The Annals of Regional Science (2019) 63:269–293
https://doi.org/10.1007/s00168-019-00924-z

SPECIAL ISSUE PAPER

Health effects of ozone and particulate matter pollution in China: a province-level CGE analysis

Kyung-Min Nam[1] · **Xu Zhang**[2] · **Min Zhong**[3,4] · **Eri Saikawa**[4] · **Xiliang Zhang**[2]

Received: 29 March 2019 / Accepted: 28 June 2019 / Published online: 9 July 2019

Abstract

In this study, we estimate the cost of $PM_{2.5}$ and O_3 pollution in China and explore how it differs by province. For the analysis, we extend the China Regional Energy Model—a computable general equilibrium model of the Chinese economy—to explicitly represent the pollution-health linkage within a larger economic system. Our results show that health damage from air pollution in China is substantially large. For each year between 2010 and 2030, China's welfare loss from excess pollution is estimated to be 3.2–5.1% of the baseline level when welfare is measured as the sum of consumption and leisure. The $PM_{2.5}$ share of the costs was > 13 times as large as the O_3 share, and premature deaths from chronic exposure to $PM_{2.5}$ were the single most important health endpoint, accounting for ≤ 56% of the total costs. Cross-regional heterogeneity is substantial, and populous and wealthy Eastern China is subject to particularly large health damage. When the size of provincial economies is controlled for, however, the dominance of the eastern region is less obvious and several inland provinces (e.g., Henan, Shanxi, and Chongqing) also suffer high pollution-health costs, due to low air quality and fast productivity growth. Finally, broader economic loss from inefficient resource allocation and its cumulative effects, which is often neglected in static analysis, accounts for > 29% of the total costs. Overlooking this cost component will, in particular, lead to substantial underestimation for China's central and western regions, whose economies are growing fast.

✉ Kyung-Min Nam
kmnam@hku.hk

✉ Xiliang Zhang
zhang_xl@tsinghua.edu.cn

[1] Department of Urban Planning and Design, The University of Hong Kong, Pokfulam, Hong Kong, SAR, China

[2] Institute of Energy, Environment and Economy, Tsinghua University, Beijing 100084, China

[3] Environmental Analysis and Outcomes Division, Minnesota Pollution Control Agency, St Paul, MN 55155, USA

[4] Department of Environmental Sciences, Emory University, Atlanta, GA 30322, USA

JEL Classification C68 · D58 · I18 · Q51 · Q52 · Q53

1 Introduction

China has long suffered excess air pollution, and the degree of that pollution has reached a level whose abatement requires immediate public action. Particulate matter (PM) concentrations in China's major cities, for example, exceed the level recommended by the World Health Organization (WHO) by a factor of five or even higher (WHO 2016). Numerous epidemiological studies show that excess air pollution carries severe health risks, posing a serious threat to human welfare. China's recent move toward "rebalancing"—structural transformation aimed at sustainable development—reflects growing recognition of the problem within its policy circles (Nam 2019).

Pollution control in China has been gradually expanded, but further spurring of mitigation efforts seems necessary, given the magnitude and urgency of the excess pollution problem. A robust impact study, examining the socioeconomic costs of neglecting excess air pollution, is perhaps a first step to raising public awareness and thus gaining broader public support. Such a study not only strengthens the need for mitigation actions with scientific evidence but also helps identify the type and magnitude of the actions required. However, the assessment of pollution-caused welfare damage has remained challenging due to the absence of market data that can be used to directly measure the cost of degraded air quality or the benefit of clean air (OECD 2016; World Bank and IHME 2016). A widely accepted approach to valuing air pollution is to treat the human body as a receptor of changed air quality (e.g., Ostro and Chestnut 1998; EPA 1999; Holland et al. 2005; Saikawa et al. 2009; Vennemo et al. 2006; West et al. 2006). Focusing on the pollution-health linkage allows us to incorporate economic transactions (e.g., medical expenses or the lost wages and leisure time required to combat illness) into a larger assessment framework, and thus to integrate environmental externalities into broader economic analyses.

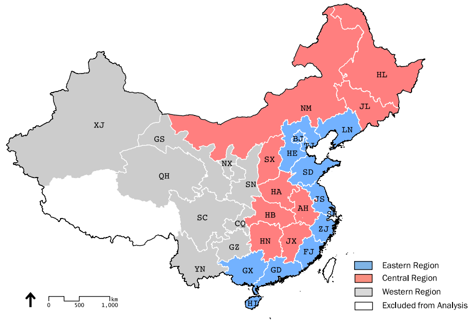
Many studies have been conducted to estimate the adverse economic effects of air pollution in China, focusing on human health. Without exception, they have arrived at very large estimates, ranging from 3 to 5% of China's historic gross domestic product (GDP) (Nielsen and Ho 2013; Zhang et al. 2017). As alarming as these estimates are, they may actually be underestimates, given the studies' methodological limitations (Matus et al. 2012; World Bank and IHME 2016). In brief, the majority of earlier studies draw aggregate damage functions and estimate pollution-health costs by applying these functions to certain air-quality targets in a static manner (e.g., Aunan et al. 2004; Hirschberg et al. 2003, O'Connor et al. 2003; World Bank and SEPA 2007). Such aggregate damage-function approaches, however, do not explicitly identify how degraded air quality reshapes the existing supply and demand in the market and thus at best can consider only part of the overall economic impacts. In addition, point estimates based on damage functions also fail to capture the pollution-health effects that remain in the economy beyond a short time period (e.g., labor losses owing to premature deaths).

More recent studies conduct dynamic analysis but treat China as a single entity—this is another critical limitation (e.g., Matus et al. 2012; World Bank and IHME 2016). A coarse spatial unit of analysis is clumsy in reflecting China's subnational heterogeneity in many aspects, such as air quality, urban population, and labor productivity, and can undermine the robustness of the results. A recent city-level study by Nam et al. (2018), for example, finds that neglecting cross-district variations even within a single city (Hong Kong) in terms of PM levels and socioeconomic conditions can lead to substantial underestimation, compared to when the district is adopted as a spatial unit of analysis. Such noise arising from spatial aggregation is likely even more obvious at the national level, given the magnitude of internal heterogeneity (Li and Nam 2017; Nam 2017; Nam and Reilly 2013; Thompson et al. 2014). Accordingly, subnational details are essential for the analysis of pollution-health effects in China, whose local conditions vary considerably by region.

Little attention to ozone (O_3) and the direct application of Western epidemiological evidence to China are other key dimensions subject to improvement. Many studies (e.g., Xie et al. 2016; Zhang et al. 2017) focus solely on PM, but excluding O_3 from analysis is a potential source of underestimation, given the solid empirical evidence on O_3-associated health damage (Selin et al. 2009). Additionally, using Western epidemiological findings for China, which is common in the literature (e.g., Matus et al. 2012; Xie et al. 2016), can lead to substantial overestimation given the nonlinearity identified in different pollution bands (Burnett et al. 2014; Cohen et al. 2017). In general, the region-neutrality assumption in concentration–response relationships is not supported, and marginal health effects of a unit pollution increase tend to decline with increased ambient concentration levels.

This study is motivated to improve such major methodological limitations and thus the robustness of estimated results. We examine the magnitude of pollution-health costs in China and its cross-provincial variations, with a dynamic and integrated assessment method where an economic simulation model is coupled with an atmospheric chemistry model. Our method explicitly describes the pollution-economy linkage and allows us to trace how economy-wide outputs may change over multiple time periods in response to a given pollution shock. We take the province as the unit of analysis to consider China's subnational heterogeneity, and our analysis focuses on both PM and O_3.[1] Of the two popular PM measurement classes for health impact studies, we focus on finer particles with an aerodynamic diameter of ≤ 2.5 µm ($PM_{2.5}$), rather than those with a diameter of ≤ 10 µm (PM_{10}), given the former's more direct relevance to human health. We have also incorporated recent Chinese epidemiological evidence to avoid potential overestimation resulting from dependence on the Western estimates.

[1] PM is either directly emitted from anthropogenic and natural/biogenic sources or produced through complex gaseous reactions in the atmosphere, often involving sulfur dioxide (SO_2), nitrogen oxides (NO_x), volatile organic compounds (VOCs), and ammonia. In contrast, O_3 is not directly emitted but is only formed through chemical reactions between NO_x and VOCs in the presence of sunlight.



CREM Regions & Sectors

Chinese Provinces and Municipalities			
BJ	Beijing	HB	Hubei
TJ	Tianjin	HN	Hunan
HE	Hebei	GD	Guangdong
HA	Henan	GX	Guangxi
NM	Inner Mongolia	HI	Hainan
LN	Liaoning	CQ	Chongqing
JL	Jilin	SC	Sichuan
HL	Heilongjiang	GZ	Guizhou
SH	Shanghai	YN	Yunnan
JS	Jiangsu	SX	Shanxi
ZJ	Zhejiang	SN	Shaanxi
AH	Anhui	GS	Gansu
FJ	Fujian	QH	Qinghai
JX	Jiangxi	NX	Ningxia
SD	Shandong	XJ	Xinjiang

Non-energy Production Sectors	
AGR	Agriculture and other primary sectors
OMN	Minerals
LID	Light industry
OIL	Petroleum and coal products
EID	Energy-intensive industry
TME	Transport and electronic equipment
OID	Other secondary sectors
GDT	Gas manufacture and distribution
WTR	Water
TRD	Trade
TRP	Transport
OTH	Other tertiary sectors

Non-Chinese Regions	
USA	The United States
EUR	Europe
ROW	Rest of the World

Energy Production Sectors	
COL	Coal
CRU	Oil
GAS	Natural gas
ELE	Electricity

Fig. 1 CREM's regional and sectoral aggregations

2 Theoretical framework and method

In this study, we explore two main research questions—how large is the socioeconomic cost of excess air pollution in China, and how does it differ by province?—by extending the China Regional Energy Model (CREM) for health effects analysis. In brief, CREM is a recursive-dynamic computable general equilibrium (CGE) model built on 2007 provincial input–output tables and energy data from China and includes 33 regions (30 Chinese provinces [except Tibet] and three global regions) and 16 production sectors (Fig. 1). The model has three agents—households and firms maximize utility and profit, respectively, while the government is modeled as a passive entity in charge of tax collection and redistribution—and conventional closure rules—market clearance, income balance, and zero profit conditions—are applied for an equilibrium.[2] A standard version of CREM is essentially an economic model, lacking representation of the link between air pollution and the economy, and thus does not immediately offer the capacity to explore our research questions. Hence, it must be extended to represent the pollution-economy dynamics, and this extension is our primary methodological contribution. Following conventional approaches, we treat the human body as a receptor of degraded air quality and create a link between air quality and the economy by focusing on pollution-health effects. We call the version of CREM extended for health-effects analysis CREM-HE.

