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Assessment of the pollution–health–economics nexus in China

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Supplementary Information

S1. Selective Literature Review

S1.1 Exposure-Response Coefficients

Particulate Matter (PM) affects human health most severely among all air pollutants and Fine Particle ($PM_{2.5}$) has substantially increased the numbers of mortality and morbidity (hospital admissions and outpatient visits) worldwide (Xu et al, 2000). The exposure-response coefficient is used to measure the quantitative relationship between PM exposure and its health outcomes. Xu et al (2000), Venners et al (2003) and Kan and Chen (2004) assessed the daily PM-induced mortality in Shenyang, Chongqing and Shanghai. Epidemic studies using exposure-response coefficients confirm increasing risks for mortality and morbidity of contaminant diseases at higher exposure (particulate concentration level).

S1.2 Health Costs Assessment

Health costs studies are dedicated to translating various health outcomes into monetary terms and two most frequently-used methods are Contingent Valuation Approach (CVA) and Human Capital Approach (HCA), where CVA focuses on the Willingness-To-Pay of households to avoid the mortality or morbidity risks of a disease whereas HCA emphasizes on Potentially Productive Years of Life Loss (PPYL) and discounted value of future earnings due to a disease. Studies using CVA can be found at national scale (Zeng and Jiang, 2010), provincial scale (Wang and Mullahy, 2006) and city scale (Kan and Chen, 2004) and studies using HCA can be found in Bradley et al (2007) and Wan et al (2004). Both approaches tend to evaluate the economic burden resulting from a particular disease from a patient's perspective that however, are subject to scope limits. CVA quantifies health costs based on respondents' risk perceptions that can be completely different and unmeasurable within different social structures and health-care systems (Kan and Chen, 2004). Meanwhile, as HCA heavily relies on PPYL, it neglects the roles of children and the elderly as well as disease-induced morbidity. Additionally, despite both approaches can provide meaningful microeconomic information regarding the monetary benefits from reducing mortality or morbidity rates, the results can hardly represent the macroeconomic impacts of disease-induced health outcomes on national GDP, especially in the cascading economic impacts occurred along production supply chain because neither of them considers industrial and regional interdependencies.

S1.3 A 'Circular Economy' in Input-Output Analysis

Assessing the macroeconomic impacts of disease-induced health outcomes requires us to consider important industrial and regional interdependencies. With regards to production supply chain, reduction in output level of a single sector can affect both sectors purchasing its outputs (downstream sectors) and selling their outputs (upstream sectors). In other words, the initial impacts on a single economic sector can affect other sectors that are not directly under shocks because of their inter-industrial transaction. Analogously, economic impacts initially occurred in a single region can spill over other regions due to intra-regional or international trades. The increasingly significant role of industrial and regional interdependencies brings Input-Output (IO) analysis under spotlights. The concept of 'circular economy' has been well understood by IO analysis developed by Wassily Leontief in 1930, which was initially applied to determination of direct and indirect input requirements for U.S. industrial sectors. Leontief suggested in his developed input-output table that, all economic activities could be assigned to production and consumption sectors. The basic structure of an input-output table is divided into four quadrants, which are intermediate transactions, final demand, and the primary inputs for production and primary requirements to final demand. The quadrant of intermediate transactions illustrates the intermediate transaction between production sectors in an economy. The final demand quadrant describes the sales to the final consumption such as households, governments and exports. Furthermore, an input-output table contains information of primary inputs, which describes not only those necessary inputs for production, such as fixed capitals, compensation of employees and taxes (the third quadrant) but also the primary inputs to the final consumption (the fourth quadrant) (Miller and Blair, 2009). The techniques of input-output analysis have been significantly enhanced while the approach was spreading out to many fields, including energy usage (Guan et al, 2016), environmental pollution (Meng et al, 2015 & 2016), climate change mitigation (Feng et al, 2013; Wiedmann et al, 2006) and adaptation and economic perturbations (Steenge and Bočkarjova, 2007; Cho et al, 2001; Santos, 2006; Crowther and Haimes, 2005; Xia et al, forthcoming) as well as to different scales, ranging from national to regional level. It worth noting that IO model possesses a fundamental assumption of production expansion path that assumes proportional increase in industrial output can be only achieved by simultaneous increases in both capital and labour, indicating that any reduction in an input can directly constrain the output growth in all industries.

