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Review

A review on health cost accounting of air pollution in China

Ruiqiao Bai[*,1], Jacqueline C.K. Lam[1], Victor O.K. Li

Department of Electrical and Electronic Engineering, The University of Hong Kong, Hong Kong

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ABSTRACT

Over the last three decades, rapid industrialization in China has generated an unprecedentedly high level of air pollution and associated health problems. Given that China accounts for one-fifth of the world population and suffers from severe air pollution, a comprehensive review of the indicators accounting for the health costs in relation to air pollution will benefit evidence-based and health-related environmental policy-making. This paper reviews the conventional static and the new dynamic approach adopted for air pollution-related health cost accounting in China and analyzes the difference between the two in estimating GDP loss. The advantages of adopting the dynamic approach for health cost accounting in China, with conditions guaranteeing its optimal performance are highlighted. Guidelines on how one can identify an appropriate approach for health cost accounting in China are put forward. Further, we outline and compare the globally-applicable and China-specific indicators adopted by different accounting methodologies, with their pros and cons being discussed. A comprehensive account of the available databases and methodologies for health cost accounting in China are outlined. Future directions to guide health cost accounting in China are provided.

Our work provides valuable insights into future health cost accounting research in China. Our study has strengthen the view that the dynamic approach is comparatively more preferred than the static approach for health cost accounting in China, if more data is available to train the dynamic models and improve the robustness of the parameters employed. In addition, future dynamic model should address the socio-economic impacts, including benefits or losses of air pollution polices, to provide a more robust policy picture. Our work has laid the key principles and guidelines for selecting proper econometric approaches and parameters. We have also identified a proper estimation method for the Value of Life in China, and proposed the integration of engineering approaches, such as the use of deep learning and big data analysis for health cost accounting at the fine-grained level (city-district or sub-regional level). Our work has also identified the gap for more accurate health cost accounting at the fine-grained level in China, which will subsequently affect the quality of health-related air pollution policy decision-making at such levels, and the health-related quality of life of the citizens in China.

1. Introduction

Over the last three decades, rapid industrialization in China has caused significant air pollution and health challenges (Diamond, 2005; Lagorio, 2010; Lim, 2007). The mean annual $PM_{2.5}$ concentration in China's major cities reported to be 43 μg/m^3, had exceeded 4 folds based on the threshold of 10 μg/m^3 annual mean concentration set by the World Health Organization in 2017 (Chan and Danzon, 2005; MEEPRC, 2017). Serious air pollution has created severe health risks (Dockery and Pope, 1994; Dockery et al., 1992, 1989), raising increasing concerns in China (Wang, 2016). People's quality of life has deteriorated continuously with increasing rates of morbidity and mortality. Pollution has also affected tourism negatively, and triggered people to move out of the polluted cities in China (Liang and Zhao, 2015).

Against such background, quantification of air pollution-related health costs is needed for reviewing how much air pollution in China has costed the health of its own citizens, and how serious the problem is, before any sound and justifiable health-related environmental policy measures can be designed. Thompson et al. has conducted a quantitative study and suggested that the costs of United State's carbon policies could be offset by 26% to 1050% due to air pollution control policies in the states that improve air quality and reduce health costs, indicating those policies are worthy of implementation (Thompson et al., 2014).

* Corresponding author.
E-mail addresses: brq17@hku.hk (R. Bai), jcklam@eee.hku.hk (J.C.K. Lam), vli@eee.hku.hk (V.O.K. Li).

[1] The authors have contributed equally significantly to this manuscript.

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Another study in China has shown that various polluted provinces in China should closely cooperate in order to minimize the regional health costs due to $PM_{2.5}$ (Wu et al., 2017). Given that China hosts one-fifth of the world's population and is a key contributor to global air pollution (Kaiman, 2013), The beneficiaries of developing reliable and precise health cost accounting methodologies for China's air pollution will not be restricted to Chinese policy-makers, but also researchers who are interested in air pollution-related health policy studies globally (OECD, 2014).

Existing methodologies concerning air pollution-related health cost accounting research have not been studied thoroughly. First, a number of models and economic hypotheses have been proposed to evaluate the health burden of air pollution in China, but no systematic research has been conducted regarding how the accounting of economic loss differs across different methodologies. The basis for selecting a particular accounting methodology is not well established (D.-S. Huang and Zhang, 2013; Huang et al., 2012b; Kan and Chen, 2004; Wenbo and Shiqiu, 2010; Zhang et al., 2010). Secondly, various indicators have been proposed for health cost accounting in China. Some of them are global indicators, while others are China-specific. Inconsistency occurs when one type of indicator is preferred to another (see Section 3.2), but not much has been documented with reasonable justification. Thirdly, as the health cost accounting with respect to China's air pollution has become a heated discussion, scholars have attempted to acquire the needed data from various sources (Ding et al., 2016; Li et al., 2017; Lv et al., 2017; Pandey et al., 2004; QOEDC, 2017; Xie et al., 2015; J.Y. Zhu et al., 2017), a comprehensive review of open data resource is needed in order to assist researchers seeking for good quality data. Last but not the least, a comprehensive literature review that reveals changes in research focus and trends of development in this field is still lacking.

This paper studies the pros and cons of the traditional and new methods of health cost accounting in China, attempts to fill the research gaps and to provide valuable insights into how our future air pollution-related health cost accounting should be, both for China and the rest of the world. Our paper is structured as follows: Section 2 outlines the static and the dynamic model employed in health cost accounting research, identifies the discrepancies in their estimated GDP losses, and the rationales for indicators selection. Section 3 summarizes the indicators employed in different models. The sets of indicators integrated and standardized at the global scale and those designed specifically for China are introduced and compared. Section 4 provides an overview of the accessible data needed for the air pollution-related health cost accounting in China. Section 5 conducts a historical review of the academic articles covering the health cost accounting methodologies published in China in the last 30 years and identifies the research trend. Finally, our conclusion section charts the future directions of health cost accounting research in China.

2. Models and methods for health cost accounting of air pollution in China

2.1. The static accounting model vs. the dynamic accounting model

Two models are most commonly utilized for health cost accounting of air pollution: the static model and the dynamic model. Each type can be subdivided into different hybrid versions. Fig. 1 presents the typical structures of both models:

The static model follows a linear process. First, it measures the dose-response relationship between air pollutants and their health endpoints, such as premature deaths and incidents of respiratory illness (Kahn and Yardley, 2007), based on epidemiological literature; second, it monetarizes the health burdens based on market or survey data (Zhang et al., 2017a).

The dynamic model has been increasingly adopted recently, characterized by a thorough examination on the dynamics of the health industry (Wu et al., 2017), and the long-term or cross-period effects of economic loss (Böhringer and Rutherford, 2008; Clarke et al., 2009; Dai et al., 2017; Karplus et al., 2016; Li et al., 2012; Qi et al., 2014; van Ruijven et al., 2012; Wang et al., 2016; Yang et al., 2005; Zhang et al., 2013; L. Zhu et al., 2017). The dynamics are principally captured by diversified Computable General Equilibrium (CGE) models (Bollen and Brink, 2014; Matus et al., 2012; Nielsen and Ho, 2013; Saari et al., 2015; Wu et al., 2017; Xie et al., 2016). As shown in Fig. 1, a typical dynamic model is configured as a closed loop model. In particular, instead of merely considering the industry's impacts on health costs, the negative feedback of health loss on the resource allocation and market demands will be taken into account (Matus et al., 2012). By taking the bidirectional influences into account, the model can capture the general equilibrium after running multiple iterations (when key parameters converge), yielding the solution in the form of a final cost (Zhang et al., 2017a). Usually, five sub-models are nested in a complete dynamic model. First, a sub-model obtains the air pollution emission inventory through industry data (e.g. energy use); second, with reference to the transmission model and the chemical reactions theories, another sub-model predicts air quality distribution from the emission data; followed by the third and fourth sub-models that monetize the health costs by multiple dose-response equations and econometric methods; and the final sub-model calculates the influence of health damage on the industry iteratively, eventually reaching the general equilibrium across all sectors (Zhang et al., 2017a). Table 1 presents a dynamic model of an energy sector for air pollution-related health impact analysis (Karplus et al., 2016; Kishimoto et al., 2017; Luo et al., 2016; Zhang et al., 2013, 2017a).

2.2. Economic methods in the models and their estimation results

Various economic methods have been adopted in health cost accounting models, including the Direct Market Method, Surrogate Market Method, Contingent Value Method and Benefit Transfer Method are most commonly used (Chen et al., 2014). The following section will elaborate the four methods, and present the estimation value of models that are designed mainly based on each method.

2.2.1. Direct Market Method

The Direct Market Method (DMM) aggregates the market prices of goods or services that are curtailed directly by air contamination. It includes Market Value Approach (MVA), Opportunity Cost Approach (OCA), Human Capital Approach (HCA), Cost of Illness (COI) and Dose-response Technique (DRT) (Chen et al., 2014). Among these approaches, COI mainly focuses on estimating the cost of morbidity (Huang et al., 2012b). It can be used to substitute the Willingness To Pay (WTP) approach since COI data is easier to be obtained (see Section 2.2.3 for WTP). The description, sample calculation formula and data required for each approach are listed in Table 2.

