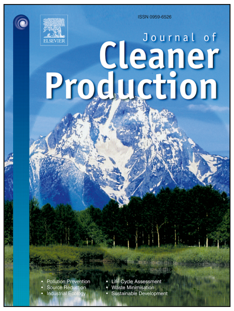

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Assessment of the Economic Impacts of Heat Waves: A Case Study of Nanjing, China

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Abstract

The southeast region of China is frequently affected by summer heat waves. Nanjing, a metropolitan city in Jiangsu Province, China, experienced an extreme 14-day heat wave in 2013. Extreme heat can not only induce health outcomes in terms of excess mortality and morbidity (hospital admissions) but can also cause productivity losses for self-paced indoor workers and capacity losses for outdoor workers due to occupational safety requirements. All of these effects can be translated into productive working time losses, thus creating a need to investigate the macroeconomic implications of heat waves on production supply chains. Indeed, industrial interdependencies are important for capturing the cascading effects of initial changes in factor inputs in a single sector on the remaining sectors and the economy. To consider these effects, this paper develops an interdisciplinary approach by combining meteorological, epidemiological and economic analyses to investigate the macroeconomic impacts of heat waves on the economy of Nanjing in 2013. By adopting a supply-driven input-output (IO) model, labour is perceived to be a key factor input, and any heat effect on human beings can be viewed as a degradation of productive time and human capital. Using this interdisciplinary tool, our study shows a total economic loss of 27.49 billion Yuan for Nanjing in 2013 due to the heat wave, which is equivalent to 3.43% of the city's gross value of production in 2013. The manufacturing sector sustained 63.1% of the total economic loss at 17.34 billion Yuan. Indeed, based on the ability of the IO model to capture indirect economic loss, our results further suggest that although the productive time losses in the manufacturing and service sectors have lower magnitudes than those in the agricultural and mining sectors, they can entail substantial indirect losses because of industrial interdependencies. This important conclusion highlights the importance of incorporating industrial interdependencies and indirect economic assessments in disaster risk studies.

Keywords: Heat Wave, Health, Productivity, Capacity, Macroeconomic, Input-output Analysis, Indirect Loss, Nanjing, China

1. Introduction

Climate change has become the most significant threat to the health of the global population by inducing more frequent extreme weather events. The resulting disastrous events can affect populations either directly through floods or hurricanes or indirectly through heat waves and cold spells (Haines et al, 2009). The increasing frequency and intensity of heat waves seriously affect both developed and developing countries (IPCC, 2012). In 2003, an extreme heat wave event occurred in Europe and caused nearly 20,000 deaths (Fouillet et al, 2006; Conti et al, 2005; Grize et al, 2005). Developing countries also encounter considerable adverse effects from heat waves. South-eastern China has suffered extreme heat waves that have frequently broken historic records (Sun et al, 2014). As a result, a rising health burden associated with heat wave events has been observed moving from the North towards the South. However, because of their less-developed heat protection infrastructure and strategies, developing countries such as China are more likely to suffer severe health outcomes from heat waves. Thus, more effort should be devoted to detecting the health impacts of heat waves in these countries.

It is important to convert health outcomes into monetary terms to develop sophisticated cost-benefit analyses of public health programmes. However, in translating ‘invisible’ health outcomes into more ‘visible’ monetary losses, existing approaches such as the Contingent Valuation Approach (CVA) and the Human Capital Approach (HCA) are better at evaluating the microeconomic costs of the potential burden of a particular disease from a patient’s perspective (Wan et al, 2004). Therefore, the results of these approaches do not fully reflect the macroeconomic impacts of a particular disease on the economic system and production supply chain. When considered at a broad macroeconomic level, an individual (the patient under consideration) acts as labour during the production process of an industry. When he/she is away from work due to sickness or becomes less productive or less capable of performing work due to safety regulations, there is a potential loss of productive working time. From a supply-driven perspective where labour is regarded as a major component of industrial input, such a loss further implies output loss for an industry, which will in turn influence other industries because of industrial interdependencies. Specifically, it will affect other industries that purchase inputs from it (‘downstream’ industries) and sell outputs to it (‘upstream’ industries) (Miller and Blair, 2009). Therefore, considering these industrial interdependencies becomes significant in macroeconomic assessments because such interconnections may result in substantial indirect loss and raise the total loss far beyond the initial output loss in a single industry.

Heat waves differ from floods or hurricanes in the sense that they are relatively ‘persistent’ and cause little damage to physical capital but substantial harm to human health, and they can therefore analogously disrupt economic activities. However, such ‘persistent’ events have hardly been considered in existing disaster risk analyses. Therefore, this paper focuses on the heat wave event that took place in Nanjing, Jiangsu Province, China, in 2013. We develop an interdisciplinary approach by integrating meteorological, epidemiological and macroeconomic analyses to assess the total indirect economic impacts of heat-induced health outcomes, productivity losses and capacity losses on the production supply chain of Nanjing city. To capture industrial interdependencies, the paper employs a supply-driven input-output (IO) analysis in which productive working time losses due to the degradation of health, productivity and capacity are used as an indicator for potential changes in the inputs/value added of the economy that will be traced along the supply chain to detect the total indirect economic loss.

The next section will review heat-related epidemiological studies, health cost assessment studies and disaster risk studies that use the IO model and provide a strong rationale for the current study. Section 3 describes the interdisciplinary methodology employed in this paper and details the methods and data used. Section 4 discusses the study results. Section 5 concludes the paper with implications, highlights and insights for future research.

2. Literature Review

To understand the economic implications of heat-induced health impacts, it is important to first specify the impacts of heat on mortality and morbidity for certain heat-related diseases, such as stroke mortality and cardiovascular and respiratory hospital admissions. Epidemiological studies on heat waves help to quantify the relationships between heat exposure and disease-specific mortality and morbidity and have confirmed that excess heat exposure induces excessive mortality and morbidity rates in Japan (Honda et al, 2007), the US (Anderson and Bell, 2011, Weisskopf et al, 2002) and Europe (Fouillet et al, 2006; Conti et al, 2005; Tataru et al, 2006; Michelozzi et al, 2009; Baccini et al, 2011). Alongside, two recent studies of significance also focus on impact of extreme heat in the US but lie in the economic literature. Barreca et al (2015) employed the panel data from 1900 to 2004 on monthly mortality rates and daily temperature variables in the US to investigate the importance of adaptation and the extent of convergence in cross-sectional adaption rates. They found that impact of extreme heat on mortality tends to be smaller in states with high frequency in extreme heat events and heat-mortality relationships in hot and cold states tend to converge over the study period. Similarly, Barreca et al (2016) confirmed the declining impact of extreme heat on mortality rates in the US during the twentieth century, which can be explained by the diffusion of residential air conditioning. Indeed, from an economic perspective, they approved the economic benefits brought by the residential air conditioning in terms of the consumer surplus ranging between $85 and $185 billion. However, when turning to the developing world, despite their less developed heat protection infrastructure and potentially greater vulnerability, there is a lack of heat episode studies.

