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A Disaster Footprint Framework for Assessing the Cascading Indirect Economic Impacts of Natural Disasters

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Abstract

This PhD thesis employs and further develops models from environmental, epidemiological and macroeconomic studies to construct an interdisciplinary 'Disaster Footprint Model' based on input-output techniques for assessing the cascading indirect economic loss resulting from both 'rapid-onset' and 'persistent' natural disasters that were happened in the UK or China at different points in time.

Each natural disaster will undermine physical capital and inhabitants differently in the form of destructions to infrastructures, roads, buildings, death or injuries, which are normally termed as 'direct impacts' of a disaster. Unfortunately, the tragedy is not over. Direct impacts of a disaster will disrupt the economic activity when machineries are out of order and labourers cannot attend the work, which will further trigger the economic output of the affected industries or regions due to the shrinking capital and labour productivity. Indeed, the initial reduction in output level of the affected industry or region can spill over those unaffected industries and regions through industrial and regional interconnectedness in the sense that each industry/region sells its outputs to or purchases commodities from other industries/regions. As a result, indirect economic loss can constitute a considerable share in total economic loss of a natural disaster. The significant role of indirect economic loss has been well documented given that the industrial and regional interdependencies have become unprecedentedly tightened under globalization in the contemporary world. In this respect, input-output model is a good candidate to cope with the cascading indirect economic loss from a disaster due to its root in 'a circular economy'. An input-output model was developed by Wassily Leontief based on the concept of 'a circular economy', suggesting that social production and reproduction activities enclose the use of high-efficiency resources and environmentally friendly. Specifically, the production of the labourers will be used in the process of nature cycle while the natural resources will be used in the perpetual cycle (Liu et al, 2016). Labourers simultaneously act as consumers and economic

production will be partially consumed by consumers and partially by other industries. In this respect, an input-output model takes the form of matrix and records the inter-industrial transaction flows. For ‘rapid-onset’ disasters that arrive rapidly with few days or without warnings, despite that a number of hybrid input-output based models have been proposed, they have heavily relied on accurate estimation of physical capital damages without conscientiously considering the distinctive characteristics of these disasters where their models might become invalidated. For ‘persistent’ disasters that persist longer and whose effects will be gradually realized over time, their ‘invisible’ health impacts provoke challenges for existing disaster risk modelling and little attention has been attached to constrained labour productivity in a post-disaster economy. Meanwhile, existing assessment tools in health costs studies mainly stem from a patient’s standpoint and quantify the disease burden at a microeconomic level, thus uncovering the need for investigating the macroeconomic implications from these health impacts. Environmental, health and economic problems are intertwining with one another in an environment-health-economy nexus. Any single phenomenon is resulting from a complexity of multi-factors and thus, should be solved by integrating these studies instead of keeping them as separate entities.

Inspired by this, Chapter 4 designs an interdisciplinary methodological framework that bridges environmental or meteorological studies, epidemiological studies and macroeconomic analysis. The framework allows several input-output based options to consider the distinctive feathers of a natural disasters where the traditional disaster modelling cannot function well, to understand and incorporate the health impacts through an angel of reducing labour availability and productive time, and to capture the cascading indirect economic loss triggered by industrial and regional interdependencies from a macroeconomic perspective. To verify the feasibility and applicability of the approach, Chapter 5, 6 and 7 select four case studies that include the economic assessments of a typical flood with special characteristics occurred in the UK; one on China's air pollution in 2012; and two on China's heat waves in Nanjing and Shanghai in 2013 and 2007, respectively.

After applying the approach on four cases covering both 'rapid-onset' and 'persistent' natural disasters, the thesis illumes future research with several important conclusions that **1)** Disaster risk studies should attach equal significance to loss in capital productivity and labour productivity; **2)** Air pollution and heat waves should be considered analogously as a natural disaster that affects human capital more than physical capital and thus, they should be investigated more deeply in disaster risk studies; **3)** Disaster risk modelling should be conducted with additional attention on disaster characteristics; **4)** 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; **5)** Input-output techniques and its modified forms are able to provide more modelling options for disaster risk assessment and management; **6)** The developed interdisciplinary approach can successfully bridge environmental or meteorological studies, epidemiological studies and macroeconomic analysis. It also allows to consider the distinctive feathers of a natural disasters, to understand and incorporate the health impacts through an angel of reducing labour availability and productive time, and to capture the cascading indirect economic loss triggered by industrial and regional interdependencies; **7)** The estimation based on such interdisciplinary model can be more accurate and effective once more comprehensive and sophisticated dataset are available, such as the occupational disease incidence rate and required time for each outpatient visit.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Natural Disaster: A Global Threat

Increasing production and consumption under economic development has put a strain on the environment, polluting the earth and further exacerbating climate change. The world population have experienced increasing intensity and frequency of natural disasters. Natural disaster stands for any catastrophic event resulting from the natural processes of the earth, examples include floods, hurricanes, tornadoes, earthquakes, tsunamis and other geologic processes that only happened to populated areas (Basicplanet, 2013). In this thesis, we also treat $PM_{2.5}$ air pollution as a natural disaster that could cause substantial damages to human health because it has been included in the Beijing Municipal Meteorological Disaster Prevention Statute as a 'meteorological disaster' (Asia Pacific, 2016). Natural disasters have become a threat to global population and economy by inducing millions of lives loss and enormous economic loss. The magnitude of a natural disaster is evaluated according to the resulting deaths, economic loss and the ability of the population to reconstruct the environment.

Gory and terrifying scenes are always centered around natural disasters. The Yellow River flood occurred in China, July 1931 is a series of devastating floods that was caused by the heavy snowstorms in the winter and the following spring thaw. Regardless the flood protection organizations, such as the Huai River Conservancy Commission, and flood control project, such as the Three Gorges Dam, the severe floods still resulted in up to 4 million deaths (Basicplanet, 2013). Another major natural catastrophe, the Indian Ocean earthquake and tsunami occurred along the west coast of Sumatra, Indonesia on 26 December, 2004. The undersea earthquake resulting from the Indian Plate subduction is the third-largest earthquake on the seismograph record with a moment magnitude between 9.1 and 9.3 that eventually resulted in 280,000 fatalities, according to the report from the Indonesian Minister of Health (BBC News, 2012). If we say floods and earthquakes are the 'visible murders', air pollution and heat waves are analogously the 'invisible killers' that gradually place human beings under risks. Millions of people in China are currently breathing toxic air substances, which has become one of the most serious topics in environmental issues in China by resulting in widespread environmental and health problems, including increasing risks for heart and respiratory diseases, stroke and lung cancer (Greenpeace, 2017). 2013 will be remembered as the year that deadly, suffocating smog consumed China. In mid-January 2013, Beijing and the surrounding regions were terribly hit by the $PM_{2.5}$ pollution. The air quality index (AQI) in Beijing soared at 993, far exceeding levels health officials deem extremely dangerous (Wong, 2013). As a consequence, the local emergency departments were crowded with thousands of respiratory patients and injection rooms have run out of beddings and nursing staffs. The 'airpocalypse' in Beijing was jokingly named as 'air pollution crisis'. It sparked outrage among the Chinese public and placed China under global media spotlights (Wong, 2013). Another 'intangible murder', heat waves, spread in the Europe in 2003. It was recorded as the hottest summer in Europe since 1540 and caused nearly 70,000 deaths. Auxerre, Yonne in France experienced 8 consecutive days with daily maximum temperature over 40 ℃ and the entire countries encountered the greatest death toll at 14,802 deaths among all affected European countries (Fouillet et al, 2006; Conti et al, 2005; Grize et al, 2005). The increasing frequency and intensity of heat waves are endangering the population in both developed and developing world.

Recurring floods and drought, earthquakes, air pollution and heat waves are all parts of the same unfolding story. Global population is confronted with the superpower of the nature. These events are shaping our planet, affecting where and how we live, challenging human's capacity to adapt to the evolving world.

1.2 Research Motivation

Each natural disasters has distinctive characteristics that affects physical capital and human capital to different extent and cause the interruption to economic activities. They can be either ‘rapid-onset’ or ‘persistent’. Existing disaster research has mostly studied the socioeconomic consequences resulting from floods or storms that are generally rapid-onset, destroying, and whose outcomes are readily visible, such as the damages to roads, buildings and other infrastructures. On the contrary, air pollution and heat waves normally would not cause much damages to physical capital but seriously threaten human health. These effects can be long-lasting and ‘persistent’ and equally impede economic functioning by preventing labourers from going to work or reducing their productivity. However, such ‘persistent’ disasters are yet to be thoroughly investigated in the disaster risk literature, or even rarely classified in the natural disaster category. To quantify these ‘invisible’ health impacts resulting from air pollution or heat waves appears to be a challenge for disaster risk analysis.

Meanwhile, a natural disaster can cause both direct economic loss, referring to the primary damages to the physical infrastructure or injuries and mortality that can be realized immediately after the occurrence of a disaster; and indirect economic loss, referring to the knock-on effects that are triggered from the direct damages of a disaster. This includes the degradation in both labour and capital productivity due to the initial loss from the impacted assets, injuries and deaths, as well as the sum of production loss during the post-disaster economic recovery process until labour and capital productivity are brought back to the pre-disaster level. It has been well documented that direct economic loss is no longer sufficient for disaster risk assessment and management (Hallegatte, 2008). Indeed, the inter- and intra-relationships between each economic sectors have been increasingly tightened through trade and globalization. This indicates the possibility that the impacts on a directly-affected sector/region can be cascaded and eventually spill over those unaffected sectors/regions through the interconnecting production supply chains and other economic mechanisms. Indirect economic loss will constitute a considerable share of the total socioeconomic burden of a disaster and seriously exacerbate the initial loss from the impacted assets and population. Therefore, to capture these cascading effects resulting from the reductions in capital and labour productivity as well as sectoral and regional interdependencies along the production supply chains is highly meaningful for understanding the macroeconomic consequences of a disaster and developing a comprehensive disaster risk assessment system. Despite that a number of advanced models have been constructed to analyze the direct and indirect economic loss of a disaster, there still lacks a systematic framework that is able to quantitatively incorporate a disaster's direct economic impacts on physical and human capital, initial economic impacts resulting from the reductions in physical and labour productivity as well as the cascading indirect economic impacts along production supply chains as a result of sectoral and regional interdependencies.

