.020 billion USD and 0.019 billion USD in 2015, respectively. In 2030, provinces with high additional medical expenditures includes Shandong, Jiangsu, Zhejiang, Sichuan and Henan, are projected to be 0.099 billion USD, 0.068 billion USD, 0.045 billion USD, 0.042 billion USD and 0.037 billion USD in 2030, respectively. The top five provinces of VSL losses include Shandong, Jiangsu, Hunan, Zhejiang and Sichuan, with figures of 10.37 billion USD, 6.55 billion USD, 5.03 billion USD, 4.70 billion USD and 4.28 billion USD in 2015, respectively. In 2030, the top five provinces of VSL losses includes Shandong, Jiangsu, Zhejiang, Sichuan and Henan, are projected to be 22.91 billion USD, 15.35 billion USD, 10.55 billion USD, 10.08 billion USD and 8.88 billion USD, respectively. The top five provinces of work time loss includes Chongqing, Shandong, Hunan, Zhejiang and Sichuan, with figures of 0.15 day/capita, 0.12 day/capita, 0.11 day/capita, 0.10 day/capita and 0.09 day/capita in 2015, and they also have high work time loss in 2030, would increase to 0.50 day/ capita, 0.42day/capita, 0.40 day/capita, 0.35 day/capita and 0.33day/capita, respectively. Figure 6 shows the macroeconomic impacts attributed to PM2.5 concentration from the industry sector, including GDP loss and welfare loss caused by work time loss. At a national level, GDP loss and welfare loss from the industry sector are 0.29% and 0.52%, respectively, in 2015 and will increase to 1.09% and 1.68% respectively in 2030 under the NEID scenario compared with BAU scenario. At a provincial level, Henan (2.20%), Hubei (1.76%), Hunan (1.70%), Tianjin (1.59%), and Chongqing (1.51%) would experience the high GDP loss in 2030. By contrast, Qinghai (0.04%), Inner Mongolia (0.04%), Heilongjiang (0.05%), Gansu (0.06%), and Xinjiang (0.12%) will have less GDP losses in 2030 compared with the 2015 levels. Furthermore, the top five provinces experienced the high welfare losses include Henan (3.73%), Tianjin (3.21%), Chongqing (2.50%), Hubei (2.36%), and Shanghai (2.32%). Projected welfare losses will be low in Inner Mongolia (0.10%), Gansu (0.13%), Qinghai (0.25%), Heilongjiang (0.41%), and Xinjiang (0.46%).