Apart from the productive time loss resulting from the heat-induced health outcomes, which is termed ‘absenteeism’ in our study, excess heat can also result in ‘presenteeism’, which refers to reductions in work productivity and work capacity. Although existing studies on heat-induced ‘presenteeism’ always treat work productivity and work capacity as interchangeable, we suggest that these two terms should be treated differently because work productivity loss emphasizes efficiency loss due to heat-induced mental distractions, such as concentration lapses, low-quality decision making and reduced cognitive performance (Gaoua et al, 2011), while capacity loss is mainly caused by occupational work safety regulations. One of the few studies on heat-induced productivity loss was conducted by Zander et al (2015), who applied a work productivity and activity impairment (WPAI) questionnaire to measure the heat-induced productivity loss due to mental distractions in Australia in 2013–14. As for work capacity loss, Wet Bulb Globe Temperature (WBGT) and ISO standards are two occupational health safety indices that are used to measure work capacity under heat exposure. The WBGT index suggests that if no break time is required, a worker’s work capacity is 100%, while if 75% rest time is required (31°C for 500 Watts work intensity), work capacity is reduced to 25% (Dunne et al, 2013).

To further translate health outcomes into monetary terms, Dell et al (2014) summarized existing literature on changes in weather realizations over time within a given spatial area and demonstrate impacts on agricultural output, industrial output, labor productivity, energy demand, health, conflict, and economic growth among other outcomes and explored the new applications of 'damage function' that is traditionally used in risk assessment for floods and earthquakes. However, their work does not treat meteorological conditions, health endpoints and macroeconomic impacts as a whole. Indeed, industrial interdependencies are yet to be fully investigated in their research. Focusing on other approaches to quantify health impacts in monetary units, CVA and HCA appear to be the two most commonly used approaches in health cost assessments. The former emphasizes individual willingness-to-pay to reduce the relative risk related to a particular disease, while the latter focuses on the potential productive life year loss. Relevant studies can be found that use the CVA (Kan et al, 2004; Zeng and Jiang, 2010) and the HCA (Zander et al, 2015). However, neither approach is able to capture the industrial interdependencies that are important when assessing economic impacts at the macroeconomic level. An initial output reduction in a single industry can cascade along the production supply chain and eventually spill over into other industries and the entire economic system, including both 'downstream' and 'upstream' industries.

To account for such interdependencies, an IO framework was developed based on the concept of a 'circular economy' that is advantageous for capturing industrial/regional interdependencies. Its applications have been extended to energy, environmental pollution, climate change mitigation and disaster risk studies. It has been widely applied to quantify the indirect impacts resulting from rapid-onset disasters, including floods (Steenge and Bočkarjova, 2007), earthquakes (Cho et al, 2001), wilful attacks (Santos, 2006) and national power outages (Crowther and Haimes, 2005). These rapid-onset disasters generally result in substantial damage to physical capital, such as bridges, roads and other infrastructures. Therefore, disaster risk studies that focus on rapid-onset disaster events tend to depend heavily on quantifying the direct damages to physical capital. However, applying IO analysis to 'persistent' disasters that substantially affect human capital but cause little damage to physical capital, such as heat waves and air pollution, remains unexplored (except Xia et al, 2016).

As a result, the current paper adopts a supply-driven IO model to evaluate the indirect economic loss on the production supply chain resulting from heat-induced health outcomes in terms of mortality and morbidity, work productivity loss due to heat-induced mental distractions and work capacity loss due to workplace safety standards. The approach perceives loss in productive time as an indicator that results in changes in industrial value added. Given that each individual can also act as labour in the economy, the proposed framework integrates meteorological, epidemiological and economic studies that are able to feed the change in value added as an input for the IO model, and it then traces the effects along the interconnected production supply chain.