1.3 Research Question, Objectives and Contributions

Given the outlined research gaps remaining in existing literature, this research is conducted to answer 'how to quantify and incorporate total economic loss from a natural disaster event into a methodological framework?' Therefore, this thesis introduce a new concept of 'disaster footprint' to denote the total economic loss resulting from a disaster event in terms of the total reduction in aggregated production. This includes the initial reduction in supply of industrial primary inputs or industrial final demand as a result of disaster-induced loss in capital and labour productivity; and the cascading indirect economic loss resulting from sectoral and regional interdependencies. It also aims to construct a disaster footprint framework for natural disasters that is able to quantify and incorporate all these economic impacts. The specific objectives of this research are:

- Providing a review on the quantitative assessment methods for damages to physical capital from rapid-onset disasters (floods), as well as the quantitative assessment methods for health impacts from persistent disasters (air pollution and heat waves) (Chapter 2).
- Providing a review on quantitative methods for assessing cascading indirect economic impacts along production supply chain with a particular focus on input-output modelling framework; Describing the evolvements of input-output analysis and its variations and applications to ecological, environmental and disaster studies (Chapter 3).
- Constructing a disaster footprint framework that is able to quantify and incorporate the resulting damages to physical capital and health impacts from certain meteorological conditions and thereby, the indirect economic impacts caused by the reductions in capital and labour productivity as well as their cascading indirect economic impacts along production supply chain, which is due to sectoral and regional interdependencies (Chapter 4).
- Applying the interdisciplinary framework that bridges existing models from environmental/meteorological, epidemiological and macroeconomic studies, onto both 'rapid-onset' and 'persistent' natural disasters that occurred worldwide at different point in time to measure and contrast their cascading indirect economic impacts from different types of natural disasters (Chapter 5, 6 and 7).
- From the modelling results in each chosen case, providing policy implications for governments and authorities, and showing directions for future risk research (Chapter 8).

This research aims to contribute from the following aspects. Firstly, the interdisciplinary approach will bridge existing models in environmental or meteorological study, epidemiological study and macroeconomic analysis, and it will be tailored according to the distinctive characteristics of either 'rapid-onset' (eg. Floods) or 'persistent' natural disasters (eg. Air pollution, heat waves). The built framework will allow us to feed the disaster-induced damages to physical capital and human health into a macroeconomic model so that the cascading economic loss along the economic production chains can be assessed. Secondly, the framework will be further applied onto selective empirical cases that are yet to be investigated in current disaster literature. They include both 'rapid-onset' and 'persistent' natural disasters that occurred in the UK and China at different points in time to measure and contrast the cascading indirect economic impacts from different types of natural disasters. By doing so, the validity of the framework can be tested in real cases and future disaster risk studies can leapfrog to a more comprehensive risk assessment and management system with macroeconomic views. Meanwhile, by focusing the case studies in the UK and China, the research is expected to contribute to the disaster preparation and management in both developed and developing countries, especially for the developing world, where the disaster protection mechanisms appear to be less developed and population are thus more vulnerable.

1.4 Research Scope and Selection of Study Sites

As the proposed approach in this research is developed based on an input-output model, the study scope is limited to a single year with unchanged technological status. Thus, this research aims to estimate the impacts of either 'rapid-onset' or 'persistent' disaster on the production level of the entire economic system at a city, regional or national level within a single year instead of considering any further impacts resulting from the disaster event that might occurred in the sequencing years.

The four selected case studies base in either the UK or China. We chose these case studies because: firstly, the chosen cases are representable for natural disaster with distinctive feathers that invalidate existing disaster risk assessment tools. Secondly, the UK is a country that frequently suffered from floods while China is currently experiencing severe air pollution and heat wave issues. Indeed, regardless a number of disaster studies, they tend to focus more on developed countries. However, developing countries like China, due to its underdeveloped disaster protection infrastructure, the population appear to be more vulnerable. Thus, the studies on China's air pollution and heat waves are expected to contribute the disaster literature for the developing world to facilitate better disaster preparation and management. Thirdly, from the empirical side, chosen studies are yet to be fully investigated in existing disaster literature and therefore, they are new cases to extend the current boundary of disaster studies.

1.5 Thesis Outline

The document has been divided into eight chapters. Both Chapter 2 and 3 can be categorized as literature review sections. Chapter 2 mainly reviews the direct damages from natural disasters and the quantitative assessment methods. It covers not only the damages to physical capital from 'rapid-onset' disasters, such as floods, and the developed assessment tools among existing literature; but also the health impacts from 'persistent' disasters, such as air pollution and heat waves, as well as the health models from existing epidemic studies that quantify the resulting health impacts. The chapter also introduces the economic loss assessments in existing literature that translate disaster-induced physical capital damages and health impacts into monetary units.

With respects to cascading indirect economic impacts caused by sectoral and regional interdependencies, Chapter 3 is a literature review on input-output analysis that comprehensively revisits the evolvements of input-output techniques, its variations and applications on ecological, environmental and disaster risk studies. Both Chapter 2 and 3 outline the progresses and remaining blanks regarding natural disaster risk studies, which pave the roads for constructing the disaster footprint framework in Chapter 4.

Chapter 4 develops a disaster footprint framework that is able to quantify and incorporate the resulting damages to physical capital and health impacts from certain meteorological conditions and thereby, the initial economic impacts caused by the reductions in capital and labour productivity as well as their cascading indirect economic impacts along production supply chain, which is due to sectoral and regional interdependencies. This interdisciplinary approach links environmental or meteorological study, epidemiological study and macroeconomic analysis with the consideration of distinctive characteristics of either ‘rapid-onset’ (eg. Floods) or ‘persistent’ natural disasters (eg. Air pollution, heat waves).

The disaster footprint framework constructed in Chapter 4 is applied onto both ‘rapid-onset’ and ‘persistent’ natural disasters that occurred worldwide at different points in time to measure and contrast the cascading indirect economic impacts from different types of natural disasters in Chapter 5, 6 and 7. They are the results chapters that totally encompass 4 cases studies, which include one study on floods occurred around Christmas time in York, UK, 2015; one studies on air pollution in China 2012; and two studies on heat waves in two Chinese cities, Shanghai and Nanjing during 2007 and 2013, respectively. Due to the distinctive characteristics of each natural disaster, each case in Chapter 5, 6 and 7 presents a separate methodology, findings and policy implications, in which the methodology is neatened from the main framework developed in Chapter 4 with additional consideration of the disaster characteristics.

Chapter 8 summarizes the main findings and lessons from the above case studies with policy recommendations for government authorities. It also highlights the research novelty, contributions and remarks on the directions for future research within the context of health costs assessment and disaster risk studies.

Finally, the thesis ends with the reference list, covering journal articles, books, online sources and other data sources. Appendices provide detailed information regarding observations on meteorological conditions, definitions for terminologies and the list of assumptions underlying the current study.

Chapter 2: 'Shambles in Post-Disaster World': Direct Impacts and Assessment Tools

This chapter provides an overview of the direct damages from natural disasters and existing quantitative assessment methods. It covers the direct damages to physical capital from 'rapid-onset' disasters, health impacts from 'persistent' disasters as well as available modelling tools to assess these impacts. Meanwhile, it reviews economic loss assessments studies that interpret disaster-induced physical capital damages and health impacts into monetary units. In particular, this chapter is designed:

1. To describe the direct impacts from 'rapid-onset' and 'persistent' disasters;
2. To investigate existing modelling tools for assessing the direct impacts from natural disasters;
3. To examine the available approaches in economic loss assessments, which interpret these direct impacts in the form of monetary loss and assist disaster burden analysis.

2.1 Rapid-onset Disasters: Floods and Earthquakes

'Rapid-onset' disasters refer to those natural disasters that arrive rapidly with few days or without warnings, such as floods and earthquakes (Development Workshop, 2017). The consequences can be easily observed immediately after the disaster's occurrence, which are usually destructive and devastating. Severe rapid-onset disasters can cause substantial direct economic impacts due to the damages to physical capital, such as the destructions to roads, bridges, buildings and infrastructure; and to the inhabitants in the form of injuries and mortalities.

With regards to floods, the direct economic impact normally refers to the direct consequences of a flood that include the short-term physical damages on natural resources, people and tangible assets (Merz et al, 2004). These short-term damages are normally resulting from the physical contact of the flood water with people, property, infrastructure or other objects (Merz et al, 2004). Direct economic impacts from a flood is often measured by government authorities (eg. China) or insurance companies (eg. UK) through primary data surveys and interviews. Alternatively, they can be estimated based on damage functions or loss functions. The damage functions assess the direct monetary damage to a building according to the inundation depth and the type or use of the building. The central concept underlying such estimation is from the observation of Grigg and Helweg (1975) who suggest that buildings with similar type or use share the similar depth-damage curves regardless of their actual values. Developing damage functions for specific buildings relies on both actual and synthetic data sources. Actual data come from damage data collection during the flood aftermath while synthetic data are generated from 'what-if analyses' in which case the damages will be estimated for a certain flood scenario (Merz et al, 2004). Apart from building type and inundation depth, flood damage also depends on factors including flow velocity, inundation duration, sediment concentration, flood warning and the quality of external response towards floods (Smith, 1994; Penning-Rowsell et al, 1994). In this respect, the most comprehensive approach in damage functions might be the Blue Manual of Penning-Rowsell that differentiates the stage damage curves for commercial property from those for residential dwellings in the UK (Merz et al, 2004). More recently, HAZUS-MH Flood Loss Estimation Model was developed by the Federal Emergency Management Agency (FEMA) in the US. It is a nationally applicable standardized methodology that employs Geographic Information Systems (GIS) software in mapping the flooding data (FEMA, 2017). The model contains over 900 damage curves for various types of infrastructure and building, based on which the direct damages from the floods and shelter needs can be estimated (Scawthorn et al, 2006). Similarly, an earthquake can cause ruinous destructions to physical infrastructure. The Earthquake Loss Estimation Methodology in HAZUS methodology also facilitates a consistent set of loss estimations. The methodology calculates the direct economic loss from the earthquake based on the repair and replacement of building stocks, building contents and inventory (Brookshire et al, 1997).