DMM is the dominant econometric method for health cost accounting in China, and the MVA, HCA, COI and DRT are most widely used. For instance, the WRF-Chemical model shows that in China, health cost due to outdoor $PM_{2.5}$ pollution was reported to be about USD 151.1 to USD 176.9 billion in 2006 (Miao et al., 2017). Similar air pollution-related health cost studies focusing on metropolises such as Beijing (Li, 2012), provinces and cities in southern China (Wang and Qu, 2002), and the northern inland areas can be found (Han and Ma, 2001; Li, 2012; Zhou and Li, 1999). Besides assessing the economic loss due to air pollution-related health degradation, DMM has been used to calculate the economic gain of ambient air quality improvement. For example, the aggressive emission control policies introduced during the Asian Games in Guangzhou in 2010 was estimated to avoid 106 premature deaths, 1869 cases of hospital admission, 20,026 cases of outpatient visits, with an overall economic gain estimated to reach CNY 165 million (Ding et al., 2016). Similarly, using the HCA and DRT accounting, it was estimated that the energy reform introduced in

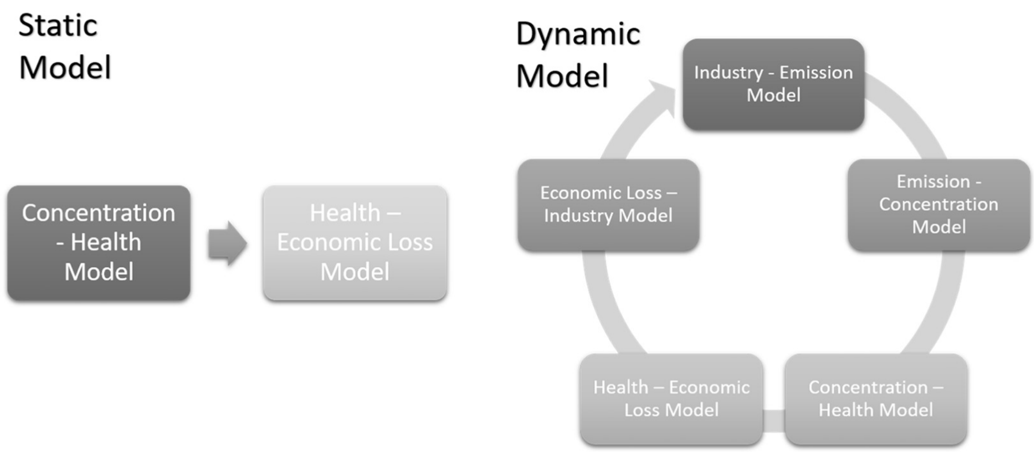

Fig. 1. A comparison of the static accounting model versus the dynamic accounting model.

Lanzhou city had reduced a health cost amounted to CNY 487 million (Yang et al., 2013). Previous COI studies conducted for China, whether prevalence-based or incidence-based, had focussed mainly on private costs, as households in China received very little subsidies in health treatment from public health institutions (Guh et al., 2008). A research conducted in 113 cities in China, based on COI, indicated that the economic loss due to human exposure to PM_{10} was amounted to CNY 341.4 billion in 2006 (Chen et al., 2010).

2.2.2. Surrogate Market Method

The Surrogate Market Method (SMM) takes on the assumption that the price of certain goods or services could indirectly reveal the public evaluation of environmental quality (Qin and Wang, 1997). The Shadow Project Approach (SPA), Travel Cost Approach (TCA), Defensive Expenditure Approach (DEA) and Hedonic Pricing Approach (HPA) are subsumed under SMM (Chen et al., 2014). Detailed descriptions are found in Table 3.

SMA has not been widely adopted for air pollution accounting in China, only a few pilot studies have adopted SPA and HPA. Based on SPA, in 2001, the value of China's forest on oxygen release and air purification was approximately CNY 1461 billion (Li, 2013). The shadow price of per ton SO_2 in China's thermal power industry was found to decrease substantially from CNY 538 k to 167 k from 2001 to 2009 (Qian, 2013). In Tsingtao, in 2006, a marginal unit increase in Air Quality Index (AQI) promoted an increase in housing price by 185.705 CNY/m^2, equivalent to a 1.8% increase in local average price (Xian, 2015). HPA is still in its infancy in China, most studies have only taken real estate prices into account (Xian, 2015), even though some comprehensive pilot studies on wages exist (Cao and Han, 2015; Peng et al., 2014). Since TCA is more suitable for accounting total natural attractions, instead of a single item such as air quality, TCA has seldom been adopted for health cost accounting of air pollution in China. Similarly, DEA has rarely been used, since low defensive expenditure will likely lead to under-estimation.

2.2.3. Contingent Valuation Method

Contingent Valuation Method (CVM) uses questionnaire surveys or interviews to enquire respondents' Willingness To Pay (WTP) or Willingness To Accept (WTA) (Ma, 2006). In the context of air pollution, WTP refers to how much respondents would like to pay in exchange for a better air quality (Dubourg et al., 1994). On the contrary, WTA refers to the amount of payment that respondents would like to accept in exchange for a lower air quality (Dubourg et al., 1994). As shown in Fig. 2, respondents' demand for better air qualities to be higher when air qualities appear to be lower, hence WTP or WTA is expected to be higher. WTP or WTA takes into account the values of corresponding environmental qualities (Lin et al., 2006). Table 4 details the CVM approaches, including WTP or WTA.

A significant number of environmental accounting studies have used the CVM approach for evaluating the health costs of subjects who are exposed to air pollution in China. In Beijing, according to a paper published in 2015, the Chinese' WTP for 30% and 60% reduction of $PM_{2.5}$ were CNY 22.78/month and CNY 39.82/month respectively. The WTP for health risk reduction was dictated strongly by one's personal

Table 1
Components of a dynamic accounting model.
Source: Xu et al., 2017

Function	Name	Key components
Industry-Emission Model	Emission Inventory Module	Spatial distribution of emissions; Regional Emission Inventory in Asia; Multi-resolution Emission Inventory for China.
Emission-Concentration Model	Atmospheric Chemistry Transport Model	Spatial concentration in different scenarios; Weather Research and Forecasting–Chemistry & Community Multi-scale Air Quality Model (WRF-Chem & CMAQ) Weather Research and Forecasting–Chemistry & Goddard Earth Observing System–Chemistry (WRF-Chem & GEOS-CHEM)
Concentration-Health Model Health-Economic Loss Model	CREM-Health Effect Module	Chronic exposure and acute exposure; Mechanism of air pollution on labor supply; Capturing the indirect loss of air pollution on the economic system; Exposure-Response relationship.
Economic Loss-Industry Model	China Regional Energy Model (CREM)	Characteristics of 30 provinces in China; Details of production sectors; Alternative energy technology; Energy flows among provinces.

Table 2
Direct Market Method.

Approach	Description	Sample formula	Data required in formula
Market Value Approach	• Evaluates the costs based on changes in products' outputs and profits due to environmental damage (Lin et al., 2006); • The economic loss can be deduced from market prices (Ye and Luan, 1994). • Can only operate under a well-developed market-based system (Fan, 2003).	$E = \left(\sum_{i=1}^{k} C_i Q_i\right)_x - \left(\sum_{i=1}^{k} P_i Q_i - \sum_{i=1}^{k} C_i Q_i\right)_y$	P_i: per unit price of product i Q_i: quantity of product i C_i: per unit cost of product i $(\ )_x$: situation before Air Pollution (AP) $(\ )_y$: situation after AP
Opportunity Cost Approach	• Defined by the best alternative value when making a decision (Palmer and Raftery, 1999; Wikipedia, 2017) • Environmental costs of over-logging, and opportunity costs can be measured by the income generated per unit forest resource and the amount of forest resource lost (Fan, 2003).	$E = PQ$	P: potential profit brought by per unit resource Q: amount of resource lost due to AP
Human Capital Approach	• Calculates the loss of productivity or labor capital due to individuals' absence of work (Raftery et al., 2012). • Controversial because it assumes the values of lives are different (Huang et al., 2012b). • A revised approach adopts the average contribution of individuals to the society instead (Yin et al., 2017).	$E = \sum_{y=1}^{t} GDP_y^{d_y}$ $= GDP_0 \sum_{y=1}^{t} \frac{(1+\alpha)^y}{(1+\gamma)^y}$	$GDP_y^{d_y}$: discounted value of per capita GDP in the y th year t: average time of life-year loss due to air pollution GDP_0: per capita GDP in a basic year α: per capita GDP growth rate γ: social discount rate
Cost of Illness Approach	• Sums up the direct and indirect costs associated with a disease type (Guh et al., 2008). • Can estimate both the 'public' costs of treating infected individuals, or 'private' costs to individuals (Guh et al., 2008).	$E = COI_d + COI_i$	COI_d: direct cost of illness COI_i: indirect cost of illness
Dose-response Technique	• Establishes the quantified relationship between environmental changes and changes in productivity or human health, and provides information for other evaluation approaches (e.g. Market Value Approach) (Lin et al., 2006). • Utilized in conjunction with other methods.	$RR = e^{\beta\ (X - X_0)}$	RR: suggested Relative Risks X: current pollutant concentration (μg/m^3) X_0: target or threshold pollutant concentration (μg/m^3) β: parameter

characteristics, economic conditions, and modes of transportation (Zeng et al., 2015). Studies found that the WTP for urban residents in China for reducing per kg of soot emission is CNY780.40 (He and Huang, 2014). A happiness-oriented research suggested that individual Chinese would like to pay USD 42/year for 1% reduction in $PM_{2.5}$ on average (Zhang et al., 2017b). In general, values vary significantly due to differences in question design (Cao and Han, 2015), making results highly uncertain. In the absence of sufficient verification, WTP becomes a not-so-reliable health cost accounting tool (Akter et al., 2008).