3. Methodology

3.1 Interdisciplinary Methodological Framework

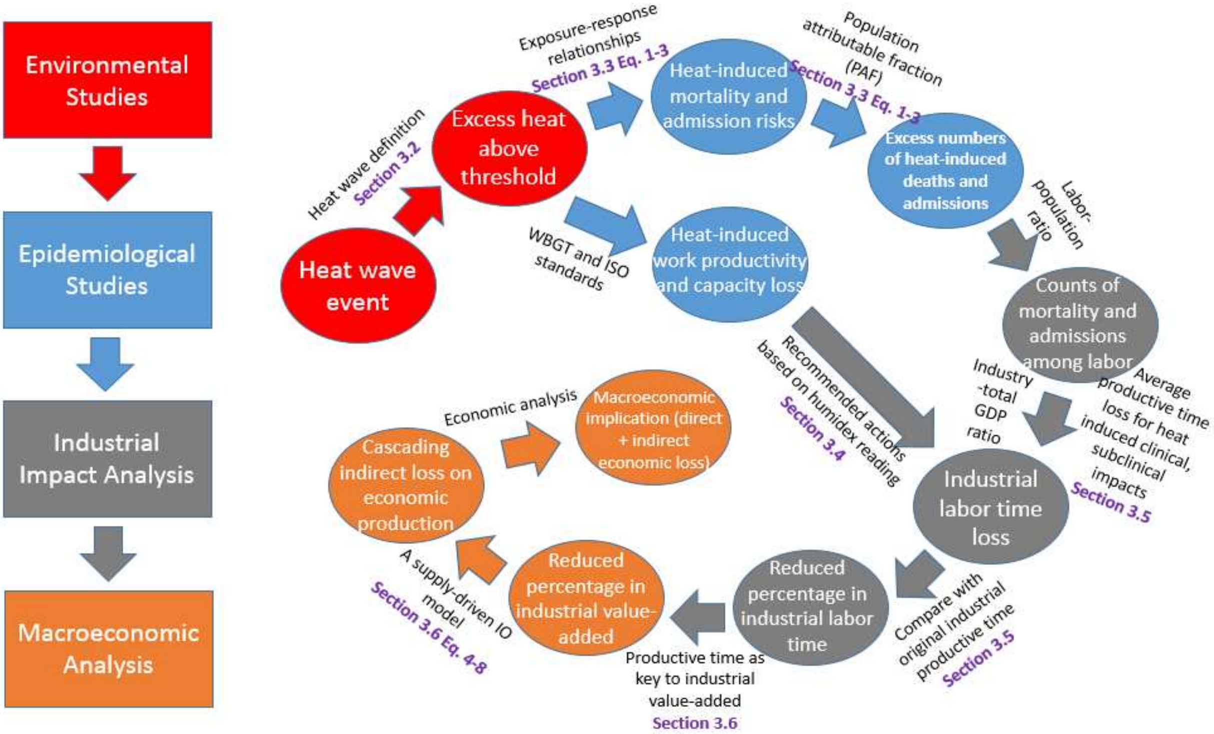


Figure 1. Methodological framework

Figure 1 illustrates the overall methodological framework employed in this study. It involves four main parts that are distinguished with four colours (boxes on the left and flow chart on the right). Detailed methods that connect each part in the flow chart refer to the corresponding sections and equations (in purple). The heat wave period was identified in Nanjing in 2013 according to the selected heat wave definition (Section 3.2). The heat-induced excess mortality and morbidity rates were then estimated based on quantitative relationships between heat exposure and health outcomes from existing epidemiological studies (Section 3.3 Eq. 1 to 3). Meanwhile, heat-induced 'presenteeism', including both work productivity and capacity loss, were inferred based on existing studies, ISO safety standards and recommended actions based on Humidex readings (Section 3.4). Additionally, heat-induced mortality, morbidity, productivity and capacity loss were translated into productive working time loss (Section 3.5), which was further compared with the original working time without the heat effect (Section 3.5) to derive the percentage reduction in industrial value added (Section 3.6). Moreover, the reduction in value added serves as an input in the supply-driven IO model to measure the total indirect economic loss incurred along the production supply chain, which is measured as the total loss in output (Section 3.6 Eq. 4 to 8). Finally, macroeconomic implications can be obtained from our model results.

The following sections present many mathematical symbols, formulas and equations. For clarity, matrices are indicated by bold, upright capital letters (e.g., $\mathbf{X}$); vectors by bold, upright lower case letters (e.g., $\mathbf{x}$); and scalars by italicised lower case letters (e.g., x). Vectors are columns by definition, so that row vectors are obtained by transposition and are indicated by a prime (e.g. $\mathbf{x}'$). A diagonal matrix with the elements of vector $\mathbf{x}$ on its main diagonal and all other entries equal to zero are indicated by a circumflex (e.g. $\hat{\mathbf{x}}$).

3.2 Identify Heat Wave Period

There are various ways to define a heat wave. In this study, we followed the heat wave definition of Ma et al (2011) as a period of at least 7 consecutive days with 1) a daily maximum temperature above 35.0 °C and 2) daily mean temperatures above the 97th percentile for the period from 2005–08 for each station. As a result, 5/8–18/8/2013 was identified as the heat wave in Nanjing in 2013 (Figure 2 and Table 1).

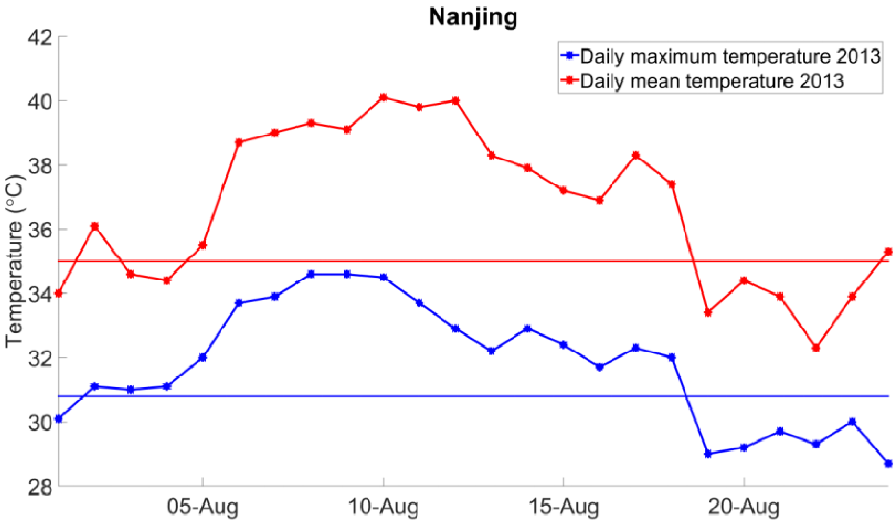


Figure 2. Heat wave period in Nanjing, 2013

Station	97th percentile	T_{mean}	T_{max}
	℃	℃	℃
Xuzhou	29.5	32.7	37.0
Nanjing	30.8	33.1	38.4
Dongtai	29.5	31.8	36.4

Table 1. Temperature observations from three meteorological monitoring stations in Jiangsu, 2013

3.3 Heat-induced Mortality and Morbidity

For heat-induced mortality in Nanjing, we selected a near-term summer reference period to control for potential time-varying confounding effects. The selected reference period has the same duration and distribution of days of the week (DOW) as the heat wave period and excludes the days immediately after the heat wave (Basu and Samet, 2002; Ma et al, 2011). The heat-induced excess deaths (all causes) were calculated as the difference in number of mortalities between the study period and the reference period (Eq. 1).

$$M_{heat} = M_s - M_r \qquad (1)$$

where M_{heat} is the heat-induced excess number of non-accidental mortalities, M_s is the number of mortalities during the heat wave and M_r is the number of mortalities during the reference period. The daily counts of death data were obtained from the China Information System Death Register and the Report of the Chinese Center for Disease Control and Prevention (China CDC) from 1 January 2007 to 31 December 2013. The causes of death were coded by the China CDC according to the International Classification of Diseases, Tenth Revision (ICD-10): non-accidental disease (A00-R99).

For heat-induced morbidity in Nanjing, we considered excess hospital admissions for respiratory and cardiovascular diseases. Because of a lack of records and data for Nanjing, we had to refer to similar episode studies on heat-induced morbidity in other cities. We employed the RRs (rate ratios) from Ma et al's (2011) study in Shanghai because Shanghai is located very close to Nanjing and has similar meteorological conditions, social context, and environment and population structure, and we therefore assumed that the populations would have similar vulnerabilities to heat exposure. The RRs for the two diseases were used in Eq. 2 to calculate the population attributable fraction (PAF) and were further used in Eq. 3 to estimate the population counts affected by a particular health endpoint.