We apply CREM-HE within an integrated assessment framework, in combination with a scientific model of atmospheric chemistry (Fig. 2). Baseline emissions data from the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) database (IIASA 2018) for years of our analysis are translated into O_3 and $PM_{2.5}$ concentrations with the Weather Research and Forecasting model coupled to Chemistry (WRF-Chem) (Fig. 3). Then, morbidities and mortalities associated with exposure to pollution are computed using epidemiological relationships, and their effects on the economy are simulated with CREM-HE. A great merit of the CGE model is that it is able to capture not only direct economic costs associated with labor/leisure

[2] See Zhang et al. (2013) for further technical details on a standard version of CREM.

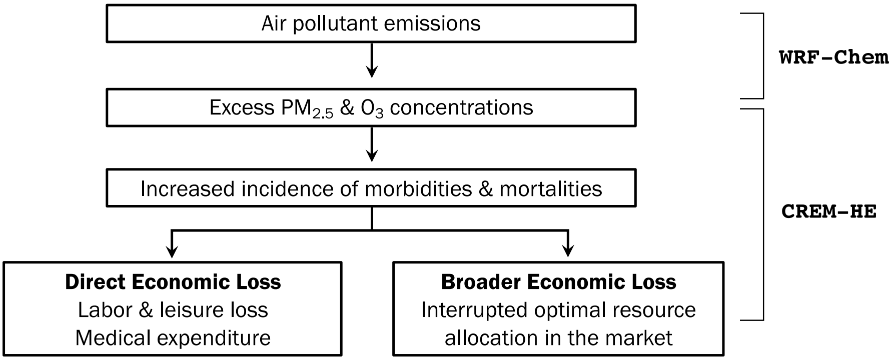


Fig. 2 Analytic framework

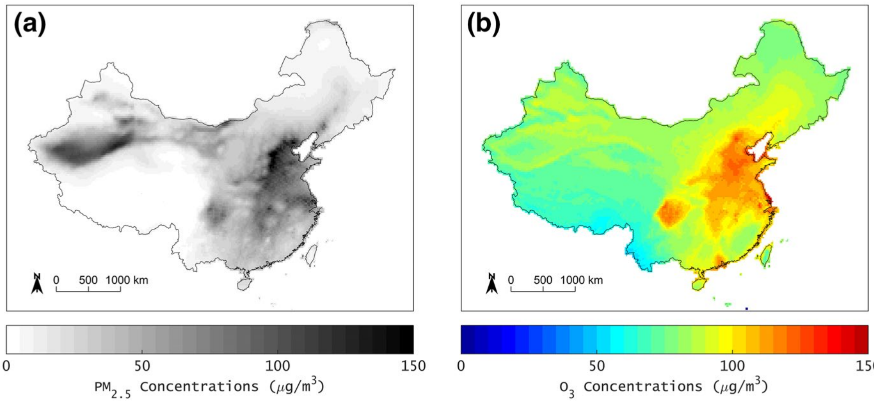


Fig. 3 Baseline air quality layers, 2015: **a** $PM_{2.5}$, 24-h mean; **b** ground-level O_3, 8-h daily maximum. *Source*: Created from WRF/Chem-simulated data

loss and medical expenditure but also broader economy-wide inefficiency caused by interrupted resource allocation and its cumulative effects over time (Reilly et al. 2013).

In detail, CREM-HE is modeled to respond to an exogenous air-quality shock in such a way that the economy requires the household sector to produce increased amounts of pollution-health-effects mitigation services, using labor, leisure, and service inputs drawn from other production sectors (Fig. 4a). In this framework, excess pollution imposes both direct (i.e., direct labor and leisure losses from increased morbidities and mortalities) and indirect costs (i.e., efficiency losses from interrupted optimal resource allocation) on the economy. The household production sector, shown in the Mitigation of Pollution Health Effects column under Household Services in the figure, provides final consumers with a pollution-health service whose amount is determined by the increased incidences of morbidity and mortality caused by acute exposure. Production of a pollution-health service requires medical

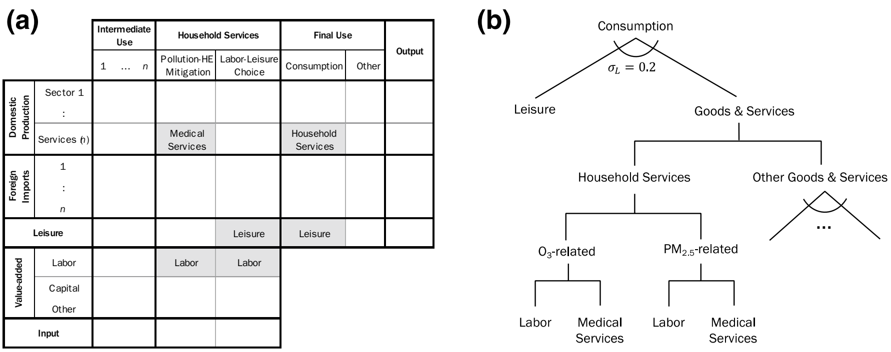


Fig. 4 Structure of CREM-HE: **a** extended social accounting matrix; **b** simplified production nest. *Source*: Modified from Matus et al. (2008), p. 67 and Nam et al. (2010), p. 5061

services (drawn from the service sector) and household labor as inputs and thus reduces the amount of service and labor inputs available for other uses. That is, pollution-created demand for health services can be met only at the expense of reduced outputs in other sectors, and its net effects on the economy can be negative.

Pollution-caused health effects are then modeled as a Hicks-neutral technical change; that is, increased (or decreased) demand for pollution-health services requires proportionally more (or less) of all inputs to deliver the same level of service. The consumption nest shown in Fig. 4b provides an alternative way to look at the extended model. As shown in the figure, the key extensions in the model include (1) leisure as a consumption component and (2) a Household Services sector that is dedicated to mitigating pollution-health effects and has separate production nests for O_3 and $PM_{2.5}$—the two most important air pollutants from a health effects perspective. The substitution elasticity (σ_L) is parameterized to reflect the own-price elasticity of labor supply, which is a widely accepted concept in the economics literature (Babiker et al. 2003). We apply the Leontief production structure to the Household Services sector in relation to other inputs and factors and among different health endpoints. The mortality effects on the economy are modeled as a negative shock to labor productivity, resulting in a loss of work and leisure hours.

Premature deaths from chronic exposure to $PM_{2.5}$ are treated differently from other health endpoints, as the cardiopulmonary diseases that lead to these mortalities take a fairly long time to develop with only minimal explicit effects during most of the development period. Mortalities in this category can occur to those with normal health conditions and do not require medical services or work/leisure hour loss while they are alive. CREM-HE is modeled to keep track of the lifetime exposure of each age cohort and to remove a fraction of the population groups subject to this mortality category prematurely from the workforce. Premature deaths from chronic exposure affect the economy beyond the specific time period in which they occur, generating dynamic, cumulative effects. For example, assuming 65 to be the average retirement age, if an individual dies at 45 years of age, the economy loses 20-year worth of labor from this individual. CREM-HE tracks these mortalities in each period and adds them forward until the time that each individual no longer remains in the workforce and such mortalities thus would not constitute an explicit economic loss to the economy. The model also conducts a parallel computation for leisure loss, assuming that individuals who left the workforce would no longer earn wage incomes and thus have leisure time alone.

3 Case calculation and valuation

Modeling health effects associated with air quality require the concentration–response (CR) function as key input, and their translation into monetary terms requires a valuation table. In this section, we determine CR functions in China's context with reference to the epidemiological surveys conducted in China and a valuation strategy for each health endpoint. Among conventional air pollutants, we in particular focus on ozone and particular matter, which are known to account for most of the pollution-health costs (Nam et al. 2010; Matus et al. 2012).

3.1 CR functions

The CR function describes how incidence of morbidity or morality responds to a unit pollution level increase. The CR function can be constructed from relative risk (RR) or excess risk (ER) estimates, available in the epidemiological literature. Here, RR is the ratio of incidence rates observed at two different exposure levels and shows the percentage increase in the rate for the experimental group (i.e., those who were exposed to pollution) from the baseline level for the control group (i.e., those who were not exposed). ER conveys similar information, but takes the difference, not the ratio, between the incidence rates where the baseline rate is normalized to one.

