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Title

Environmental and health co-benefits from de-capacity in Chinese industrial sectors

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Table of Contents

ABSTRACT

With the rapid development of China's industrial economy, the problem of excess capacity in the industrial sector has been increasingly severe, causing not only a waste of natural, economic and social resources, but also serious adverse impacts on the environment and public health. In order to conduct more precise and effective policy to solve this problem, the key industries and regions with the most obvious capacity problems should first be identified, and quantifying the green and low-carbon co-benefits of over-capacity management policies can further reflect the long-term benefits of capacity removal and structure adjustment. In view of this, this study constructs a comprehensive research framework, including data envelopment analysis (DEA) model, GAINS-China model (Greenhouse gas - Air pollution Interactions and Synergies model), meta-analysis and air pollution - health risk assessment (AP - HRA) module, measured the capacity utilization rate of 41 industrial sectors in China in 2018, and analyzed the current situation of excess capacity and the characteristics of industry and geographical distribution in China. What’s more, based on scenario analysis of fully effective implementation of overcapacity management policies from 2025 to 2050, and co-benefits of low-carbon management, air quality promotion and positive public health were further estimated.

The results show that the overall average capacity utilization rate of China's industrial sector is 64.13% in 2018, which is lower than the consensual value of 75%, indicating that the problem of overcapacity in China's industrial sector is really serious and there is large potential room for greater capacity removal. From the perspective of industrial sectors, capacity utilization rates in the mining industry and electricity, heat, gas and water production and

supply sectors are generally low, with capacity utilization rates of just between 53% and 65%; while in the manufacturing sector, capacity utilization rates are generally higher in light industry (around 70%) and lower in heavy industry (between 50% and 60%). From the perspective of regions, the overall capacity utilization rate in East China and South-Central China is significantly higher than other regions, where the capacity utilization rate of economically developed coastal provinces is generally higher. Guangdong, Jiangsu, Fujian, Shandong, Zhejiang, Shanghai and Beijing cover the top seven, whose overall industrial capacity utilization rate is 96.7%, 85.6%, 79.2%, 77.9%, 77.5%, 77.4%, 73.3%; while Gansu, Qinghai, Ningxia, Xinjiang and Tibet have the lowest capacity utilization rate, generally below 40%. Under the scenario of full implementation of the de-capacity policy in 2050, CO_2 emissions from China's industrial sector could be reduced by about 1.05 billion tons, accounting for 9.6% of total CO_2 emissions in 2050. $PM_{2.5}$ emissions could be reduced by about 57.8 kilotons, accounting for 5.8% of total $PM_{2.5}$ emissions in 2050. At the same time, $PM_{2.5}$ emission reduction will further reduce air pollution-related deaths nationwide, which is expected to be reduced by about 792,100 cases in 2050, accounting for 1.6% of the total number of deaths in 2050. In order to implement overcapacity management policies more accurately and effectively, it is recommended that priority be given to targeting industries with low capacity utilization rate, as well as regions with intensive heavy industry, high levels of greenhouse gas emissions, severe air pollution, and dense population for improved optimization of industrial restructuring and resource allocation.

Key words: Over capacity, Capacity utilization rate, DEA method, GAINS-China, Health impact assessment

Chapter 1 Introduction and Background

1.1 Research Background and Significance

China has experienced rapid industrialization and urbanization since the reform and opening up in the late 1970s. However, problems such as haphazard investment, inefficient scale expansion, lower resource efficiencies, and environmental pollution have emerged, which impede China's macroeconomic development [1]. According to several critical governmental reports, industrial sectors, which is the major part of China's economy and also the main generators of air pollutants and GHG (Greenhouse Gases) emissions, are facing severe excess capacity problem. Thus, to resolve such an issue has become a key focus on promoting industrial restructuring by the central government [2]. Under such circumstances, it is critical to evaluate the impact of excess capacity so that appropriate policies can be raised to those decision makers. In addition, the successful resolution of this issue can lead to significant environmental benefits (i.e. the reduction of GHG and air pollutant emissions) and social benefits (i.e. improved public health) [3]. This means that co-benefits can be obtained if the excess capacity of industrial sectors can be removed [4].

1.2 Literature Review

An increasing number of researchers have discussed the quantification methods of excess capacity. Generally, researchers introduce the capacity utilization rate indicator, as the ratio of actual output value to the ideal capacity value, to measure the degree of excess

capacity [5-8]. The higher the capacity utilization rate, the smaller the degree of excess capacity. Judging from international experience, some European and American studies set the threshold value of capacity utilization rate between 79% and 82% [9-12], which indicates the overcapacity problem for the values lower than 79%. While the typical value for the case of China is 75% [13,14], which is also the threshold standard set in this research. Most studies focus on existing micro-data to speculate on the capacity utilization of industrial enterprises, mainly using the methods including Function Method (FM) and Data Envelopment Analysis (DEA). Cassels [15] and Morrison [16] proposed the input level corresponding to the lowest point of the short-term average total cost curve to realize the capacity conversion. The Wharton index series published by the United States since the 1960s uses a continuous method based on the ratio of capital and the cumulative net investment at the end of the previous period to predict the conversion of production capacity. Gallofalo and Malhotra [17] used the Cost Function Method to measure the production capacity of manufacturing in various states in the United States. Kirkley [18] used the Data Envelopment Analysis method (DEA) and Stochastic Production Frontier method (SPF) to measure the productivity and capacity conversion of the US fisheries.

Compared with foreign countries, domestic research started relatively late in China. Han [19] first adopted the cost function method combined with the generalized matrix method (GMM) of the panel model to measure the capacity utilization of 28 heavy industries in China and found that seven industries had serious overcapacity, most of which belong to heavy industries. Huang and Lv [20] and the research team of the People's Bank of China Business Management Department [21] found China's potential output value undergoing an obvious

expansion trend, using traditional Cobb-Douglas (C-D) production function. Wang and Zhang [22] developed the production function method to investigate the capacity utilization rate of China's photovoltaic industry from 2005 to 2012, with the result showing that value decreased to just around 60%. Dong et al. [23] applied the DEA method to measure the capacity utilization rate of China's industrial sectors and found that the average value was 69.3%. Feng et al. [24] also used the DEA method to estimate the capacity utilization rate of China's coal industry in consideration of the impact of resource depletion, and in 2012 the situation was the worst, with the value of 69.88%. Cheng [25] used the stochastic frontier function analysis method to measure the capacity utilization rate of China's industrial sectors. The result showed that the overall capacity utilization rate of the eastern region was lower than that of the central and western regions.

With China's efforts to deal with the excess capacity problem, dual challenges of air pollution and climate change, which are highly relevant to industrial development, have also promoted the significance of studying the co-benefits of GHG and air pollutants. The concept of co-benefit was first proposed by Herman Haken, referring to the additional benefits obtained from implementing a policy, rather than the direct benefits expected at the initial stage of the policy design [26]. Later, the Intergovernmental Panel on climate change (IPCC) made a clear definition of the co-benefits about GHG emission reduction, that is, the quantitative monetization results of additional benefits after a GHG mitigation policy is implemented [27]. Therefore, co-benefits has gained increasing population in the integrated management research of energy, environment and climate change, and many methodologies of co-benefit evaluation such as greenhouse gas – air pollution interaction and synergies

(GAINS), integration of environmental strategy (IES) of EPA and energy-environment-economics (3E) model for quantification of co-benefits have been widely applied [28]. Many researchers have also focused on domestic studies of co-benefits in the past decade, covering model application, policy analysis and case discussion. Li et al. [29] studied a co-benefit project for total emission reduction based on three industrial mitigation approaches and found that different technologies and measures would contribute to different co-benefits and the structural adjustment could provide the most value. Wang and Chen [30] used LEAP model to estimate energy consumption and air pollutants emission in Shanghai under both the basic scenario and the low-carbon scenario, and the result revealed that the total emission of CO_2, SO_2 and PM would decrease by 20%, 72% and 78% respectively in 2020. He et al. proposed an integrated model to predict energy consumption and GHG and air pollutants emission under different scenarios and compared the monetized benefits of emission reduction and public health, which would reach 100 billion dollars in 2030 [31]. Mao analyzed a case study of the thermal power industry using the 3E model and proposed a method to estimate the co-benefits of technical mitigation measures, which supported that the front-end control measures and in-the-process control measures had better synergy [32].

In the case of the de-capacity scenario, the emission of GHG and air pollutants would be reduced due to less use of fossil fuels and resources and indirect benefits from energy efficiency and local employment, and then the public health associated with air pollution would also gain a positive impact. Therefore, the consideration of co-benefits could provide a complete profile of the impact assessment of de-capacity policies, including the aspects of economy, energy, environment and society.

1.3 What Will Be Elucidated in This Research

In general, the function methods such as the cost function method and production function method have certain advantages in data availability, but the disadvantages include complicated calculations and possible errors. As a non-parametric method, the DEA method can estimate the inefficiency that deviates from the production frontier. Considering the backward production capacity of China's industry is widespread, the capacity utilization rate calculated by the production capacity from the perspective of the technical case may be more suitable [23].

However, most of the existing studies on capacity assessment of China focus mainly on one specific industrial sector or one region, mainly because of data limitations [33-36]. Moreover, further research about co-benefits under the excess capacity adjustment policy is rarely considered. Consequently, this study aims to fill such a gap. First, it quantifies the capacity utilization rate of all 41 industrial sectors in all Chinese provinces. It then evaluates both the expected environmental and the public health benefits from implementing the de-capacity strategies by 2050 by integrating the GAINS-China model and air pollution health risk assessment method.