$$\mathrm{PAF} = \frac{\mathrm{RR} - 1}{\mathrm{RR}} \tag{2}$$

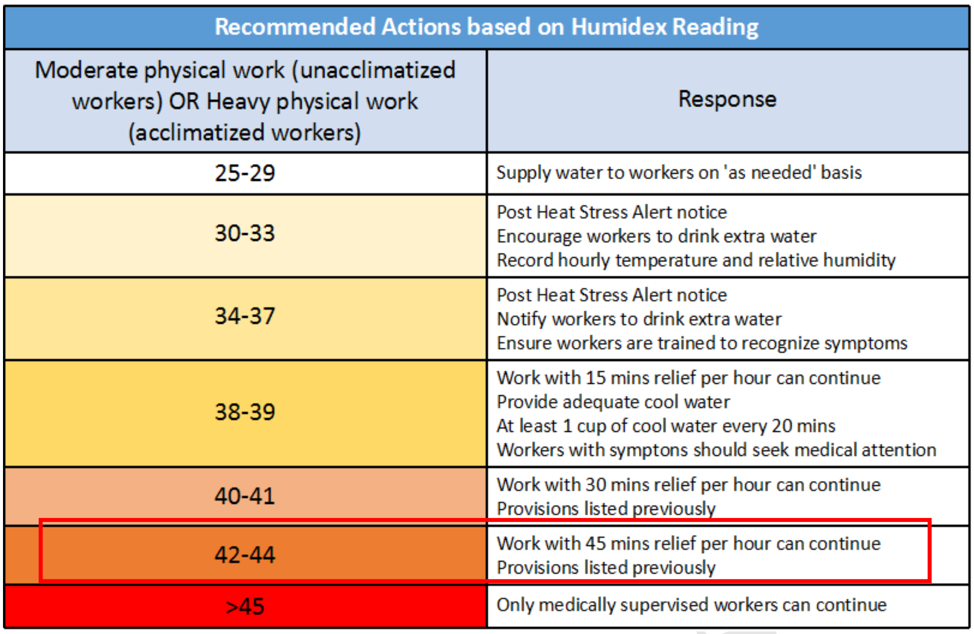
$$\mathrm{E} = \mathrm{PAF} \times \mathrm{B} \times \mathrm{P} \tag{3}$$

where PAF is the population attributable fraction that measures the fraction of the affected population that can be attributed to a certain risk factor, RR is the rate ratios for a particular health endpoint, '1' corresponds to the counterfactual risk ratio using a theoretical-minimum-risk exposure distribution, E is the total affected counts of a particular health endpoint that are attributable to a certain risk factor, B is the national level admission incidence of a given health effect and P is the exposed population (WHO, 2016). The RRs for cardiovascular and respiratory hospital admissions are 1.08 (95% CI) and 1.06 (95% CI), respectively (Ma et al, 2011).

3.4 Productivity and Capacity Loss

For heat-induced productivity loss due to mental distraction or reduced cognitive skills, we assumed that excess heat only induces productivity loss for workers in the manufacturing, energy supply and service sectors, who mostly work indoors with light work intensity (Zander et al, 2015). However, as existing studies have not identified a quantitative relationship between heat exposure and the resulting productivity loss, we referred to Bux (2006) and assumed a 12% reduction in productive working time for workers in the three sectors. Bux (2006) suggested that the reduction in productive time for indoor self-paced workers can range from 3% to 12% under moderate or extreme heat. Considering that the daily average and maximum temperatures in Nanjing far exceeded those in Bux (2006), there was extreme heat during the heat wave in Nanjing in 2013 that resulted in a 12% loss of productive time.

For heat-induced work capacity loss due to workplace safety regulations, we assumed that excess heat only affects the work capacity of workers in the agricultural, mining and construction sectors, who mostly work outdoors with heavy work intensity and are directly exposed to heat. We estimated the work capacity loss in terms of working time loss for outdoor workers using the Humidex plan, which was developed based on different humidity and temperature ranges to protect workers from heat stress (Occupational Health and Safety, 2010). According to Nanjing Meteorology (2016), the summer average humidity in Nanjing ranges from 45% to 70%, which corresponds to 45 minutes per hour of relief time required for outdoor workers with high work intensity (Figure 3; Occupational Health and Safety, 2010).



Recommended Actions based on Humidex Reading	
Moderate physical work (unacclimatized workers) OR Heavy physical work (acclimatized workers)	Response
25-29	Supply water to workers on 'as needed' basis
30-33	Post Heat Stress Alert notice Encourage workers to drink extra water Record hourly temperature and relative humidity
34-37	Post Heat Stress Alert notice Notify workers to drink extra water Ensure workers are trained to recognize symptoms
38-39	Work with 15 mins relief per hour can continue Provide adequate cool water At least 1 cup of cool water every 20 mins Workers with symptons should seek medical attention
40-41	Work with 30 mins relief per hour can continue Provisions listed previously
42-44	Work with 45 mins relief per hour can continue Provisions listed previously
>45	Only medically supervised workers can continue

Source: Modified from Occupational Health and Safety, 2010

Figure 3. Humidex-based Heat Response Plan (humidity range and corresponding relief time required are highlighted in red box)

3.5 Productive Working Time Loss

We assumed that each worker in Nanjing works 8 hours per day and 250 days in 2013. Each heat-induced death therefore results in 250 working days lost. Each cardiovascular admission causes 11.9 working days lost, and each respiratory admission causes 8.4 working days lost (National Bureau of Statistics of China, 2016). Heat-induced outpatient visits and weekends lost for admissions are not considered in the current study. Mortality and hospital admission counts were scaled down to mortality and hospital admission counts among labourers using the city labour-population ratio (Nanjing Statistical Yearbook, 2014) and further distributed into 42 industries according to the industrial-total output ratio (IO table). Meanwhile, extreme heat also results in a 12% loss of daily working time for indoor workers in the manufacturing and service sectors during the 14 days of the heat wave (5/8–18/8/2013), while it induces a daily loss of 6 hours (45 minutes times 8 hours per day) of working time for outdoor workers in the agricultural, mining and construction sectors during the heat wave period due to the occupational health safety plan. The reductions in industrial working time are summed and compared with the original industrial working time when there is no heat wave and thus no heat-induced health impact or productivity or capacity loss. The calculated percentage reduction in industrial working time is used as an indicator for the same percentage reduction in industrial value added that is used as an input in the supply-driven IO model in the next step. We did so by considering labour as a major component of industrial value added.

3.6 Supply-driven IO Model

A supply-driven IO model was derived from a traditional Leontief IO model. The Leontief model assumes that sectors interact within an economic system, and each sector produces a distinct commodity that is used for either final consumption or the inputs for other sectors during production processes. The total output of sector i, x_i, in an n-sector economy can be illustrated in Eq. 4 or 5.

$$x_i = z_{i1}+....+z_{ij}+....+z_{in}+f_i = \sum_{j=1}^{n} Z_{ij} + f_i \qquad \text{(4) or}$$

$$\mathbf{x} = \mathbf{Z_i} + \mathbf{f} \qquad (5)$$

where $\sum_{j=1}^{n} Z_{ij}$ is the monetary value sum of sector i's output in all other sectors as intermediate transactions and f_i is sector i's final demand. The technical coefficient or direct input coefficient, a_{ij}, can be obtained using Eq. 6. The Leontief IO model assumes fixed technical coefficients that suggest fixed relationships between industries.

$$a_{ij} = z_{ij} / x_j \qquad (6)$$

By combining Equations (4) and (6), the basic Leontief IO model can be derived and put into matrix notation as in Eq. 7a and b.

$$\mathbf{x} = \mathbf{Ax} + \mathbf{f} \qquad \text{(7a)}$$

$$\mathbf{x} = (\mathbf{I}-\mathbf{A})^{-1}\mathbf{f}, \ \mathbf{L}=(\mathbf{I}-\mathbf{A})^{-1} \qquad \text{(7b)}$$

where **L** is known as the Leontief inverse. It measures the impact of a dollar's worth of change in the final demand of a sector on the total output value across the economy through industrial interdependencies (Miller and Blair, 2009).