In the case studies from Chapter 5 in this thesis, the primary and initial reduction in industrial value added or final demand due to capital and labour productivity loss is referred as direct economic loss while the secondary cascading economic loss resulting from industrial and regional interdependencies is specifically termed as indirect economic loss. The purpose of doing so is to highlight the important role of industrial and regional interdependencies in macroeconomic costs assessments.

2.2 Persistent Disasters: Air Pollution and Heat Waves

Compared with 'rapid-onset' disasters, 'persistent' disasters refer to natural disasters that persist longer and whose effects will be gradually realized over time. Although air pollution, heat waves, droughts, and other environmental degradation normally last for days or months, they should be equally considered as natural disasters due to their damage to inhabitants in terms of the health impacts (Development Workshop, 2017).

2.2.1 Air Pollution and Impacts on Human Health

Particulate air pollution is an air-suspended mixture of solid and liquid particles with various number, size, shape, surface area, chemical composition, solubility and origin (Arden Pope III and Dockery, 2006). They have severely impacted human health and it is associated with increasing risks for mortality, hospital admissions and outpatient visits due to respiratory and cardiovascular diseases (Xia et al, 2016[1]). The size distribution of total suspended particles in the ambient air includes coarse particles, fine particles and ultrafine particles, from which fine particles are primarily from

[1] The previous study on China's air pollution 2007 has been published in Xia, Y., et al. (2016). "Assessment of socioeconomic costs to China's air pollution." Atmospheric Environment **139**: 147-156.

direct emissions derived from combustion processes in terms of vehicle use of gasoline and diesel, coal burning to generate power, and smelters, cement plants and steel mills during industrial production processes (Arden Pope III and Dockery, 2006). Regarding the fine particle matter, the most common indicator is $PM_{2.5}$, which refers to particles with an aerodynamic diameter equal or less than 2.5 μm and was identified as the main contributing factor to the severe smog in China (Zhao et al, 2014; Huo et al, 2014). The serious haze in China, 2013 should be deeply memorized, which has brought China under the global media spotlights. The daily average $PM_{2.5}$ concentration in Capital Beijing far exceeds the health safety standards suggested by the World Health Organization (WHO) (Guan et al, 2014a).

Research on ambient pollution can be dated back to the 1990s when the National Ambient Air Quality Standards (NAAQS) was promulgated by the US Environmental Protection Agency (EPA) after a lawsuit by the American Lung Association in 1997 (Arden Pope III and Dockery, 2006). The standard imposed new regulatory limits on $PM_{2.5}$ pollution. Later in 2006, new NAAQS for $PM_{2.5}$ was raised after a review of the scientific literature. Public health policy have primarily focused on $PM_{2.5}$ because it was suggested to play the greatest role in damaging human health by increasing the risks of respiratory disease, cardiovascular disease, Chronic Obstructive Pulmonary Disease (COPD) and lung cancer (Greenpeace, 2017). On the one hand, $PM_{2.5}$ contains more toxic components, including sulfates, nitrates, acids or metals. On the other hand, its diameter is small enough to be breathed deeply into the lungs, suspended for longer and penetrate into indoor places (Wilson and Suh, 1997).

The earliest studies on short-term air pollution exposure change and mortality employed formal time series modelling based on Poisson regression to examine the relationships between air pollution at common levels and daily mortality counts (Schwartz and Dockery, 1992; Dockery et al, 1992; Schwartz, 1993). Along with the time series studies, case-crossover study design appear to be another early methodological innovation for air pollution epidemic studies. The approach adapts the common retrospective case-control design, in which exposure at the time of death was contrasted with the exposure without death occurrence and thereby, the excess risk can be assessed using conditional logistic regression (Neas et al, 1999; Lee et al, 1999; Pope, 1999). Early studies on short-term exposure to particulate air pollution and mortality are mainly single-city daily time series mortality analysis or the meta-analyses of these single-city time series studies (Dockery and Pope, 1994; Ostro, 1993; Schwartz, 1994; Levy et al, 2000; Anderson et al, 2005). One of the few multicity time series studies is a study of six US cities (Schwartz et al, 1996) in which strongest association was found between daily mortality counts and $PM_{2.5}$. Thereafter, Burnett et al (2000) investigated the relationships between daily mortality counts and various measures of air pollution for eight Canada's cities, where statistically significant PM-mortality relationships were discovered. One of largest-scale multicity daily time-series studies appears to be the National Morbidity, Mortality, and Air Pollution Study (NMMAPS) based on the replication of several early single-city studies, where the levels of $PM_{2.5}$ was found to be associated with all-cause mortality and cardiovascular and respiratory illness (Samet et al, 2000). By that time, daily time series studies of acute exposures for either single-city or multi-cities have both focused on short-term acute PM effects without much attention on the PM effects on long-term mortality rates, life shortening and exacerbating the progress of chronic disease. By 1997, two cohort-based studies have approved the effects on mortality counts from chronic exposure to $PM_{2.5}$, including the Harvard Six Cities Study (Dockery et al, 1993) and the ACS study (Pope et al, 1995) that covered over 8,000 and 500,000 adults, respectively and were reanalyzed in 1997. The mortality effects of PM turn to be much stronger in long-term cohort studies than short-term daily time series studies due to the substantial difference in time scales of exposure. The huge gap between the mortality effects inspired studies of intermediate time scales of exposure and daily time series studies with longer time scales or extended distributed lags (Arden Pope III and Dockery, 2006). Examples can be the study of Clancy et al (2002) for Dublin, Ireland, where statistically significant decreases were found in the deaths of nontrauma, cardiovascular and respiratory deaths after adjusting for temperature, day of week, respiratory epidemics and so on; the study of Zeger et al (1999) that proposed frequency decompositions for both mortality counts and air pollution data, suggesting a larger PM effects with relatively longer time scales. With a growing number of improved long-term cohort studies on air pollution and mortality, the concentration-response relationships, the shape of the function as well as the existence of a counterfactual concentration level have been better understood. Ostro (1993) examined the shape of concentration-response function and the counterfactual threshold for 14 winters in London during 1958-1972 where mortality effects exist even for the winters but no threshold was discovered. Similarly, no threshold was found by Schwartz and Marcus (1990), which replotted the London data and showed a steeper shape at lower concentration levels. After that, a number of studies set about to exploring the PM-mortality concentration-response relationships and the shape of functions in daily time series studies of multiple cities (eg. Schwartz and Zanobetti, 2000; Schwartz et al, 2001; Daniels et al, 2000; Dominici et al, 2003; Dominici et al, 2002 & 2003; Samoli et al, 2005). The shape of concentration-response functions from several daily time series mortality studies and most illustrated a linear-like relationship. Similarly, cross-sectional and prospective cohort studies examining the concentration-response relationships have been conducted. The long-term cohort studies modelling the concentration-response relationships mainly focused on $PM_{2.5}$ pollution and show that the mortality effects of $PM_{2.5}$ can be modeled as linear or log linear, where the slope is steeper at lower concentration levels than at higher concentration levels. In particular, the extended analysis of the ACS study assessed exposure-response relationships between disease-specific mortality and long-term exposure to $PM_{2.5}$, including all-cause, cardiopulmonary and lung cancer, from which long-term exposure to $PM_{2.5}$ was most significantly associated with lung cancer death.

Before the mid-1990s, the majority of research emphasized on respiratory disease, such as asthma, obstructive pulmonary disease and lung function (Arden Pope III and Dockery, 2006). Starting from the mid-1990s, epidemic studies on concentration-response relationships turn to more focus on hospitalizations for cardiovascular disease (Burnett et al, 1995; Schwartz and Morris, 1995; Pantazopoulou et al, 1995; Poloniecki et al, 1997; Schwartz, 1997). To differentiate according to the time scale, Schwartz (2001) and Souza et al (1998) focused on long-term pollution exposure and cardiovascular disease risk whereas Peters et al (2001) and Peters et al (2004) emphasized on the short-term exposure and the relationships with cardiovascular disease risks in Boston area and Southern Germany, respectively. Studies concerning other specific disease types include physiologic measures of cardiac risk (Pope et al, 1999; Demeo et al, 2004; Gong et al, 2005), accelerated progression of Chronic Obstructive Pulmonary Disease (Brauer et al, 2001; Churg et al, 2003), lung function (Schwartz, 1989; Chestnut et al, 1991; Tashkin et al, 1994; Raizenne et al, 1996; Ackermann-Liebrich et al, 1997), pulmonary inflammation (Nemmar et al, 2002, 2003, 2003 & 2005; Tan et al, 2000; van Eeden and Hogg, 2002; van Eeden et al, 2001; Terashima et al, 1997; Mukae et al, 2000, 2001; Fujii et al, 2002; Goto et al, 2004; Suwa et al, 2002), altered cardiac autonomic function (Schwartz et al, 2005), vasculature alterations (Brook et al, 2004; van Eeden et al, 2005) and modulated host defenses and immunity (Thomas and Zelikoff, 1999; Zelikoff et al, 2002 & 2003).

Since $PM_{2.5}$ is the main component for China's air pollution, this research focuses particularly on $PM_{2.5}$ air pollution in China and the major health endpoints[2], including mortality, hospital admissions and outpatient visits for respiratory disease, cardiovascular disease, COPD and lung cancer.

2.2.2 Heat Waves and Impacts on Human Health

In relating heat waves with population health, *Figure 2.1* summerizes the main pathways via which heath waves influence labour health and then, the economic system with four main causal stages. The pathway involves firstly, identifying extreme

[2] Health endpoint refers to occurrence of a disease, symptom, sign or labouratory abnormality that constitutes one of the target outcomes of the trial.

weather events, such as heat waves period (in orange), which requires the precise definition of heat wave. There are many ways to define heat waves. With changing climatic means and variability, it is important to incorporate duration and intensity into the definition of heat waves (McCarthy et al, 2001; McMichael et al, 2006; McMichael et al, 2008; Bobb et al, 2011). Following Meehl and Tebaldi (2004) and Bobb et al (2011), 'heat waves' is defined by involving two temperature thresholds T_1 and T_2 which are the 97.5th and 81st percentiles of the maximum temperatures distribution in observations, respectively. 'Heat waves' is then referred to the longest time period consisted of consecutive days that at least three consecutive days whose daily highest temperature are all above T_1; none of the days during the entire period whose daily highest temperature is below T_2 and the average daily highest temperature during the whole period is above T_1 (Meehl and Tebaldi, 2004).