The rest of this article is organized as follows. Section 2 illustrates the method to evaluate the capacity utilization rate and assess co-benefits by combining the DEA model, GAINS-China model, meta-analysis module and the health module. Then research results are presented in Section 3, including analysis of over-capacity characteristics, estimated emission of CO_2 and $PM_{2.5}$, and positive public health impact associated with mitigation of air pollution. Section 4 discusses the promising policy decision-making auxiliary means with

attention paid to considering the relationship between de-capacity effects and co-benefits. Finally, the conclusion and future prospects are presented in Section 5.

Chapter 2 Methods and data sources

Figure 1 shows the main methodological approach used in this research. First, the data envelopment analysis (DEA) model was used to quantify the content of the over-capacity problem to assess the potential improving room for the scenario of de-capacity implementation. Second, the modified activity level derived from DEA analysis was used the GAINS-China model to simulate the air quality index, especially the concentration of CO_2 and $PM_{2.5}$. These two parts composed the analysis of environmental effect, which is one aspect of the co-benefit assessment. Third, the meta-analysis was conducted to measure the value of the China-specified relative risk. Fourth, the health impact assessment model was used to forecast the total mortality cases attributable to $PM_{2.5}$ pollution.

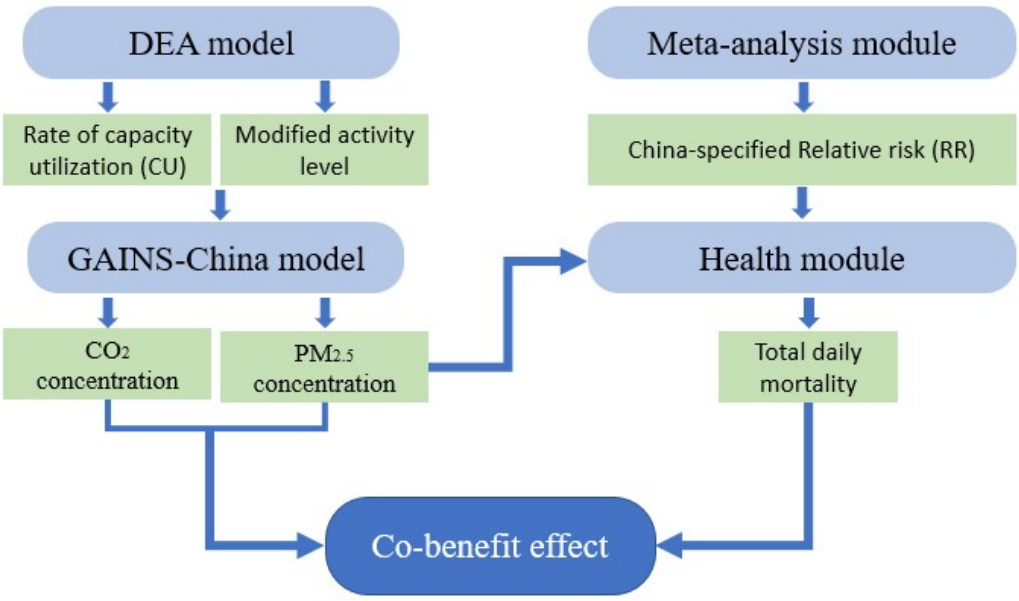


Figure 1. Research flow diagram

2.1 Data envelopment analysis (DEA) model

Data envelopment analysis (DEA) is a linear programming quantitative analysis method based on multiple input and output indicators. In the case of excess capacity problem, it's applied to estimate the maximum production capacity of equipment when variable input is not limited. The overall calculation flowchart of capacity utilization rate using the DEA method is depicted in Figure S1 of supporting material.

Capacity utilization rate CU is the ratio of actual output y to potential production capacity $Y(F)$:

$$CU = \frac{y}{Y(F)} \tag{1}$$

According to the DEA principle, potential production capacity (*i.e.,* the gross industrial output value) refers to the maximum capacity of production equipment when the variable input *(i.e.,* intermediate economic input and labor resources*)* is unlimited. Therefore, $Y(F)$ can be expressed as the function of an initial fixed input *F (i.e.* fixed capital*)*, while in fact, the actual output *y* is always limited by input variables.

To establish the optimization formula of $Y(F)$, the input-output tables at the industrial sector level in all the investigated provinces are established. For example, in terms of the maximum production capacity of the coal industry in Shanghai ($Max\ Y(F_{p,q})$ with p being the coal industry and q being Shanghai), the total actual output of all the industries in Shanghai ($\sum_{i=1}^{n} y_{i,q}$ with i as each industry, $n = 41$) that is transferred from the total current fixed input ($\sum_{i=1}^{n} F_{i,q}$) would be reallocated to a certain situation by introducing a

weight vector ($\lambda_{i,q}$). The more expected output of coal industry ($\sum_{i=1}^{n} \lambda_{i,q} y_{i,q}$) is, the less expected input of coal industry ($\sum_{i=1}^{n} \lambda_{i,q} F_{i,q}$) is. In other words, this is the optimal allocation process of existing fixed resources, which aims to realize the most potential output.

Based on the above idea, the basic optimization formula of $Y(F)$ for industry *j* in each province is established as below [37]:

$$Max\ Y(F_{p,q}) = \sum_{i=1}^{n} \lambda_{i,q} y_{i,q} \tag{2}$$

$$s.t. \sum_{i=1}^{n} \lambda_{i,q} y_{i,q} \geq y_{p,q},\ \ \sum_{i=1}^{n} \lambda_{i,q} F_{i,q} \leq F_{p,q},\ \ \sum_{i=1}^{n} \lambda_{i,q} = 1,\ \ \lambda_{i,q} \geq 0 \tag{3}$$

After calculating the capacity utilization rate of each industry in each province, (i) the overall capacity utilization rate of the industry p (CU_p), (ii) the overall capacity utilization rate of the province q (CU_q), and (iii) the overall capacity utilization rate of the whole country (CU) can be calculated as follows:

$$CU_p = \frac{y_p}{Y_p} = \sum_q y_{p,q} \,/\, \sum_q Y_{p,q}(F) \tag{4}$$

$$CU_q = \frac{y_q}{Y_q} = \sum_p y_{p,q} \,/\, \sum_p Y_{p,q}(F) \tag{5}$$

$$CU = \frac{y}{Y} = \sum \sum_q y_{p,q} \,/\, \sum \sum_q Y_{p,q}(F) \tag{6}$$

This study includes the estimation of 41 industries in 31 provinces, cities, and autonomous regions (hereinafter referred to as "provinces") with 2018 as the base year, and furthermore, the capacity utilization rate on both levels of province and industry is also measured.

For some cases that the ready data of fixed capital is starved, it's estimated using the

perpetual inventory method through the following formula [38,39]:

$$K_t = K_{t-1}(1 - \delta_t) + I_t/P_t \tag{7}$$

Among them, K_{t-1} and K_t represent fixed capital in period $t-1$ and period t, respectively; δ_t represents the depreciation rate in period t; I_t represents the amount of new investment in period t, and P_t represents the price index of investment products. The value of these parameters can be estimated as follows:

- New investment amount each year: using the original price difference of fixed assets in two consecutive years as a substitute;

- Investment product price index: using the fixed asset investment price index of each province and municipality as a substitute;

- Base period capital stock: using the original price of fixed assets in 2015 Interpolation with accumulated depreciation is used as the base period data;

- Depreciation rate: The difference between the accumulated depreciation amount of each year and the previous year is regarded as the depreciation of fixed assets this year, and the depreciation rate is compared with the original price of fixed assets of the previous year.

The database of the actual output of each industry in each province ($y_{p,q}$) was collected from "2019 China Economic Census Yearbook" [40], the "2019 China Statistical Yearbook" [41] and the "2019 China Industrial Statistics Yearbook" [42], and the database of fixed input of each industry in each province ($F_{p,q}$) was collected provincial and local statistical yearbooks in 2019, and China's economic and social big data research platform, etc. The

overall calculation flowchart of capacity utilization rate using the DEA method is depicted in Figure 2.