Production in a particular industry could influence other sectors in the economy in two directions. The Leontief model suggests that production affects sectors that provide its primary inputs; thus, it focuses on the demand side of the economy. However, production could also affect sectors that purchase its outputs as inputs in their production processes; thus, it focuses on the supply side of the economy. A supply-driven IO model is used to calculate the sectoral gross production changes caused by changes in the amount of primary inputs, including capital and labour. The supply-driven IO model follows the basic structure shown in Eq. 8a and b.

$$\mathbf{x'} = \mathbf{v'}\ (\mathbf{I}-\mathbf{B})^{-1} \qquad \text{(8a)}$$

$$\mathbf{x'} = \mathbf{v'}\ \mathbf{G},\ \mathbf{G} = (\mathbf{I}-\mathbf{B})^{-1} \qquad \text{(8b)}$$

where **B** is the allocation coefficient (direct-output coefficient) that is calculated by dividing *Zi* by *Xi* and b_{ij} in the supply-driven IO model, which refers to the distribution of sector i's outputs in sector j. It also assumes fixed allocation coefficients in the economy. V is the industrial value added, including capital and labour input, and G is the Ghosh inverse, which measures the economic impacts on other sectors' output resulting from the initial change in a sector's value added (Miller and Blair, 2009).

Because there is no city-level IO table for Nanjing, we scaled down the provincial IO table for Jiangsu Province for 2012 using the Nanjing-Jiangsu population ratio and assuming the same technology for Nanjing and Jiangsu province. Employment and output data were obtained from the Nanjing Statistical Yearbook 2014.

4. Results and Discussion

4.1 Industrial Reduced Productive Working Time

The 14-day heat wave in Nanjing in 2013 caused a substantial loss in labour productive working time along the production supply chain by inducing excess mortality and hospital admission rates, mental distractions that reduce the cognitive skills and productivity of indoor workers (manufacturing, energy supply and services) as well as the work capacity of outdoor workers (agriculture, mining and construction). The average percentage reduction in industrial productive working time is 2.50% across all 42 industries in Nanjing in 2013 compared with full productivity and capacity without any heat effect. The greatest losses in industrial productive working time occur in the agricultural (4.50%), mining (4.22%) and construction (4.20%) sectors, where most labourers work outdoors (Figure 4). These workers have higher work intensity and are more directly affected by extreme heat during a heat wave, and their working capacity is more likely to be constrained by occupational health and safety regulations. Compared with outdoor industries, workers in the manufacturing, energy supply and service sectors encounter productive time loss in terms of degraded productivity resulting from heat-induced mental distractions (Zander et al, 2015). Their percentage reductions in productive time are 0.69%, 0.70% and 0.67%, respectively (Figure 4).

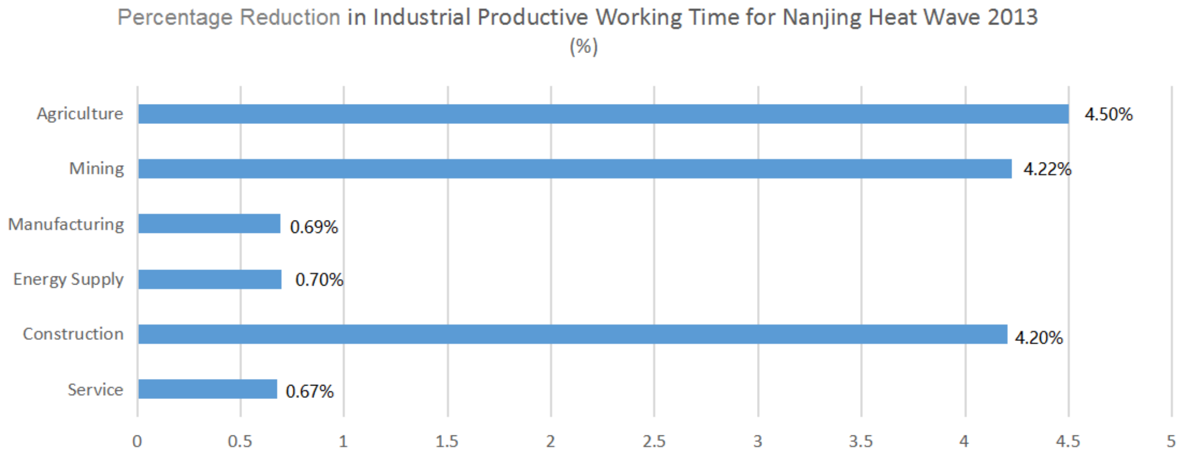


Figure 4. Percentage Reduction in Industrial Productive Working Time for Nanjing Heat Wave 2013

4.2 Industrial Economic Loss

By using heat-induced productive working time loss as an indicator for reductions in industrial value added, which further serve as an input for the supply-driven IO model, our results show that this single heat wave event, together with the resulting impacts on health, work productivity and capacity, caused a total economic loss of 27.49 billion Yuan for Nanjing in 2013 (Figure 5), which is equivalent to 3.43% of the city’s gross value of production in 2013. The manufacturing sector was the most severely hit and suffered the majority of the total economic loss (63.1%, 17.34 billion

Yuan), followed by the service sector (14.3%, 3.93 billion Yuan) and the construction sector (10.7%, 2.95 billion Yuan; see Figure 5). The industrial heat-induced economic loss depicted in the diagram shows the values for both the initial reduction in industrial value added due to productive time loss and the cascading effects that occurred along the production supply chain resulting from industrial interdependencies. To emphasize the important role of sector interdependencies in disaster risk analyses and disaster impact assessments, the next subsection will present a direct and indirect impact analysis in order to compare and contrast the relative magnitudes of the direct and indirect economic losses.