Then, heat wave was related to direct health outcomes based on exposure-response relationships (in red in *Figure 2.1*). 'Exposure' refers to human's exposure to heat that is above minimum-risk threshold while 'response' include the excess relative risks for mortality and morbidity rates for certain disease types, such as respiratory disease, cardiovascular disease and stroke (see section 2.2.2.1 (a) and (b)). The increasing frequency and intensity of heat waves will also cause changes in outburst and prevalence of some infectious diseases as well as the yields of agricultural products that might induce malnutrition, especially among children (see section 2.2.2.1 (c)). Both changes will also contribute to excess mortality and morbidity counts but in a more indirect way. At the same time, heat exposure will also result in subclinical impacts which is termed as 'presenteeism' (see section 2.2.2.2). These impacts include work productivity loss among self-paced workers due to heat-induced mental distractions and reducing cognitive skills, and work capacity loss among outdoor workers as a result of occupational health and safety regulations. Concerning translating the health impacts into industrial labour time loss and further into macroeconomic implications (shown in grey and yellow in *Figure 2.1*, respectively), more details can be found in Chapter 4.

There are several factors are notice-worthy in *Figure 2.1* (in light green ellipses). Firstly, mitigation policies stand for those preventive interventions targeting the CO_2 emission resulted from increasing anthropogenic activities. With different mitigation targets, temperature increase at 2090-2099 relative with 1980-1999 is estimated at 1.8℃, 2.8℃ and 3.4℃ under low- (B1), middle- (A1B) and high-emission (A2) scenarios, respectively (Hübler et al, 2008; Baccini et al, 2011). Secondly, adaptation policies aim to reduce the negative health impacts from heat waves, including physiological, behavioural, cultural and technological adaptations (Roklöv and Forsberg, 2008; McMichael et al, 2006; Kovats et al, 2005; McMichael et al, 2008; Keatinge et al, 2000). Besides, as health impacts of heat waves can be affected by both climatic and non-climatic factors, demographical factors including population growth and age structure as well as socioeconomic factors involving GDP growth can also act as moderators to influence the current and future vulnerability among populations and result in distinctive heat exposure-response relationships across countries (McMichael et al, 2006; McMichael et al, 2008; McMichael et al, 2004; Keatinge et al, 2000; McMichael et al, 2003; Kinney et al, 2008). Therefore, different thresholds with minimum level of mortality and morbidity level as well as disease occurrence rate should be applied in analyzing heat waves-health exposure-response relationships. Populations in countries with overall high mean summer temperatures tend to better adapt to heat events (Roklöv and Forsberg, 2008; McMichael et al, 2006) while populations in low-income countries are more vulnerable to severe health impacts and sub-clinical effects from heat waves due to less developed ventilation, healthcare services or air conditioning coverage (McMichael et al, 2006; Kovats et al, 2005; Keatinge et al, 2000).

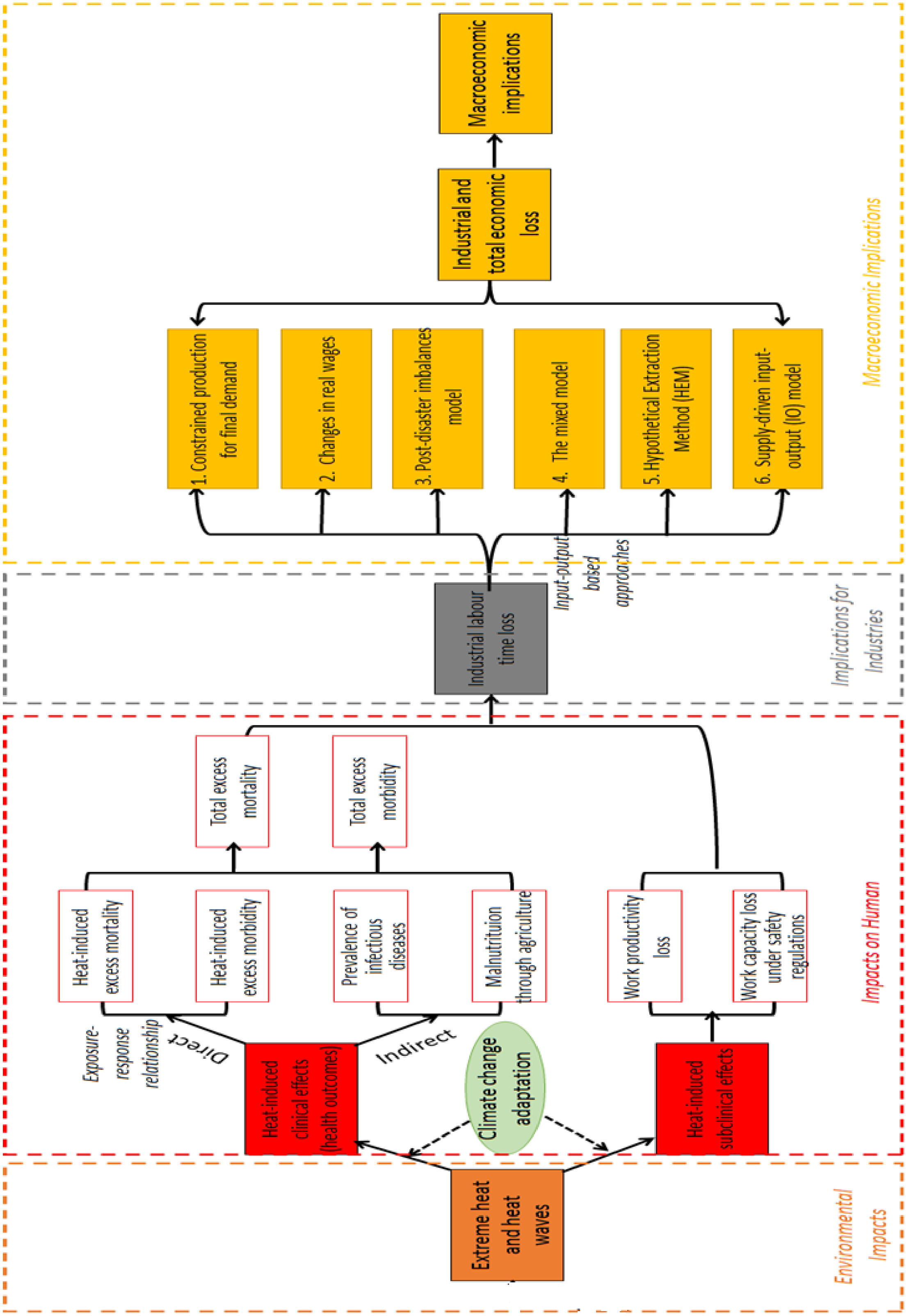


Figure2.1 Influencing pathways of heat waves on human health and economy

The diagram summerizes the main pathways via which heath waves influence labour health and then, the economic system with four main causal stages.

2.2.2.1 Heat Waves Induced Physical Health Impacts

This section discusses the physical health impacts of heat waves, ranging from direct effects on heat-related mortality and morbidity to indirect effects on vector-borne diseases and malnutrition through degradation in agricultural yield.

(a). Direct Effects on Heat-related Mortality

Exposure-mortality relationship is used to detect number of heat-attributable deaths in a city when temperature rises above certain threshold corresponding to the minimum level of heat-related mortality (Roklöv and Forsberg, 2008; Baccini et al, 2011). Such 'optimal temperature' may differ across geographical locations due to different climatic and non-climatic factors and thus, should be determined individually for each study location. Although heat waves can be regarded as the environmental effect of climate change, the extrapolation of long-term climate change-health relationship from short-term weather-health relationship is problematic with the difficulties in monitoring the effects of long-term climate change on specific diseases and controlling the effects of the changing non-climatic factors on population health in the future. This means that current estimation of exposure-mortality relationship is based on the observations of recent past and present short-term climate variation (McMichael et al, 2006; Kovats et al, 2005; McMichael et al, 2004; Campbell-Lendrum et al, 2002, p205).

Existing studies on modeling the heat waves-mortality relationships generally stay at a city level and most of them were conducted in developed countries, such as OECD countries, Japan and North America (Basu and Samet, 2002; Honda et al, 2007; Curriero et al, 2002). Studies show that focusing on the thermal stress, heat-mortality follows a J-shaped relation with steeper slope at higher temperature and majority of heat-related deaths are caused by respiratory and cardiovascular diseases (Roklöv and Forsberg, 2008; McMichael et al, 2006; Baccini et al, 2011; Patz et al, 2005). Roklöv and Forsberg (2008) analysed the temperature-mortality relationship with specific focus on respiratory and cardiovascular diseases in Stockholm, Sweden during 1998-2003. Apart from specifying age groups, they also compared the effects of lag structure between high and low temperatures. They concluded that 'comfortable' temperature in Stockholm was 11℃, above which every ℃ rise will result in a 1.4% increase in cumulative general relative risk (RR) with more significant harm on the respiratory conditions of the elderly (>74 years). Indeed, they suggested heat tends to have more direct mortality effects than cold. Similar J-shaped heat-mortality relationship was confirmed by Baccini et al (2011), who estimated the number of heat-related deaths across 15 European countries during the 1990s. Three main contributions were achieved in their study. Firstly, city-level threshold and slope above the threshold of the heat effect were combined into Mediterranean and North-Continental cities using Bayesian random-effects meta-analysis models. Secondly, a Monte Carlo approach was employed to evaluate the uncertainty in city-level threshold and slope above the threshold of the heat effect and most importantly, Baccini et al (2011) projected the heat effect on mortality by 2030 based on three selected IPCC CO_2 emissions scenarios with different combinations of changing demographical, socioeconomic and technological factors. Although their results reveal an increasing trend of heat effect on mortality, especially under warming scenarios, potential linkages between the developments of non-climatic factors and future heat effect on mortality is more difficult to be predicted (McMichael et al, 2006; Kovats et al, 2005; McMichael et al, 2004; Campbell-Lendrum et al, 2002, p205). Whereas most existing European studies highlight the significance of developing more efficient CO_2 mitigation and heat adaptation strategies by warning the rising heat effect on mortality, Keatinge et al (2000) rebuilt the confidence that European population is able to adapt successfully to a 2℃ increase of global warming. I indicate that their 'optimistic' results may be due to the offsets by the substantial decrease in short-term cold-related mortality during the winter and the relatively small focus group for the observational study (65-74 years only) in Northern Europe while in some European countries, such as Budapest, Rome and Valencia, large numbers of heat-attributable deaths have been also observed from younger age groups (Baccini et al, 2011). It is crucial to consider heat effect on mortality among the youth as these groups constitute a large proportion of active labour supporting industrial economic production. However, Keatinge et al (2000) still stressed the potential obstacles in achieving same pace between physiological acclimatization and behavioural, technological adaptations.