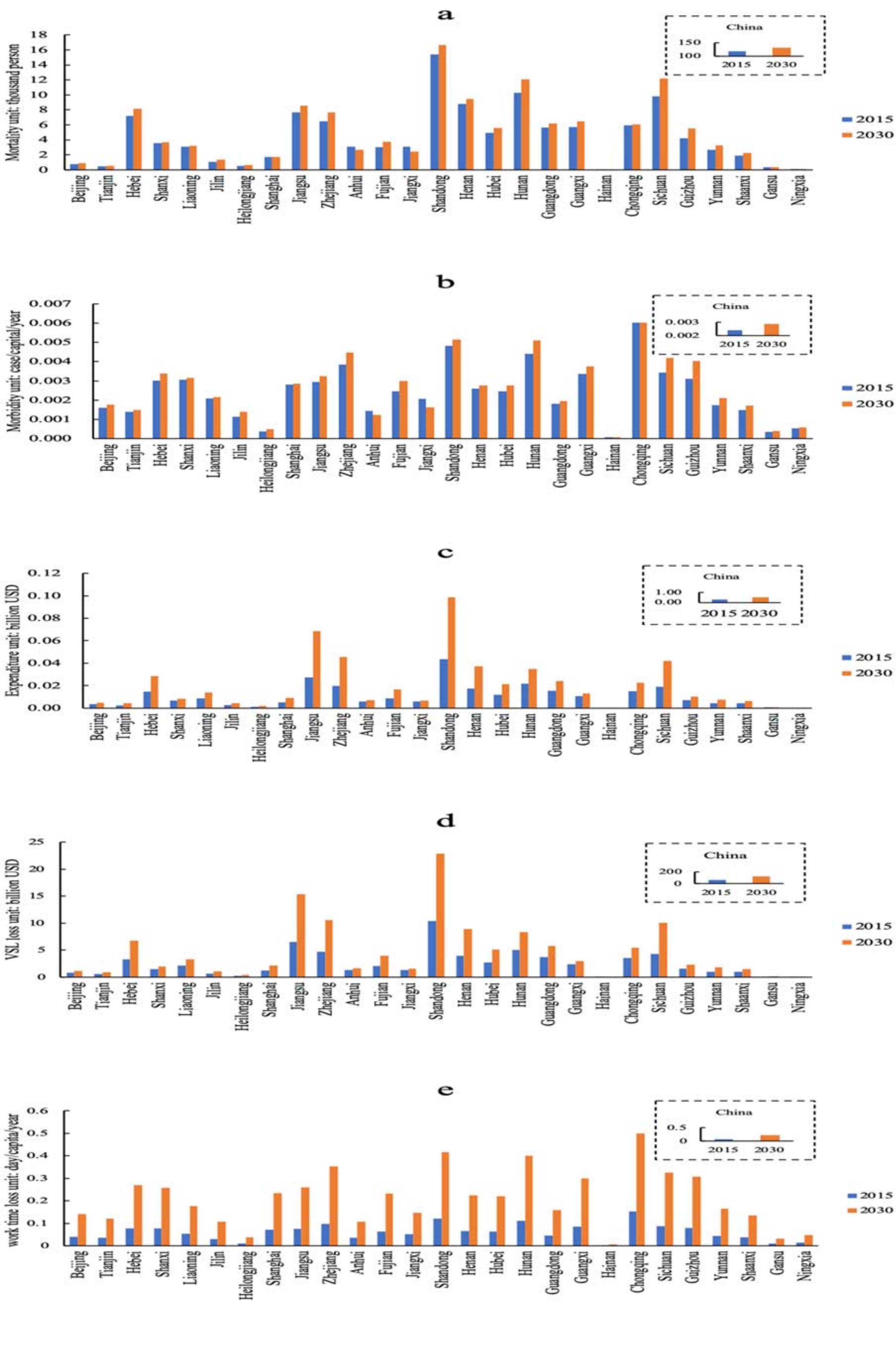

Figure 5 Health impacts attributable to the industry sector in 2015 and 2030

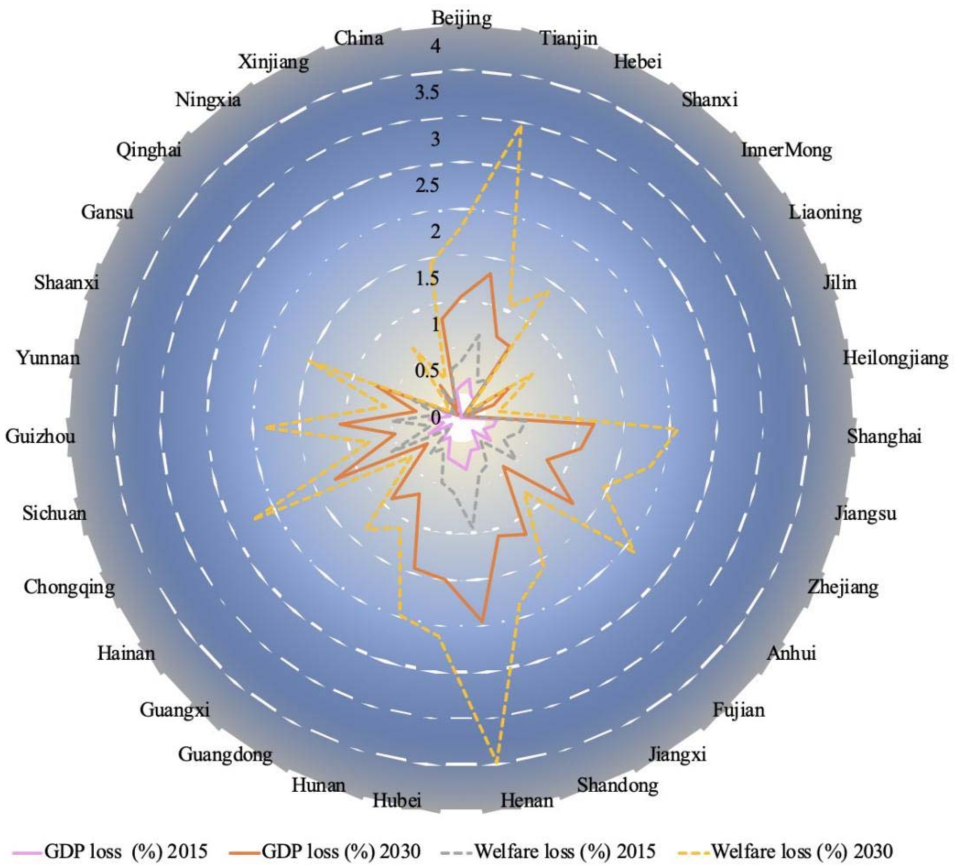

Figure 6 Macroeconomic impacts from industry sector

3.3 The impacts of the technology measures on industry sector

The implementation of air pollution mitigation technologies is simulated to understand the potential health and economic impacts. Figure 7 shows the air pollutant emissions reduction and PM2.5 concentration reduction under TEC scenario in 2030 compared with the REF scenario. At the provincial level, in 2030, the top five provinces of PM2.5 emissions reduction includes Hebei (0.0563Mt), Jiangsu (0.0348Mt), Shandong (0.0330Mt), Liaoning (0.0294Mt) and Zhejiang (0.0252Mt). In 2030, the top five provinces of NO_x emissions reduction include Hebei (0.2798Mt), Shandong (0.2312Mt), Jiangsu (0.1861Mt), Liaoning (0.1776Mt) and Zhejiang (0.1568Mt). The top five provinces of SO_2 emissions reduction includes Zhejiang (0.4625Mt), Hebei (0.3198Mt), Jiangsu (0.2504Mt), Sichuan (0.2364Mt), and Liaoning (0.1716Mt) in 2030. PM2.5 concentration would decrease in Zhejiang (by 2.939μg/m^3), Shandong (by 2.428μg/m^3), Hunan (by 2.266μg/m^3), Chongqing (by 2.120μg/m^3), and Jiangsu (by 1.762μg/m^3) in 2030.