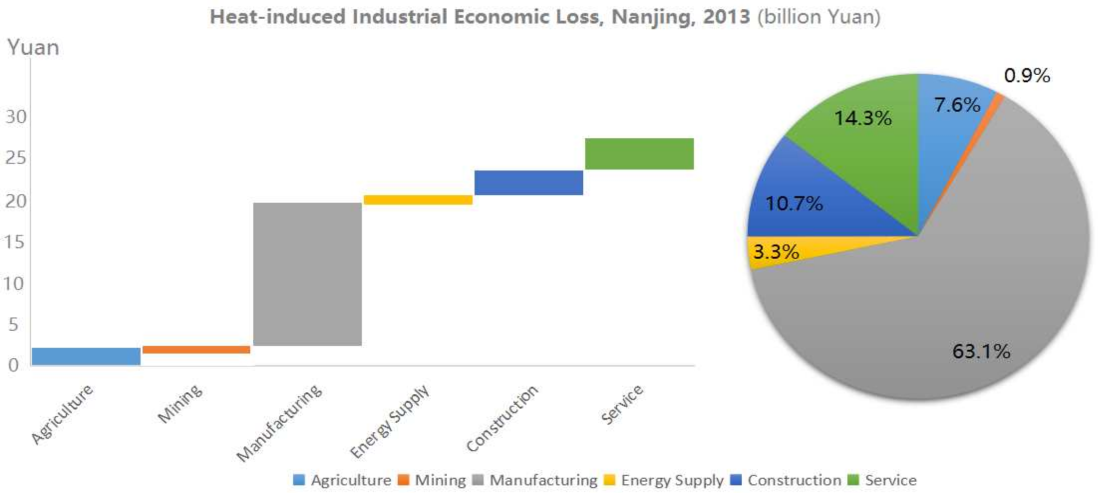


Figure 5. Heat-induced Industrial Economic Loss, Nanjing 2013

4.3 Direct and Indirect Impact Analysis

The direct and indirect impact analysis highlights the significance of industrial interdependencies. As shown in Figure 6, all sectors except agriculture experienced a greater indirect economic loss resulting from the interdependencies than the direct economic loss resulting from the initial decrease in value added. Of the 17.34 billion Yuan of total economic loss in the manufacturing sector, 88% came from indirect economic loss, while the remaining 12% was from direct economic loss. The indirect loss was over seven times greater than the direct loss in the manufacturing sector, potentially because of its close industrial relationships with the other sectors and the rest of the economy. An even wider direct-indirect loss gap can be observed in the energy supply sector, where the indirect economic loss accounted for 90% (828.54 million Yuan) of the total economic loss. The service sector also showed a greater indirect loss than direct loss at 2.28 billion Yuan (58%) and 1.65 billion Yuan (42%), respectively. The results show that although the potential productive time loss for work productivity of self-paced indoor workers was less than that for the work capacity constraints of outdoor workers, the former did not necessarily entail less economic loss because the initial reduction in productive time or industrial value added was not sufficient to reflect the relative magnitudes of the economic loss between sectors. Although the productive time of the indoor industries of manufacturing, energy supply and services decreased by only 0.69%, 0.70% and 0.67%, respectively, these sectors can still cause considerable indirect economic loss as a result of their close linkages with other ‘upstream’ and ‘downstream’ industries. This situation is particularly true for Jiangsu Province, where the manufacturing and service sectors lead the provincial economy. In contrast, the agricultural and mining sectors encountered greater direct economic loss than indirect loss, mainly because the labour in these sectors features high work intensity, and therefore, the work capacity is more constrained by external heat conditions due to certain occupational health and safety regulations.

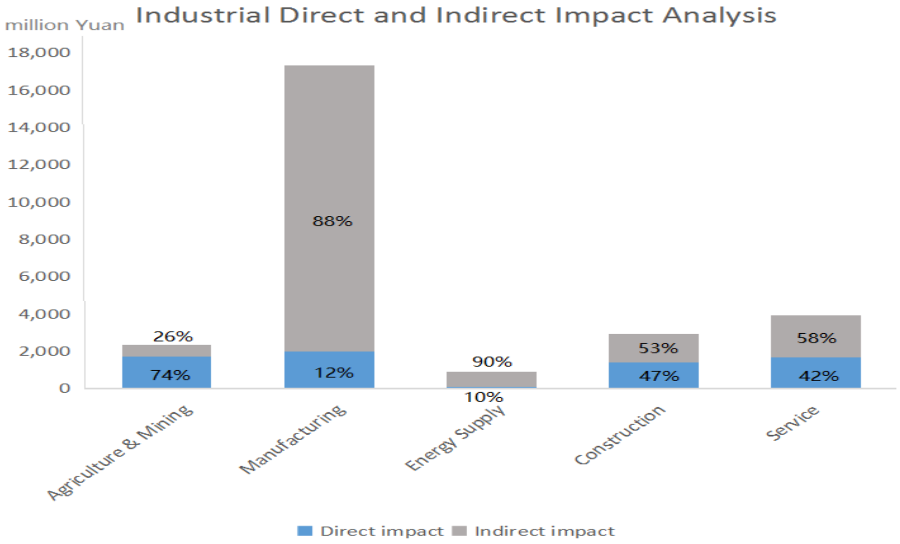


Figure 6. Direct and Indirect Impact Analysis

5. *Conclusions*

This paper develops an interdisciplinary approach by combining meteorological, epidemiological and economic analyses to investigate the macroeconomic impacts of heat waves on the economy of Nanjing in 2013 to contribute from the following research gaps: 1) the existing episodic studies on heat mostly focus on developed countries, whereas studies on developing countries, whose social and economic structures are entirely different from those in the developed world, are non-existent; 2) the existing episodic studies on heat mostly quantify the heat-mortality relationship and lack quantitative analyses of heat's effect on morbidity, productivity and capacity loss due to mental distractions and safety regulations; 3) the existing approaches used in health cost assessments generally take the patient's perspective in evaluating the economic burden of a particular disease, which is insufficient for investigations of the macroeconomic implications on the entire economic system because industrial interdependencies and indirect economic losses are extremely important for such macroeconomic evaluations; and 4) heat waves can be analogously viewed as a 'persistent' disaster that affects human capital more than physical capital. However, the challenge of quantifying the invisible effects on human capital prevents their integration into disaster risk studies. By adopting a supply-driven IO model, labour is perceived as a key factor input, and any heat effect on humans can be viewed as a degradation of productive time and human capital. With this interdisciplinary tool, our study shows a total economic loss of 27.49 billion Yuan for Nanjing in 2013 due to the heat wave, which is equivalent to 3.43% of the city's gross value of production in 2013. The manufacturing sector suffered 63.1% of the total economic loss at 17.34 billion Yuan. Indeed, with the IO model's ability to capture indirect economic losses, our results further suggest that although the productive time losses in the manufacturing and service sectors have lower magnitudes than those in agriculture and mining, they can entail substantial indirect loss because of industrial interdependencies. This conclusion highlights the importance of incorporating industrial interdependencies and indirect economic assessments into disaster risk studies because even for a small percentage reduction in the primary inputs of a sector, such interdependencies can raise the total economic loss far beyond the direct economic loss measured by reduced industrial value added. As a result, the current paper contributes to filling the four research gaps described above among existing studies on heat epidemiology, health cost assessments and disaster risk analyses.