For short-term effects estimation associated with acute exposure to pollution, we consider three dimensions—health endpoint i, region r, and time t—and use the CR function shown in Eq. 1 (Nam et al. 2018).

$$y_{irt}^{\mathrm{SE}} = \frac{1}{10}\left(1 - \frac{1}{\mathrm{RR}_i}\right) \cdot F_i \cdot P_{rt} \cdot x_{rt} \tag{1}$$

In the equation, y^{SE} is the net incidence of morbidities and premature deaths attributable to acute exposure to pollution level x (measured in μg/m^3), and RR, F, and P refer to relative risk, baseline incidence rate, and total population, respectively. The constant $1/10$ of the right-hand side of the equation is to convert the available RR estimates for a 10 μg/m^3 pollution band into a unit value defined on a 1 μg/m^3 concentration change.

In the case of long-term effects associated with chronic exposure to $\mathrm{PM}_{2.5}$, the integrated exposure–response (IER) function, shown in Eq. 2, is used to consider a nonlinear epidemiological response with regard to ambient pollution level (Burnett et al. 2014).

$$\mathrm{RR}(x) = \begin{cases} 1 & \text{for} \quad x < x_{cf} \\ 1 + \alpha\left(1 - e^{-\gamma\left(x - x_{cf}\right)^{\delta}}\right) & \text{for} \quad x \geq x_{cf} \end{cases} \tag{2}$$

Here, α, γ, δ, and x_{cf} are parameters and are as defined in Burnett et al. (2014). The IER posits that the marginal effect of a unit pollution level increase on mortality rate tends to decline as a background ambient pollution level increases (Cohen et al. 2017).

The CR function for long-term effects having four dimensions—health endpoint i, age cohort j, region r, and time t—is then constructed as shown in Eq. 3 (Nam et al. 2018).

$$y_{ijrt}^{\mathrm{LE}} = \left(1 - \frac{1}{RR_i\left(x_{rt}\right)}\right) \cdot F_i \cdot w_j^F \cdot P_{rt} \cdot D_{jrt} \tag{3}$$

In the equation, y^{LE} is the number of premature deaths that occurred due to chronic exposure to pollution level x, and RR is a nonlinear function of x, as described in Eq. 2. F and P are as defined earlier, and D_{jrt} is the share of age group j in region r at time t. Addition of an age dimension j is to consider age-varying long-term effects, and F_i is adjusted with j-specific weight (w_j^F) (Matus et al. 2012). Here, w_j^F is defined as the relative importance of cardiopulmonary diseases (CPL) in all-cause mortality rates for age group j (M_j^{CPL}/M_j), compared with that for entire population group (M^{CPL}/M) (Nam et al. 2010).

3.2 Health endpoints and selection of RR estimates

In this study, we consider nine health endpoints in total, whose epidemiological relationship with O_3 and $PM_{2.5}$ exposure is well established (WHO 2016). Five of them fall into the acute-exposure category: mortality from acute exposure (AM), hospital admissions associated with cardiovascular (CHA) or respiratory diseases (RHA), emergency room visits (ERV), and outpatient visits (OV). The other four health endpoints are cardiopulmonary diseases, known as the main causes of premature deaths associated with long-term exposure to $PM_{2.5}$ pollution. This chronic exposure category includes ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), and lung cancer (LC). These diseases take substantial time to develop with chronic exposure, and gradual damage to heart and lung functionalities over a long-term period eventually reduces life expectancy.

A good number of RR estimates are available for acute-exposure endpoints, but are subject to significantly large standard deviations, depending on the time and place each study is conducted. A main reason is the nonlinearity that exists in the epidemiological relationship: marginal health effects of a unit pollution level change tend to decline when absolute ambient pollution levels increase. Accordingly, RR estimates for China, which suffers fairly high O_3 and PM levels, tend to be lower than those for Western countries located in much lower pollution bands. Given this fact, we avoid applying Western RR estimates to China, and consider only those estimates from China-conducted studies, displayed in Figs. 5 and 6. Among these Chinese estimates, we eventually pick one for each endpoint by prioritizing those estimates located near the median and subject to lower levels of uncertainty. The RR estimates finally chosen for CREM-HE are listed in Table 1.

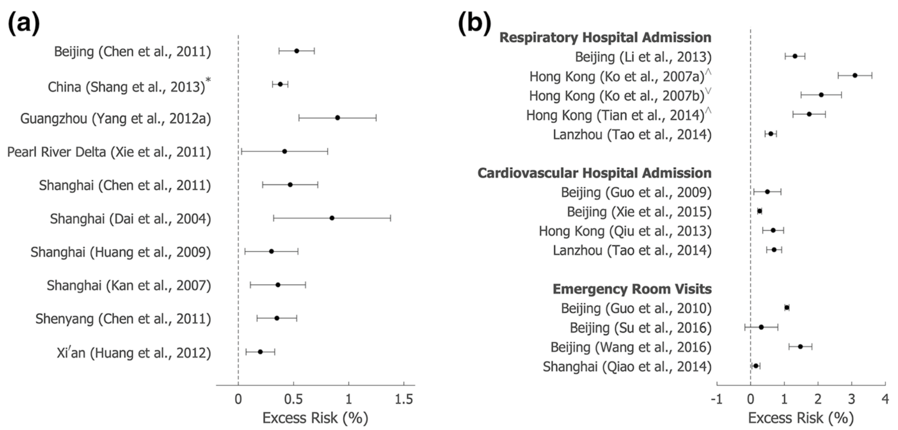


Fig. 5 Excess risk (%) per 10 μg/m^3 increase in $PM_{2.5}$ concentrations: **a** mortality from acute exposure; **b** morbidities. *Note*: *Meta analysis of multiple Chinese studies; ^estimate for COPD; $^{\vee}$estimate for asthma

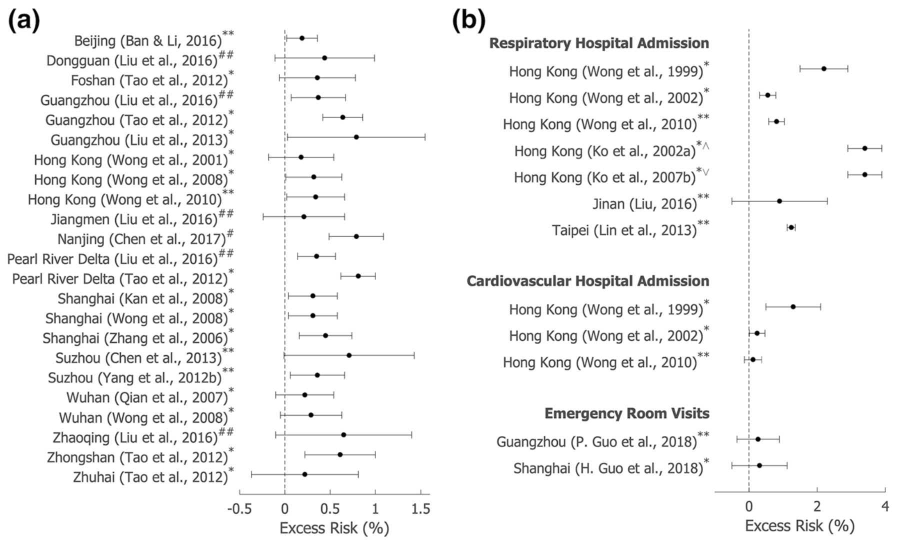


Fig. 6 Excess risk (%) per 10 μg/m^3 increase in O_3 concentrations: **a** mortality from acute exposure; **b** morbidities. *Note*: *8-h mean; **8-h daily maximum; #1-h mean; ##24-h mean; ^estimate for COPD; $^{\vee}$estimate for asthma

For chronic exposure effects analysis, we adopt IER parameter estimates by Morita et al. (2014), based on the 2013 Global Burden of Disease study (GBD 2013 Risk Factors Collaborators 2015) database (Table 2). As explained earlier, premature mortalities from chronic exposure take a long time to develop and mostly occur to adult groups. In this regard, we assume that only those at the age of ≥ 30 are subject to the long-term effects, following the literature (e.g., Bickel and Friedrich

Table 1 Relative risk estimates used in this study for short-term exposure endpoints. *Source*: Created by the authors

Impact category	Pollutant	Relative risk[a]	C.I. (95%)		Source	Studied region
			Low	High		
Mortality from acute exposure (AM)	O_3	1.0031	1.0004	1.0058	Kan et al. (2008)	Shanghai
	$PM_{2.5}$	1.0042	1.0003	1.0081	Xie et al. (2011)	China[c]
Respiratory hospital admission (RHA)	O_3	1.0081	1.0058	1.0104	Wong et al. (2010)	Hong Kong
	$PM_{2.5}$	1.0132	1.0102	1.0161	Li et al. (2013)	Beijing
Cardiovascular hospital admission (CHA)	O_3	1.0012	0.9987	1.0037	Wong et al. (2010)	Hong Kong
	$PM_{2.5}$	1.0066	1.0036	1.0097	Qiu et al. (2013)	Hong Kong
Emergency room visits (ERV)	O_3	1.0027	0.9965	1.0124	Guo et al. (2018b)	Guangzhou
	$PM_{2.5}$	1.0148	1.0114	1.0183	Wang et al. (2016)	Beijing
Outpatient visits (OV)	$PM_{2.5}$	1.0034[b]	1.0010	1.0059	Xu et al. (1995)	Beijing

[a]Relative risk is defined on an increment of 10 μg/m^3 in pollutant concentrations

[b]Converted from an estimate on TSP, applying the $PM_{2.5}$/TSP ratio of 1/3 (Burnett et al. 2014; Cao et al. 2011)

[c]Meta analysis of multiple epidemiological studies conducted in Chinese cities, including Beijing, Shanghai, Chongqing, Wuhan, Taiyuan, and Hong Kong

Table 2 IER parameters used for long-term effects analysis. *Source*: Morita et al. (2014), p. 14661