2.2.4. Benefit Transfer Method

Benefit Transfer Method (BTM) applies original or adjusted information from a prior study, such as parameters or formulas, to a new research (Lin et al., 2006). The prerequisite for such transfer is the high similarity of characteristics shared between these two studies, for instance, the similarity across environmental, geological and/or socio-economic domains (Chen et al., 2014). When there are restrictions on fund, time or human resource, BTM is a simple and feasible alternative to supplement the missing model components (Xu, 2008). The specific steps and guidelines of BTM are documented in Table 5 (Platjouw, 2016).

Table 3
Surrogate Market Method.

Approach	Description	Calculation formula	Data required in formula
Shadow Project Approach	• When the environment degrades, an artificial project might be constructed to complement the function of the original ecosystem. The project's cost is taken as the loss (Fan, 2003). • When a river is polluted, and a water diversion project is constructed to supply drinking water, the cost of the water diversion project will be taken as the economic loss (Fan, 2003).	$E = C_{shadow\ project}$	$C_{shadow\ project}$: cost of shadow project
Travel Cost Approach	• Evaluates natural attractions by the benefits that tourists gain, namely, their willingness to pay for travelling to the natural attractions (Ma, 2006). E.g. tourists may have to pay for transportation, and the time spent for such visits can be regarded as payments (Ma, 2006).	$E = C_{travel}$	C_{travel}: cost of traveling
Defensive Expenditure Approach	• Takes any expenditure on preventing environmental degradation as cost. • Covers a part of the total loss only (Lin et al., 2006). • For instance, the waste gas emitted by factories is treated to meet emission standards, and the cost of gas treatment can be taken as the loss (Cao and Han, 2015).	$E = \sum_{i=1}^{k} C_i Q_i$	C_i: per unit cost of defensive equipment i Q_i: amount of defensive equipment i
Hedonic Pricing Approach	• Assumes that people's evaluation of the environment can be inferred from the price of goods they purchase if these goods are related to environmental quality. • For instance, houses located in places with better environmental qualities might be more expensive (Wu et al., 2007), and the difference in wages or working hours might also be used to reflect the values of such environment qualities (Qin and Wang, 1997).	$\ln V = \sum B_i \ln X_i + \sum r_j I_j + e$	V: housing price X_i: quantified house character i B_i: parameter I_j: the value equals 1 when the house is sold on period j, or the value equals 0 r_j: the fluctuation of housing prices in period j e: random error

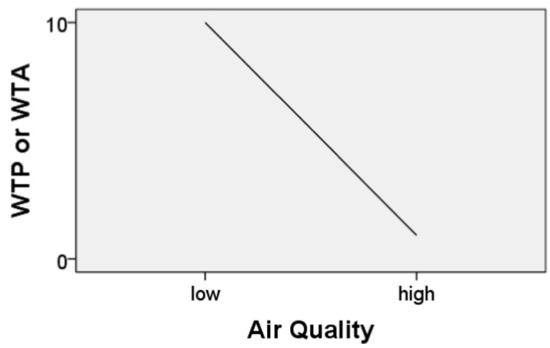

Fig. 2. WTP or WTA by air quality.

BTM has been dominantly utilized when scholars are seeking parameters or formulas for DRT. Specifically, values in publications of international authorities such as WHO and World Bank are acknowledged as high-quality data, and suitable for BTM (Cao and Han, 2015; Shen and Yu, 1999). In addition, prior research results of adjacent geographical areas might be transferable. For instance, when accessing the health cost of air pollution in the Pearl River Delta, China, scholars transfer value of statistical life in Chongqing to calculate the mortality and morbidity of chronic bronchitis (D. Huang and Zhang, 2013). As for developing countries, adopting the dose-response function in developed countries, mostly from the United States, is a common practice (Lelieveld et al., 2015). However, it has been reminded that the effectiveness of the approach might be compromised due to the gaps between the target and the reference areas, such as differences in levels of air pollution, baseline health conditions, and healthcare (Deyu and Zahur, 2017).

2.3. A comparison of the static accounting model versus the dynamic accounting model

Static accounting models usually yield smaller output values than dynamic accounting models. Previous static models demonstrate that air pollution-related health costs could vary from 3.5 to 5.9% of China's GDP (Cai, 2009; Gao et al., 2015; Greenpeace, 2015; Hammitt and Zhou, 2006; Huang et al., 2012a; Johnson et al., 1997; Kan et al., 2004; LINKS, 1997; Mu and Zhang, 2013; OECD, 2014; Xie et al., 2016; Xu et al., 2015, 2016; Zeng et al., 2015; Zhang et al., 2017a; Zhou et al., 2014), while the dynamic model based on a CGE model, the MIT EPPA (version 4) model (Paltsev et al., 2005) gives a higher estimation of GDP loss due to air pollution as compared to the static model, ranging from 6% to 9%, for the period 1995 to 2005 (Matus et al., 2012).

The static model has been criticized for under-estimating health costs, due to the failure to embody the long-lasting impacts of workers' health loss to the industry (Matus et al., 2012; Nam et al., 2010; Reilly et al., 2013). Firstly, the pollution-induced loss in workers' income and saving might lead to less capital investment, impeding future economic growth (Nam et al., 2010). Secondly, the worsening in health of the whole population accelerates the demand for healthcare services, requires more resource to be allocated to medical institutions, and curtails the capital goods available to other industries (Matus et al., 2012). This distorted resource allocation may induce inefficiency in maximizing the social welfare (Zhang et al., 2017a). The dynamic model, in comparison, is more effective in reducing the potential of

Table 5
Procedures and guidelines of Benefit Transfer Method.
Source: Platjouw, 2016

Step	Guideline
1	Identify existing studies or values that can be used for the transfer.
2	Decide whether the existing values/studies are transferable. The existing values or studies would be evaluated based on several criteria, including: ● Is the service being valued comparable (or similar) to the service valued in the existing studies? ● Are characteristics of the relevant population comparable? E.g. are demographics similar between the referencing area and the area being valued? If not, are data available to make the necessary adjustment?
3	Evaluate the quality of studies to be transferred. The better the quality of the initial study, the more accurate and useful the transferred value will be. This requires the professional judgment of the researcher.
4	Adjust the existing values to better reflect the values for the study under consideration, using whatever information available and relevant. Researchers might adjust the values by applying demographic data to adjust for differences across users. For instance: $\mathrm{WTP}_i = WTP_j \times \frac{per\ capita\ GDP_i}{per\ capita\ GDP_j}$ Here WTP_i and WTP_j refer to an individual's WTP in country i and j correspondingly, which are adjusted by the ratio of per capita GDP in these two countries.

Table 4
Contingent Value Method.

Approach	Description	Calculation formula	Data required in formula
Bidding Game Approach	● Consists of Single-stage Bidding Game and Multi-stage Bidding Game. ● Single-stage Bidding Game: ask the participants on how much he/she is willing to pay in order to improve environmental quality, or how much he/she would like to accept to tolerate environmental degradation (Ma, 2006). ● Multi-stage Bidding Game: ask participants whether they were willing to pay/accept a given amount of money, and then repeatedly change the given amount until the maximum willingness to pay or the minimum compensation they are willing to accept is achieved (Ma, 2006).	$E = \max(\mathrm{WTP})$ or $\mathrm{E} = \min(WTA)$ WTP or $\mathrm{WTA} = \alpha X + \beta$	WTP: a respondent's maximum willingness to pay for a unit of improvement in air quality WTA: a respondent's minimum willingness to accept for a unit of deterioration in air quality X: Current pollutant concentration, $\mu g/m^3$ α, β: Coefficient, $\alpha < 0$
Trade-off Game Approach	● Investigate the participants' evaluation of environmental quality by asking them to choose from two programs offered (Qin and Wang, 1997). ● For instance, the participants are asked whether they would like to accept a certain amount of money or a group of environmental goods or services, then raise or drop the amount of money until the participants think both programs are equally acceptable, and the final amount of money is deemed as the participants' evaluation (Ma, 2006).	E = V	*V*: the value of money received when respondents take the two programs as equally acceptable
Costless Choice Approach	● Requires participants to choose among groups of programs offered, but no money is involved. ● For instance, the participants are asked to choose between a bigger house with poor environmental quality and a smaller house with high environmental quality, and the amount of furniture in either house could be modified until the participants think both choices are equally good, then the difference in market prices between the two choices is regarded as the value of environmental quality difference (Qin and Wang, 1997).	$\mathrm{E} = \Sigma\,\Delta V_i$	ΔV_i: the value difference between non-environmental factor i in the two programs

underestimation, as it takes into account the general equilibrium over the long term, and can better depict any negative impacts caused by air pollution.