The current paper makes several assumptions and thus is subject to uncertainties that open up new research directions for future studies. First, we assumed that heat-induced productivity loss due to mental distractions induced a 12% loss of daily productive time during the heat wave period. We made this assumption based on Bux (2006) by considering the heat wave in Nanjing in 2013 to be an extreme one and because of the lack of identified quantitative relationships between heat exposure and productivity loss. We also assumed 45 minutes' relief time per hour will be required for outdoor workers during the heat wave period. Second, we assumed that extreme heat exposure would only limit work productivity for workers in the manufacturing, energy supply and service sectors, where workers mostly work indoors, as well as the work capacity of workers in the agricultural, mining and construction sectors, where workers generally work outdoors and are more likely to be harmed by direct heat exposure. We did not differentiate between indoor and outdoor workers within the same industry, which might lessen the accuracy of the results. Third, current study only considered that each cardiovascular admission would cause 11.9 working days lost while each respiratory admission would cause 8.4 working days lost. because of the lack of quantitative relationships or records on heat admission and heat outpatient visits for Nanjing, we referred to a heat admission study conducted in Shanghai in 2011 (Ma et al, 2011) and did not consider any heat effect on increasing rates of outpatient visits for other diseases. Future studies should account for heat-induced outpatient visits once such data are available because they also constitute a major aspect of productive time loss that should be considered in any macroeconomic assessment of heat-induced health impacts. For these assumptions, we conducted a sensitivity analysis in the Supplementary Information to test the impact of alternative assumptions on study results. We found that study results are subject to sharpest increase when workers in all industries are affected by both heat-induced productivity and capacity loss. Total economic loss would rise to 95.65 billion Yuan. Total economic loss would be also expected to rise significantly with rising percentage of productivity loss for indoor self-paced workers during heat wave period. With percentage reduction in labour time due to productivity loss increases from 10% to 30%, the total economic loss rise from 25.74 to 43.22 billion Yuan. This highlights the significance of considering heat-induced mental distraction and the resulting productivity loss for indoor workers in health cost assessment studies for heat waves. Fourthly, current study does not consider any compensatory or avoidance behaviour, which implies that agents cannot optimize their behaviour or efficiency under extreme heat conditions. We made such assumption as a result of relatively short study period during which agents cannot have sufficient time to adapt themselves to extreme heat. Although the ignorance of adaptive behaviour may lead to overestimation of heat-induced labour time loss due to productivity and capacity constraints, we believe our findings could provide an alarm for both indoor, outdoor labourers and government in the face of future heat wave events. Finally, the current paper employed a supply-driven IO model by perceiving labour as a key primary input and reduced productive time as an indicator of reduced value added. There are certain limitations surrounding an IO model. An input-output model generally focuses on a single year's time frame a city, regional or national level. This means that our proposed framework can be only used to estimate the economic impacts of heat wave on a city, region or nation during a year instead of considering any persistent impacts during the sequencing years. It can neither be applied on several connecting regions because of the lack in multi-regional input-output tables. The model also has limitations in inflexibility, regarding the price or substitutions for demand and supply (Hallegatte, 2008). This indicates that the model does not consider discounted value of economic output and suppliers cannot seek for substitutive factor inputs when several labourers become absent for sickness. Moreover, the model does not consider any productive capacity or possibility of overproduction capacity (Hallegatte, 2008). Data on inter-industrial transaction flows are estimated and calculated based on the assumption of industrial full production capacity.

However, the current paper provides a way to incorporate health impacts into disaster risk analyses using the IO model and an alternative approach for health cost assessments to evaluate health impacts using other microeconomic tools, such as CVA and HCA. It is a good candidate model to reflect the macroeconomic impacts of changes in value added (degradation in labour time) on the entire economy by capturing industrial interdependencies and indirect economic losses. It does not consider any extra compensations for working during the hot days and the resulting positive effects on economic activities due to rising wages.

References

Dell, M., Jones, B.F., and Olken, B.A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature* 52 (3): 740-798.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., and Shapiro, J.S. (2015). Convergence in adaptation to climate change: evidence from high temperatures and mortality, 1900-2004. *The American Economic Review* 105 (5): 247-251.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., and Shapiro, J.S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over twentieth century. *Journal of Political Economy* 124 (1): 105-159.

Haines A, McMichael AJ, Smith KR, Roberts I, Woodcock J, Markandya A, et al. 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: overview and implications for policy makers. Lancet 374 (9707): 2104-14.

IPCC. 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*. [C.B.Field CB, V.Barros V, T.F.Stocker TF, D.Qjn D, D.J.Dokken DJ, K.L.Ebi KL, M.D.Mastrandrea MD, K.J.Mach KJ, G.-K.Plattner G-K, S.K.Allen SK, M.Tignor M, P.M.Midgley PM (eds.)]. Cambridge, UK and New York, NY, USA: Cambridge University Press.

Fouillet A, Rey G, Laurent F, Pavillon G, Bellec S, Guihenneuc-Jouyaux C, et al. 2006. Excess mortality related to the August 2003 heat wave in France. *Int Arch Occup Environ Health* 80 (1): 16-24.

Conti S, Meli P, Minelli G, Solimini R, Toccaceli V, Vichi M, et al. 2005. Epidemiologic study of mortality during the Summer 2003 heat wave in Italy. *Environ Res* 98 (3): 390-9.

Grize L, Huss A, Thommen O, Schindler C, Braun-Fahrlander C. 2005. Heat wave 2003 and mortality in Switzerland. *Swiss Med Wkly* 135 (13-14): 200-5.

Sun X, Sun, Q, Zhou X, Li X, Yang M, Yu A, Geng F. 2014. Heat wave impact on mortality in Pudong New Area, China in 2013. *Science of the Total Environment* 403 (2014): 789-94.

Wan Y, Yang H, Masui T. 2004. Air pollution-induced health impacts on the national economy of China: demonstration of a computable general equilibrium approach. *Reviews on environmental health* 20: 119-140.

Miller RE, Blair PD. 2009. *Input-output analysis: foundations and extensions*. Cambridge University Press.

Honda Y, Ono M, Sasaki A, Uchiyama I. 2007. Relationship between daily high temperature and mortality in Kyushu, Japan. *Japanese journal of public health* 42: 260-68.

Anderson GB, Bell ML. 2011. Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. *Environ Health Perspect* 119: 210-8.

Weisskopf M, Anderson H, Foldy S, Hanranhan I, Blair K, Torok T, et al. 2002. Heat wave morbidity and mortality, Milwaukee, Wis, 1999 vs 1995: an improved response. *Am J Public Health* 92: 830.

Tataru N, Vidal C, Decavel P, Berger E, Rumbach L. 2006. Limited impact of the summer heat wave in France (2003) on hospital admissions and relapses for multiple sclerosis. *Neuroepidemiology* 27: 28-32.

Michelozzi P, et al. 2009. High temperature and hospitalizations for cardiovascular and respiratory causes in 12 European cities. *American journal of respiratory and critical care medicine* 179: 383-9.

Baccini M, et al. 2011. Impact of heat on mortality in 15 European cities: attributable deaths under different weather scenarios. *Journal of epidemiology and community health* 65: 64-70.

Gaoua N, Racinais S, Grantham J, El Massioui F. 2011. Alterations in cognitive performance during passive hyperthermia are task dependent. *International Journal of Hyperthermia* 27: 1-9.

Zander KK, Botzen WJ, Oppermann E, Kjellstrom T, Garnett ST. 2015. Heat stress causes substantial labour productivity loss in Australia. *Nature Climate Change*.