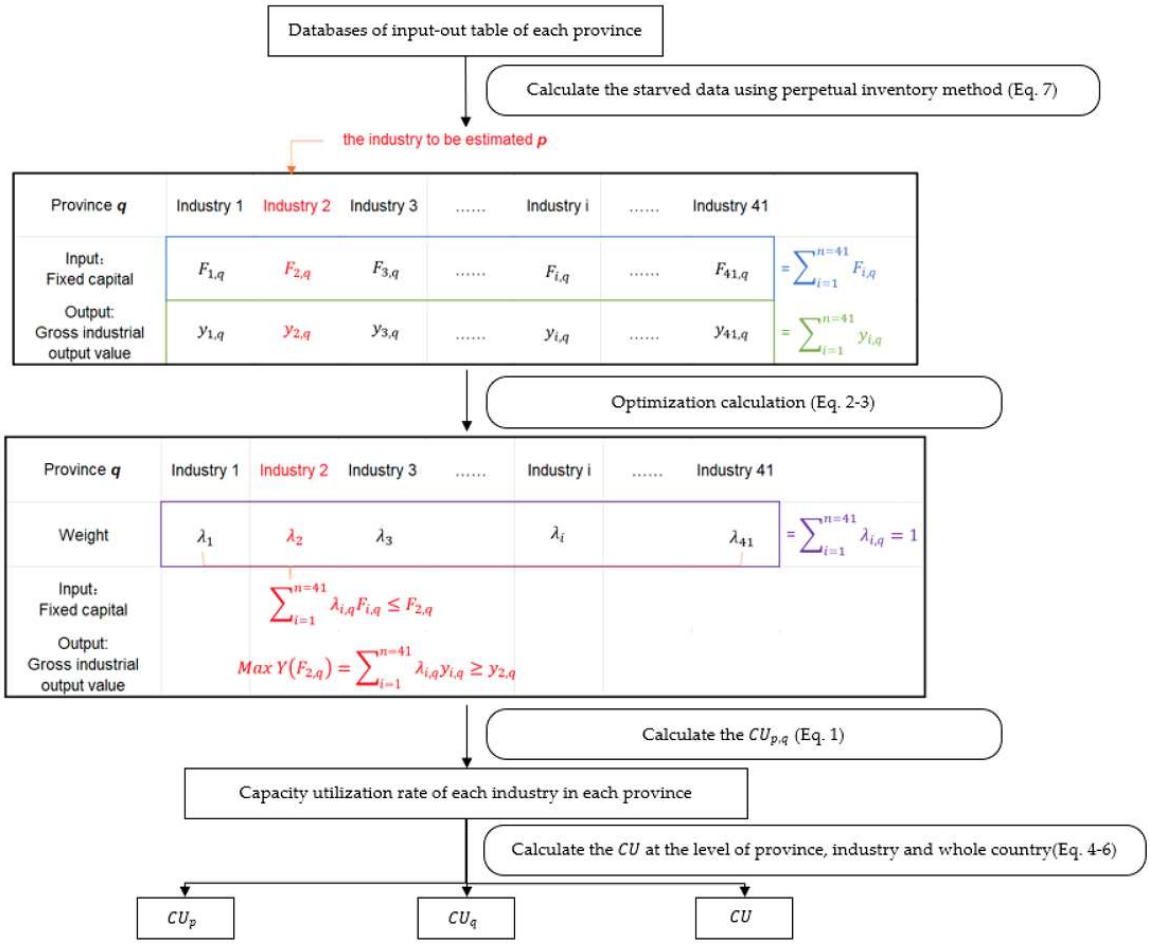


Figure 2. Calculation flowchart of capacity utilization rate using DEA method

2.2 Emissions estimation model

2.2.1 GAINS-China model

In order to calculate the environmental benefit, the GAINS-China model provides a consistent framework for the analysis of emission reduction strategies that simultaneously

deal with air pollution and greenhouse gases [43]. On the one hand, the GAINS model allows exploring the key characteristics of each region, including future energy use, emission control measures, measure costs, and air pollutant emissions. The GAINS-China model is an extended application of the GAINS model, which combines the specific characteristics of China. It has been widely used in combination with other models to forecast the co-benefit of air pollution and climate change mitigation in Chinese provinces and regions [44,45] and the economic and health impact caused by ozone and $PM_{2.5}$ pollution [46].

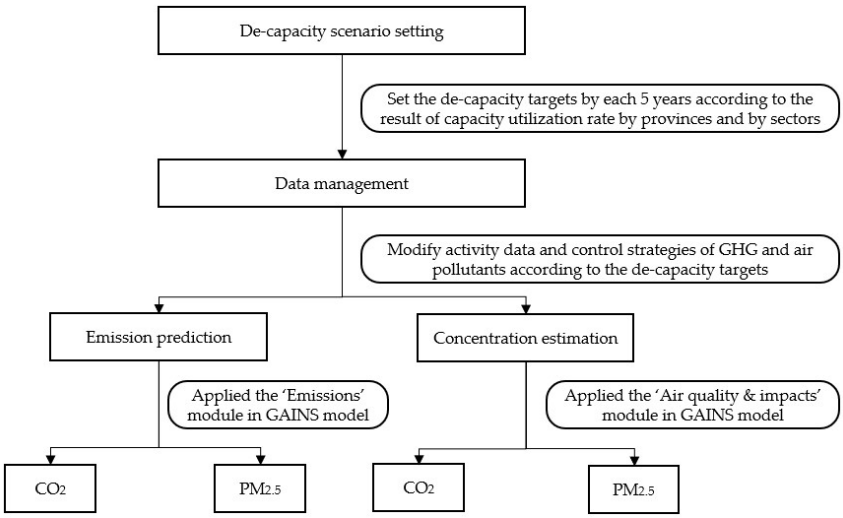


Figure 3. Overall methodological framework of the GAINS-China model

2.2.2 Scenario definition

Two scenarios were defined in the GAINS-China model as follows.

a) BaU (S1: business as usual): This scenario reflects current air pollution policies in China, considering sectoral and provincial differences with respect to emission limit

values and the time of their introduction. The mitigation technologies are listed in Table 1.

b) DE (S2: de-capacity): In this scenario, de-capacity policies are set for each province according to the result of capacity utilization rate from the DEA model, so that the energy intensity of each province will be reduced gradually from 2025 to 2050. The GAINS-China model calculates the potential reduction of CO_2 and $PM_{2.5}$.

Table 1. Mitigation technologies adapted in this study

Air pollutant		Name	Application sector
PM	1	Cyclone	Industry, power plants
	2	Electrostatic precipitator	Industry, power plants, industrial process
	3	High efficiency deduster	Industrial process
	4	Good practice	Industrial process
SO_2	1	Limestone injection	Industry, power plants
	2	Wet flue gas desulfurization	Industry, power plants
	3	Low sulphur coal	Industry, power plant
	4	Process emissions - stage 1 SO_2 control	Industrial process
NOx	1	Combustion modification on existing hard coal power plants	Power plants

2.2.3 Estimation of the avoided emissions

The following formula is used to calculate the avoided emission rates in this study:

$$E_{i,p,t} = \sum_k \sum_m A_{i,k,t} ef_{i,k,m,t} x_{i,k,m,p,t} \quad (8)$$

Where, i, k, m, p, t represent province, activity type, abatement measure, pollutant (CO_2, $PM_{2.5}$), period (2025, 2030, 2035, 2040, 2045, 2050), respectively. $E_{i,p,t}$ represents emissions of pollutant p in province i during period t. $A_{i,k,t}$ represents activity level of type k in province i during period t. $ef_{i,k,m,t}$ represents emission factor of pollutant p for activity type k in province i after application of control measure m during period t. $x_{i,k,m,p,t}$ represents the share of total activity type k in province i to which a control measure m for pollutant p is applied during period t.

For scenario S1 (Business as Usual)

$$x_{i,k,m,p,t} \neq 0 \quad (9)$$

For scenario S2 (De-capacity)

$$f_{i,k,t} = \frac{CU_{i,k}}{75\%} * \frac{t-201}{2050-2018} \quad (10)$$

$$\hat{A}_{i,k,t} = A_{i,k,t} f_{i,k,t} \quad (11)$$

Here $CU_{i,k}$ is the capacity utilization rate for activity type k in province i in 2018. Assuming that the excess capacity problem would be solved in 2050, that is, the capacity utilization rate should reach the threshold value of 75%, the expected activity level at that time will decrease to $\frac{CU_{i,k}}{75\%}$ times of the original level in 2018. If this optimization progress just advances linearly, the factor in year t should be the $f_{i,k,t}$ which can be calculated by using Equation (11). Therefore, $\hat{A}_{i,k,t}$ refers to the modified activity data that is input into the GAINS-China model.

2.3 Health risk assessment model

2.3.1 Methodological approaches

The critical section of health impact assessment associated with air pollution is to use concentration-response functions (CRF) to establish the mathematical model of adverse health impact assessment. There are generally three steps to link the change of air pollutant concentration $\Delta \boldsymbol{C}$, and the change of incidence or mortality cases $\Delta \boldsymbol{y}$:

(i) identify the functional form of CRF;

(ii) complete the coefficient in CRF;

(iii) establish the relationship between $\Delta \boldsymbol{C}$ and $\Delta \boldsymbol{y}$.

To perform computations, relevant data is necessary, such as population data, air quality indicators and health risk coefficient (health impact on changes of air pollutant concentration, β) derived from epidemiological studies [47].

In this study, the linear functional form of CRF, which is often used for simplification based on biological evidence, is adopted to assess the expected deaths caused by $PM_{2.5}$ pollution as [48]:

$$\mathbf{y} = \boldsymbol{\alpha} + \boldsymbol{\beta} \times \mathbf{C} \tag{12}$$

where $\boldsymbol{\alpha}$ represents a combination of all the independent variables, $\mathbf{C}$ refers to the concentration of the certain air pollutant, and the coefficient β is typically derived based on Equation (13) from the level of Relative risk (also called risk ratio, RR) [49]:

$$\boldsymbol{RR} = \mathbf{exp}(\boldsymbol{\beta} \times \Delta\mathbf{C}) \quad (13)$$

where β refers to the excess incidence rate of total mortality per 1 μg/m^3 increase of pollutants.

Therefore, the expected total mortality (ETM) of daily deaths due to $PM_{2.5}$ exposure derived from an increase in concentration can be calculated as follows, assuming all the residents are exposed to the mean concentration in the city:

$$\Delta\mathbf{y}_{\boldsymbol{i}} = \boldsymbol{\beta}_{\boldsymbol{i}} \times \Delta\mathbf{C}_{\boldsymbol{i}} \quad (13)$$

$$\mathbf{ETM}_{\boldsymbol{i}} = \Delta\mathbf{y}_{\boldsymbol{i}} \times \boldsymbol{P}_{\boldsymbol{i}}$$

(14)

Here $\boldsymbol{i}$ refers to different provinces and $\boldsymbol{P}_{\boldsymbol{i}}$ represents the population number in province $\boldsymbol{i}$. ΔC is the difference between the annual concentration of $PM_{2.5}$ in each province and the threshold level determined by the WHO report.