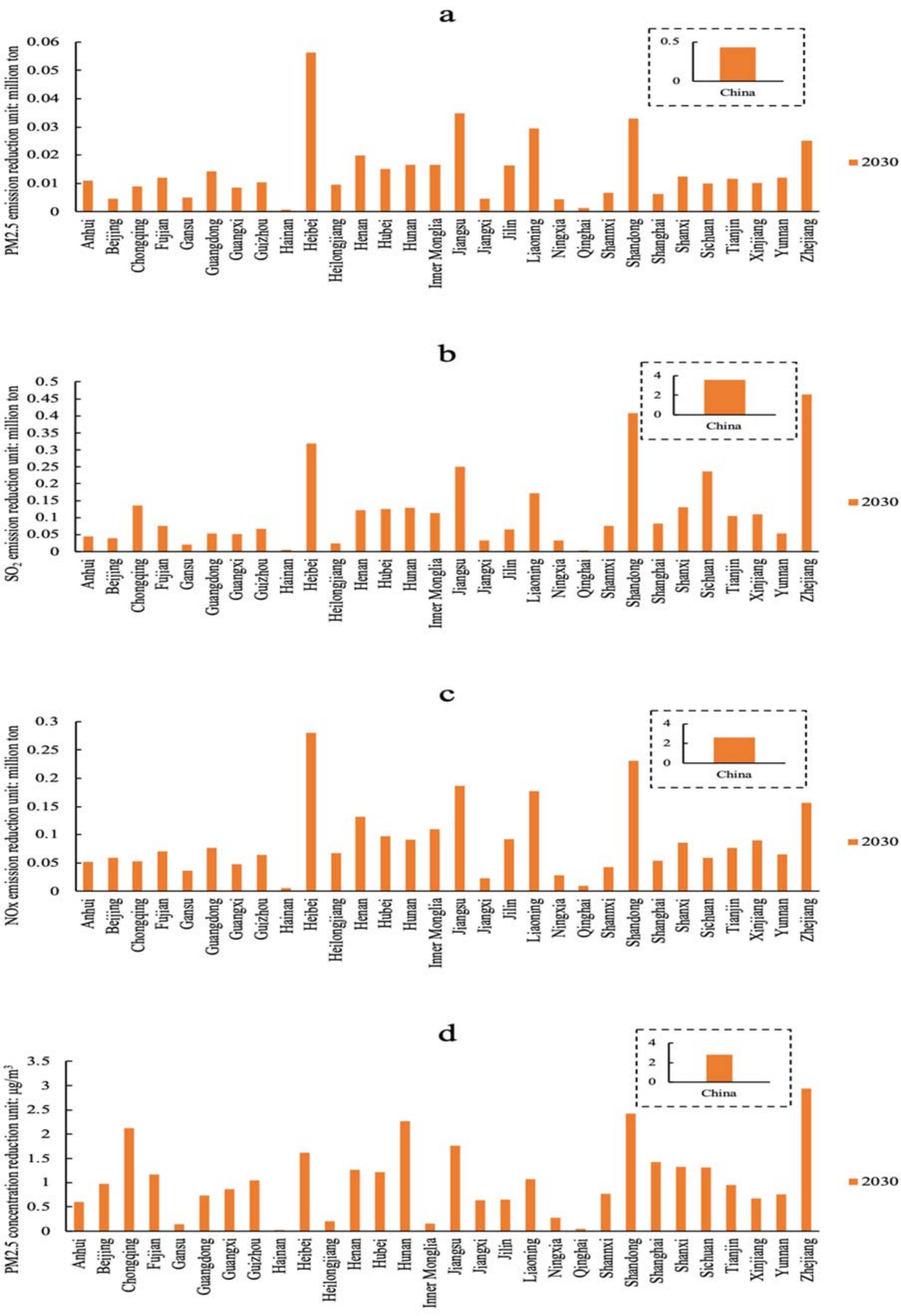

Figure 7 Air pollutants emissions reductions and PM2.5 concentration reductions caused by industry sector under the REF scenario and TEC scenario in 2030

The implementation of air pollution mitigation technologies will reduce the negative impact on health. Figure 8 shows that at a national level, annual mortality would be reduced by 48.67 thousand deaths in 2030. The morbidity would decrease by 0.0009 case/capita. Total additional medical expenditures would be reduced by 0.19 billion USD. VSL loss would be reduced by 46.21 billion USD. Work time loss would be reduced by 0.06 day/capita.

At the provincial level, annual mortality would decrease most in Shandong, Hunan, Zhejiang, Jiangsu, and Hebei, which are projected to decrease by 6.77 thousand people, 4.60 thousand people, 4.30 thousand people, 4.00 thousand people, and 3.35 thousand people, respectively. The morbidity would decrease most in Zhejiang, Shandong, Hunan, Chongqing and Jiangsu. Health care expenditures would be reduced most in Shandong, Jiangsu, Zhejiang, Henan and Hunan, with reduced 0.040 billion USD, 0.032 billion USD, 0.026 billion USD, 0.015 billion USD, and 0.013 billion USD, respectively. For VSL loss, Shandong, Jiangsu, Zhejiang, Henan and Hebei would reduce 9.30 billion USD, 7.19 billion USD, 5.95 billion USD, 3.49 billion USD and 2.80 billion USD, respectively, which have a significant effect. For work time loss, Zhejiang (0.135 day/capita), Shandong (0.111 day/capita), Hunan (0.104 day/capita), Chongqing (0.097 day/capita) and Jiangsu (0.080 day/capita) would have the most reduction effects.

Table 5 shows GDP loss and welfare loss from the industry sector at the national level under the TEC scenario compared with the BAU scenario. Figure 9 shows that at a national level, technology measures would reduce GDP loss and welfare loss to 1.14% and 1.76%, respectively.