S1.4 Input-Output Model in Disaster Risk Studies

An IO model was developed based on the concept of a 'circular economy' and its advantages in capturing industrial and regional interdependencies enable to quantify disaster-induced indirect impacts, including floods (Steenge and Bočkarjova, 2007), earthquakes (Cho et al, 2001), wilful attacks (Santos, 2006) and national power outages (Crowther and Haimes, 2005). These events can be categorized as rapid-onset disasters that generally result in substantial damage to physical capital, such as bridges, roads and other infrastructures and thus, rapid-onset disaster risk assessment will largely depend on quantifying the direct damages to physical capital. On contrast, PM pollution is different in nature from disasters mentioned above because it will last longer and cause severe harm on human health but little damage to physical capital. We term such kind of disaster as 'persistent' disasters. Assessing the economic impacts of persistent disasters may require a different method, which lacks exploration in existing risk analysis literature.

S2. Additional Information in Methods

Table S1. Concentration-response coefficients for morbidity that were used in this study

Concentration-response Coefficients for Morbidity		
Health Impacts	Coefficient	Reference
cardiovascular HA	0.0009059	Health risks of air pollution in Europe – HRAPIE project
respiratory HA	0.001882	
outpatient visits	0.000389241	Xu et al. (1995)

S3. Sensitivity Analysis

Due to data unavailability in several aspects, the current study is subject to some uncertainties that on the other hand, open up more research space for scholars. Firstly, labour time loss resulting from outpatient visits was estimated as 4 hours per visit in order to provide a realistic boundary for study results when specific time loss data is not available. This assumption was made according to Chinese medical system which has no pre-booking and follow-up services. I suggest that such conservative assumption could provide a lower boundary in model results. Secondly, the distribution of the mortality and morbidity counts into industries was based on the occupational respiratory conditions incidence rate from the Bureau of Labour Statistics in the US due to the lack of occupational illness data in China. The data suggest that manufacturing workers entail the highest respiratory condition incidence rate at 2.1%, followed by workers in services sectors at 1.8%, natural resources and mining sector at 1.5% and construction sector at 1.2%. However, the data follows the US sector categorization. As a result, 30 industries in China were re-categorized into four large sectors to be aligned with the US sector categorization. The mortality and morbidity counts were firstly assigned to these four sectors and sectoral mortality and morbidity counts were further distributed into industries according to the industry-to-sector output ratio. Therefore, model results can be more accurate when data on industrial disease incident rates in China become available because outdoor workers in some sectors appear to be more directly exposed to $PM_{2.5}$ pollution than indoor workers in other sectors. To differentiate the disease incidence rates for various occupations is crucial because workers in different sectors normally have different working environment with different exposures to $PM_{2.5}$ pollution. Thirdly, the study employs a supply-driven input-output model is frequently criticized in its ignorance regarding the effect of changing output on further changes in industrial value added and possible nonlinear relationships between labour inputs and economic outputs in sectors dominated by monetary capital (Miller and Blair, 2009). However, it is still found to be a suitable candidate model to reflect a more straightforward linkage between changing value added and the entire economy in a way that captures industrial and regional interrelationships and indirect economic loss along production supply chain.

This section provides a sensitivity analysis for the study on China's air pollution in 2012 to test the impacts of alternative data or assumptions regarding time required for each cardiovascular admission, each outpatient visit, equal distribution of mortality and morbidity counts into industries and industrial specific air pollutant exposure levels on the modelling results in terms of total economic loss resulting from $PM_{2.5}$-induced health effects.

S3.1 Timed Required for Each Cardiovascular Hospital Admission

In the main study, each cardiovascular admission will require 11.9 working days. However, according to Wang and Li (2008), more severe symptom in cardiovascular disease will require over 30 days for each admission. Without considering the possible weekends or holidays, I tested the variation range in total economic loss when each cardiovascular admission takes 30, 60 and 90 working days, respectively. The results can be observed in *Table S2*. It shows a rising trend from 417.49 to 481.31 billion Yuan for 2012. Regardless the increase in working days lost for each cardiovascular admission, the variation range in test results is relatively small.

Table S2 Varying Working Day Lost for Each Cardiovascular Admission

Sensitivity Analysis – cardiovascular hospital admission time	
Number of working days lost	Output Loss (billion Yuan)
30	417.49