Research studies adopting the dynamic model have provided a better account of the health cost of air pollution in China. Incorporating local epidemiological data and regional energy model, one study estimated that the health cost of $PM_{2.5}$ nationwide in 2015, China would be USD 248 billion, though such cost varies across provinces due to differences in air quality, population density, and level of economic development (Zhang et al., 2017a). The dynamic model performs well in recovering historical data. The latest EPPA–Health Effects (EPPA-HE) model, takes into the account the incidences and overall costs of individual health outcomes. This hybrid model is based on the EPPA model (version 4), which has developed a soft-link between a CGE model and air quality and health impacts models, and has taken into account of the physical and biological variables. The incidence and the overall cost of individual health outcomes, such as restricted activity days, respiratory hospital admissions, asthma attacks, and other morbidity and mortality outcomes from acute and chronic exposure have been covered. The results generated from this hybrid model has revealed that deterioration in air quality led to a five-fold increase in annual economic loss during the period of 1975 to 2005 in China (Matus et al., 2012). A study adopting the latest non-linear dose-response functions has predicted that, without introducing proper $PM_{2.5}$ pollution control policies, a 2% reduction in GDP due to health loss could be expected by 2030 in China (Xie et al., 2016). Another study based on the CGE model ENV-Linkages designed by OECD has indicated a 2.6% GDP loss in China due to outdoor air pollution by 2060 (Burniaux and Château, 2008). Moreover, climate change policies have been considered in a recent study as well, which has adopted the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model, and has predicted that Shanghai would gain an increase in local GDP by 1% in 2030 due to synergistic effects between air pollution control and climate change policies (Wu et al., 2017).

Despite the strengths and advantages of dynamic health costs accounting, such model still presents some limitations. At the moment, the robustness of most CGE models is dependent upon careful calibration, which requires massive data inputs to determine the parameters. In real life, these parameters are determined based on very few observations (Roberts, 1994). This may eventually undermine the performance of deterministic calibration. To improve the accuracy of GCE models, simulations will be required to check the robustness of such models (Harrison et al., 1993; Roberts, 1994). The robustness of GCE model requires further improvement in the future, and future dynamic model should also address the socio-economic impacts, including benefits or losses of air pollution polices to provide a more robust policy picture (see Section 6.1).

For the economic methods adopted by these models, their advantages and challenges are presented in Table 6. Among the four methods, CVM tends to produce a higher estimation, especially when compared to the COI approach in DMM (Harrington and Portney, 1987; Zmirou et al., 1999), as it accounts not only for the physical damage, but also the subjective loss in well-being (Viscusi et al., 2005).

Table 7 compares the health cost accounting methods in terms of the number of research papers, reliability of results, complexity and extensibility, and requirement for supporting data. DMM has the highest no of papers covered due to its high objectivity, credibility, and the relative ease of obtaining source data (Chen et al., 2014; Chen et al., 2010). The extensibility of methods refers to the methods' usefulness to different research topics. CVM has the highest extensibility, since it can fit a range of topics by simply modifying questionnaires or interviews; while the extensibility of BTM is restricted due to the requirement on similarity across different studies (Chen et al., 2014). The comparison table provides a better guideline on what methodology one should use.

Besides, the choice of health cost accounting methodology will depend on the research focus (Ma, 2006). The suggested approaches for different research foci are shown in Table 8.

3. Indicators of health cost accounting of air pollution in China

3.1. Introduction to health cost indicators

Below sub-section will describe and compare the globally-applicable and China-specific indicators developed for air pollution-related health cost accounting. In this paper, the term "indicator" refers to the variable in calculations, and the term "parameter" refers to the fixed numerical factor in the health cost accounting formula.

3.1.1. Globally-applicable health cost indicators

We use "globally-applicable indicator" to refer to the indicator applicable to all nations worldwide. As for the globally-applicable indicator in measuring the impact of rising morbidity, Disability Adjusted Life Years (DALYs) and Value of Statistical Life (VSL) are two most important ones in health cost frameworks. They are strongly recommended by international organizations such as WHO, Organization for Economic Co-operation and Development (OECD), World Bank, etc.

DALYs refers to the total number of years of healthy life lost from onset (Ostro and WHO, 2004). To enable the DALYs' incorporation of non-fatal diseases threatens, WHO assigns different weights (from 0 to 1) to diseases according to their severity (Mathers, 2008; Shen and Yu, 1999). The value of DALYs is then acquired by multiplying the expected years of disability (until recovery or death) with corresponding severity weight (Shen and Yu, 1999). The formula of DALYs is summarized in Table 9. The total DALYs in 2014–2015 associated with air pollution (including PM_{10} and $PM_{2.5}$) in China were estimated to be USD 20.66 million, with a total cost of USD 304 billion, 2.94% of GDP (Maji et al., 2017). The cost of 18 morbidities due to respiratory illnesses amounted to USD 95 billion including USD 40.5 billion for lower respiratory symptoms (restricted to wheezes in adults), USD 25.8 billion for chronic bronchitis (applicable to all ages), and USD 10.1 billion for restricted activity days (Maji et al., 2017).

VSL is defined as "an aggregation of individual values for small changes in risk of death (OECD, 2012)", and is based on the CVM. For instance, if a survey finds that on average participants would like to pay USD 10 for reducing the annual death rate by 1% in the whole society, the one-year VSL value per capita as USD 1000, obtained by summing up the USD 10 paid by 100 people in the society. The VSL is a standardized method spearheaded by international authorities for monetizing increased mortality (OECD, 2014). A recent study applying VSL indicated that a 50% reduction in air pollution emissions from the agricultural sector could avoid over 90,000 deaths per year in China, with additional economic benefits of over USD 90 billion (Giannadaki et al., 2018).

For estimating the respiratory, cardiopulmonary and other mortality caused by air pollution, WHO has put forward a set of indicators, formulas and coefficients to support DRT (Ostro and WHO, 2004). In recent years, more sophisticated models, including the Integrated Exposure-Response (IER), have been developed to investigate exposure dose gaps among populations exposing to the same level of air quality (Burnett et al., 2014; Liu, 2016; Smith, 1993; Wang et al., 2012). Table 10 provides the sample formulas adopted by these mortality estimation models.

Besides, various shadow prices implemented in SPA have been devised globally for the cost accounting of air pollutants (Lin et al., 2006). Table 11 summarizes the per unit shadow price of air pollutants previously used by 37 organizations in the world (Wang, 1999), and a large gap is observed between the maximum and the minimum numerical values. The gaps are attributed to different local air pollution concentrations, population densities, income levels, etc. (Zhang et al., 2017a). Hence, when researchers intend to select shadow prices for air pollutants in China, it is important that they should follow the standard screening procedures of BTM (see Section 2.2.4).

Table 6
Advantages and uncertainties of accounting methods.
Source: Harrington and Portney, 1987; Zmirou et al., 1999; Chen et al., 2010; Chen et al., 2014; Ma, 2006

Method	Approach	Advantages	Uncertainties
Direct Market Method	Market Value Approach	The evaluation is relevant objective, less controversial and has higher credibility	• Production loss considered might be incomprehensive.
	Opportunity Cost Approach	High credibility	• The resource involved might not be scarce and versatile enough.
	Human Capital Approach	Can quantify the value of life, which is difficult using other approaches	• The quantification of life might be unethical or inaccurate.
	Cost of Illness Approach	Can value the cost of morbidity, with the required data being relatively easy to obtain	• The estimates have not captured the pains and sufferings, preventive expenditures associated with an illness, or the values of any reduced mortality risks.
	Dose-response Technique	Can demonstrate the extent that environmental changes affect the receptor and quantify the impact of environmental damage	• It might be difficult to separate the impact of environmental pollution from other factors.
Surrogate Market Method	Shadow Project Approach	The cost of shadow projects might be easier to access	• Non-uniqueness of shadow projects
	Travel Cost Approach	Could reveal the value of the natural attraction	• The travel cost might be lower than the travelers' evaluation of natural resource
	Defensive Expenditure Approach	The market price for defensive expenditure might be more readily available	• The defensive equipment considered might be insufficient to fully prevent the loss caused by air pollution
	Hedonic Pricing Approach	Data on the price of real estates and wages might be easier to access	• Besides air quality differences, the impact of other factors on real estate prices or wages is difficult to be excluded
Contingent Value Method	Bidding Game Approach; Trade-off Game Approach; Costless Choice Approach	Easy to directly infer the cost based on participants' answers	• Strategy bias: participants may deliberately give a biased answer in order to influence the result • Information bias: When participants are asked to value attributes, but they do not know or even understand them • Starting point deviations: When participants are asked to choose from a set of pre-set possible answers, and the answers are biased • Hypothesis bias: when participants only need to give an answer rather than make a choice in the reality, they may give an answer without careful consideration • Payment method bias: the way in which people pay may affect the participants' willingness to pay
Benefit Transfer Method		Low cost, time-saving	• Uncertainty regarding the difference in assumptions in terms of populations and environments in the targeted areas and the reference areas

3.1.2. China-specific health cost indicators

We use “China-specific indicators” to refer to the various aggregative indicators, or frameworks, that have been designed especially for China's statistical system. Some of those indicators have been embedded in the national or provincial sustainable development assessment models for China (Chen et al., 2016; Wen et al., 2004). Table 12 shows an example of the China-specific framework on air pollution health cost accounting. The basic data and some auxiliary data, used for supplementing or correcting basic data, are shown. Table 12 provides intermediate indicators that shall be calculated by empirical basic data and the corresponding formulas. It could be seen that $PM_{2.5}$ and SO_2 are the two main air pollutants included in the China-specific framework, and the impact of NOx would sometimes be integrated as well (Lin et al., 2006).