Table 5 National GDP loss and welfare loss in 2030

Scenario	GDP loss (%)	Welfare loss (%)
REF	1.16	1.79
NEID	1.09	1.68
TEC	1.14	1.76

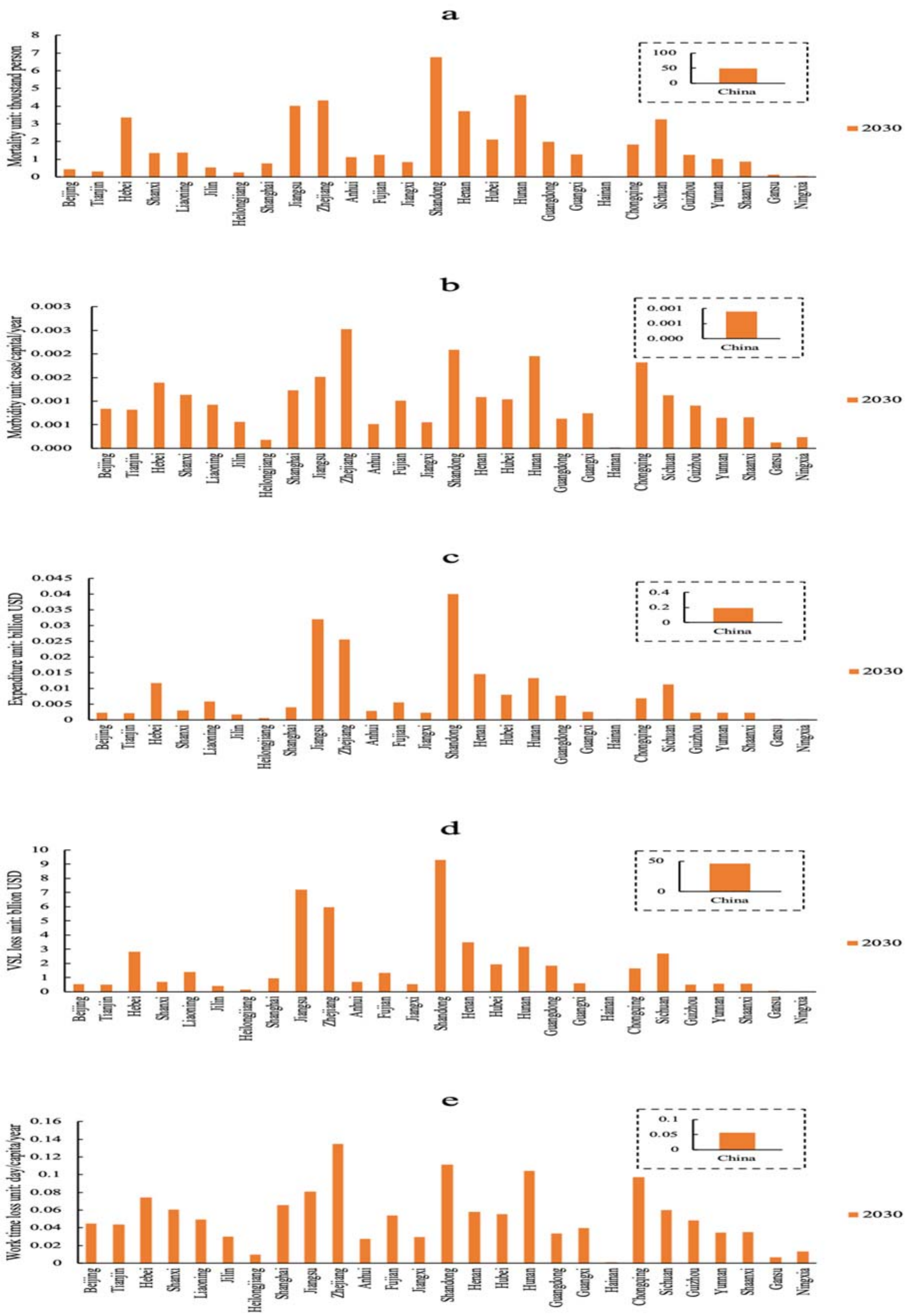

Figure 8 Health impacts from the industry sector under the REF scenario and TEC scenario in 2030