The above health impact assessment model is used to estimate the potential reductions in number and percentage of death attributable to $PM_{2.5}$ reduction under the scenario assuming the de-capacity competition. The assessment is made for the whole mainland of China. Consensus data of each province was obtained from the latest report of the Seventh National Census [50].

2.3.2 Meta-analysis module

As discussed above, RR is a key parameter in the CRF model for health impact assessment. However, the value in the GAINS-China model is fixed and mainly derived from

American or European research [47]. Considering the difference in air pollution levels between China and other developed countries, the more reliable RR values of mortality attributable to the average concentration of $PM_{2.5}$ for China are needed. To this aim, a meta-analysis is performed in this study, as a kind of systematic quantitative review, using a statistical method to collect and combine all relevant empirical evidence that meets the pre-specified eligibility standard and criteria to drive a pooled estimate closest to China-specified RR values. The procedure of collecting and sifting through relevant literature is shown in Figure 4. The meta-analysis database was developed based on a systematic search and review of related studies on the estimation of daily mortality effects attributable to $PM_{2.5}$ exposure in China between 2003 to 2020, which is given in Table 2. The database includes studies conducted in medium-to-large size cities with dense populations and severe air pollution levels in the past decade, including Beijing, Shanghai, Shenzhen, Jiangsu, Xi'an, Hefei, Chongqing, Shenyang, Dongguan, Foshan, Gansu, and the Pearl River Delta (PRD) cities.

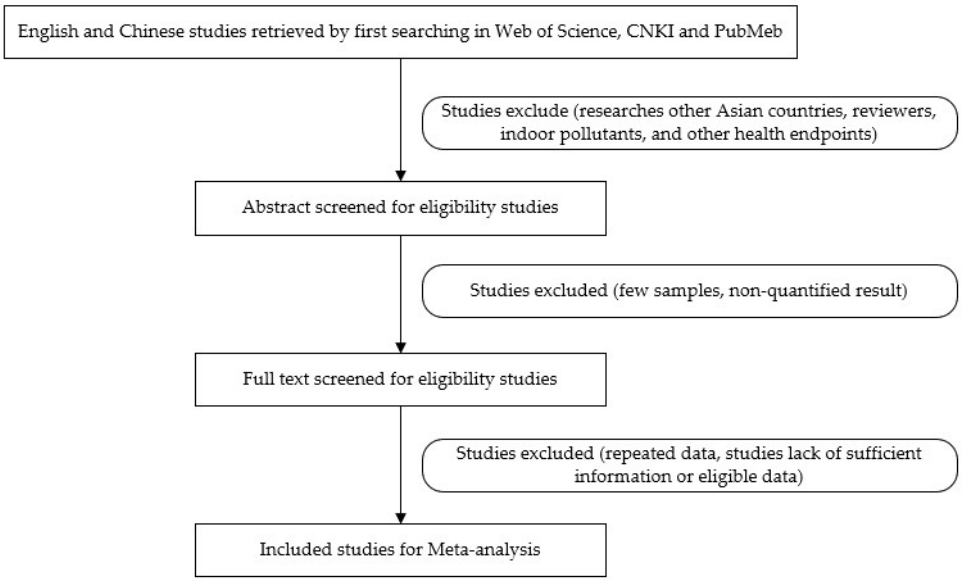


Figure 4. Database development process in the meta-analysis used in this research

Table 2. Literature review on the change in the mortality with every increase of 10μg/m^3 in $PM_{2.5}$ concentration

First author	Publication Year	Area	Year of study	RR	95% Confidence interval (CI)
Scott A. Venners	2003	Chongqing	1995	1.0000	0.9928, 1.0068
Haixia Dai	2004	Shanghai	2002-2003	1.0085	1.0032, 1.0139
Haidong Kan	2007	Shanghai	2004-2005	1.0036	1.0011, 1.0061
Wei Huang	2009	Shanghai	-	1.003	1.0006, 1.0054
Yanjun Ma	2011	Shenyang	2006-2008	1.0049	1.0019, 1.0079
Wei Huang	2011	Xi’an	2004-2008	1.002	1.0007, 1.0033
Renjie Chen	2011	Beijing	2007-2008	1.0053	1.0037, 1.0069
Renjie Chen	2011	Shanghai	2004-2008	1.0047	1.0022, 1.0072
Renjie Chen	2011	Shenyang	2006-2008	1.0035	1.0017, 1.0053
Chunxue Yang	2012	Guangzhou	2007-2008	1.009	1.0055, 1.0126
Junji Cao	2012	Xi'an	2004-2008	1.0016	1.0007, 1.0024
Fuhai Geng	2013	Shanghai	-	1.0057	1.0012, 1.0101
Pei Li	2014	Beijing	2005-2009	1.0042	1.0030, 1.0055

Hyewon Lee	2015	11 Asian cities	-	1.0038	1.0021, 1.0055
Yuxia Xiong	2016	Guangzhou	2013-2015	1.0169	1.0094, 1.0245
Hualiang Lin	2016	6 cities of the Pearl River Delta region	2013-2015	1.0176	1.0147, 1.0206
Hualiang Lin	2016	Dongguan	2013-2015	1.0176	1.0155, 1.0399
Hualiang Lin	2016	Foshan	2013-2015	1.0237	1.0138, 1.0337
Fengying Zhang	2016	Shenzhen	2013	1.0069	1.0055, 1.0083
Renjie Chen	2017	272 Chinese cities	2013-2015	1.0022	1.0015, 1.0028
Chen Chen	2018	30 Chinese counties	2013-2015	1.0013	1.0004, 1.0022
Qingqing Wang	2019	Jiangsu	2015-2017	1.0029	1.0018, 1.0041
Ruoqian Lei	2019	Hefei	2013-2017	1.0056	1.0033, 1.0080
Bowen Huang	2019	Shenzhen	2013-2017	1.01	1.0018, 1.0183
Haiping Luo	2020	Gansu	2015-2018	1.0038	1.0031, 1.0045

The statistical method used in the meta-analysis is shown as below [51]:

$$\boldsymbol{w_i} = \frac{\mathbf{1}}{\boldsymbol{SE}\{\mathbf{log}\,\boldsymbol{RR_i}\}^{\mathbf{2}}} \tag{15}$$

$$\boldsymbol{RR}^{*} = \frac{\sum_{\boldsymbol{w_i}} \boldsymbol{RR_i}}{\sum \boldsymbol{w_i}} \tag{16}$$

Here $\boldsymbol{SE}$ refers to the standard error and $\boldsymbol{RR}^{*}$ is the pooled result from the meta-analysis.

Chapter 3 Results

3.1 Characteristics of overcapacity of Chinese industry

According to the DEA model, the capacity utilization rates of various industries of 31 Chinese provinces in 2018 are obtained, as depicted in figure 5. The industries with darker colors (that is, higher capacity utilization) are mainly light industry and fine manufacturing industry, such as the manufacture of metal products, textile, and instruments, which are mainly located in the economically developed provinces in coastal areas such as Guangdong, Jiangsu, Fujian, Shandong, Zhejiang, *etc*. This indicates that the overcapacity situation of heavy industries and less developed provinces/cities are usually more severe. In 2018, China's industrial average capacity utilization rate was 64.13%, which is much lower than the consensus value of 75% for overcapacity. Thus, there is still a lot of room for overcapacity adjustment in the future for China.