The “estimated loss of one case of premature death” in Table 12 is obtained by multiplying VSL with the year lost triggered by premature death. However, due to the lack of large-scale VSL investigation in China, scholars usually prefer two alternative choices. The first choice is to use BTM, and transfer VSL value from developed countries. The second choice is adopting the individual's labor value calculated by HCA.

Scholars have tried to merge the globally-applicable indicators into the China-specific framework. Generally, health cost is consisted of four components: First, the cost of making appointments in the hospital and relevant work absence; Second, the cost of living in the hospital and relevant work absence; Third, the cost of premature death; Fourth, the “DALYs” (Cao and Han, 2015), which is the globally-applicable indicator of disabilities. The mathematical equations are represented in Table 13.

3.2. A comparison of globally-applicable indicators versus China-specific indicators

3.2.1. Single economic approach versus hybrid economic approach

A key difference between globally-applicable and China-specific indicators being that, multiple economic methods are commonly involved in one China-specific aggregative indicator, while each globally-applicable indicator is usually derived from one single economic method. The single method-based indicator ensures consistency among pre-assumptions of accounting. However, this type of indicator could hardly cover all aspects of health cost. Hybridizing economic approaches, in contrast, has the advantage of covering more aspects of health cost. Besides, by freely switching partial econometrics in the framework, scholars are more likely to reduce the burden of data gathering. One drawback of such a framework, however, is that the underlying assumptions of different economic approaches are diverse and might be contradictory to each other. Hence, a reliable guideline would best be put forward to recommend when and where certain approaches could be deployed in the same framework.

3.2.2. Globally-applicable parameters versus China-specific parameters

“Parameter” refers to the fixed numerical value in the health cost accounting formula. The globally-applicable parameters sometimes employ a set of fixed value parameters in different domains. Applying a set of unified values among different countries may decrease accuracy. However, when compared to conducting one survey for each region, fewer research efforts are required for obtaining a unified set of parameters for all regions. Hence, it is more likely that the unified parameters on different diseases are provided by one single research study, using similar statistical methods. This would ensure that the parameters are more comparable to each other.

Table 7
Comparison of health cost accounting approaches.

Method	Number of research papers	Reliability of results	Complexity of methods	Extensibility of methods	Requirements on data used	References
Direct Market Method	Relatively high	High	High	Middle	A large amount of high-accuracy data, and relatively easy to acquire	Zmirou et al., 1999; Lin et al., 2006; Guh et al., 2008; Chen et al., 2010; Raftery et al., 2012; Chen et al., 2014;
Surrogate Market Method	Relatively low	Relatively high	High	Middle	Indicators selected could well reflect changes in the target value	Qin and Wang, 1997; Palmer and Raftery, 1999; Fan, 2003; Lin et al., 2006; Ma, 2006; Chen et al., 2010;
Contingent Valuation Method	Relatively low	Low	Middle	High	Should minimize the subjective randomness of interviewees and improve the understandability of questions	Qin and Wang, 1997; Lin et al., 2006; Ma, 2006; Chen et al., 2010;
Benefit Transfer Method	Relatively low	Relatively low	Low	Low	Similarity between data on study area and area in reference research	Lin et al., 2006; Chen et al., 2010; Platjouw, 2016

Table 8
Approach suggested for research with different foci.
Source: Ma, 2006; Guh et al., 2008

Focus point	Approach suggested
Productivity	Market Value Approach Opportunity Cost Approach Dose-response Technique Defensive Expenditure Approach Shadow Project Approach
Health impact	Human Capital Approach Cost Of Illness Approach Dose-response Technique Defensive Expenditure Approach Contingent Value Method
Comfort	Travel Cost Approach Hedonic Pricing Approach Contingent Valuation Method

Table 9
Formula and indicators for calculating DALYs.
Source: Shen and Yu, 1999

Indicator calculated	Sample formula	Data used in formula
Disability Adjusted Life Years (DALYs)	$DALYs = \int_{x=\alpha}^{x=\alpha+\delta} cxe^{-\beta x}e^{-\gamma(x-\alpha)}dx$	α: Onset age Δ: Years lost due to premature death γ: Discount rate c: Constant 0.16 β: Constant 0.04

The China-specific parameters require surveys conducted in the context of China. They outperform the globally-applicable parameters in terms of regional accuracy, and reflect better the local characteristics. Take the exposure-response model as an example, there is a huge difference in terms of background concentration between the Western countries and China, which could result in very different exposure-response relationships (Cohen et al., 2017; Giannadaki et al., 2018; Huang et al., 2017). Therefore, China local epidemiological evidence is much needed, and should be incorporated into the application while retaining the cumulative dimensions of the pollution-health effects. However, conducting empirical surveys in China can be highly time- and resource-consuming. Alternatively, scholars may gather information from existing papers, but comparability across parameters might be compromised due to differences in statistical approach and assumption. To fill this gap, it would be desirable to design an integrated parameter-measurement standard for China's local-specific health cost accounting.

3.2.3. Estimation methods for the values of life

VSL is a globally-applicable indicator which indicates ones' WTP for reducing mortalities. However, restricted by time and funding, very few investigations on China's urban residents' WTP have been conducted (Zeng and Jiang, 2010) and such results could barely be applicable to the countryside or other cities due to the huge gap in socio-economic conditions across different parts of China (Xu et al., 2013).

Hence, many China-specific studies utilize the BTM or HCA to replace VSL. For instance, studies sometimes transfer VSL from developed countries. However, results of meta-analysis have suggested that VSL is significantly lower in China than in the developed OECD countries (Xu et al., 2013). This gap can mainly be explained by differences in income levels, a previous paper has used a log-log regression to calculate the income elasticity of VSL by country, which is shown as below (Miller, 2000). Here Y is an income measure, Z is a vector of other explanatory variables, and a, b, c are coefficients (Miller, 2000).

$$\ln(VSL) = a + b\ln(Y) + cZ$$

Nevertheless, acknowledged guidelines on VSL transfer are deficient. As for the modified HCA (see Table 1), which avoids the ethical

Table 10
Indicators for mortality estimation.
Source: Ostro and WHO, 2004; Wang et al., 2012; Burnett et al., 2014

Target indicator	Sample formula	Data used in formula
All-cause mortality and short-term exposure to PM_{10} Cardiopulmonary mortality/lung cancer and long-term exposure to $PM_{2.5}$	$RR = e^{\beta\,(X - X_0)}$ $RR = [(X+1)/X_0 + 1]^{\beta}$	RR: Suggested relative risk β: Coefficient X: Current pollutant concentration, μg/m^3 X_0: Target or threshold concentration of pollutant, μg/m^3
Mortality of ischemic heart disease, cerebrovascular disease, chronic obstructive pulmonary disease, and lung cancer due to $PM_{2.5}$	$RR_{(Z)} = \begin{cases} 1 & , z < z_{cf} \\ 1 + \alpha\{1 - e^{-\gamma(z - z_{cf})^{\delta}}\}, & z \geq z_{cf} \end{cases}$	RR: Suggested relative risk z: Current pollutant concentration, μg/m^3 z_{cf}: Counter-factual concentration below, assuming no additional risk, μg/m^3 α, γ, δ: Coefficient
Incidence of acute lower respiratory infection (ALRI) due to $PM_{2.5}$	$RR_{(z_i,z_j)} = I_{(z_i)}/I_{(z_j)} = \frac{1 + \alpha\{1 - e^{-\gamma(z_i - z_{cf})^{\delta}}\}}{1 + \alpha\{1 - e^{-\gamma(z_j - z_{cf})^{\delta}}\}}$	$I_{(z_i)}$: Incidence rates corresponding to the 10 decile values of $PM_{2.5}$, denoted by zi for $i = 1, \ldots 10$
Exposure dose to air pollutants	ADD = C × IR × ET × EF × ED/(BW × AT)	ADD: Average daily dose of air pollutants, mg/(kg·d) C: Ambient concentration, mg/m^3 IR: Respiration rate, m^3/d ET: Exposure time, h/d EF: Exposure frequency, d/a ED: Exposure duration, a BW: Body weight, kg AT: Average exposure time in days, d

Table 11
Per unit cost (USD/tonne) of air pollutants by global organizations.
Source: Wang, 1999

Pollutant	Minimum	Maximum	Mean	Median	Number of organizations
CO_2	2	84	25	20	26
NO_2	42	40,000	8212	4209	36
SO_2	405	21,185	4011	1793	34
TSP	167	8780	3401	2496	20

issues by using an individual's average contribution to the society (Xu, 2008), its performance is usually lower than normal VSL (Zeng and Jiang, 2010). For instance, a research conducted in Beijing shows that the external cost of $PM_{2.5}$ based on VSL is equivalent to 0.9% of the local GDP, while only representing 0.3% of the local GDP when accounted by HCA (Yin et al., 2017). It also ignores individuals' need to trade-off between the costs due to risks of death and risks of prevention (Freeman III et al., 2014; Tang, 2011).