At a provincial level, GRP (Gross Regional Product) loss and welfare loss would be reduced in all provinces. For GRP loss, provinces with relatively higher losses are Henan, Hubei, Hunan, Chongqing, and Tianjin. GRP losses will be low in Inner Mongolia, Gansu, Qinghai, Heilongjiang and Xinjiang. For welfare loss, Henan, Tianjin, Chongqing, Hubei and Anhui will have relatively higher losses, while the losses will be lower in Inner Mongolia, Gansu, Qinghai, Heilongjiang, and Xinjiang.

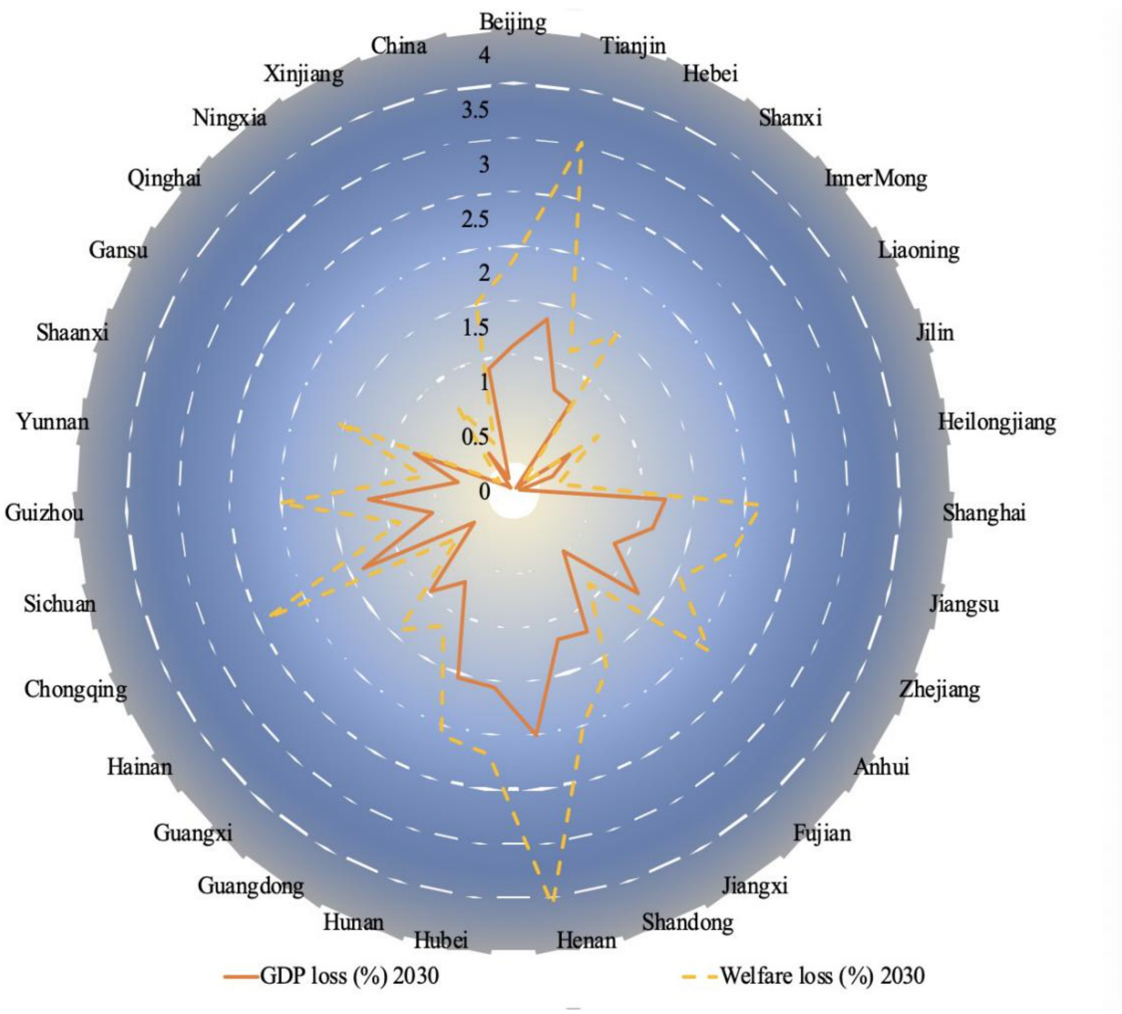

Figure 9 Economic impacts from the industry sector under control scenario in 2030