Health Endpoint (i)	α_i	γ_i	δ_i
Ischemic heart disease (IHD)	9.56E−01 (1.12E+00, 1.24E+00)	7.95E−02 (4.81E−02, 3.38E−02)	4.80E−01 (4.08E−01, 8.61E−01)
Stroke	1.09E+00 (9.36E−01, 1.42E+00)	3.76E−02 (2.35E−02, 2.07E−02)	8.61E−01 (5.50E−01, 1.16E+00)
Chronic Obstructive Pulmonary Disease (COPD)	1.54E+01 (5.70E+00, 7.89E+01)	1.10E−03 (5.92E−04, 4.37E−04)	6.83E−01 (8.68E−01, 6.27E−01)
Lung Cancer (LC)	2.11E+02 (4.40E+01, 2.23E+02)	8.88E−05 (3.93E−05, 1.81E−04)	7.37E−01 (1.01E+00, 6.60E−01)

For all cases, x_{cf} is given as 7.5 μg/m^3; 95% confidence intervals are within parentheses

Table 3 Costs associated with short-term exposure health endpoints

Health endpoint	2007 US$
Mortality from acute exposure[a]	10,602
Hospital admission, respiratory[b]	519
Hospital admission, cardiovascular[b]	1128
Emergency room visits[c]	53
Outpatient visits[b]	26
Chronic bronchitis[d]	3332

[a]Half the value of a life year computed from Hoffmann et al. (2017), with urban–rural population and income ratio adjustments

[b] 2005 estimates by Lei and Ho (2013) are adjusted for 2007 by using the GDP deflator. Final values include the value of associated leisure loss, referring to Yang (2004) and Matus (2005)

[c]Twice the value for an outpatient visit is assumed, based on World Bank and SEPA (2007)

[d]1999 estimates by Zhou and Hammitt (2007) are adjusted for 2007 by using GDP deflator

2005; Matus et al. 2012; Nam et al. 2010). The incidence of such premature deaths also tends to be an increasing function of age (i.e., cumulative time of being exposed to pollution), and these age-varying effects are considered with an age-specific adjustment term w_j^F in Eq. 3.

3.3 Valuation

Health damage from air pollution incurs to the economy both market (increased medical expenditure and reduced labor hours) and non-market (leisure loss) impacts. Accordingly, morbidity and mortality cases computed using CR functions are valuated in monetary terms, considering both impact dimensions. For the valuation of health endpoints associated with acute exposure, we apply the valuation table constructed from available market and surveyed data (Table 3). For hospital admission and outpatient visit categories, we adopt the 2005 estimates by Lei and Ho (2013),

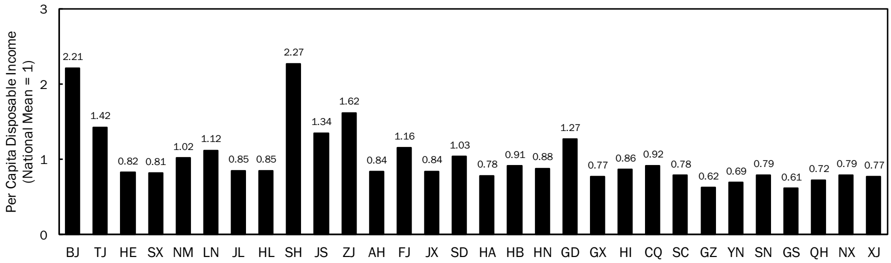


Fig. 7 Disposable income per capita by province, 2015. *Source*: Created from National Bureau of Statistics of China (2016)

which include medical expenditure and associated wage loss computed directly from the P.R.C. Ministry of Health statistics. We then add our estimates for leisure loss to these estimates[3] and adjust them for 2007 by using the GDP deflator. In the absence of available statistics, we assume twice the costs for outpatient visits for the emergency room visit category, referring to World Bank (1997). China's national estimates are then adjusted for each region, using cross-provincial per capita disposable income ratios (Fig. 7).

Valuation of mortality is based on a stated preference approach (Viscusi et al. 2005). Mortalities from acute exposure to excess PM pollution occur mostly to those whose health conditions are already impaired and who are close to death from other causes (Pope et al. 1995, 2002). For this reason, labor and leisure loss associated with premature deaths from acute exposure is conventionally valuated at a quarter to a full life year (Holland et al. 1999, 2005). In this study, we assume that a mortality from acute exposure incurs to the economy the cost equivalent to half a life year. The value of a life year (VOLY) estimate used for our study is based on the 2006 willingness-to-pay (WTP) survey conducted for three Chinese cities by Hoffmann et al. (2017). The value of statistical life (VSL) estimate, drawn directly from the surveyed results for China, is 2016 US$614,805, and this estimate is further adjusted to 2007 prices considering inflation, income growth, and urbanization ratios. The adjusted VSL estimate for the sample with mean age 54 is then 2007 US$336,685, and the corresponding VOLY at a discount rate of 3% is 2007 US$21,204.

Premature deaths from chronic exposure are valuated in a different way, as they can occur to those with normal health conditions without involving explicit medical expenses. Primary socioeconomic costs associated with this endpoint are related to the loss of the labor and leisure that would not have occurred if those who died prematurely avoided their chronic exposure. Once premature deaths are computed by region and age group, the net loss of labor and leisure is estimated, considering each region's mean life expectancy. Each mortality case in this category is then valuated using mean wage levels for each region, which are endogenously determined within

[3] Leisure loss associated with AM, RHA, CHA, ERV, and OV is assumed to be 77%, 11%, 11%, 18%, and 18% of the total cost, respectively (Holland et al. 1999; Yang 2004).

CREM-HE. A unit leisure loss is evaluated at the same level as a unit labor loss, as lost wage is treated as an opportunity cost of leisure in our model (i.e., each worker has a choice between labor and leisure, and leisure is chosen over labor only when the former is seen as at least as valuable as the latter).

4 Results

4.1 Scenarios

For our analysis, we simulate CREM-HE with four scenarios, each of which assumes different O_3 and $PM_{2.5}$ levels. First, the *Reference* (business-as-usual) scenario assumes no further pollution abatement efforts beyond the existing ones. Baseline O_3 and $PM_{2.5}$ levels used for this scenario are from WRF-Chem with GAINS-East Asia emissions data (ECLIPSE 5Va scenario reflecting China's legislation during the FYP12 period), and CREM-HE is calibrated to simulate baseline gross domestic product (GDP) levels for each region under this scenario. This calibration setup intends to benchmark an extant market equilibrium which already incorporates the effects of historic ambient air pollution (Nam et al. 2010). A pairwise comparison of a counterfactual scenario case with the *Reference* simulation outcomes will then help us analyze the *net* effects of associated policy shocks measured in equivalent variation, which is a standard approach to impact assessment in dynamic CGE studies (Paltsev et al. 2005). Baseline GDP values for past years are set at historic levels drawn from official statistics, and historic provincial growth trends are extrapolated to future years with an assumption of convergence at an annual growth rate of 3% by 2050 (Chen et al. 2017; Zhang et al. 2013).

Second, the *Green* scenario adopts background air quality close to preindustrial levels (10 μg/m^3 for O_3 and 2.5 μg/m^3 for $PM_{2.5}$), which could be achieved with minimal anthropogenic pollution. Third, the *Policy I* scenario assumes that all Chinese regions meet WHO or comparable global pollution control targets (70 μg/m^3 for O_3 and 10 μg/m^3 for $PM_{2.5}$). Finally, the *Policy II* scenario assumes that province-specific $PM_{2.5}$ reduction targets proposed during the 13th Five Year Plan (FYP13) period (2016–2020) are met while O_3 levels in the same period are set at the baseline levels in the *Reference* scenario (see Sect. 4.4 for province-specific mitigation targets).

4.2 National level analysis

Excess $PM_{2.5}$ and O_3 pollution is estimated to cause substantial socioeconomic costs to the Chinese economy during the time period analyzed. Throughout this study, we report the costs in two metrics, using an equivalent variation concept. One is consumption loss, which counts net wages lost due to pollution and thus captures market effects alone; the other is welfare loss, which tracks net changes in both wage and leisure given a pollution shock and thus considers non-market impacts, as well.

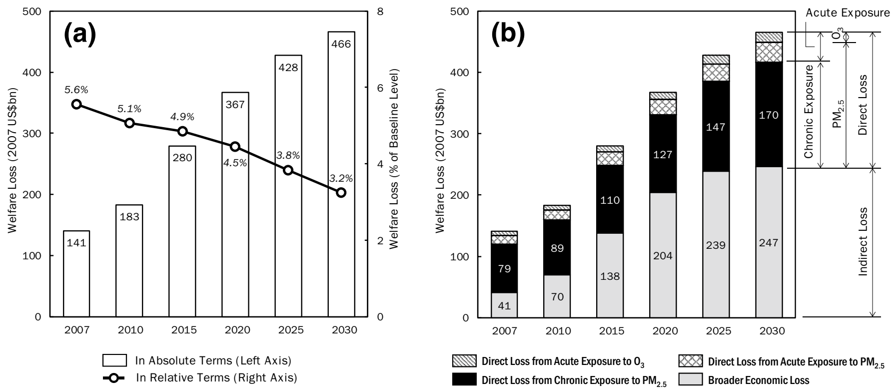


Fig. 8 Pollution-health costs in China, and their decomposition

Table 4 Estimated costs of anthropogenic air pollution in China. *Source*: Numbers within parentheses refer to the shares of baseline consumption or welfare levels

Year	Green (vs. Reference)		Policy I (vs. Reference)	
	Consumption loss	Welfare loss	Consumption loss	Welfare loss
2007	75 (5.6)	141 (5.6)	56 (4.2)	106 (4.2)
2010	98 (5.2)	183 (5.1)	74 (3.9)	139 (3.8)
2015	150 (5.0)	280 (4.9)	113 (3.7)	212 (3.7)
2020	200 (4.6)	367 (4.5)	151 (3.5)	279 (3.4)
2025	238 (4.0)	428 (3.8)	180 (3.0)	326 (2.9)
2030	263 (3.4)	466 (3.2)	199 (2.6)	355 (2.5)

Unit: billions of 2007 US$

Absolute welfare costs from excess pollution continue to rise during the period analyzed, due to solid labor productivity growth (i.e., growing unit value of labor lost from pollution) (Fig. 8a). When the *Green* case is compared with the *Reference* results—health damage associated with anthropogenic pollution—consumption loss in each year between 2007 and 2030 is estimated to range from US$75 billion to US$263 billion, showing an increasing time trend (Table 4).[4] Estimated welfare loss is greater (US$141 billion to US$466 billion), but shows a similar time trend. When the *Policy I* case is compared with the *Reference* case—welfare costs that could be avoided with realistic air-quality control—consumption and welfare loss is US$56 billion to US$199 billion and US$106 billion to US$306 billion, respectively.