Compared with developed countries, low-income developing countries are more likely to suffer from heat-related mortality with less developed protective infrastructure. Therefore, understanding how populations in low-income countries respond to heat appears to be equally important for developing a sustainable world in the face of global urbanization and the resulting 'urban heat island effect' (McMichael et al, 2006). Xu et al (2009) projected a 40-50 days' increase in heat wave durations in middle-lower reaches of Yangtze River Basin (YRB) of China while the upper reaches may subject to more excessive increase. As a hub city in lower reaches of the YRB, Nanjing has experienced frequent extremely high temperature events. The severe heat wave during July and August 2010 caused dramatic rise in cardiovascular mortality (Wu et al, 2013). With the focus on this particular case study, Chen et al (2015) conducted a sub-city level study to examine the spatial variations of stroke mortality risks between rural and urban districts in Nanjing during 2010 and also compared them with two reference periods in 2009 and 2011, respectively. The significantly higher stroke mortality relative risk (RR) in rural districts (RR=1.89, 95% CI: 1.63-2.17), including Luhe, Lishui and Gaochun, underscores the fact that rural districts with lower socioeconomic level and air conditioning coverage tend to have higher vulnerability to heat wave event (Chen et al, 2015). In other words, the population vulnerability towards heat-related mortality depends on not only how much they are exposed, but also the capability of them in coping with high temperature. Meanwhile, at the city level, McMichael et al (2008) selected 12 cities from middle- or low-income countries to describe the different responses towards heat by diverse populations. Results across 12 cities generally confirmed a U-shaped relations between temperature and cardiorespiratory mortality. Heat threshold shows a wide range across cities from 16-31℃, implying the geographical variations in heat threshold which depend on a mix of climatic and non-climatic factors.

(b) Direct Effects on Heat-related Morbidity

Effects of heat waves on mortality have been better documented than those on morbidity in episode studies (Michelozzi et al, 2009). Nevertheless, in quantifying the economic impacts of heat wave induced health impacts on labour through the perspectives of reduced labour time, heat wave resulting hospital admissions are innegligible. In European countries, Michelozzi et al (2009) evaluated the effects of heat on respiratory and cardiovascular hospital admissions across 12 European cities. Similar approach with Baccini et al (2011) was applied to figure out the city level thresholds and slope above the threshold. Random effect meta-analysis was used in grouping 12 cities into Mediterranean and North-Continental cities. Compared with the severer impacts of heat waves on cardiovascular mortality, more significantly positive relations were found between high temperature and respiratory admissions than cardiovascular admissions and especially for the elderly (>75 years) in Mediterranean cities. Earlier studies have been aware of the potential harm of heat on respiratory systems which however indicated a more indirect pathway of influence. Hales et al (1998) suggested that increasing average temperature will accelerate the prevalence of asthma in New Zealand. Similar arguments can be found in Curson (1993) and McMichael et al (2003) that heat will change the life cycle of plants and animals which may further induce asthma prevalence in Australia. While it is feasible to quantify the relationships between short-term high temperature and respiratory admissions, it becomes more complicated to infer effect of long-term climate change on a specific disease, such as asthma due to the multi-causality of disease initiation and the unclear mechanism for their relationships (McMichael et al, 2003). Similar studies in Europe can be also found in Kovats et al (2004) and Tataru et al (2006).

North America has also reported extensively heat-morbidity studies. The severer impacts of extreme temperature on respiratory conditions for the elderly are also true at the city level of North America. Lin et al (2009) investigated the effects of temperature and humidity on daily respiratory and cardiovascular admissions in New York city during 1991-2004. They noticed that with the health risk threshold at 29-36℃, per ℃ increase above the threshold will cause a 2.7-3.1% rise in respiratory admissions and 1.4-3.6% rise in lagged cardiovascular admissions while even greater increases in respiratory admissions can be realized among the elderly at 4.7%. In a country level study, Knowlton et al (2009) analyzed the effects of 2006 California heat waves on both hospital admissions and emergency department (ED) visits in which effects on different age and race groups were specified. Excess morbidity and elevated rate ratios(RRs) can be seen during the heat waves with greater influences on both the youngest and the elderly group as well as cardiovascular patients. It is interesting to notice that even regions with relatively modest temperature can suffer substantial effects on morbidity, confirming the fact that acclimatization and adaptive capacity determine the health risks and population vulnerability.

In this respect, different demographic and socioeconomic structures of developing countries may potentially affect their population acclimatization and adaptive capacity and thus, the overall vulnerability. With burgeoning population and geographical uneven development status, Chinese population may encounter higher vulnerability towards more frequent heat waves. However, I found few studies on measuring the heat effect on morbidity outcomes in China. Ma et al (2011) investigated the effects of heat waves on daily admissions in Shanghai during 2005-2008. Results showed a 2% increase in total hospital admissions during the heat period, with relatively higher impacts on cardiovascular (8%, 95% CI: 5-11%) than respiratory admissions (6%, 95% CI: 0-11%). It is undoubted that more cities like Shanghai will be affected if the projected increase in heat waves durations among the YRB becomes true (Xu et al, 2009). Therefore, there remains a need for replicating the study results from developed nations in China.

(c) Indirect Effects on Infectious Diseases and Malnutrition through Degraded Agriculture

Apart from the comparatively direct effects on mortality and morbidity, heat waves can also affect population health through indirect pathways of infectious diseases and malnutrition resulting from degraded agricultural production. The reproductions of biting insects that transmit viruses and bacteria are also sensitive to increasing temperature. Rapid proliferation of both salmonella and cholera bacteria in warmer environment have been already recognized[3] while most studies try to establish the linkages between infectious diseases and climate change as a whole rather than more specific apparent temperature. Based on present or past climate variation-disease relationships, they modeled the changes in future climate sensitivity of vector-borne diseases with typical focuses on malaria and dengue fever in tropical world (McMichael et al, 2004). Researches in South Asia and South America have started exploring the relationships between malaria and El Niño Southern Oscillation (ENSO) (Bouma and Kaay, 1996; Bouma and Dye, 1997; Bouma et al, 1997). ENSO induces the temperature and rainfall fluctuations worldwide. In South America, it is suggested that the reduced rainfall during the warm event (El Niño) are associated with malaria prevalence which is more likely to occur with drought in humid climates or excess rainfall in arid regions (Bouma and Dye, 1997). Frequent El Niño events in Venezuela have raised the Malaria mortality and morbidity by 36% (95%CI, 3.7-69.3%) and Malaria mortality shows a stronger relationship with drought in the preceding year of disease outbreaks. However, in poorer African countries, although the close relationship between malaria transmission and the anomalies of the max temperature in Kenya's highlands has been confirmed, study results on such linkages remain ambiguous (Patz et al, 2005).

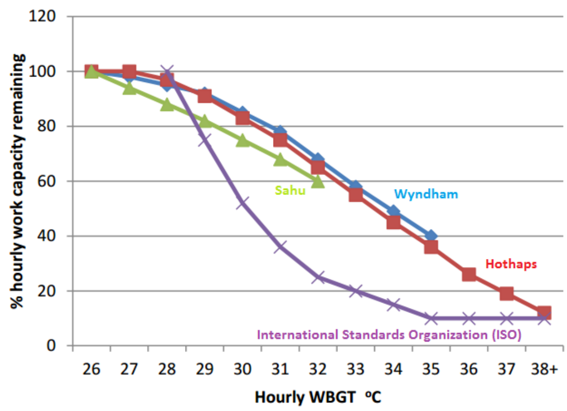
Rising global temperature can also affect the reproduction of *Aedes* and *aegypti* mosquitoes, which are the major vector of dengue fever (Patz et al, 2005). In Thailand, the spatial-temporal dynamics of dengue hemorrhagic fever (DHF) have been captured in DHF incidence study by Cummings et al (2004) using a wavelet analysis method. They indicated that the 3 years' DHF periodic cycle started from

Bangkok and moved radially. Wavelet approach was also applied in another study in Thailand, Cazelles et al (2005) analyzed the associations between climate viability and dengue epidemics during 1983-1997 and they concluded that the 3 years' cycle (Cummings et al, 2004) may be resulted from the El Niño and climate viability remains significant in shaping interannual pattern of dengue epidemics. Recently, Bouzid et al (2014) adopted a Generalized Additive Model (GAM) to model the dengue fever risk as a function of both climatic variables and socioeconomic factors, which were later applied to estimate the future dengue incidence in Europe under three climate change scenarios. Results reveal that whereas most European are currently at low dengue risk, the risks are expected to increase under certain climate change scenarios and especially in coastal areas of the Mediterranean and North Eastern areas of Italy. European cities with warmer temperatures and greater population density are more likely to suffer higher dengue risks in the future (Bouzid et al, 2014; Rogers et al, 2014). While the higher temperature is necessary for certain vector existence, high temperature and vector presence are not sufficient in themselves for the disease occurrence (Rogers et al, 2014). Indeed, the occurrence of infectious diseases depend on both climatic and socioeconomic factors as population may get well protected by developing disease control programs and healthcare services (McMichael et al, 2006; McMichael et al, 2004; Patz et al, 2005; Bouzid et al, 2014; Rogers et al, 2014).