60	449.40
90	481.31

S3.2 Required Times for Each Outpatient Visit

In the study, it was assumed that 4 hours (0.5 working day) were required for each outpatient visit and each outpatient visits the clinic once during the study year. Due to the lack of data on the required time for each outpatient visit in China, this assumption was made based on the current status of Chinese medical system where no pre-booking and follow-up services are available. Therefore, this section tests the impacts of alternative time required for each outpatient visit on the modelling results as shown in *Table S3* As can be seen from the tables, the total economic loss rise from 366.58 to 461.53 billion Yuan with the rising amount of time required for each outpatient visit from 2 to 8 hours, confirming the impacts of required time for outpatient visit on the overall model results. The results tend to be more sensitive to the required outpatient time due to a relatively large size of pollution-induced outpatients. This indicates the needs for more accurate data on frequency and time required for outpatient visits in order to further improve the accuracy of model results. However, I suggested that the current assumptions concerning outpatient visits are consistent with the ongoing situation in Chinese medical system in a background of extreme air pollution condition throughout the year and thus, they tend to provide a conservative estimation in total economic loss by considering time for queuing, inquiry and medical treatment. It is noteworthy that no holiday that might be potentially embodied in the working days lost was considered.

Table S3 Varying Time Required for Each Outpatient Visit

Sensitivity Analysis – time required for each outpatient visit (hour)	
Hours Lost	Output Loss (billion Yuan)
2	366.58
6	429.88
8	461.53

S3.3 Equal Distribution of Mortality and Morbidity Counts in Industries

Another assumption in the study is the distribution of mortality and morbidity counts into industries, which was based on the occupational respiratory conditions incidence rate from the Bureau of Labour Statistics in the US due to the lack of occupational illness data in China. The data suggest that manufacturing workers entail the highest respiratory condition incidence rate at 2.1%, followed by workers in services sectors at 1.8%, natural resources and mining sector at 1.5% and construction sector at 1.2%. When equally assigning these counts into a total number of 886 industries in terms of 896 deaths, 813 cardiovascular admissions, 1688 respiratory admissions and 89362 outpatient visits, the total economic loss become 446.55 billion Yuan. Such case, however, can hardly happen in the real case.

S3.4 Distribution of Mortality and Morbidity Counts based on Industrial Exposure Rates

We also employed another approach in distributing counts of mortality, hospital admissions and outpatient visits from Xia et al (2016) that was based on the data related to occupational exposures to harmful substances or environments (Bureau of Labour Statistics, 2007). It sketches a relatively comprehensive picture regarding the exposure coefficients for all industries and the belonging sub-industries for four main sectors, including natural resources and mining, manufacturing, construction and service. The 30 Chinese industries in each province from our multi-regional input-output table were mapped into each of these sectors. For those industries with combinative features, including food and beverage and tobacco manufacturing; financial activities and rental and leasing; electric power generation, transmission and distribution; water, sewage and other systems; and wholesale and retail trade, I summed up the exposure coefficient for each industry and used the averaged industrial values for those with missing data. For example, regarding the construction sector that is normally regarded as a principle sector in the US, is however classified as a sub-industry under secondary industry in China without any further specification. Therefore, for the construction sector, the total number of exposure cases was calculated as 182. The overview of occupational exposures to harmful substances or environments is summarized in *Table S4*. Mortality, hospital admissions and outpatient visits counts in each province were assigned to industries according to these exposure proportions. For industries without output, I focused on the industrial-to-total provincial proportions. The total economic loss based on such distribution of mortality and morbidity counts was 344.89 billion Yuan. Therefore, model results were not significantly affected by the ways to assign mortality and morbidity counts. Since the US sector categorization tends to attach greater importance to service sector, it might be inconsistent with the Chinese economic structure. The model estimations can be more robust once the specific dataset for different occupational exposure levels is available in China.

Table S4 Occupational Exposure to Harmful Substances or Environment

Occupational Exposure to Harmful Substances and Environments	
Occupation	**Exposure**
Natural resources and mining	
Agriculture, forestry, fishing, hunting	35
Coal mining	17
Oil, gas wells	8
Metal ore mining	17
Nonmetal mineral mining, quarrying	17
Manufacturing	
Food, beverage and tobacco product	10
Textile mills	3
Textile clothing product	3
Wood product	3
Paper and printing related support activities	3
Petroleum and coal product	3
Chemical manufacturing	3

Nonmetal mineral product	3
Primary metal manufacturing	3
Fabricated metal product	10
Machinery manufacturing	3
Transportation equipment	3
Electrical equipment, appliance, component	3
Computer and electronic product	3
Furniture, institutional-related product	3
Miscellaneous manufacturing	3
Service-providing	
Natural gas distribution	4
Electric power generation, transmission, distribution and water, sewage, other systems	15
Transportation	37
Wholesale trade, retail trade	23
Accommodation and food service	11
Financial activities, rental, leasing	13
Professional scientific, technical service	5
Other services	10
Construction	
Construction	182

(Source: US Bureau of Labour Statistics)