When the costs are measured in relative terms, however, they show a declining trend over time. In the *Green-Reference* comparison, the pollution-health costs

[4] Throughout this paper, US$ refers to 2007 US$ unless stated otherwise.

decline from 5.6% of the baseline consumption level (or 5.6% of the baseline welfare level) in 2007 to 3.4% (or 3.2%) in 2030. Similarly, the costs under the *Policy I* scenario drop from 4.2% of the baseline consumption level (or 4.2% of the baseline welfare level) in 2007 to 2.6% (or 2.5%) in 2030. These results are closely related to a declining trend in O_3 and $PM_{2.5}$ pollution since 2015, which contrasts continued national economic growth. That is, China's overall economic growth increasingly exceeds the rate at which the pollution-health costs increase.

When the welfare loss is decomposed into direct and indirect components, each category accounts for a comparable share of the total loss (Fig. 8b). Direct loss includes payment for medical services and labor/leisure hours lost to combat illness and contributes to 44–71% of the total welfare loss. Premature deaths from chronic exposure to $PM_{2.5}$ is the single most important health endpoint sub-group, accounting for 78–80% of the direct loss or 34–56% of the total welfare loss in each year between 2007 and 2030. Morbidities and mortalities associated with acute exposure to O_3 and $PM_{2.5}$ also cause substantial costs, explaining 20–22% of the direct loss. When decomposed by pollutant, $PM_{2.5}$ dominates O_3, in terms of cost share. $PM_{2.5}$ accounted for > 93% of the direct loss, presenting > 13 times the O_3 share.

We also consider indirect loss, arising from cumulative allocative inefficiency and welfare damage. At one level, pollution interrupts an efficient market equilibrium achievable in its absence. Meeting increased demand for health services leads to service-biased resource allocation while reducing inputs available for other sectors and thus curbing their production. At another level, labor loss from pollution reduces regional product, and lower gross income at one time point leads to less consumption and investment in later years, undermining future growth potential. Thus, the effects of welfare loss remain in an economy over a fairly long time period. We call such indirect costs *broader economic loss* (Matus et al. 2012). The broader economic loss category, which is often neglected in the literature, accounts for 30–56% of the total welfare loss. This result suggests that conventional static analysis failing to capture such dynamic dimensions of the pollution-health damage is likely subject to substantial underestimation.

4.3 Cross-regional variations

In absolute terms, welfare loss from pollution is high in the Eastern region (Fig. 9a/c). Guangdong, Jiangsu, Shandong, and Zhejiang, in particular, suffer particularly large welfare damage—e.g., ≥ US$15 billion in 2010 and ≥ US$30 billion in 2030—compared to other Chinese regions, during the period analyzed. Key drivers underlying these results are the absolute size of pollution-exposed urban population and the level of labor productivity, as evinced by the fact that all these provinces are among the most populous and affluent local economies. Air quality also contributes to these results, but not as much as those two drivers do. For example, annual $PM_{2.5}$ and O_3 levels in Guangdong and Zhejiang are substantially below the population-weighted national mean, while those in Jiangsu and Shandong exceed the latter by a wide margin.

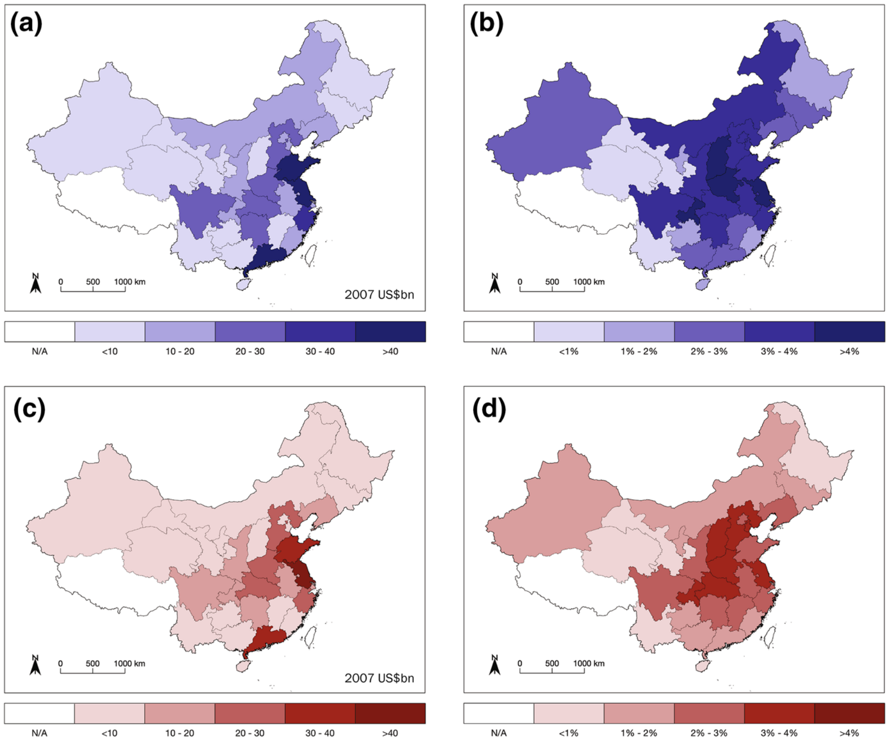


Fig. 9 Provincial distribution of welfare loss in 2010 and 2030: **a** absolute loss in 2010, *Green* (vs. *Reference*); **b** relative loss in 2010, *Green* (vs. *Reference*); **c** absolute loss in 2030, *Policy I* (vs. *Reference*); **d** relative loss in 2030, *Policy I* (vs. *Reference*)

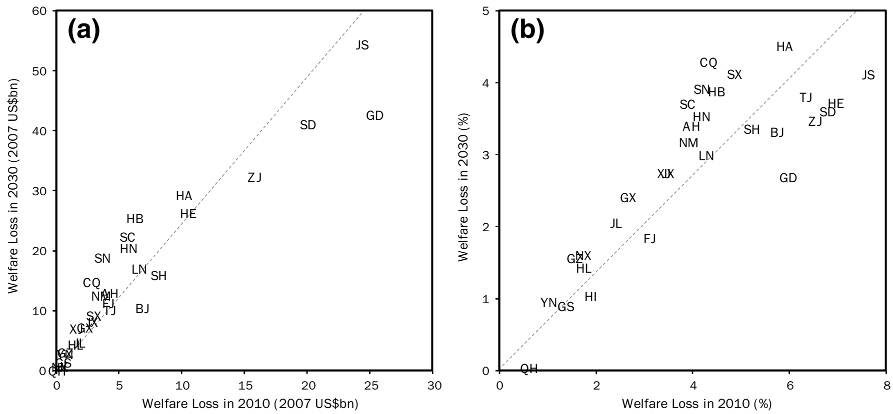


Fig. 10 Pollution-health costs by province in 2010 and 2030: **a** in absolute terms; **b** in relative terms. *Note*: Dashed lines indicate a national mean of province-level welfare damage

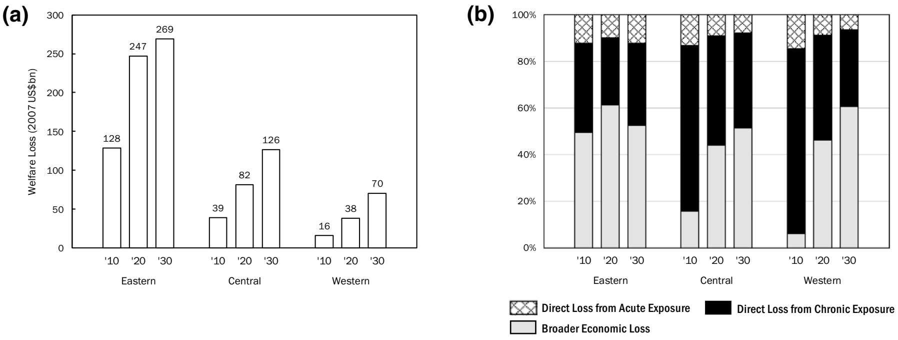


Fig. 11 Pollution-health costs in China, and their decomposition

Despite overall air-quality improvement, the absolute size of welfare loss in most regions tends to increase over time due to population and productivity growth, but the pace of its increase varies across regions. Overall, absolute damage grows faster in inland provinces than coastal regions (Fig. 10a). Most notably, the welfare costs in Hubei, Hunan, Sichuan, Shaanxi, and Chongqing are increased by a factor of 3.5–5.3 between 2010 and 2030, compared with a factor of 1.7–2.2 for Guangdong, Jiangsu, Shandong, and Zhejiang. This result is closely related to East-biased pollution regulations (i.e., greater air-quality improvement in coastal mega-city regions) and cross-provincial productivity convergence (i.e., faster productivity growth in inland regions).