Higher global temperature can also impose knock-on health effects on population health through the impacts on food production and water supplies (McMichael et al, 2006). In the studies of crop yields and world food trade, exposure distributions regarding temperature and precipitation are linked with crop yields, which are further used as inputs in world food trade model to add in non-agricultural factors including market forces, government policies, agricultural trends, economic and technological conditions. The model results appear to be the approximation of national food availability which is finally used to calculate per capita food availability of each country. Preliminary studies correlated the model output with direct measure of malnutrition for the 1990s at the model regional level and implied a positive relationship between food unavailability and incidence of underweight, especially among children (<5 years) (McMichael et al, 2004). As with infectious diseases, the occurrence of malnutrition and its resulting diseases can be affected by both climatic and socioeconomic factors. Moreover, it depends on the productivity and economic capacity for those regions with food poverty problems (McMichael et al, 2004; Parry et al, 1999) as well as the ability of the world food trade system in adapting to the changing production (Dyson, 1999). Due to the great uncertainties in predicting future socioeconomic evolvements and the fact that infectious diseases and malnutrition affect only certain age groups in certain countries, they are not sufficiently representative for the entire global working population. Thus, I will neither specify infectious diseases and malnutrition here nor consider fitting them into my proposed economic modeling framework in the following sections.

2.2.2.2 Heat Waves Induced Sub-clinical impacts

Heat effect on labour capacity and productivity can be analogous to the disability induced by heat induced clinical health effects (Kjellstrom et al, 2009; Zander et al, 2015). Regarding the reduced work capacity, the most commonly accepted indicator for occupational health safety is the Wet Bulb Globe Temperature (WBGT) index by United States military (Kjellstrom et al, 2009; Dunne et al, 2013). The index was developed based on meteorological records and it provides thresholds for environmental heat stress for different work intensity, based on which international standard states the proportions of working hours that break periods are required (International Organization for Standardization, 1989). Therefore, if no break time is required, a worker’s work capacity is 100% while if 75% rest time is required (31℃ for 500 Watts work intensity), work capacity is reduced to 25% (Kjellstrom et al, 2009). *Figure 2.2* shows the risk functions relating hourly workplace heat levels measured by WBGT with percentage of remaining work capacity according to two epidemiological studies (Wyndham and Sahu), a best fit function (Hothaps) and ISO standard values (Nr 7243, 1989). The diagram reveals a steeper slope under ISO standards, indicating that in order to protect heat-vulnerable workers, greater reductions in working time and output production can be expected under the ISO standards. Therefore, enforcing ISO standards, extreme workplace heat exposure will result in increasing productive time loss for the sake of labour health protection. In a city level study, it was reported that the average work capacity for a heavy work intensity worker (500 Watts) is only 20% at noon during May in Delhi, India (Kjellstrom et al, 2009). Similarly, Dunne et al (2013) measured the global reduced work capacity as a function of WBGT during 1948-2011 and suggested a 10% decrease in work capacity during the peak months due to heat waves. Indeed, future further decrease in work capacity was estimated across different Representative Concentration Pathways (RCP) scenarios. They predicted a further 10% reduction in global work capacity by 2050 and an extra 5% reduction beyond 2050 by 2200 even with the active CO_2 emissions mitigation (RCP 4.5) to limit the future global temperature rise within 2°C. Despite recognized approaches preventing reduced work capacity, these approaches generally expose a fundamental aim in minimizing workplace health damages, which however, hardly improve or even exacerbate work productivity.



(Modified from: Tord Kjellstrom, 2014)

Figure2.2 Exposure-response functions for labour in moderate intensity work (300 Watts)

Existing studies often treat work capacity and productivity as inter-convertible. However, I suggest that these two terms should be treated differently as the former stems from labour safety perspectives while the latter is more related with the mental distractions for self-paced workers and can be termed as ‘presenteeism’. Whereas the previously discusses WGBT index and ISO standards both relate to work capacity under heat exposure, the negative effects of heat exposure on occupational productivity has been recognized early in the 1970s (Axelson, 1973), yet their quantified relationships have been rarely discovered. These negative impacts may include concentration lapses, low-quality decision making and reduced cognitive performance (McMorris et al, 2006; Gaoua et al, 2011), which will caused ‘presenteeism’ among labour. Zander et al (2015) investigated the productivity loss due to heat stress induced ‘presenteeism’ among 1,726 Australia adults during 2013-2014. The cost of productivity loss in the sample group was extrapolated to assess the annual economic burden of productivity loss among entire Australian workforce due to heat waves. Their results show that 7% of the sample had had more than one day being absent from work due to heat during the past 1 year while 70% reported they had more than one day being less productive, which were equivalent with an additional 13.3 working days’ loss. Data were collected by work productivity and activity impairment (WPAI) questionnaire, which is an instrument designed to study the economic burden of diseases in health economics (Zander et al, 2015). Lofland et al (2004) reviewed 11 workplace productivity loss survey instruments which are all designed from societal perspectives. Both Osterhaus technique and Migraine Work and Productivity Loss Questionnaire (MWPLQ) were designed for measuring the work productivity loss due to migraine headache. Health and Labour Questionnaire (HLQ) is also meaningful to patients while Worker Productivity Index (WPI) is designed specifically for customer services workers. The latter has become a gold standard for absenteeism data for such particular occupation as it provides an objective measure regarding workers’ absenteeism by electronically monitoring their working time through computer-based system. WPAI was firstly designed to assess presenteeism due to broad range of diseases by asking employees the percentages of health induced working time loss, impairment while working, activity impairment and the overall work impairment score. The above 5 survey instruments not only capture ‘presenteeism’ in terms of productivity loss, but data on 'presenteeism' are measured in working time loss so that they can be readily quantified into monetary term (Lofland et al, 2004).

2.2.3 Economic Loss Assessment

While translating the health impacts into economic loss, Human Capital Approach (HCA), Contingent Valuation Approach (CVA) and the Friction Cost Approach (FCA) appear to be the commonly used methods. Stemming from the patients' standpoints, HCA measures the economic burden of disease based on the Potentially Productive Years of Life Loss (PPYL) and discounted value of future earnings (Johnson et al, 2005). This means that HCA is a function of an individual's compensation and it tends to provide critical information regarding the monetary benefit of reductions in disease-related mortality and morbidity (see *Equation 2.1*). One of the few studies on assessing the economic burden of heat induced work productivity loss in Australia also applied HCA (Zander et al, 2015). Based on the information obtained from WPAI questionnaire, individual economic loss from absenteeism were calculated by multiplying number of days absent per year with daily income while loss from presenteeism were obtained by multiplying number of hours per less productive day with number of less productive day per year and further with hourly income rate. Following these steps, total economic burden of all Australian labour due to heat stress resulting productivity loss during 2013-2014 reached US$6.2 billion (95% CI: 5.2-7.3 billion) with a majority of economic burden came from workers who spent little working time outside, such as most expensive loss of managers (Zander et al, 2015). In another cost study in Germany (Hübler et al, 2008), potential costs from heat-related hospitalizations and productivity loss under future climate change scenario were projected separately, based on the general costs for each admission case in each federal state and the wage share of the reference year in Germany, respectively. The latter is similar to a HCA and attached great weight on patients and workers. This study, although appears to be one of the very few cost study on quantitatively modeling the heat-economic costs relationships, has involved great uncertainties because it applied the quantitative relationships of heat-hospitalization and heat-productivity loss from other countries (Johnson et al, 2005; Bux, 1987) onto Germany without considering the distinctive thresholds and responses of populations in different countries determined by both climatic and socioeconomic factors. Other studies using HCA can be found in Bradley et al (2007) and Wan et al (2004).

$$DVFE_{(i,j)} = \sum_{i=s_j}^{n_j} \frac{(l_{i,j} * W_{ij})}{(1+r)^{i-s_j}} \tag{2.1}$$

$DVFE_{(i,j)}$: Discounted value of future earnings;

j: Gender;

s_j: Starting age for gender j;

n_j: Life expectancy for starting age for gender j;

$l_{i,j}$: Economic activity rate for age i and gender j;

W_{ij}: Annual wages for age i and gender j;

r: Discounted rate.

On the contrary, CVA focuses on the Willingness-To-Pay of households to avoid the mortality or morbidity risks of a disease (see *Equation 2.2*), where data on individual Willingness-To-Pay are obtained through surveys and interviews. 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). Mitchell and Carson (1989) suggested that CVA is the only effective means to value the utility of a commodity through fictive markets. Thus, it has been widely applied on environmental economics and other research areas when the subject of interests has neither price nor physical market.

$$V = \frac{C}{\Pi} \tag{2.2}$$

V: Value of life;

C: Cost of life-saving good and services;

Π: Reduced probability of dying.

FCA measures costs of productivity loss based on the length and frequency of friction periods and the costs occurred due to friction period (Koopmanschap, 1994) (see *Equation 2.3*). Friction period refers to the time required to replace a sick worker in order to return to the previous productivity level while friction costs can involve the production loss appeared until an absent work is replaced, the productivity loss of the new worker and all expenses associated with recruitment and training (Lofland et al, 2004). A FCA has the basic assumption of same productivity level in paid work between A and B ($P_a^h = P_b^e$), suggesting that after B's replacement for A, production level will return to the level before A's sickness. Therefore, FCA follows an employer perspective in which the costs are evaluated at a microeconomic or individual level to estimate production loss occurred only during the friction period (Brouwer and Koopmanschap, 2005).

$$T_a^h = P_a^h + U_a^h + L_a^h \tag{2.3}$$

$$T_b^u = U_b^u + L_b^u$$

$$T_a^i = U_a^i + L_a^i$$

$$T_b^e = P_b^e + U_b^e + L_b^e$$

T_a^h: Total amount of time available to person A;

P_a^h: Time spent on paid work when person A is healthy;

U_a^h: Time spent on unpaid work when person A is healthy;

L_a^h: Time spent on leisure when person A is healthy;

T_b^u: Total time available for unemployed person B;

U_b^u: Time spent on unpaid work for unemployed person B;

L_b^u: Time available for leisure for unemployed person B;

i: The status that person A is ill;

e: The status that B is employed.