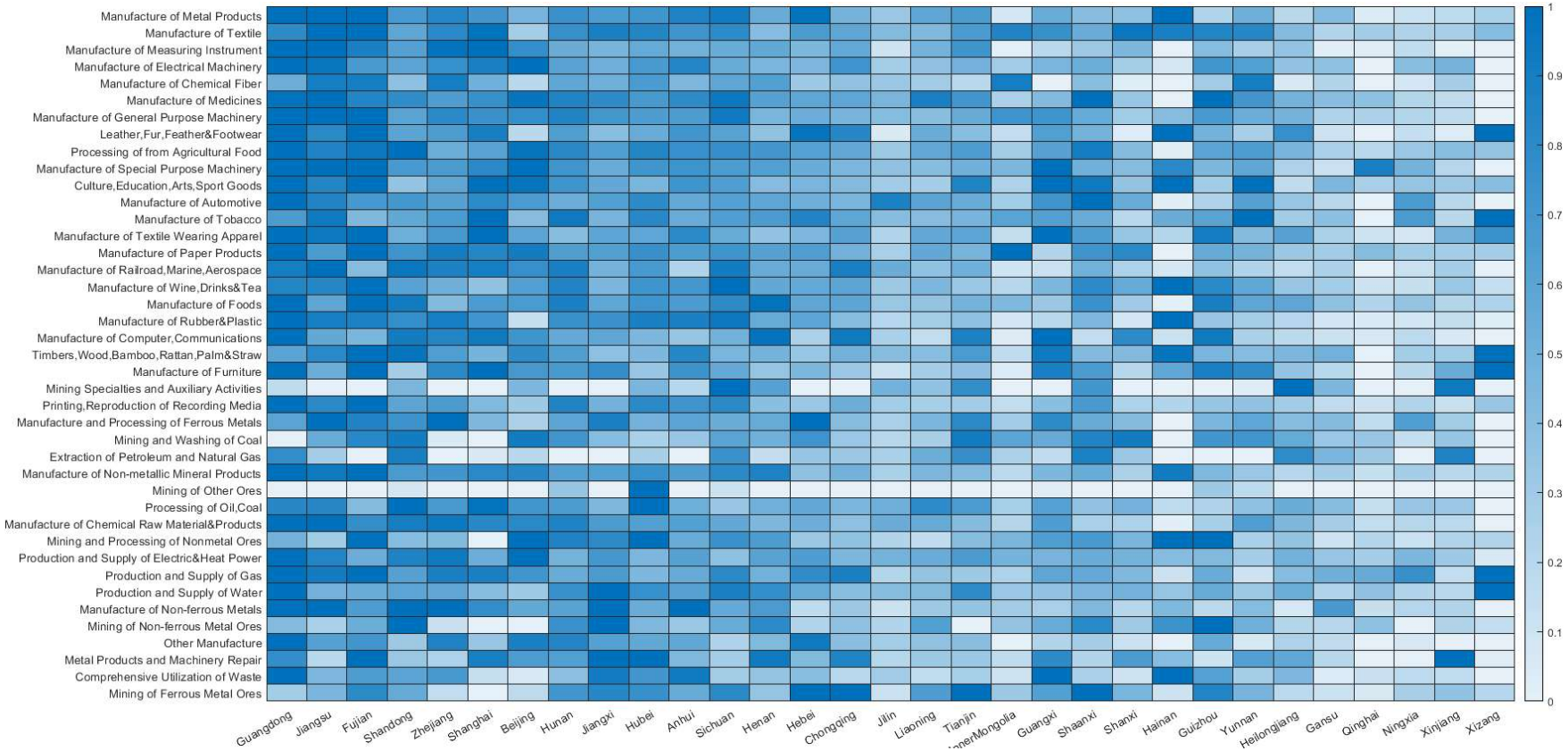


Figure 5. Capacity utilization rate by industry in 31 provinces across in China (2018)

3.1.1 Comparison between industrial sectors

Table 3 lists the capacity utilization rates of various industrial sectors of China in 2018. the mining industry (Main category as B) and the production and supply industry of electricity, heat, gas & water (Main category as D) generally have low capacity utilization rates between 53% to 65%. On the other hand, in the manufacturing industry (C), the capacity utilization rate of the light industry is generally high, and the capacity utilization rate of heavy industry is usually low. Manufacture of metal products, textile, instruments, electrical machinery and equipment, and chemical fiber rank in the top five, with values of 75.37%, 74.71%, 73.85%, 73.74%, and 73.41%, respectively. However, mining of non-ferrous metal ores, other manufacturing industries such as repairment of metal products, machinery and equipment, comprehensive utilization of waste resources, and mining of ferrous metal ores rank at the bottom, with capacity utilization rates generally being lower than 56%.

Table 3. Capacity utilization rates of various industrial sectors in China (Base year=2018)

Rank	**Category**	**Name of industrial sectors**	**CU**
1	C	Manufacture of metal products	75.37%
2	C	Manufacture of textile	74.71%
3	C	Manufacture of instruments	73.85%
4	C	Manufacture of electrical machinery and equipment	73.74%
5	C	Manufacture of chemical fiber	73.41%
6	C	Manufacture of medicines	73.17%
7	C	Manufacture of general equipment	72.96%

8	C	Manufacture of leather, fur, feather products and footwear	72.15%
9	C	Processing of agricultural and sideline food	71.87%
10	C	Manufacture of special equipment	71.77%
11	C	Manufacture of culture, education, arts, sports and entertainment products	70.04%
12	C	Manufacture of automotive	69.32%
13	C	Manufacture of tobacco	69.14%
14	C	Manufacture of textile and clothing	68.97%
15	C	Manufacture of paper and its products	68.16%
16	C	Manufacture of railway, shipbuilding, aerospace and other transportation equipment	67.86%
17	C	Manufacture of wine, drinks and refined tea	67.85%
18	C	Manufacture of foods	67.53%
19	C	Manufacture of rubber and plastic	67.50%
20	C	Manufacture of computer, communications and other electronic equipment	67.42%
21	C	Processing of timbers and manufacture of wood, bamboo, rattan, palm and straw products	66.05%
22	C	Manufacture of furniture	65.36%
23	B	Mining professional and auxiliary activities	64.97%
24	C	Printing and reproduction of recording media industry	64.64%
25	C	Manufacture and processing of ferrous metals	64.64%
26	B	Mining and washing of coal	64.13%

27	B	Extraction of petroleum and natural gas	62.31%
28	C	Manufacture of non-metallic mineral products	62.11%
29	B	Mining of other ores	61.49%
30	C	Processing of oil, coal and other fuel	60.75%
31	C	Manufacture of chemical raw material and chemical products	60.40%
32	B	Mining and processing of non-metallic ores	60.14%
33	D	Production and supply of electric and heat power	59.41%
34	D	Production and supply of gas	57.75%
35	D	Production and supply of water	56.76%
36	C	Manufacture and processing of non-ferrous metals	56.17%
37	B	Mining of non-ferrous metal ores	55.11%
38	C	Other manufacture industry	54.61%
39	C	Repairment of metal products, machinery and equipment	54.58%
40	C	Comprehensive utilization of waste resources	53.19%
41	B	Mining of ferrous metal ores	52.91%

Note: The industry classification is implemented in accordance with the "National Economic Industry Classification GB/T 4754-2017".

3.1.2 Comparison between provinces

China's industrial capacity utilization rate has not only significant industry differences, but also large regional differences. Figure 6 shows the overall industrial capacity utilization rate of each province in 2018. On the whole, the overall capacity utilization rate of eastern China is significantly higher than that of other regions, among which Guangdong Province,

Jiangsu Province, Fujian Province, Shandong Province, Zhejiang Province, Shanghai and Beijing take the top seven, with values of 96.7%, 85.6%, 79.2%, 77.9%, 77.5% and 77.4%, 73.3%, respectively. However, Gansu, Qinghai, Ningxia, Xinjiang and Tibet have the lowest capacity utilization rate, generally ranging from 20% to 40%.

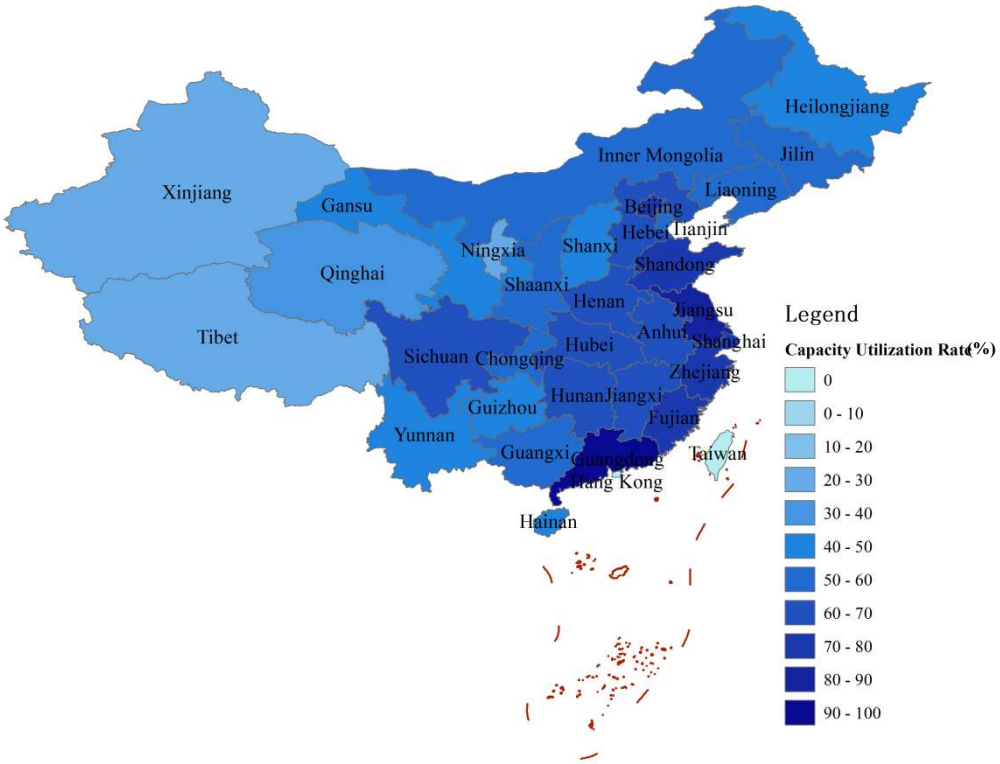


Figure 6. Distribution of capacity utilization rates in China (Base year=2018)

3.2 CO_2 and $PM_{2.5}$ emissions under different scenarios

According to the consensus value for capacity utilization rate as 75% proposed by domestic scholars in line with China's national conditions [14], the overcapacity adjustment threshold was determined for 31 provinces and different industries to investigate the de-capacity scenario (S2). There are two adjustment strategies for industries with varying extents of excess capacity problems. For industries with a capacity utilization rate between 50% to 75%, it is assumed that the value can be increased to 75% by 2050. For industries with a

capacity utilization rate of less than 50%, it is more challenging to reduce capacity, so it is assumed that their capacity utilization rate can increase to 50% in 2050.

The GAINS-China model is used to evaluate the carbon emission reduction potential of overcapacity adjustment, and the results of CO_2 and $PM_{2.5}$ emissions under business as usual scenario (S1) and de-capacity scenario (S2) are shown in Figure 7. It can be observed that, the CO_2 emissions under both scenarios remain relatively stable, around 8276 million tons and 8003 million tons from 2025 to 2035, and then increase to 10931 million tons and 9881 million tons till 2050, respectively. The $PM_{2.5}$ emissions decrease from 2025 to 2035 and then show a similar increasing trend with CO_2 emissions. Considering the release potential from excess capacity, the emission reduction of both CO_2 and $PM_{2.5}$ from industries show a growing trend from 2025 to 2050, resulting in about 1.05 billion tons of CO_2 emission reduction and 57.8 kilotons of $PM_{2.5}$ emission reduction in 2050, respectively. This indicates that, by adjusting the overcapacity of Chinese industry, 9.6% of CO_2 emission reduction and 5.8% of $PM_{2.5}$ emission reduction can be achieved in 2050.