Dunne JP, Stouffer RJ, John JG. 2013. Reductions in labour capacity from heat stress under climate warming. *Nature Climate Change* 3: 563-6.

Kan H, Chen B. 2004. Particulate air pollution in urban areas of Shanghai, China: health-based economic assessment. *Science of the Total Environment* 322: 71-9.

Zeng X, Jiang Y. 2010. Evaluation of value of statistical life in health costs attributable to air pollution. *China Environmental Science* 30: 284-8.

Steenge AE, Bočkarjova M. 2007. Thinking About Imbalances in Post-Catastrophe Economies: An Input-Output Based Proposition. Economic Systems Research 19 (2): 205-23.

Cho S, et al. 2001. Integrating transportation network and regional economic models to estimate the costs of a large urban earthquake. *Journal of Regional Science* 41: 39-65.

Santos JR, Haimes YY. 2004. Modeling the Demand Reduction Input-Output (I-O) Inoperability Due to Terrorism of Interconnected Infrastructures. *Risk Analysis* 24: 1437-51.

Crowther KG, Haimes YY. 2005. Application of the inoperability input—output model (IIM) for systemic risk assessment and management of interdependent infrastructures. *Systems Engineering* 8: 323-41.

Xia Y, Guan D, Jiang X, Peng L, Schroeder H, Zhang Q. 2016. Assessment of socioeconomic costs to China's air pollution. *Atmospheric Environment* 139: 147-56.

Ma W, Xu X, Peng L, Kan H. 2011. Impact of extreme temperature on hospital admission in Shanghai, China. *Science of The Total Environment* 409: 3634-7, doi:http://dx.doi.org/10.1016/j.scitotenv.2011.06.042.

Basu R, Samet JM. 2002. Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. *Epidemiol Rev* 24: 190-202.

World Health Organization. 2016. *Matrics: Population Attributable Fraction (PAF)*. [Online]. Available at http://www.who.int/healthinfo/global_burden_disease/metrics_paf/en/ Accessed 2/12/2016.

Bux K. Klima am Arbeitsplatz–Stand arbeitswissenschaftlicher Erkenntnisse–Bedarfsanalyse für weitere Forschungen. 2006. (1987 eds.) *Bundesamt für Arbeitsschutz und Arbeitsmedizin, Dortmund, Forschung Projekt F*.

Occupational Health and Safety. 2010. *Working in Hot Weather or Hot Workplace Environments. Procedure and Guidelines for Working in Hot Environments* (Number 2010-06). [Online]. Available at https://www.uwo.ca/hr/form_doc/health_safety/doc/procedures/working_in_hot_environments.pdf Accessed 2/12/2016.

NanJing Meteorology. 2016. *Average Summer Humidity in Nanjing.* [Online]. Available at http://www.njqxj.gov.cn Accessed 3/12/2016.

Bureau of Statistics of Nanjing. 2016. *Nanjing Statistical Yearbook 2014*. [Online]. Available at http://www.njtj.gov.cn/47664/ndsj/ Accessed 3/12/2016.

Supplementary Information - Sensitivity Analysis

This supporting information presents a sensitivity analysis for the case study on Nanjing heat wave in 2013 to test the impacts of alternative data or assumptions on the modelling results in terms of total economic loss resulting from $PM_{2.5}$-induced health effects. These alternative assumptions involve: 1) percentages of labour time loss due to heat-induced productivity loss; 2) industries are affected by both productivity and capacity loss regardless the indoor or outdoor working environment; 3) time required for break during heat wave period/working hours lost due to heat-induced capacity loss; and 4) required time for each case of heat-induced cardiovascular admission.

1. Percentages of Labour Time Loss due to Productivity Loss

In the case study, heat-induced productivity loss due to mental distractions was assumed to induce a 12% loss of daily productive time during the heat wave period according to Bux (2006), as a result of a lack in the quantitative relationships between heat exposure and productivity loss. Therefore, this section will test the total economic loss when extreme heat in Nanjing induces a 10%, 20% or 30% reduction in productive working time for indoor workers during the heat wave period. The results from alternative assumptions are displayed in *Table 1.* With percentage reduction in labour time due to productivity loss increases from 10% to 30%, the total economic loss rise from 25.74 to 43.22 billion Yuan.

Table 1. Percentage Productive Working Time Reduced

Sensitivity Analysis - percentage productive working time reduced	
Percentage Reduced	Output Loss (billion Yuan)
10%	25.74
20%	34.48
30%	43.22

2. Industries Affected by Both Productivity and Capacity Loss

The second assumption in the case study is that extreme heat exposure would only limit work productivity for workers in the manufacturing, energy supply and service sectors, where workers mostly work indoors, as well as the work capacity of workers in the agricultural, mining and construction sectors, where workers generally work outdoors and are more likely to be harmed by direct heat exposure. Here, model results will be tested when both indoor and outdoor workers are affected by productivity loss and capacity constraints with the same reductions in labour time as in the case study. The total economic loss based on this assumption rise significantly to 95.65 billion Yuan as a result of considerable increase in total labour time loss.

3. Labour Hours Loss due to Capacity Loss

Additionally, the study assumes heat-induced capacity constraints would cause a daily loss of 6 hours (45 minutes times 8 hours per day) of working time for outdoor workers. The model results will be tested based on the alternative daily working hours lost at 2, 4 and 8 hours, respectively. The results are shown in *Table 2.* Compared with figures in *Table 1*, the results appear to be less sensitive to capacity constraints than to productivity loss, which highlights the importance in considering potential impacts of heat-induced mental distractions and in ensure the size of self-paced labourers that will suffer from heat-induced mental distractions or degraded cognitive skills.

Table 2. Labour Hours Loss due to Capacity Constraints

Sensitivity Analysis - labour hours loss from capacity constraints	
Labour Hours Loss	Output Loss (billion Yuan)
2	16.57
4	22.03
8	32.94

4. Timed Required for Each Cardiovascular Hospital Admission

Finally, the study also makes assumption on time required for each cardiovascular admission. Thus, we tested the variation range in total economic loss when each cardiovascular admission takes 30, 60 and 90 working days, respectively. The results for the alternative required time are provided in *Table 3*. The results only change slightly, suggesting that model results are not sensitive towards changes in time required for each cardiovascular hospital admission.

Table 3. Varying Working Day Lost for Each Cardiovascular Admission

Sensitivity Analysis - cardiovascular hospital admission time	
Number of Working Days Lost	Output Loss (billion Yuan)
30	27.49
60	27.50
90	27.52

1. The study assesses the heat wave impact on health, labour productivity and labour working capacity.
2. By perceiving working time loss as degradation in value added, the interdisciplinary approach bridges meteorological study, epidemic study and macroeconomic impact evaluation.
3. By using an IO model, the study incorporates interdependencies analysis into health costs assessment and also heat-wave impact analysis into disaster risk study.