4. Discussion

It can be seen from the results that the health impact of PM2.5 pollution from industry sector differs by province in China. Provinces such as Shandong and Sichuan have high health impacts. However, provinces such as Beijing and Shanghai have lower health impacts attributable to air pollutants from the industry sector. There are many complicated reasons behind it. PM2.5 concentration leads to different types of health effects. High concentrations of PM2.5 lead to higher health effects. Shandong is dominated by the secondary industry thus it has higher levels of NO_X, SO_2, and PM2.5 emissions from the industry sector. Furthermore, long-range atmospheric transport and chemistry of PM2.5 pollution are important factors as well (Song *et al.*, 2016; Song, Zheng and Wang, 2016). For instance, in Sichuan province, which locates in the Sichuan Basin where pollution does not disperse easily due to its geographical location, more emissions are accumulated locally, causing increases in the concentration level, and may cause more severe health impacts (Tian *et al.*, 2018).

The results in this study also show that controlling PM2.5 pollution from the industry sector can help to reduce the impact on health. In China, at the end of 2015, there were 579, 000 boilers nationwide, and most of them industrial boilers. Industry boilers are widely used, which are all high consumption and heavy pollution (R. Liu *et al.*, 2018). China has a large number of backward production processes, simple environmental protection treatment facilities, and even no environmental protection facilities, the level of development of the industry is uneven. Therefore, it will be crucial to promote the implementation of upgrading and deep management of industrial boilers. Industrial enterprises should vigorously promote flue gas desulfurization, flue gas denitrification and high efficiency dust removal devices. Meanwhile, emission standards issued by the state should be implemented strictly. In addition, this study also found that the concentration of PM2.5 in less developed provinces, such as Inner Mongolia, Qinghai and Xinjiang, is relatively low due to the industry sector. However, this does not mean that there is no need to control PM2.5 in these provinces, because PM2.5 concentration depends not only on emissions from one area, but also on transboundary emissions from neighboring areas (Xie *et al.*, 2016). In order to effectively control air pollution, the provinces need to cooperate with each other. Air pollution in the industry sector has also an impact on the economy. This study shows that PM2.5 pollution from the industry sector causes GDP loss of 1.09%. In other word, the implementation of control PM2.5 pollution from the industry sector will bring China 1.09% of GDP benefits. Provinces which suffer more health impacts from the industry sector (such as Shandong and Hunan) would gain more benefits after the implementation of control PM2.5 pollution, which further shows that control measures will have functions in these provinces.

5. Conclusion

This study combined with three models of GAINS, IMED/HEL and IMED/CGE to evaluate the economic impact of PM2.5 pollution-related health effects in China's industry sector. There are three innovations in this study. The first is to evaluate the health impacts of PM2.5 pollution from industry sector at the national and provincial level in 2015 and 2030. The second aspect is to evaluate the economic impact of PM2.5 pollution related health effects in China's industry sector and the third aspect is to evaluate the impact of air pollution control measures on reducing PM2.5 pollution related health effects and economic effects in China's industry sector.

There are several research limitations which need to be improved in the future. In the GAINS model, the concentration of PM2.5 in some provinces is higher than the actual concentration, while some are significantly lower than the actual concentration. The Chinese government and people pay more and more attention to air pollution, because they are more and more aware of the threat of high concentration of PM2.5 to health, as well as many impacts of air pollution on human life, such as health expenditure related to air pollution, inability to travel due to reduced visibility, flight cancellation. Local governments in China will introduce new policies to improve air quality based on actual pollution. Moreover, the additional health expenditures could be underestimated in this study as not considering other health expenditures caused by PM2.5 pollution, such as cost of purchasing masks. These issues should be further investigated in the future research work.

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