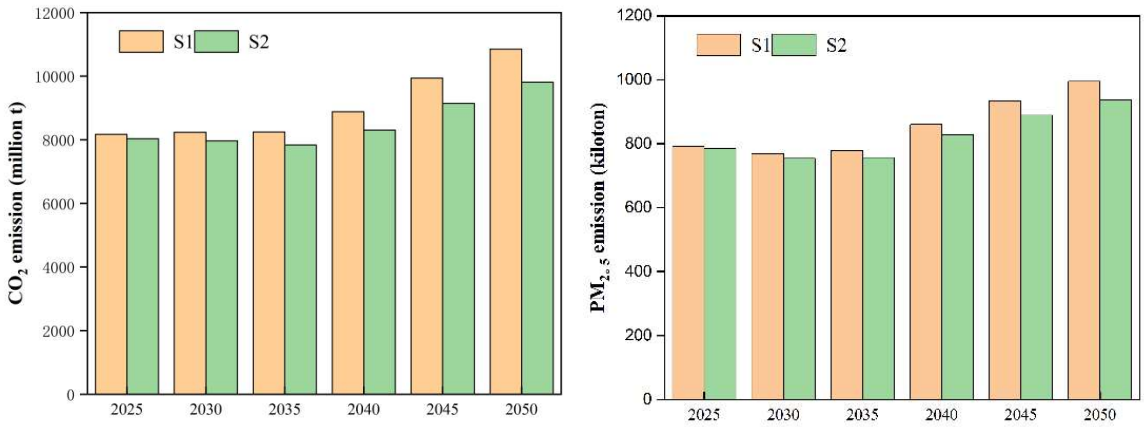
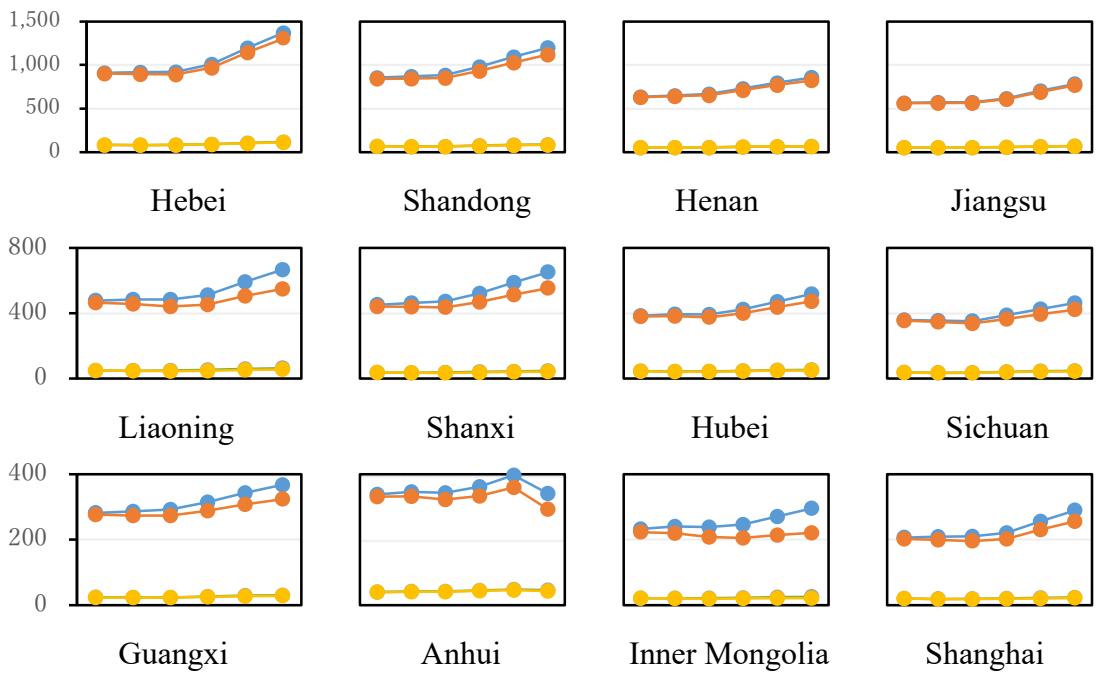


Figure 7. CO_2 and $PM_{2.5}$ emissions under the business as usual (S1) and de-capacity (S2) scenarios

Figure 8 further provides detailed information about the emission trend of CO_2 and $PM_{2.5}$ under both scenarios in each province from 2025 to 2050, and figure 9 represents the exact reduction amount as well as the reduction rate in 2050. It turns out that the emission of CO_2 remains increasing in major provinces with large bases ranging from 150 to 1,500 million tons, while it remains stable in Inner Mongolia, Fujian, Heilongjiang, Jilin, Xinjiang and Ningxia, and it tends to decrease in Anhui, Guangdong, Qinghai and Hainan. As it can be observed from Figure 9, the provinces with high carbon emission industries such as Liaoning, Shanxi, Shandong, Inner Mongolia, and Hebei have higher carbon emission reduction potentials, with values of 117.21, 97.27, 80.39, 75.18, and 65.97 million tons, respectively. Provinces with lower capacity utilization rates, such as Hainan, Qinghai, Ningxia, Xinjiang, and Inner Mongolia, have low carbon emission bases; thus, the total amount of emissions reduction is small, but the proportion is considerable, about 40.4%, 34.2%, 29.1%, 26.8% and 25.5%, respectively.