2.2.4 Research Gap in Health Costs Assessment

Despite that all approaches can provide useful information about the potential monetary benefits of any reductions in health effects or the economic burden for healthcare sectors, each approach encounters certain drawbacks. Regarding HCA, as it heavily relies on PPYL, it neglects the roles of children and the elderly as well as disease-induced morbidity. Indeed, its reliance on discounted value of future earnings indicates the exclusion of people who are not officially paid or those outside the labour market. Similar problem also exists for FCA. Indeed, workers playing crucial roles in industry production process do not necessarily receive higher wage rates. This is potentially the reason that men or indoor-working managers accounted for the majority of costs from productivity loss as Zander et al (2015) suggested because men and managers usually receive higher salaries than women or salespersons. Therefore, using the labour compensations as a key indicator for costs of health impacts might be misleading and simply summing up the employees' compensations or employers' replacement costs does not comprehensively reflect the effects on the whole population or the national economy. With respects to CVA, it quantifies health costs based on respondents' risk perceptions that can be completely different and unmeasurable within different social structures and healthcare systems (Kan and Chen, 2004). Besides, its applicability might be limited in developing countries. This is because, firstly, there is always a lack of market research among consumers in developing countries, which might deteriorate the accuracy of study results; and secondly, Willingness-To-Pay of households may be lower than the actual value of the commodity as a result of the relatively low income in developing countries (Yang et al, 2002). Although a FCA tends to provide indirect economic loss resulting from labour sickness during the friction period, its estimation is conducted at a microeconomic level by focusing on employer or employee.

However, a national economic system consists of many economic agents interacting with each other. Production in a particular sector can affect other sectors in the economy through production supply and demand chains. In other words, changing production in a sector will influence sectors that provide its primary inputs with a focus on the backward linkages along demand side of the economy. Meanwhile, it can also affect sectors that purchase its outputs as inputs in their production processes, referring the forward linkages on the supply side of the economy. In the face of globalization, such relationships between industries, sectors and regions have become unprecedentedly tightened. Thus, although all the three 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 and their focus on individuals at a microeconomic level. In this respect, assessing the cascading indirect economic impacts on national economy should take such relationships into account by perceiving labour as a principle for economic activities and the diminishing labour time as a result of health impacts that will not only reduce the output level in a single sector but also other interconnecting sectors along production chains due to sector and regional interdependencies (see Chapter 3). Therefore, I suggest that to evaluate the total economic impacts, analyses should touch upon both micro and macroeconomic levels as a combination of economic burden for healthcare sectors, patients, employees and economic production processes.

Chapter 3: 'The Illusion of Direct Impacts': Cascading Indirect Economic Impacts

This chapter provides the literature review on input-output analysis from the origin of the concept, to its later evolvements by Wassily Leontief and the variations in the basic Leontief input-output framework, and further to its extensive applications on ecological, environmental and disaster risk studies. In the light of the research topic of this document, this chapter particularly emphasizes on the applications of input-output model on disaster risk studies. The specific objectives of this chapter are:

1. To trace the concept of input-output and *production of circular flows* back to the 17th century when the early conceptualizations of input-output systems were sketched in terms of the production relationships in the economic system (section 3.1);
2. To describe the structure of basic Leontief input-output model and explain the mathematical meanings for its key variations (section 3.2);
3. To discuss the extensive applications of input-output techniques (section 3.3) on ecological studies (section 3.3.1), environmental studies (section 3.3.1) and disaster risk studies (section 3.3.2).

3.1 Input-Output Analysis: The Origin and Evolvements

An input-output analysis was developed by Wassily Leontief in the 1930s that is an analytical quantitative framework to examine the complex interrelationships between economic sectors within an economic system. Input-output analysis is developed with the central idea of the circular flow of the economy in equilibrium, which can be seen from the PhD thesis of Leontief (1928) as he stated that "*Economic analysis should rather focus on the concept of circular flow which* *expresses one of the fundamental 'objective' features of economic life*" (quoted after Kurz et al. 1998). The key concept of *'a circular economy'* was largely inspired by economic concepts from early classical political economy, including *'productive interdependences within an economy'* and '*social surplus'* (William Petty) as well as '*general equilibrium analysis'* (Léon Walras). For instances, by saying "*Labour is the Father and active principle of Wealth, as Lands are the Mother",* William Petty highlighted the productive interdependence in an economic system with labour division and his belief in the interconnections between production, distribution and disposal of the national wealth. He also pointed out that the agricultural surplus is equivalent with the rent of the land that is the difference between corn output and corn input, part of which constitutes the subsistence of labourers. His idea regarding the agricultural surplus was later known as the concept of *social surplus*. In the light of Petty's idea on interdependence and surplus, Cantillon (1755) reemphasized that all societal members relied on the production of land for reproduction. This is the very first time when the concept of *reproduction* was mentioned (Kurz et al, 1998).

Later in 1758, a French economist, François Quesnay suggested that the production of commodities rely on commodities in his work "*Tableau Économique*". Quesnay sketched a circulated process of reproduction with commodities and money circulating among production, distribution and expenditure. He also discovered two goods flows between three classes during the reproduction process, including the productive class, such as farmers, the proprietary class, such as landlords, as well as the sterile class, such as merchants. Practically, farmers produce agricultural commodities. The difference between the value of agricultural commodities and costs of agricultural inputs is paid to landlords as rent for purchasing agricultural and industrial products, while merchants working in the manufacturing sectors do not generate a surplus directly but produce means of production for agricultural sector and thus, they are categorized as non-productive class (Kurz et al, 1998). Quesnay's sagacity in pointing out the intersectoral flows was later praised in Leontief's work in 1936 that "*The statistical study presented ... may be best defined as an attempt to* *construct, on the basis of available statistical materials, a Tableau Économique of the United States for 1919 and 1929*" (Leontief 1936, p.105). Despite that *Tableau Économique* confronts several limitations, especially in mix producers and consumers, as well as physical and monetary flows, it largely contributes to and paves the way for the development of input-output analysis (Miller and Blair, 2009).

After a century, another French economist, Léon Walras constructed a general equilibrium theory in 1874. He suggested that an economy contains both consumers and producers. The former tends to maximize their utilization while the latter maximizes the profits. Consumers also act as labourers who provide fixed capitals to producers for production. In return, commodities produced by producers will be sold to consumers again for revenue. Walras also designated a set of production coefficients to measure the required quantities of various factor inputs to produce a single unit of a certain product, which appears to be similar with the technical coefficients in the basic Leontief input-output model (Miller and Blair, 1985, p2). Similarities and differences exist between the two approaches. On the one hand, both approaches possess the theoretical background of general equilibrium and concern interdependence between national income and product (Davar, 2005). On the other hand, the mutual interdependence suggested by Walras depends on the prices of factor inputs and outputs, which are further determined by the supply of factor inputs and the demand of outputs. In contrast, Leontief interpreted such interdependence in a more implicit way. Monetary term is the only uniform measurement in a basic Leontief input-output model. Moreover, Leontief also added public sector (government), capital formation and exports in final consumption category, while tax and imports in primary input category as complements (Davar, 2005). Thereafter, with the advantages in capturing the interrelationships between sectors and regions based on the concept of *'a circular economy'*, Leontief input-output model has been continuously developing and advancing, and its application boundary has been extended towards ecological, environmental and disaster risk studies.

3.2 Leontief Basic Input-Output Model and its Variations

In 1930, Wassily Leontief made a significant step towards a systematic input-output analysis by applying the framework to measure the direct and indirect input requirements of industrial sectors in the US. An input-output table demonstrates a detailed flow regarding the goods and services between producers and consumers, which also assigns all economic activities to either production or consumption categories. By presenting the inter-industrial transactions within the entire economy in a transparent and linear array, an input-output model allows to evaluate the knock-on effects along value chains while its objectivity remains. The original input-output model is subject to several shortcomings. For example, as it is a static model, it implies the fixed-proportion approach in the production functions with fixed prices and without inputs or imports substitution (Cole, 2003; Greenberg et al, 2007; Okuyama, 2007 & 2009; Rose, 2004). Therewith, input-output techniques have continuously improving and its application boundary has been broaden towards many fields, including ecological, environmental and disaster risk studies, at different levels, from local, national to global level (Miller and Blair, 2009, p2).

3.2.1 Structure of a Leontief Input-Output Model

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

The structure of a basic Leontief input-output table can be presented in *Table 3.1* below. The structure encompasses four quadrants, including intermediate transactions (Processing sectors), final demand, primary inputs for production

(Payments sectors) and primary requirements for final demand (Payments sectors). Among them, the quadrant of intermediate transactions describes the intermediate sells, purchases and deliveries between production sectors in an economy and each of them produces a distinctive product (boxes in yellow). The quadrant of final demand illustrates the sales to final consumers that include households, governments and exports (boxes in blue). Meanwhile, the information regarding the value of required inputs for production are provided in the quadrant of primary inputs, which contains fixed capital, land rental, employees' compensations and taxes (boxes in green). It also illustrates the primary inputs required for the final consumption (boxes in grey). Each inter-industrial flow *z* represents a transaction from a corresponding column sector among selling sectors to a corresponding row sector from a buying sector. The total output *x* in each sector is the sum of all items in the corresponding row from intermediate transactions $\sum_{j=1}^{n} Zij$ and final demand f_i. Similarly, the total input x' used in each sector is the sum of the corresponding column items, which includes the inter-industry input purchases and required value added (v') to produce the given amount of outputs in this sector.

The basic Leontief input-output model is essentially a demand-driven model. In other words, the technology of production is determined by the final demand of the users of the product (Duchin and Lange, 1994, p28). This implies the possibility of coordination or transformation in the economic structure once households' consumption patterns and lifestyle evolve over time.