Welfare loss in relative terms shows a slightly different picture (Figs. 9b/d and 10b). When the size of each region's economy is controlled for, northern and inland regions subject to higher pollution levels, as well as populous coastal provinces, tend to suffer greater welfare loss than other parts of China. Those northern regions include the capital region (Beijing, Tianjin, and Hebei) and Shandong, showing a welfare damage of 3.3–7.0% of the baseline levels between 2010 and 2030, and those inland regions include Henan, Shanxi, Chongqing, Hubei, Hunan, and Sichuan, presenting a welfare damage of 3.7–5.9% during the same period. In contrast to the absolute welfare loss case, relative welfare damage tends to decline over time with gradually improving air quality—pollution-health costs grow more slowly than provincial GDP does.

When China is split into three regions, the Eastern region is distinguished from its Central and Western counterparts, in terms of the time trend of regional pollution-health costs (Fig. 11). In absolute terms, pollution-health costs in all three regions tend to increase over time, but the Eastern region suffers much higher welfare damage (US$128–269 billion) than the Central (US$39–126 billion) or Western region (US$16–70 billion). This result is understandable, given that the Eastern region consists of wealthy and populous coastal provinces: a greater urban population in this region is exposed to excess pollution, and the region's higher labor productivity translates the health damage of the exposed population into larger labor and leisure loss value. The growth of the welfare damage in the Eastern region slows down over time—more obviously between 2020 and 2030—while it maintains a quasi-linear

Table 5 Estimated pollution-health costs with lower bounds of CR functions. *Source*: Numbers within parentheses refer to the shares of baseline consumption or welfare levels

Year	Green (vs. Reference)		Policy I (vs. Reference)	
	Consumption loss	Welfare loss	Consumption loss	Welfare loss
2007	32 (2.4)	61 (2.3)	23 (1.7)	44 (1.7)
2010	43 (2.2)	81 (2.2)	31 (1.6)	58 (1.6)
2015	66 (2.1)	123 (2.1)	47 (1.5)	89 (1.5)
2020	88 (2.0)	162 (1.9)	63 (1.4)	117 (1.4)
2025	104 (1.7)	189 (1.7)	75 (1.2)	137 (1.2)
2030	115 (1.5)	205 (1.4)	84 (1.1)	148 (1.0)

Unit: billions of 2007 US$

pattern in the Central and Western regions. The main reason is that compliance with more stringent pollution regulations, which have been imposed on the Eastern region since the FYP12 period, will lead to regional air-quality improvement in greater magnitude, compared with its Central and Western counterparts.

Cost decomposition also exhibits striking cross-regional variations. In the Eastern region, the share of the broader economic loss category remains quite stable at 50–61% of the total welfare loss during the period between 2010 and 2030. In the Central and Western regions, however, the direct loss category dominates the total welfare loss in 2010, but its share becomes increasingly overshadowed by the broader economic loss category over time. In these regions, the share of the broader economic loss is only 6–16% in 2010, but increases to 52–61% in 2030. This is primarily due to relative regional growth rates—the Central and Western regions are behind the Eastern region in development in absolute terms, but are projected to continue to grow faster than the latter, presenting a tendency of beta-convergence. Labor and consumption loss at one time point may lead to lower investment and production in the future time periods in a cumulative manner, and the magnitude of such cumulative effects tends to be greater for faster-growing economies.

4.4 Sensitivity analysis with regard to RR factors

Among the key parameters used for this study, RR factors are subject to relatively large uncertainty, and can potentially introduce substantial noise into our central estimation results presented in earlier sections. For this reason, we conduct a sensitivity analysis with regard to RR, taking its known 95% confidence interval for each health endpoint, and report the upper and lower bounds of the cost estimates. The high and low RR threshold values tested in this section are drawn directly from the literature and are as listed in Tables 1 and 2.

The pollution-health costs estimation results tend to be sensitive to RR parameters. When the *Green* scenario is compared with the *Reference* case, consumption loss associated with O_3 and $PM_{2.5}$ pollution is estimated to range from US$32 billion to US$115 billion (1.5–2.4% of the baseline level) with lower RR thresholds

Table 6 Estimated pollution-health costs with upper bounds of CR functions. *Source*: Numbers within parentheses refer to the shares of baseline consumption or welfare levels

Year	Green (vs. Reference)		Policy I (vs. Reference)	
	Consumption loss	Welfare loss	Consumption loss	Welfare loss
2007	106 (8.2)	198 (8.0)	85 (6.5)	160 (6.5)
2010	137 (7.3)	253 (7.1)	111 (6.0)	208 (5.9)
2015	208 (7.0)	387 (6.8)	170 (5.7)	319 (5.6)
2020	277 (6.5)	506 (6.2)	227 (5.3)	418 (5.2)
2025	328 (5.6)	588 (5.4)	269 (4.6)	487 (4.4)
2030	363 (4.8)	639 (4.5)	298 (3.9)	530 (3.7)

Unit: billions of 2007 US$

(Table 5) and from US$106 to US$363 billion (4.8–8.2% of the baseline level) with upper RR thresholds (Table 6). Welfare loss also presents a similar pattern, with the cost estimates of US$61 billion to US$205 billion (1.4–2.3% of the baseline level) at their lower bounds and US$198 billion to US$639 billion (4.5–8.0% of the baseline level) at their upper bounds. This result suggests that RR-involved uncertainty can lead to a bias of [−57%, 41%] from our central estimates in absolute terms. The *Policy I* case comparison results are similar to the *Green* case comparison, presenting an estimated consumption (or welfare) damage of US$23 billion to US$84 billion (or of US$44 billion to US$148 billion) with lower bound RRs and that of US$85 billion to US$298 billion (or of US$160 billion to US$530 billion) with upper bound RRs. In this case, the potential bias introduced by RR-embedded uncertainty ranges in [−59%, 51%].

Despite the sensitivity, our central findings and general conclusions are left intact. First, pollution-health costs in China's context are not trivial, given the size of China's economy and its rapid growth. Even the lower bound cost estimates under the *Green* and *Policy I* scenarios reach ≥ 1.4% and ≥ 1.0% of the baseline welfare levels. Second, two key time trends found in our central results—*growing* absolute pollution-health costs with labor productivity growth and *declining* relative costs reflecting air-quality improvement over time—still hold in our sensitivity analysis. Finally, error bars apply to each region and each health endpoint in the same direction and with a comparable magnitude; thus, the patterns of cost distributions across regions and among health endpoints are found to be consistent with our main results.

4.5 Health benefits from FYP13 $PM_{2.5}$ reduction targets

Since 2013, China has imposed strict air-quality control targets on its major urban agglomerations, such as Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Pearl River Delta (PRD), with a goal to push these regions meet the national class 2 ambient air-quality standards (35 μg/m^3 in annual means) by 2035 (CAAC 2013; Xu and Stanway 2017). In line with this effort, FYP13 specifies official national level PM reduction targets for the first time in its history, and Chinese local

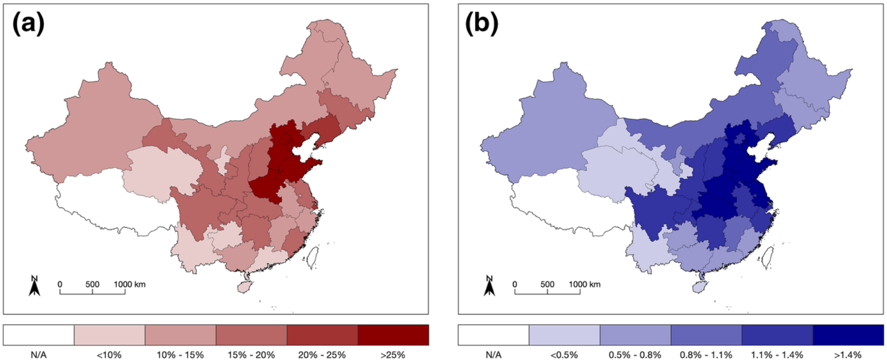


Fig. 12 FYP13 $PM_{2.5}$ reduction targets and expected welfare benefit: **a** provincial reduction targets for 2020 (vs. 2015 concentration level); **b** avoided health damage with compliance with the FYP13 targets, 2020 (vs. baseline welfare level)

governments have introduced their own mitigation targets in accordance with the national goals. Subnational FYP13 PM reduction targets for 2020 vary by province, ranging up to 36% reduction from the 2015 concentration levels (Fig. 12a). As briefly mentioned in Sect. 4.1, the *Policy II* scenario is simulated with CREM-HE to estimate potential health benefits which can be attained when these PM mitigation targets are met.

Our results show that compliance with FYP13 $PM_{2.5}$ mitigation targets will help the Chinese economy avoid substantial health damage from pollution. In 2020 alone, for example, avoided welfare (or consumption) loss thanks to FYP13-stated stricter $PM_{2.5}$ regulations is estimated to be US$98 billion (or US$50 billion), comparable to 1.2% (or 1.1%) of the baseline welfare (or consumption) levels. When the avoided damage is measured in GDP, it is US$137 billion or 1.2% of the baseline GDP level. At local levels, the avoided damage tends to be positively associated with the relative stringency of the proposed targets, and those with more ambitious reduction targets, such as the BTH region, Shandong, and Henan, demonstrate particularly large benefits from the proposed PM regulations in both absolute and relative terms (Fig. 12b).