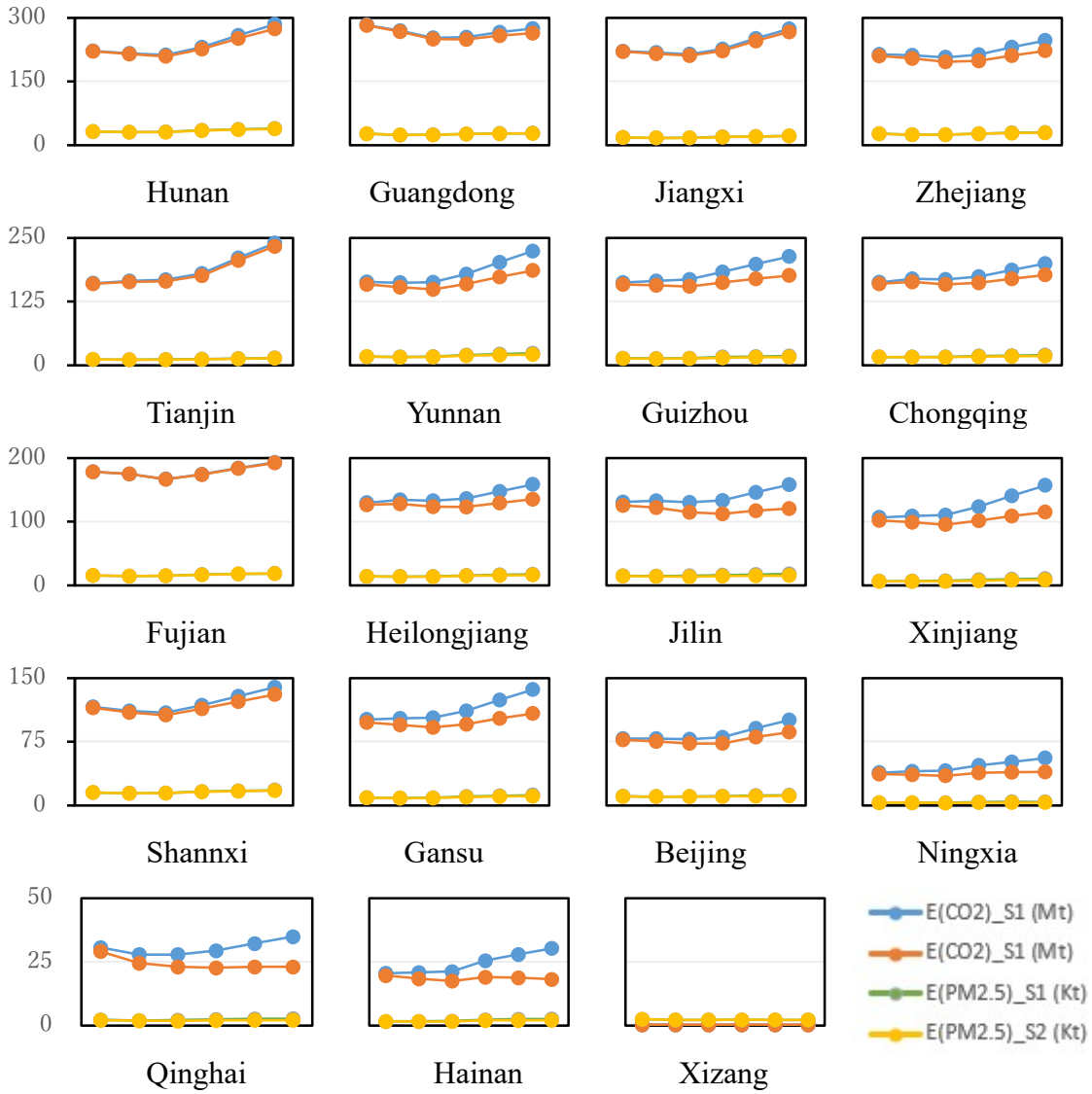


Figure 8. CO_2 and $PM_{2.5}$ emission trend from 2025 to 2050

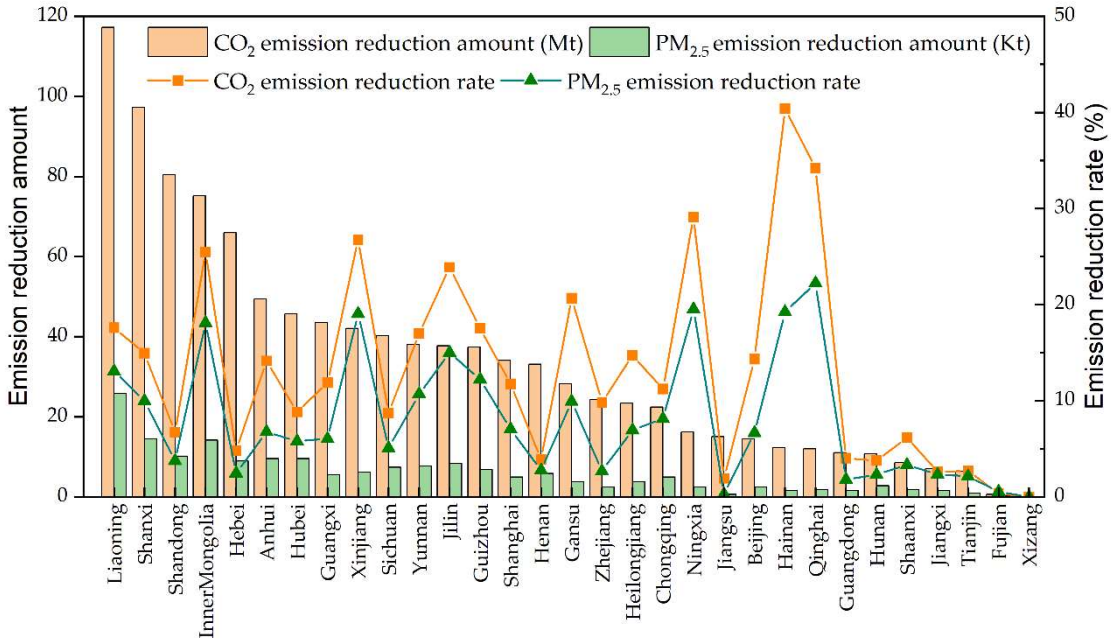


Figure 9. CO_2 and $PM_{2.5}$ emission reduction potential under the de-capacity scenario in 2050

3.3 Health impact assessment

The numbers of selected studies and combined estimates derived in the present meta-analysis are summarized in Table 4. According to the algorithm computed by the software (Review Manager), the pooled result for China-specified RR value is 1.0057 (95% CI: 0.43, 0.71). This finding is consistent with those previous studies that focused on the daily mortality attributable to $PM_{2.5}$ pollution in China and proposed the RR value ranging from 1.0038 to 1.0090 [52,53]. The statistical data I^2 is 95% ($P<0.00001$), which indicates the extent of inconsistency among these studies' results, and is interpreted as the proportion of total variation due to heterogeneity rather than sampling error [51].

The RR value 1.0057 obtained in this study means that total mortality will increase by 0.57% with per 10 μg/m^3 increase of $PM_{2.5}$ concentrations. The RR value applied in the

GAINS-China model is 1.06, demonstrating that total mortality will increase by 6% with per 10 μg/m^3 increase of $PM_{2.5}$ concentrations. By comparing the two RR values obtained from the GAINS-China model and the meta-analysis in this study, it is obvious that the adjusted mortality rate of China is only 1/10 of the European countries. The differences in concentration and source of air pollutants, population size and chemical composition of $PM_{2.5}$ in various regions may partially explain this heterogeneity. In addition, the non-linear shape of the death-$PM_{2.5}$ concentration function may also be an important reason. According to Bernett et al [54], although total death increases with the increase of $PM_{2.5}$ concentrations, the increase rate (RR value) decreases with the increase of $PM_{2.5}$ concentrations. In other words, the extra risk (RR) is high in regions with low $PM_{2.5}$ concentration levels such as the developed countries, while in regions with high exposures of $PM_{2.5}$ such as China, the extra risk (RR) is relatively low. The adjusted RR value for China becomes smaller in our study, which is in line with this principle. Therefore, our study provides a more precise estimation of air pollution-related daily mortality cases in China when using GAINS-China model.

Table 4. Meta-analysis result for $PM_{2.5}$ combined with total mortality

Study	**Log[RR]**	**SE**	**Weight**	**RR [CI]**
Venners 2003	0	0.00037	4.8%	1.0000 [0.9993, 1.0007]
Chen 2017	0.0022	0.0004	4.8%	1.0022 [1.0014, 1.0030]
Luo 2020	0.0038	0.0004	4.8%	1.0038 [1.0030, 1.0046]
Chen 2018	0.0013	0.0005	4.7%	1.0013 [1.0003, 1.0023]
Cao 2012	0.0016	0.0005	4.7%	1.0016 [1.0006, 1.0026]

Wang 2019	0.0029	0.0006	4.7%	1.0029 [1.0017, 1.0041]
Li 2014	0.0042	0.0006	4.7%	1.0042 [1.0030, 1.0054]
Zhang 2016	0.0069	0.0007	4.6%	1.0069 [1.0055, 1.0083]
Huang 2011	0.002	0.0007	4.6%	1.0020 [1.0006, 1.0034]
Chen_a 201	0.0053	0.0008	4.6%	1.0053 [1.0037, 1.0069]
Chen_c 2011	0.0035	0.0009	4.5%	1.0035 [1.0017, 1.0053]
Lee 2015	0.0038	0.0009	4.5%	1.0038 [1.0020, 1.0056]
Lin_b 2016	0.0174	0.0011	4.3%	1.0176 [1.0154, 1.0197]
Lei 2019	0.0056	0.0012	4.3%	1.0056 [1.0033, 1.0080]
Huang 2009	0.003	0.0012	4.3%	1.0030 [1.0006, 1.0054]
Kan 2007	0.0036	0.00113	4.2%	1.0036 [1.0011, 1.0062]
Chen_b 2011	0.0047	0.0013	4.2%	1.0047 [1.0022, 1.0073]
Ma 2011	0.0049	0.0015	4.0%	1.0049 [1.0020, 1.0079]
Lin_a 2016	0.0174	00.0015	4.0%	1.0176 [1.0146, 1.0205]
Yang 2012	0.009	0.0018	3.7%	1.0090 [1.0055, 1.0126]
Geng 2013	0.0057	0.0023	3.2%	1.0057 [1.0012, 1.0103]
Dai 2004	0.0085	0.0027	2.8%	1.0085 [1.0032, 1.0139]
Xiong 2016	0.0168	0.0038	2.0%	1.0169 [1.0094, 1.0245]
Huuang 2019	0.01	0.0042	1.8%	1.0101 [1.0018 1.0184]

Lin_c 2016	0.0234	0.005	1.4%	1.0237 [1.0137, 1.0338]
Total (95% CI)			100%	1.0057 [1.0043, 1.0071]

The above obtained China specific RR values through meta-analysis are further put into the health model to evaluate the health benefit caused by mortality reduction due to $PM_{2.5}$ reduction among the population with ages above 30 years (Figure 10). The health benefit from overcapacity adjustment was conducted for all 31 provinces in China, based on the BAU pollution level of $PM_{2.5}$ (S1), the emission reduction potential derived from the release of excess capacity under the de-capacity scenario (S2), and the population density. The results indicate that northern and central provinces with heavy industries and large population such as Henan, Anhui, Sichuan, Shandong and Jiangsu have relatively more mortality reduction cases than Hainan, Inner Mongolia, Ningxia, Qinghai, Tibet and Xinjiang. It is also revealed that the provinces with lower levels of $PM_{2.5}$ pollution and higher population density have higher reduction rates. The prevented mortality cases in provinces such as Sichuan, Henan, Shandong, Hunan and Chongqing are estimated at 116,700, 64,900, 53,000, 50,400, and 49,100, respectively. The top 5 provinces in terms of the reduction rate are Inner Mongolia, Ningxia, Qinghai, Xinjiang, Hainan and Tibet as 4.92%, 4.58%, 4.03%, 3.87%, 3.67% and 3.59%. More precisely, the implementation of the de-capacity policy reveals significant prevention of about 792,100 mortality cases in all provinces across the country, which is about 0.094% of the national targeted population.