4. Data resources for health cost accounting in China

Data supporting China's air pollution-related health cost accounting are becoming increasingly abundant. Resources, including the precision and the time range documented in official yearbooks or other documents, are summarized in Table 14. Apart from the data covered in the table, for air pollution data at the municipal level after 2013, including the real-time hourly average concentrations of six pollutants (SO_2, NO_2, PM_{10}, $PM_{2.5}$, O_3, CO), detected by air quality monitoring stations in China's major cities, are posted online (QOEDC, 2017). To fill in the potential missing data, the World Bank has proposed an air quality estimation model based on regional energy consumption, atmospheric and geographical factors, city and national population density, local urban population density, local intensity of economic activity, national income per capita, etc. (Pandey et al., 2004).

The health costs (represented by GDP loss and welfare loss) of air pollution in China have varied across different time spans. Hence, it is important to take into account the temporal variation of health cost accounting. For instance, according to the EPPA (version 4) model (see Fig. 3, the welfare loss due to ozone and particulate matter in China was increased five-fold from USD 22 billion in 1975 to USD 112 billion in 2005).

China's statistical yearbooks have mainly provided air quality and social-economic data on the national, provincial or municipal levels, and other methods have been developed to further enhance the spatio-temporal resolution of data. Calculating the health cost at a finer spatial resolution instead of averaging the health costs of a whole region is important, since the regional variations due to varying economic circumstances and air quality are huge in China (Maji et al., 2017; Zhang et al., 2008). A finer spatial analysis would facilitate policy makers to develop regional-specific policies, and laying a good foundation for other social or environmental research at finer resolutions, such as studies of environmental inequality (Huby et al., 2009). The inverse pollution data from Aerosol Optical Depth (AOD), which are measured by satellite remote sensing, have been used extensively (Lv et al., 2017; Xie et al., 2015). For instance, a recent daily AOD-$PM_{2.5}$ model, utilizing the 3-km resolution MODIS AOD data, has achieved an R^2 ranging from 0.81 to 0.83 for $PM_{2.5}$ prediction in Beijing (Xie et al., 2015). In addition, other scholars have achieved a much fine-grained estimation of air pollution distribution by adopting machine learning and big data techniques (Ding et al., 2016; Li et al., 2017; J.Y. Zhu et al., 2017). Such attempts would enhance precision of health cost accounting, and eliminate estimation uncertainty in the future.

5. Trends of academic research in health cost accounting related to air pollution in China

Establishing and improving frameworks of the air pollution-related health cost accounting require ample academic research, as well as technical and financial support. Based on China's Knowledge Resource Integrated Database,[2] we have conducted a bibliometric review of research papers since 1980 with "air pollution", "health" and "cost" as their themes simultaneously. The historical records on the number of research papers, research fields, research organizations and funding sources will be traced in the following section.

5.1. Number of publications

The number of publications from 1980 to 2016 is shown in Fig. 4.

[2] www.cnki.net.

Table 12
Summary of the China-specific aggregative indicator on health cost of air pollution.
Source: Lin et al., 2006

Basic data	Auxiliary data	Indicators calculated	Sample formula (I function equals 1 when the condition in brackets is satisfied, or it equals 0; the units of results are ten thousand people for population, and one hundred million yuan for money)
Urban population (UP) Regional mortality (RM) WHO air quality standards/ China national air quality standard Level II for SO2 and PM_{10} (SD)		Exposed population (EP)	EP = UP × 0.75
SO2 annual average concentration (CSO2)		Pre-mature death caused by SO2 (PDS)	PDS = I (CSO2 > SD) × 0.00048 × (CSO2 − SD) × RM × EP
		Changes in respiratory symptoms caused by SO2 (CRS)	CRS = I (CSO2 > SD) × 0.0181 × (CSO2 − SD) × EP
PM_{10} annual average concentration (CPM10)	TSP annual average concentration	Pre-mature death caused by PM_{10} (PDP)	PDP = I (CPM10 > SD) × 0.00096 × (CPM10 − SD) × RM × EP
		Number of annual appointments made due to respiratory symptom caused by PM_{10} (NARP)	NARP = I (CPM10 > SD) × 1.2 × (CPM10 − SD) × EP
		Number of annual emergencies due to respiratory disease caused by PM_{10} (NERP)	NERP = I (CPM10 > SD) × 0.2354 × (CPM10 − SD) × EP
		Number of annual appointments made due to asthma caused by PM_{10} (NAAP)	NAAP = I (CPM10 > SD) × 32.6 × (CPM10 − SD) × EP
		Number of annual appointments made due to chronic bronchitis caused by PM_{10} (NABP)	NABP = I (CPM10 > SD) × 0.0612 × (CPM10 − SD) × EP
		Number of annual appointments made due to children lower respiratory disease caused by PM_{10} (NALP)	NALP = I (CPM10 > SD) × 1.69 × (CPM10 − SD) × EP
		Changes in respiratory symptoms caused by PM_{10} (CRP)	CRP = I (CPM10 > SD) × 183 × (CPM10 − SD) × EP
		Days when activities are restricted caused by PM_{10} (DAP)	DAP = I (CPM10 > SD) × 57.5 × (CPM10 − SD) × EP
Cost of a single appointment made due to respiratory disease (CSAR)		Cost of total appointments made due to respiratory disease (CTAR)	CTAR = CSAR × Number of relevant appointment caused by SO2 and PM_{10}
Cost of a single emergency (CSE)		Cost of total emergency (CTE)	CTE = CSE × Number of emergency caused by SO2 and PM_{10}
Cost of a single appointment made due to asthma (CSA)		Cost of total appointments made due to asthma (CTA)	CTA = CSA × Number of relevant appointments due to PM_{10}
Cost of a single appointment made due to chronic bronchitis (CSB)		Cost of total appointments made due to chronic bronchitis (CTB)	CTB = CSB × Number of relevant appointments due to PM_{10}
Per unit medical cost due to changes in respiratory symptoms (PMR)		Total medical cost due to respiratory symptoms (TMR)	TMR = PMR × Changes in respiratory symptoms caused by SO2 and PM_{10}
Cost of a single appointment made due to children lower respiratory disease (CSL)		Cost of total appointments due to children lower respiratory disease (CTL)	CTL = CSL × Number of relevant appointments due to SO2 and PM_{10}
Average wage of workers (W)		Economic loss due to days when activities are restricted (EA)	EA = W × Days when activities are restricted caused by PM_{10}
Estimated loss of one case of premature death (LOD)	Human Capital Approach: Discount rate (real interest rate / nominal interest rate + wage increasing rate) Contingent Value Approach (CVA): Local per capita GDP + America per capita GDP + loss of premature death obtained by CVA in America	Total loss of premature death (LTD)	LTD = LOD × Number of premature death caused by SO2 and PM_{10}

(continued on next page)

Table 12 (*continued*)

Basic data	Auxiliary data	Indicators calculated	Sample formula (I function equals 1 when the condition in brackets is satisfied, or it equals 0; the units of results are ten thousand people for population, and one hundred million yuan for money)
Air pollution treatment cost	Investment in environmental pollution treatment Proportion of air pollution treatment in all pollution treatment investment		

The health cost of air pollution = Total loss of premature death + Total appointment cost due to respiratory disease + Total emergency cost + Total appointment cost due to asthma + Total appointment cost due to chronic bronchitis + Total appointment cost due to respiratory symptom + Total appointment cost due to children lower respiratory disease + Economic loss due to days when activities are restricted + Air pollution treatment cost.

We have divided the research history into three stages: Stage 1 (1980–1997), Stage 2 (1998–2007) and Stage 3 (2008–2016). In Stage 1, the health cost of air pollution in China did not draw much attention from scholars. In Stage 2, from the period of 1998 to 2007, only a few publications related to this topic each year were found. The implied that the health cost induced by air pollution had gradually increasingly brought to the public's attention. In Stage 3, started from 2008, partially due to the Beijing 2008 Olympic Game, air pollution and resultant health cost brought forth increasing global attention, as witnessed by the dramatic increase in the number of related publications. The publications appeared in diversified forms including conference papers, master theses, doctoral theses and journal articles. However, the annual quantity of publications was still limited compared to research on other topics (Bai et al., 2017). Given the increasing public concern about air pollution in China, continuous annual increase in the number of relevant publications in the future could be expected.