5 Conclusions

In this study, we first introduce an analytic framework for pollution-health effects analysis and then apply the methodology to China at the province level. Our results show that health damage from O_3 and $PM_{2.5}$ pollution in China is still substantially large, although associated welfare loss in relative terms (vs. baseline welfare levels) presents a declining trend with China's increased mitigation effort. For each year between 2010 and 2030, China's welfare (or consumption) loss from excess pollution is estimated to be $\leq 5.1\%$ (or $\leq 5.2\%$) of the baseline level, suggesting the need for continued pollution control. The $PM_{2.5}$ share of the costs was > 12 times as large as the O_3 share, and premature deaths from chronic exposure to $PM_{2.5}$ were the single most important health endpoint, accounting for ≤56% of the total costs. This result justifies increased stringency of China's ambient $PM_{2.5}$ control standards. Compliance with FYP13-proposed PM reduction targets, for example, is estimated to help China avoid a welfare damage of US$98 billion in 2020 alone.

Cross-regional heterogeneity is substantial, and populous and industrialized Eastern China is subject to particularly large health damage in absolute terms. When the size of provincial economies is controlled for, however, Eastern dominance is less obvious and several inland provinces (e.g., Henan, Shanxi, and Chongqing) also suffer large welfare loss from O_3 and $PM_{2.5}$ pollution, due to low air quality and fast productivity growth. Broader economic loss from pollution—indirect economic costs arising from inefficient resource allocation and its cumulative effects—accounts for > 29% of the total costs for the Chinese economy, and the share is particularly large in the Central and Western regions (> 50%) during the later periods analyzed. Overlooking this indirect cost component, prevalent in typical static analysis, likely leads to substantial underestimation for fast-growing economies like China—its Central and Western regions, in particular.

Our study can contribute to the literature in several aspects. First, our analytic framework embodies a methodological advancement in bringing environmental pollution into conventional macroeconomic accounts within a top-down modeling structure. Pollution is modeled as an explicit external shock to the economy, and its market (labor and production sectors) and non-market (leisure) effects can be examined in a dynamic setting. Second, improved unit of analysis with reasonable subnational level details is another aspect to be highlighted. CGE application to China often takes a coarse model resolution (e.g., entire country as a single entity) due to data constraints and is thus clumsy in considering subnational heterogeneity. In contrast, CREM-HE is built on a comprehensive subnational dataset and offers capacity for realistic province-level analysis. This is a great merit, given that the magnitude of pollution-health effects is a function of varied local conditions. Also, the model's incorporation of local epidemiological evidence drawn from China-conducted studies represents an improvement over many existing studies adopting Western estimates for China, given the recent empirical evidence on nonlinearity in CR relationships. Finally, our analysis focuses not only on fine particles but also on ozone, which is often excluded from analysis despite its critical impacts on human health.

The significance of the study may go beyond its methodological contribution, given the topic's close relevance to China's ongoing debates on rebalancing or new-type urbanization. Realistic estimates of pollution-health costs at the province level, drawn from this study, could serve as the basis for drafting effective pollution abatement strategies at multiple administrative levels. It is a caveat, however, that this study focuses on the potential benefits from pollution mitigation (or the health damage that could be avoided in the absence of excess air pollution) without considering associated policy-compliance costs. A balanced cost–benefit study would need to attend to the cost dimension, as well, and thus a follow-up study could incorporate such regulatory costs into a dynamic impact assessment framework.

Acknowledgements We acknowledge the financial support of the Hong Kong Research Grant Council (ECS Award No.: 27200915) and the National Natural Science Foundation of China (Project No.: 71690244). The authors would like to express our special thanks to Da Zhang and Xiaohan Zhang for their helpful comments and input.

References

Aunan K, Fang J, Vennemo H, Oye K, Seip HM (2004) Co-benefits of climate policy—lessons learned from a study in Shanxi, China. Energy Policy 32:567–581

Babiker MH, Metcalf GE, Reilly JM (2003) Tax distortions and global climate policy. J Environ Econ Manag 46:269–287

Ban J, Li T-t (2016) Short-term effects of different ozone metrics on daily mortality in Beijing. J Environ Health 33:287–291

Bickel P, Friedrich R (eds) (2005) ExternE—externalities of energy: methodology 2005 update. European Commission, Luxembourg

Burnett RT et al (2014) An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. Environ Health Perspect 122:397–403

Cao J, Yang C, Li J, Chen R, Chen B, Gu D, Kan H (2011) Association between long-term exposure to outdoor air pollution and mortality in China: a cohort study. J Hazard Mater 186(2–3):1594–1600

Chen R et al (2011) Coarse particles and mortality in three Chinese cities: the China air pollution and health effects study (CAPES). Sci Total Environ 409:4934–4938

Chen H et al (2017) The MIT economic projection and policy analysis (EPPA) model: version 5. Technical note 16. MIT Joint Program on the Science and Policy of Global Change, Cambridge, MA

Chen K, Yang HB, Ma ZW, Bi J, Huang L (2013) Influence of temperature to the short-term effects of various ozone metrics on daily mortality in Suzhou, China. Atmos Environ 79:119–128

Chen Q, Sun H, Chen X-d, Ding Z (2017) Acute health impacts of ozone exposure on daily mortality in Nanjing. Jiangsu J Prev Med 28:366–386

Clean Air Alliance of China (CAAC) (2013) Twelfth five-year plan on air pollution prevention and control in key regions: english translation. Clean Air Alliance of China, Beijing

Cohen AJ et al (2017) Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the global burden of diseases study 2015. Lancet 389:1907–1918

Dai H, Song W, Gao X, Chen L, Hu M (2004) Study on relationship between ambient PM_{10}, $PM_{2.5}$ pollution and daily mortality in a district in Shanghai. J Hyg Res 33:293–297

Environmental Protection Agency (EPA) United States of America (1999) The benefits and costs of the clean air act 1990 to 2010. National Technical Information Service, Springfield, VA

GBD 2013 Risk Factors Collaborators (2015) Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks in 188 countries, 1990–2013: a systematic analysis for the global burden of disease study 2013. Lancet 386:2287–2323

Guo Y, Jia Y, Pan X, Liu L, Wichmann H-E (2009) The association between fine particulate air pollution and hospital emergency room visits for cardiovascular diseases in Beijing, China. Sci Total Environ 407:4826–4830

Guo Y, Tong S, Zhang Y, Barnett AG, Jia Y, Pan X (2010) The relationship between particulate air pollution and emergency hospital visits for hypertension in Beijing, China. Sci Total Environ 408:4446–4450

Guo H, Huang S, Chen M (2018a) Air pollutants and asthma patient visits: indication of source influence. Sci Total Environ 625:355–362

Guo P et al (2018b) Short-term associations of ambient air pollution and cause-specific emergency department visits in Guangzhou, China. Sci Total Environ 613–614:306–313

Hirschberg S et al (2003) Environmental impact and external cost assessment. In: Eliasson B, Lee YY (eds) Integrated assessment of sustainable energy systems in China. Kluwer, Dordrecht

Hoffmann S, Krupnick A, Qin P (2017) Building a set of internationally comparable value of statistical life studies: estimates of Chinese willingness to pay to reduce mortality risk. J Benefit Cost Anal 8:251–289
Holland M, Berry J, Forster D (eds) (1999) ExternE: externalities of energy vol 7: methodology 1998 update. European Commission, Luxembourg
Holland M, Watkiss P, Pye S, Oliveira Ad, Regemorter DV (2005) Cost-benefit analysis of policy option scenarios for the clean air for Europe programme
Huang W et al (2009) Visibility, air quality and daily mortality in Shanghai, China. Sci Total Environ 407:3295–3300
Huang W et al (2012) Seasonal variation of chemical species associated with short-term mortality effects of $PM_{2.5}$ in Xi'an, a Central City in China. Am J Epidemiol 175:556–566
International Institute for Applied Systems Analysis (IIASA) (2018) Greenhouse gas and air pollution interactions and synergies (GAINS) for East Asia. http://gains.iiasa.ac.at/gains/EAN. Accessed 1 Dec 2018
Kan H et al (2007) Differentiating the effects of fine and coarse particles on daily mortality in Shanghai, China. Environ Int 33:376–384
Kan H et al (2008) Season, sex, age, and education as modifiers of the effects of outdoor air pollution on daily mortality in Shanghai, China: the public health and air pollution in Asia (PAPA) study. Environ Health Perspect 116:1183–1188
Ko FWS, Tam W, Wong TW, Chan DPS, Tung AH, Lai CKW, Hui DSC (2007a) Temporal relationship between air pollutants and hospital admissions for chronic obstructive pulmonary disease in Hong Kong. Thorax 62:780–785
Ko FWS et al (2007b) Effects of air pollution on asthma hospitalization rates in different age groups in Hong Kong. Clin Exp Allergy 37:1312–1319
Lei Y, Ho MS (2013) The valuation of health damages. In: Nielsen CP, Ho MS (eds) Clearing skies over China: reconciling air quality, climate, and economic goals. MIT Press, Cambridge
Li X, Nam K-M (2017) One country two "Urban" systems: focusing on bimodality in China's city-size distribution. Ann Reg Sci 59:427–452
Li P et al (2013) The acute effects of fine particles on respiratory mortality and morbidity in Beijing, 2004–2009. Environ Sci Pollut Res 20:6433–6444
Lin Y-K, Chang S-C, Lin C, Chen Y-C, Wang Y-C (2013) Comparing ozone metrics on associations with outpatient visits for respiratory diseases in Taipei metropolitan area. Environ Pollut 177:177–184
Liu W (2016) Effects of air pollution on hospital emergency room visits for respiratory diseases and assessment of residents' willingness-to-pay for good air quality. Unpublished Master's Thesis, Shandong University, Qingdao
Liu T et al (2013) The short-term effect of ambient ozone on mortality is modified by temperature in Guangzhou, China. Atmos Environ 76:59–67
Liu T et al (2016) Temporal–spatial distribution of mortality risk caused by ambient ozone and its modification factors in the Pearl River Delta region. South China J Prev Med 42:201–207
Matus K (2005) Health impacts from urban air pollution in China: the burden to the economy and the benefits of policy. Unpublished Master's Thesis, Massachusetts Institute of Technology
Matus K, Yang T, Paltsev S, Reilly JM, Nam K-M (2008) Toward integrated assessment of environmental change: air pollution health effects in the USA. Clim Change 88:59–92
Matus K, Nam K-M, Selin NE, Lamsal LN, Reilly JM, Paltsev S (2012) Health damages from air pollution in China. Glob Environ Change 22:55–66
Morita H, Yang S, Unger N, Kinney PL (2014) Global health impacts of future aviation emissions under alternative control scenarios. Environ Sci Technol 48:14659–14667
Nam K-M (2017) Is the spatial distribution of China's population excessively unequal? A cross-country comparison. Ann Reg Sci 59:453–474
Nam K-M (2019) Environmental challenges in Chinese mega-city regions: focusing on air quality management. In: Yeh AGO, Lin GCS, Yang FF (eds) Mega-city region development in China. Routledge, Abingdon
Nam K-M, Reilly JM (2013) City size distribution as a function of socioeconomic conditions: an eclectic approach to downscaling global population. Urban Stud 50:208–225
Nam K-M, Selin NE, Reilly JM, Paltsev S (2010) Measuring welfare loss caused by air pollution in Europe: a CGE analysis. Energy Policy 38:5059–5071