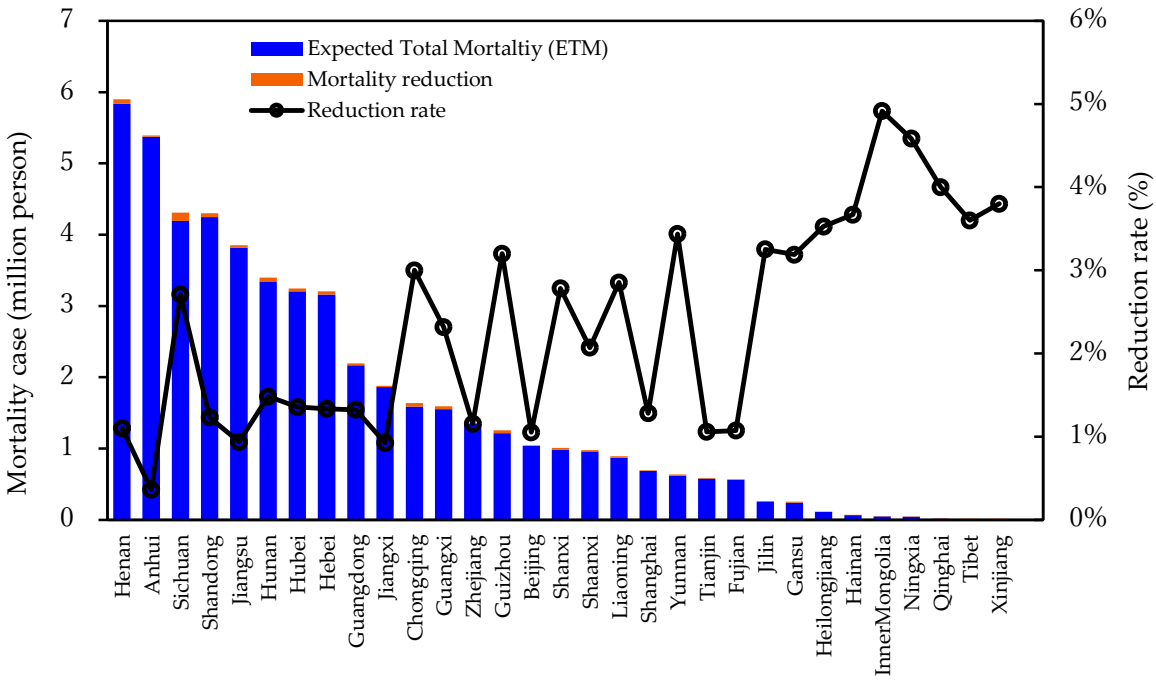


Figure 10. Provincial public health benefits from the de-capacity policy in 2050

This study further explores the relationship between de-capacity potential and expected co-benefits. The multiple linear regression analysis is conducted in order to explore the linear relationship existing between the capacity utilization rates (*CU*), $PM_{2.5}$ emission reduction (*ER*), and mortality cases reduction (*MR*) as follows:

$$\ln(MR) = 0.3090 * \ln(CU) + 1.0933 * ln(ER)$$

(17)

The coefficient of determination, R^2 is more than 0.96, indicating reliable regression results. Furthermore, the F-statistic reaches 338.46 with a significance F of $3.78852*10^{-16}$. More relevant statistical indicators are shown in Table 5.

Table 5. Statistical indicators of the regression

	R^2	Standard Error	F-statistic

Regression Statistics	0.984840395	0.969910603	338.4601323

	Standard Error	**T-statistic**	**p-value**
$\boldsymbol{ln(CU)}$	0.104614409	2.953470026	0.00758557987
$\boldsymbol{ln(ER)}$	0.10597475	10.31622969	0.00000000112

The above model can be a supplementary tool to measure the public health benefit from the contribution of de-capacity policies and regulations.

Chapter 4 Discussion

4.1 Comparison with existing studies

Several studies assessed the excess capacity of one or more industrial sectors in China. We find that most of their results are consistent with our result. For instance, the capacity utilization rate in our study is 64.13% for the whole country in 2018, with variations in different industries and provinces. The study from Yu and Shen [55] showed that the industrial capacity utilization from 30 Chinese provinces reached 69.56% in 2015, which is similar to our result. Another study analyzed the coal resource differences within regions and pointed out that the capacity utilization rate of China's coal industry was 68% in 2016 [56], which is also similar to our result.

With regards to co-benefits, this study evaluates CO_2 emission reduction, $PM_{2.5}$ emission reduction and related health benefits from de-capacity, while other relevant studies evaluate co-benefits from other policies such as technological control, administrative regulations and economic instruments. For example, carbon emission and $PM_{2.5}$ emission can be reduced by 12-32% under traditional command and control measures [57,58], by 10-40% if renewable energy development can be implemented [59], by 15-40% if carbon tax and carbon emissions trade policies can be implemented [60-62], and by 6-14% if industrial and urban symbiosis can be applied [63,64]. Our results present that carbon emission can be reduced by 9.6% from de-capacity, which is neither too significant nor too small compared with existing studies. With regards to the $PM_{2.5}$ emission and the related public health co-benefit, it is about 5.8% and 1.6% in our study, respectively. Comparing with other co-benefits studies, although the overall co-benefits from de-capacity are not as significant as the application of $PM_{2.5}$ control

technologies (70% reduction) [53,65], it is still promising and reasonable since the application of such technologies is costly and time-consuming. De-capacity can optimize industrial structure, improve the overall resource efficiency, and avoid long term environmental pressures with relatively less financial investment.

4.2 Policy implications

Based upon our research findings and considering the Chinese realities, we propose the following policy recommendations.

First, appropriate differentiated target value for de-capacity (i.e. capacity utilization rate) should be determined for different regions and industries when implementing de-capacity policy. As discussed in this study, capacity utilization rate is the key indicator to measure the overcapacity level, and its implementation can lead to less use of fossil fuels, economic input and labor resources, rather than the output value that is always set as the goal in many de-capacity policies. Therefore, to make the de-capacity policy more effective, the capacity utilization rates for different industries in different provinces should be appropriately set, based on the industrial characteristics and the current situation that is reflected by the quantitative results shown in Figure 2. Furthermore, when implementing de-capacity policies, it is encouraged that explicit criteria and related parameters for monitoring the de-capacity process be also provided to facilitate the enterprise and local government for accurate understanding, supervising and implementation of de capacity policy. The parameters include the output values and input resources of different industries in different provinces, which are closely related with the industrial structure adjustment.

Second, three regions/industries are identified for accurate and effective implementation of de-capacity policies. In terms of the overcapacity level, regions with lower levels of

capacity utilization rates such as Gansu, Qinghai, Ningxia, Xinjiang, and Tibet, and industries such as the *Mining* and the *Production & Supply of Electricity, Heat, Gas & Water* should be selected for optimizing their industrial structure and adjusting their industrial layouts. In terms of environmental benefits, regions with heavy industries and higher emissions such as Liaoning, Shanxi, Shandong, Inner Mongolia, and Hebei should make more efforts to improve their capacity utilization rates. Meanwhile, these regions can reduce their air pollutant emissions and greenhouse gas emissions through various control methods, especially technological measures. In terms of public health benefit, regions with higher air pollution emissions and dense population intensities, such as Sichuan, Henan, Hunan, Chongqing, and Hubei, should improve their air quality by more serious enforcement and application of more advanced technologies.

Finally, the integrated research framework proposed in this study can be further applied to other international countries although the application of this framework should be adjusted by considering the local realities. Pursuing co-benefits should be recognized as an international goal since it can facilitate the achievement of United Nations' Sustainable Development Goals (SDGs).

Table 6. Priority of provinces and industries

In terms of overcapacity extent		
	Province	**Capacity Utilization Rate**
1	Gansu	40.8%
2	Qinghai	33.0%
3	Ningxia	29.0%

4	Xinjiang	28.1%
5	Tibet	21.3%
	Industry sector	**Capacity Utilization Rate**
1	The mining industry	Mostly 52%-65%
2	The production and supply industry of electricity, heat, gas & water	< 60%

In terms of environmental benefit

	Province	**CO_2 Emission reduction amount (Mt)**
1	Liaoning	117.2
2	Shanxi	97.3
3	Shandong	80.4
4	Inner Mongolia	75.2
5	Hebei	66.0

In terms of public health benefit

	Province	**Mortality cases reduced (person)**
1	Sichuan	116,700
2	Henan	64,900
3	Hunan	50,400
4	Chongqing	49,100

5	Hubei	44,000

4.3 Research limitations

There are two limitations that exist with the current evaluation of the de-capacity policy implementation and its related co-benefits in this study:

Firstly, the statistical data required for capacity utilization evaluation is incomplete at the provincial level and the industrial sector level, so there may be some deviation. Those missing data are calculated by other available data according to specific principles and functions. Therefore, if the databases at the provincial level and the industrial sector level are more sufficient and complete, the results should be more reasonable.

Secondly, the air pollutant mitigation technologies and their penetration rates are determined according to the database embodied in the current GAINS-China model. It is assumed that these mitigation technologies and penetration rates have not changed when activity data (energy consumption data) are updated because of de-capacity implementation. Therefore, it will be more perfect if the GAINS optimization model can be further developed to optimize the current air mitigation technology penetration rate according to the activity data adjustment to achieve a more accurate result.

Chapter 5 Conclusion

With China's continuous overcapacity growth and increasing environmental emissions, it is critical to make appropriate mitigation policies. In order to fill such a study gap, this paper first estimated the capacity utilization rates by 41 industrial sectors of 31 provinces in China and then assessed the CO_2 and $PM_{2.5}$ emission reduction and total mortality associated with air pollution under the de-capacity implementation. Based on the results obtained from the BaU scenario, China's industrial average capacity utilization rate in 2018 was estimated at 64.13%, with a relatively lower value among mining industries and the production and supply industry of electricity, heat, gas and water. The de-capacity scenario revealed a significant reduction potential of CO_2 and $PM_{2.5}$ emissions from industries by 1.05 billion tons (9.6%) and 57.8 kilotons (5.8%) in 2050, respectively. Generally, the mitigation potential of $PM_{2.5}$ pollution derived from the release of excess capacity can decrease the number of mortality cases in all provinces across the country by 792,100 by 2050.

However, besides the less input of resources, the reduction of excess production capacity can also be derived from the higher technical production level and the improved operation of enterprises or industries. The higher technical production level would enhance the conversation rate from input to output, and the improved operation is essentially the redistribution of inter-industrial interests. In this context, the whole model in this study should further consider more aspects, including:

- Insert the parameter reflecting the technical level in the optimization formula by the DEA model to consider the positive impact of technology development.
- Establish the link between industries and analyze the redistribution of inter-industrial resources and co-benefits.

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