5.2. Research fields, organizations and funding sources

As illustrated in Fig. 5, the core research areas of publications can be classified into eight categories: Economics & Management, Energy & Transportation, Environmental Science & Resource Utilization, Chemistry, Engineering & Industry, Legislation and Others. This is a re-classification of the research disciplines identified by China's Knowledge Resource Integrated Database. The trend of diversification could be observed across three periods, and scholars from various research fields have all been drawn to this research topic.

Fig. 6 outlines changes in leading research organizations. In Stage 1, the Chinese government functioned as the dominant leading organization, whereas in Stage 2 and Stage 3, universities have taken the role of leading academic research. This indicates that scholars in China have become more active and self-motivated in exploring air pollution-related health cost accounting.

Fig. 7 shows that recently the Chinese government has provided much more funding opportunities to support research on air pollution-related health cost accounting. While the central government is the major funding resource, the funding opportunities from local governments have also increased. Even though international cooperation might enhance the research quality, very few papers supported by international funding are written by Chinese scholars. Although international organizations such as OECD have conducted research on China's health cost regarding air pollution, the number of Chinese scholars participated in these research remains limited (OECD, 2014).

6. Recommendations and conclusions

This study provides recommendations and conclusions on air pollution-related health cost accounting research in China, by studying the differences among different health cost accounting models and their related economic parameters, the China-specific and globally-applicable indicators, data resource, and conducting a bibliometric review on the past 30-year research trend. Finally, we conclude this paper by recommending areas of improvements and highlighting the general research directions for health cost accounting.

6.1. Select the best model for health cost accounting

More attentions should be paid to the choice of appropriate model for health cost accounting. The static model is likely to underestimate the total health costs, mainly by ignoring the long-term effects of cross-sectoral interactions (Matus et al., 2012; Nam et al., 2010; Reilly et al., 2013); the dynamic model based on CGE model can take into account of the interaction effects, and create a soft-link between the CGE model and models on air quality and health impacts to better represent the true costs of health due to air pollution in China. However, though the dynamic model has been developed, further effort is needed in future to improve the model structure to address the robustness of the parameters, and to take into account any country specific variables that may contribute to the final health costs of individuals. At the moment, the efficiency of the dynamic model in China may be affected if there is not enough empirical data available to facilitate parameter calibration. However, with increasing attention paid to the health effects of air pollution in China by the government and the public, the scale and quality of available health and air pollution data to be fed into the CGE model should be improved subsequently.

At the moment, the MIT EPPA model has calculated health costs based on the emission levels and the related costs covering service inputs, leisure and lost productivities (Paltsev et al., 2005). Nevertheless, current model lacks a dynamic module that takes into account the cost of implementing air quality control policy to restore the level of air

Table 13
Formula and indicators on total health cost.
Source: Cao and Han, 2015

Indicator calculated	Sample formula	Data used in formula
Total Health Cost (THC)	$\mathrm{THC} = \sum_{i=1}^{2}\sum_{j=1}^{3} \Delta E_{ij} \times V_{ij} + Dalys \times V_4$	i: The value is 1 or 2, corresponding to PM_{10} and $PM_{2.5}$, respectively J: The value is 1–3, every j corresponds to a level of air pollution and economic loss ΔE_{ij}: Population suffering from health impacts caused by air pollution; includes death, emergency or hospitalization caused by disease V_{ij}: Economic loss corresponding to death, diverse direct cost related to medical care, loss of income DALYs: Disability Adjusted Life Years

Table 14
Information on data resource, precision and time range related to health cost accounting of air pollution.
Source: Xia and Zhao, 1995; Liu, 2004; Lin, 2005; WHO and UNAIDS, 2006; Cao and Han, 2015

Data	Data resource	Data precision	Year	Source/website
WHO air quality standards/China national air quality standard	Air quality guidelines-global update 2005; Ambient Air Quality Standards GB 3095-2012	Annual/daily average standards	–	(WHO and UNAIDS, 2006); http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/dqhjzlbz/201203/t20120302_224165.htm
The concentration of pollutants such as SO2, PM_{10}, etc.	China Statistical Year Book on Environment	Municipal; main cities in each province; annual	1997–2015	http://www.stats.gov.cn/tjsj./tjcbw/201706/t20170621_1505831.html
Number of days when air quality is higher than China national air quality standard Level II	China Statistical Year Book on Environment	Municipal; main cities in each province; annual	1997–2015	http://www.stats.gov.cn/tjsj./tjcbw/201706/t20170621_1505831.html
Urban air quality	China Environmental State Bulletin	Municipal; main cities in each province; annual	1988–2015	http://www.zhb.gov.cn/hjzl/zghjzkgb/lnzghjzkgb/
	Environmental state bulletins in each province	Municipal; cities & districts; annual/monthly	–	–
GDP per capita	China Statistical Yearbook	Provincial; annual	1980–2015	http://www.stats.gov.cn/tjsj/ndsj/
	Statistical yearbooks in each province	Provincial; annual	–	–
Urban population	China Statistical Yearbook	Provincial; annual	1980–2015	http://www.stats.gov.cn/tjsj/ndsj/
	Statistical yearbooks in each province	Provincial; annual	–	–
	National Bureau of Statistics of the People's Republic of China online database	National; annual	2002–2015	http://www.stats.gov.cn/
Mortality	China Statistical Yearbook	Provincial; annual	1980–2015	http://www.stats.gov.cn/tjsj/ndsj/
	Statistical yearbooks in each province	Provincial; annual	–	–
	China Health Statistical Yearbook	Provincial; annual	2002–2016	http://www.nhfpc.gov.cn/zwgk/tjnj1/ejlist.shtml
Loss of working time due to various respiratory diseases	Economic measurement and research on the cost of environmental pollution in China	Research findings in the mid-80s	–	(Xia and Zhao, 1995)
Time of absence from work due to various respiratory diseases	Economic measurement and research on the cost of environmental pollution in China	Research findings in the mid-80s	–	(Xia and Zhao, 1995)
The difference of respiratory diseases' morbidities between polluted area and clean area	Economic measurement and research on the cost of environmental pollution in China	Research findings in the mid-80s	–	(Xia and Zhao, 1995)
Urban/rural tuberculosis/respiratory disease mortality rate	National Bureau of Statistics of the People's Republic of China online database	National; annual	2009–2015	http://www.stats.gov.cn/
Medical costs due to various diseases	China Health Statistical Yearbook	National; annual	2002–2015	http://www.nhfpc.gov.cn/zwgk/tjnj1/ejlist.shtml
Basic data covering hospitalization or emergency treatment	China Health Statistical Yearbook	Provincial; annual	2002–2016	http://www.nhfpc.gov.cn/zwgk/tjnj1/ejlist.shtml
Basic data on hospitalization	National Bureau of Statistics of the People's Republic of China online database	National; annual	1990–2015	http://www.stats.gov.cn/
	China Health Statistical Yearbook	Provincial; annual	2002–2016	http://www.nhfpc.gov.cn/zwgk/tjnj1/ejlist.shtml
Basic data on emergency treatment	National Bureau of Statistics of the People's Republic of China online database	National; annual	2010–2015	http://www.stats.gov.cn/
	China Health Statistical Yearbook	Provincial; annual	2002–2016	http://www.nhfpc.gov.cn/zwgk/tjnj1/ejlist.shtml
Average wage of workers	Statistical yearbooks in each province	Provincial; annual	–	–
	China City Statistical Yearbook	Municipal; cities; annual	1984–2015	http://www.stats.gov.cn/tjsj/tjcbw/201706/t20170613_1502795.html
Average daily household working hours of urban residents	A comparison of time distribution and lifestyles between Chinese and American residents	Municipal; several cities; annual	1980–1998	(Liu, 2004)
Household number	China Population Statistics Yearbook	Provincial; annual	1987–2015	http://www.stats.gov.cn/tjzs/tjsj/tjcb/zjxs/200612/t20061213_36342.html
	China Statistical Yearbook	Provincial; annual	1980–2015	http://www.stats.gov.cn/tjsj/ndsj/
Investment in air pollution treatment	National Bureau of Statistics of the People's Republic of China online database	Provincial; annual	2003–2015	http://www.stats.gov.cn/

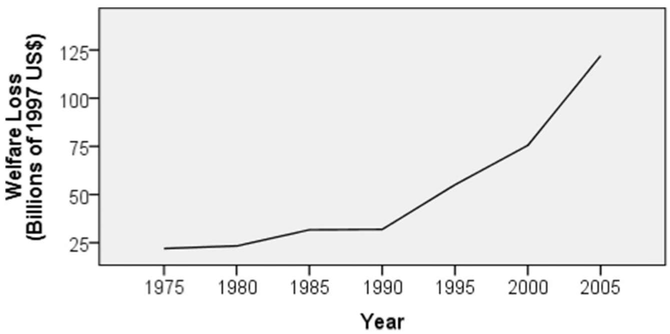

Fig. 3. Welfare loss due to ozone and particulate matter in China (Matus et al., 2012).

all countries. Hence, policy decisions should not be based purely on the numerical results derived from any single health cost accounting model. Policy-makers are suggested to check if the results generated from any CGE models will fit the context of China. For instance, it would be wise to compare the results generated from EPPA (version 4) models, with that of REACH (Zhang et al., 2017a), or the AIM/CGE-China model (Xie et al., 2016), which have taken into account the China-specific economic/energy conditions in their model design, when making environmental policy decisions for China.