Nam K-M, Li M, Wang Y, Wong KKH (2018) Spatio-temporal boundary effects on pollution-health costs estimation: the case of $PM_{2.5}$ pollution in Hong Kong. Int J Urban Sci. https://doi.org/10.1080/12265934.2018.1514275

National Bureau of Statistics of China (2016) China statistical yearbook. China Statistics Press, Beijing

Nielsen CP, Ho MS (2013) Atmospheric environment in China: introduction and research review. In: Nielsen CP, Ho MS (eds) Clearing skies over China: reconciling air quality, climate, and economic goals. MIT Press, Cambridge

O'Connor D, Zhai F, Aunan K, Berntsen T, Vennemo H (2003) Agricultural and human health impacts of climate policy in China: a general equilibrium analysis with special reference to Guangdong. Technical paper series no. 206. OECD Development Centre, Paris

Organisation for Economic and Co-operative Development (OECD) (2016) The economic consequences of outdoor air pollution: policy highlights. OECD, Paris

Ostro BD, Chestnut L (1998) Assessing the health benefits of reducing particulate matter air pollution in the United States. Environ Res 76:94–106

Paltsev S et al (2005) The MIT emissions prediction and policy analysis (EPPA) model: version 4. Report 125. MIT Joint Program on the Science and Policy of Global Change, Cambridge, MA

Pope CAI, Thun MJ, Namboodiri MM, Dockery DW, Evans JS, Speizer FE Jr, CWH (1995) Particulate air pollution as a predictor of mortality in a prospective study of US adults. Am J Respir Crit Care Med 151:669–674

Pope CAI, Burnett RT, Thun MJ, Calle EE, Krewski D, Ito K, Thurston GD (2002) Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. J Am Med Assoc 287:1132–1141

Qian Z et al (2007) Short-term effects of gaseous pollutants on cause-specific mortality in Wuhan, China. J Air Waste Manag Assoc 57:785–793

Qiao L et al (2014) $PM_{2.5}$ constituents and hospital emergency-room visits in Shanghai, China. Environ Sci Technol 48:10406–10414

Qiu H, Yu IT, Wang X, Tian L, Tse LA, Wong TW (2013) Differential effects of fine and coarse particles on daily emergency cardiovascular hospitalizations in Hong Kong. Atmos Environ 64:296–302

Reilly JM et al (2013) Valuing climate impacts in integrated assessment models: the MIT IGSM. Clim Change 117:561–573

Saikawa E, Naik V, Horowitz LW, Liu J, Mauzerall DL (2009) Present and potential future contributions of sulfate, black and organic carbon aerosols from China to global air quality, premature mortality and radiative forcing. Atmos Environ 43:2814–2822

Selin NE, Wu S, Nam KM, Reilly JM, Paltsev S, Prinn RG, Webster MD (2009) Global health and economic impacts of future ozone pollution. Environ Res Lett 4(4):044014

Shang Y et al (2013) Systematic review of Chinese studies of short-term exposure to air pollution and daily mortality. Environ Int 54:100–111

Su C, Breitner S, Schneider A, Liu L, Franck U, Peters A, Pan X (2016) Short-term effects of fine particulate air pollution on cardiovascular hospital emergency room visits: a time-series study in Beijing, China. Int Arch Occup Environ Health 89:641–657

Tao Y et al (2012) Estimated acute effects of ambient ozone and nitrogen dioxide on mortality in the Pearl River Delta of Southern China. Environ Health Perspect 120:393–398

Tao Y, Liu Y, Mi S, Guo Y (2014) Atmospheric pollution characteristics of fine particles and their effects on human health. Acta Sci Circum 34:592–597

Thompson TM, Saari RK, Selin NE (2014) Air quality resolution for health impact assessment: influence of regional characteristics. Atmos Chem Phys 14:969–978

Tian L et al (2014) Ambient carbon monoxide and the risk of hospitalization due to chronic obstructive pulmonary disease. Am J Epidemiol 180:1159–1167

Vennemo H, Aunan K, Jinghua F, Holtedahl P, Tao H, Seip HM (2006) Domestic environmental benefits of China's energy-related CDM potential. Clim Change 75:215–239

Viscusi WK, Harrington JE Jr, Vernon JM (2005) Economics of regulation and antitrust, 4th edn. MIT Press, Cambridge

Wang X et al (2016) Study of relationship between atmospheric fine particulate matter concentration and one grade a tertiary hospital emergency room visits during 2012 and 2013 in Beijing. Chin J Prev Med 50:73–78

West JJ, Fiore AM, Horowitz LW, Mauzerall DL (2006) Global health benefits of mitigating ozone pollution with methane emission controls. Proc Natl Acad Sci USA 103:3988–3993

Wong TW, Lau TS, Yu TS, Neller A, Wong SL, Tam W, Pang SW (1999) Air pollution and hospital admissions for respiratory and cardiovascular diseases in Hong Kong. Occup Environ Med 56:679–683

Wong C-M, Ma S, Hedley AJ, Lam T-H (2001) Effect of air pollution on daily mortality in Hong Kong. Environ Health Perspect 109:335–340

Wong C-M, Atkinson RW, Anderson HR, Hedley AJ, Ma S, Chau PY-K, Lam T-H (2002) A tale of two cities: effects of air pollution on hospital admissions in Hong Kong and London compared. Environ Health Perspect 110:67–77

Wong C-M, Vichit-Vadakan N, Kan H, Qian Z, PAPA Project Teams (2008) Public health and air pollution in Asia (PAPA): a multicity study of short-term effects of air pollution on mortality. Environ Health Perspect 116:1195–1202

Wong C-M et al (2010) Public health and air pollution in Asia (PAPA): coordinated studies of short-term exposure to air pollution and daily mortality in four cities, vol 154. Health Effects Institute, Boston, MA

World Bank (1997) Clear water, blue skies: China's environment in the new century. China 2020. World Bank, Washington, D.C.

World Bank, Institute for Health Metrics and Evaluation (IHME) (2016) The cost of air pollution: strengthening the economic case for action. World Bank, Washington, DC

World Bank, State Environmental Protection Administration (SEPA) PRC (2007) Cost of pollution in China: economic estimates of physical damages. World Bank, Washington, DC

World Health Organization (WHO) (2016) Ambient air pollution: a global assessment of exposure and burden of disease. WHO, Geneva

Xie P, Liu X, Liu Z, Li T, Zhong L, Xiang Y (2011) Human health impact of exposure to airborne particulate matter in Pearl River Delta, China. Water Air Soil Pollut 215:349–363

Xie W et al (2015) Relationship between fine particulate air pollution and ischaemic heart disease morbidity and mortality. Heart 101:257–263

Xie Y, Dai H, Dong H, Hanaoka T, Masui T (2016) Economic impacts from $PM_{2.5}$ pollution-related health effects in China: a provincial-level analysis. Environ Sci Technol 50:4836–4843

Xu M, Stanway D (2017) China aims to meet air quality standards by 2035: Minister. Reuters. October 23

Xu X, Li B, Huang H (1995) Air pollution and unscheduled hospital outpatient and emergency room visits. Environ Health Perspect 103(3):286–289

Yang T (2004) Economic and policy implications of urban air pollution in the United States: 1970 to 2000. Unpublished Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA

Yang C, Peng X, Huang W, Chen R, Xu Z, Chen B, Kan H (2012a) A time-stratified case-crossover study of fine particulate matter air pollution and mortality in Guangzhou, China. Int Arch Occup Environ Health 85:579–585

Yang C, Yang H, Guo S, Wang Z, Xu X, Duan X, Kan H (2012b) Alternative ozone metrics and daily mortality in Suzhou: the China air pollution and health effects study (CAPES). Sci Total Environ 426:83–89

Zhang Y et al (2006) Ozone and daily mortality in Shanghai, China. Environ Health Perspect 114:1227–1232

Zhang D, Rausch S, Karplus VJ, Zhang X (2013) Quantifying regional economic impacts of CO_2 intensity targets in China. Energy Econ 40:687–701

Zhang X, Ou X, Yang X, Qi T, Nam K-M, Zhang D, Zhang X (2017) Socioeconomic burden of air pollution in China: province-level analysis based on energy economic model. Energy Econ 68:478–489

Zhou Y, Hammitt JK (2007) The economic value of air-pollution-related health risks in China: a contingent valuation study. In: Ho MS, Nielsen CP (eds) Clearing the air: the health and economic damages of air pollution in China. MIT Press, Cambridge