6.2. Select the accounting method and follow the guidelines on econometrics selection

Among all economic method used in the models, SMM has an out-

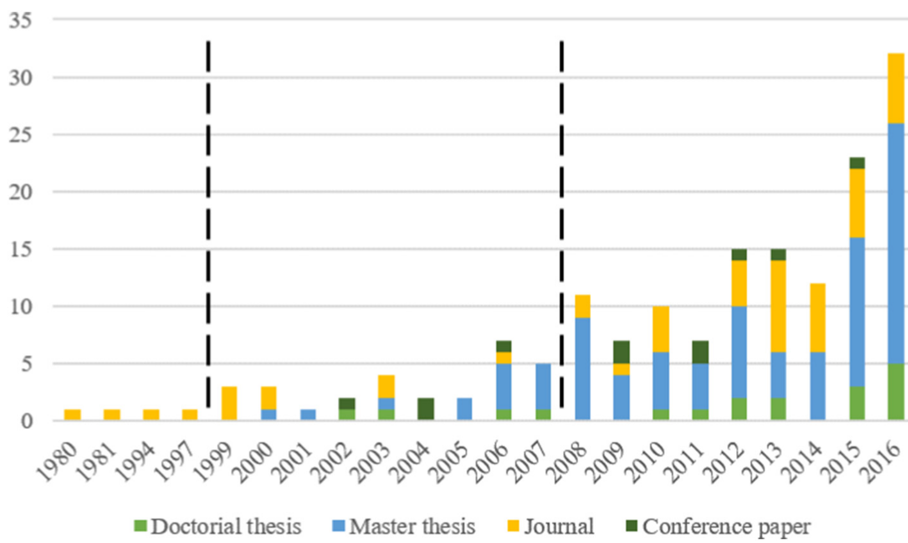

Fig. 4. The number of publications on air pollution-related health cost accounting in China.
Data source: www.cnki.net.

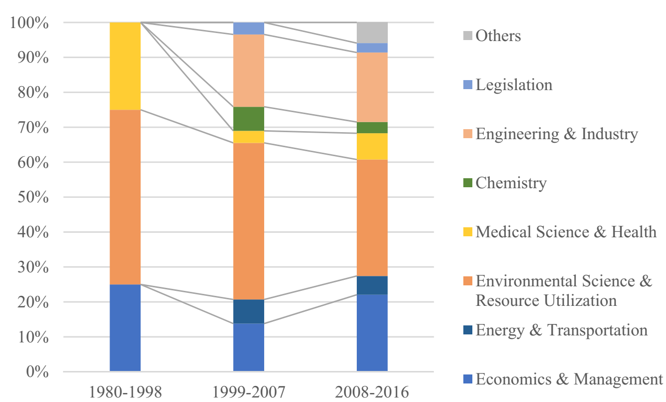

Fig. 5. Research fields of publications on air pollution-related health cost accounting in China.
Data source: www.cnki.net.

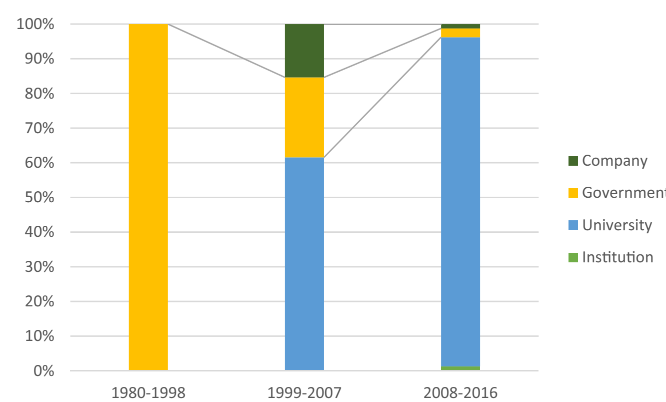

Fig. 6. Research organizations of publications on air pollution-related health cost accounting in China.
Data source: www.cnki.net.

quality back to the current level (Matus et al., 2012). Future dynamic model should address the socio-economic impacts, including benefits or losses of air pollution polices to provide a more robust policy picture. In addition, these CGE models have taken on the assumptions that reflect the countries' specific economic development (e.g. technical ability, elasticity of substitution and transformation, and exogenous variables such as national endowments of labor, capital, land, natural resources) (Berrittella et al., 2006; De Melo and Robinson, 1989; Doroodian and Boyd, 2003; Okagawa and Ban, 2008), which may not be applicable to

standing performance, since it reveals public evaluation on environmental goods by looking at the existing market price, instead of depending on the questionnaire survey. Such features may provide a higher objectivity and credibility to the research results, making SMM more suitable for evaluating the non-tradable air quality. However, this method has yet to be applied in China and requires further development. As for HPA, most current research investigate only one single good. This leads to bias and incomprehensive consideration issues. In the future, prices of multiple goods shall be integrated into the same

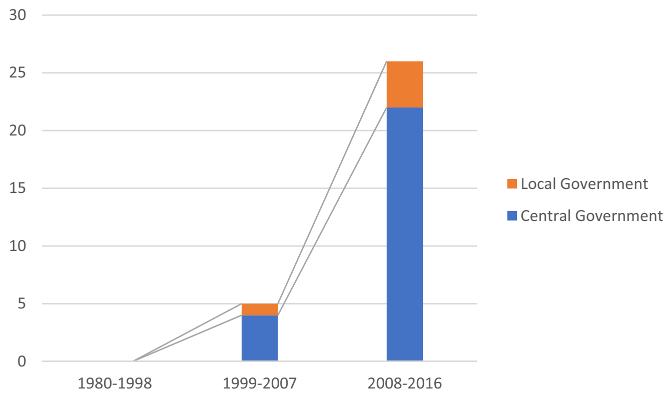

Fig. 7. Funding resource and number of funded publications in air pollution-related health cost accounting in China.
Data source: www.cnki.net.

research to more comprehensively account for the health cost of air quality degradation.

In practice, when selecting econometrics, the following principles are recommended. First, outline the major target of one's health cost accounting research, select the proper methods accordingly with reference to Table 7. Second, when high accuracy and objectivity are the keys, DMM is preferred to other accounting methods. Third, when there are strong limitations on time or funding, BTM can be a good choice. Fourth, when more than one accounting method are being integrated and used for health cost accounting, one should ensure that the assumptions that govern these accounting methods should be consistent with each other.

6.3. Follow the principles on globally-applicable and China-specific parameter selection

Given the pros and cons of the global and China-specific parameters, the following recommendations are made in selecting parameters. First, check if comparison across different countries is needed, globally-applicable parameters are preferred. Second, check if high data accuracy is needed, China-specific parameters are preferred, especially for certain parameter values. In reality, globally-applicable parameters normally reflect the global situation, and are often derived from a small sample size in China, hence not statistically significant. Third, check if data is available; indicators that could be calculated from the existing official yearbooks or documents are preferred, which may reduce impacts due data validity, and the extra research time and finance spent in data verification.

6.4. Provide the guidelines for hybridizing econometrics in the China-specific aggregative indicator

China-specific frameworks based on multiple economic measures may facilitate all-round evaluation, but it may lack the credibility due to potential contradictory assumptions adopted by divergent economic methods. It is necessary that clear instructions can be provided with regard to when certain economic approaches can be hybridized.

6.5. Develop proper health accounting methods for the values of life in China

The value of life derived from BTM or HCA in China-specific studies may be problematic due to regional differences, ethical disputes, ill-founded designation. The main challenge of using the standardized VSL for China, as suggested by WHO, is the need to rely on large-scale surveys via CVA. A more cost-efficient method of VSL estimation is preferred for health cost accounting in China.

6.6. Utilize deep learning and big data analysis in future health cost accounting

Deep learning models and big data analysis have the potentials to enhance the accuracy of health cost analysis at the sub-national level or at even finer spatial scales, and target at a smaller/more vulnerable group of population, for instance, the COPD/asthma patients. The change in health cost accounting target would help air pollution induced health cost accounting move beyond traditional national, macro-area accounting, to more specific, micro-area accounting, to provide more specific environmental policy insights into how one can more precisely control and mitigate area-based air pollution at the sub-regional or city-district level, while developing more health-oriented policies to improve the health of the most vulnerable groups in a specific region (Li et al., 2018). Scholars have started using deep learning models and big data to formulate maps of air pollution distribution at high resolution (J.Y. Zhu et al., 2017), while socio-economic data at comparable resolution are in shortage. At the same time, calculating health costs at a finer spatial resolution is crucial for developing proper regional-specific policies and laying a good foundation for other scientific researches. Enhancing socio-economic data precision via big data and deep learning models might be a possible research direction for health cost accounting at a high spatial resolution in the future.

6.7. Strengthen international cooperation

As of to date, few studies have covered the health cost accounting of air pollution in China, and very few have been conducted jointly by the Chinese and international researchers. Chinese researchers may have a better understanding of China's own local characteristics, while international counterparts may possess more international experience and global knowledge. Strengthening international communication and cooperation in health cost accounting would eventually benefit both parties mutually.

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