Table3.1: Structure of a Basic Leontief Input-Output Table **(Unit: Dollar)**

		Processing Sectors (Buying)			Final Demand	**Total Output**
Processing Sectors (Selling)		1 ….	j ….	n		
	1	z_{11}	z_{1j}	z_{1n}	f_1	x_1
	….. j	z_{j1}	z_{jj}	z_{jn}	f_j	x_j
	….. n	z_{n1}	z_{nj}	z_{nn}	f_n	x_n
Payments Sectors	Value Added	v'_1	v'_j	v'_n	v'_f	
Total Input		x'_1	x'_j	x'_n		

(Modified from Xia et al, 2016)

3.2.2 Mathematical Interpretations of a Leontief Input-Output Model

A Leontief input-output model presents an economy where sectors are interacting with each other and each of them produces an unique commodity either for final consumption by the final users or for intermediate transactions by other sectors (Miller and Blair, 2009, p2). The monetary value of the transaction from sector *i* to *j* is represented as z_{ij} and final demand of sector *I* is designated as f_i. Each sector needs to produce commodities that are sufficient to fulfil intermediate transactions and final demand (Xia et al, 2016). In an economy with n sectors, the total output of sector *i* is shown in *Equation 3.1*.

$$x_i = z_{i1}+....+z_{ij}+....+z_{in}+f_i = \sum_{j=1}^{n} Zij + fi \qquad i = 1, 2, ..., n \qquad (3.1)$$

n: the number of economic sectors of an economy;

x_i: the total output of sector *i*;

f_i: the total final demand for sector *i*'s product;

z_{in}: the intermediate delivery from i^{th} sector to the n^{th} sector;

$\sum_{j=1}^{n} Zij$: the monetary value sum of sector i's output in all other sectors.

With the notation, *Equation 3.1* can be summarized as matrix term in *Equation 3.2*.

$$\mathbf{x} = \mathbf{Z_i} + \mathbf{f} \qquad (3.2)$$

By dividing z_{ij} by x_j (the total output of j^{th} sector) one can obtain the ratio of input to output z_{ij}/x_j, denoted as a_{ij} in *Equation 3.3.* It is known as the technical coefficient or direct requirement coefficient that reflects the requirement from economic sector *i* to produce one monetary unit of product in economic sector *j*. It also measures the production efficiency under current technology.

$$a_{ij} = z_{ij}/x_j \qquad (3.3)$$

With the notion of technical coefficients, *Equations 3.1* can be rewritten as *Equation 3.4* or *3.5*.

$$\begin{aligned} x_1 &= a_{11}x_1 + a_{12}x_2 + \cdots + a_{1j}x_j + \cdots + a_{1n}x_n + y_1 \\ x_2 &= a_{21}x_1 + a_{22}x_2 + \cdots + a_{2j}x_j + \cdots + a_{2n}x_n + y_2 \\ &. \\ &. \\ &. \\ x_i &= a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{ij}x_j + \cdots + a_{in}x_n + y_i \\ &. \\ &. \\ &. \\ x_n &= a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nj}x_j + \cdots + a_{nn}x_n + y_n \end{aligned} \qquad (3.4)$$

or,

$$x_i = \left\{ \sum_j a_{ij}x_j + f_i \right\} \forall i \qquad (3.5)$$

Equation 3.4 and *3.5* can be transformed into matrix term in *Equation 3.6*.

$$\mathbf{x} = \mathbf{Ax} + \mathbf{f} \qquad (3.6)$$

A: the $n \times n$ matrix of technical coefficients;

x: the output matrix for *n* sectors;

f: the final demand matrix for *n* sectors.

The technical coefficient matrix **A** can be displayed in *Table 3.2.*

Table3.2: Technical Coefficients (A Matrix) for an n-sector Economy

Sectors	1 .... j .... n		
1	$z_{11} / x_1 = a_{11}$	$z_{1j} / x_j = a_{1j}$	$z_{1n} / x_n = a_{1n}$
..... j	$z_{j1} / x_1 = a_{j1}$	$z_{jj} / x_j = a_{jj}$	$z_{jn} / x_n = a_{jn}$
..... n	$z_{n1} / x_1 = a_{n1}$	$z_{nj} / x_j = a_{nj}$	$z_{nn} / x_n = a_{nn}$

(Modified from Xia et al, 2016)

Equation 3.6 can be rearranged as *Equation 3.7.*

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{f}\ ,\ \mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} \qquad (3.7)$$

$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is known as the Leontief inverse matrix, which measures how a dollar's worth of change in final demand of a sector affects the total output value across the economy through inter-industrial linkages. In other words, it evaluates the total accumulative effects including direct and indirect effects on sectoral output from the changes in final demand. Thus, it reflects the technical change in an economy in terms of input-output relations between economic sectors (Miller and Blair, 2009, p13).

The basic Leontief input-output model has several assumptions. Firstly, the total output of sector *j* in a given period of time determines the inter-industrial flow from sector *i* to *j*, suggesting a demand-driven feature for the basic input-output model. Thus, z_{ij} depends entirely on x_j. Secondly, technical coefficient a_{ij} is fixed that indicate the fixed relationships between a sector's input and output. It will change only when the technology in the economy is improved. Additionally, fixed proportions assumption holds for primary inputs of production. In other words, the Leontief production function requires the same proportional increases in all inputs to expand the output in the same proportion (Miller and Blair, 2009, p13).

3.2.3 A Rotated View of Leontief Input-Output Model

Changes in production of a sector can affect other sectors in the economy through two directions, including those that provide its primary production inputs and those that purchase their production inputs for it (Miller and Blair, 2009, p543). The relationships embodied in the latter are described by a supply-driven input-output model, which is derived from a Leontief input-output model with a focus on supply side of an economy. As it is a rotated view of a Leontief model, they are two sides of the same coin. By rotating the vertical view of *Table 3.1* to a horizontal view, allocation coefficients **B** can be obtained, which are similar with technical coefficients **A** but describe the distributions of sectoral output across all the remaining sectors. The allocation coefficients are assumed to be fixed in a supply-driven input-output model. For each column in *Table 3.1*, the sectoral input can be interpreted as:

$$\mathbf{x}'=\mathbf{i}'\mathbf{Z}+\mathbf{v}',\ \mathbf{B}=\mathbf{Z}/\mathbf{x} \qquad (3.8)$$

B: the $n \times n$ matrix of allocation coefficients;

x: the output matrix for *n* sectors;

v: the value added matrix for *n* sectors.

From *Equation 3.8*, a supply-driven input-output model can be obtained as *Equation 3.9* and *4.0*.

$$\mathbf{x}'=\mathbf{v}'(\mathbf{I}\text{-}\mathbf{B})^{-1},\ \mathbf{G}=(\mathbf{I}\text{-}\mathbf{B})^{-1} \qquad (3.9)$$

$$\text{so}\ \ \mathbf{x}'=\mathbf{v}'\mathbf{G}\ \text{or}\ \mathbf{x}=\mathbf{G}'\mathbf{v} \qquad (3.10)$$

G, **G'**: output/Ghosh inverse and the element g_{ij} indicates the value of each unit of primary inputs in sector i that enters sector j.

Therefore, a supply-driven input-output model describes the impacts of change in primary input in a single sector on the outputs of all the remaining sectors.

3.3 The Applications of Input-Output Model

This section introduces the recent applications of input-output techniques on ecological, environmental and disaster risk studies by reviewing the model developments and modifications. It particularly emphasizes on disaster risk study domain by covering both historical approaches and contemporary developments.

3.3.1 Applications in Ecological and Environmental Studies

The input-output techniques were initially applied on environmental problems by Cumberland in 1966 as he introduced a model that adds columns and rows into an input-output table to investigate both environmental benefits and costs resulting from economic development *(Table 3.3)*. In his approach, **q** and **c** stand for the value of sector-specific environmental benefits and costs, respectively, measured as positive and negative correspondingly. **r** is the subtraction of **q** and **c**, representing the net effects on environment from economic development. **b** is the costs for cleaning up the pollution, normally paid by the public or private sectors (Richardson, 1972). However, his model has the limitation in ignoring the flows between environment and economy.

Table3.3: Cumberland's Input-Output Based Environmental Approach

<table>
<tr><td>A</td><td>f</td><td>X</td><td rowspan="4">Cost of Environmental Restoration b</td></tr>
<tr><td>V'</td><td rowspan="3"></td><td rowspan="3"></td></tr>
<tr><td>x'</td></tr>
<tr><td>Environmental Benefit q</td></tr>
<tr><td>Environmental Cost c</td><td></td><td></td><td></td></tr>
<tr><td>Environmental Balance r =(q-c)</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
</table>

(Modified from: Richardson, 1972)

Later, Daly (1968) and Isard (1972) proposed an 'economic-ecological model' which can reflect the intra- and interrelationships between environment and economy

(Table 3.4 and *3.5*). In Daly (1968)'s model, an input-output table was divided into four sub-matrices to represent flows between industries, flows within ecosystem, flows from industries to ecosystem and flows from ecosystem to industries. Nevertheless, his model is subject to shortcomings in mixing up non-priced ecological commodities with priced economic commodities. Compared with Daly's model, the model proposed by Isard (1972) is similar but using production coefficients. His model also allows to include various ecological commodities in each sector and different substances in ecological sectors. Both Daly and Isard's models are comprehensive which fully implemented land, water, chemical reactions in the air. However, their models are limited by the data requirements, especially regarding environmental subsystems and their interactions (Richardson, 1972).

Table3.4 Daly's Model

	Industry	**Ecological processes**
Industry	Flows between industries	Flows from industry to the ecosystem
Ecological processes	Flows from the ecosystem to industry	Flows within the ecosystem

Table3.5 Isard's Model

<table>
<tr><th colspan="2"></th><th>Industry</th><th>Ecological processes</th></tr>
<tr><td rowspan="2">Commodities</td><td>Economic</td><td>A_{xx}</td><td>A_{xe}</td></tr>
<tr><td>Ecological</td><td>A_{ex}</td><td>A_{ee}</td></tr>
</table>

(Modified from: Miller and Blair, 2009, p446)

Inspired by Daly and Isard's models and the difficulties in obtaining data, Victor (1972) introduced a model with limited scope that is first to capture the material flows (*Table 3.6*). The model typically focuses on flows from environment to economy in terms of ecological commodities, as well as flows from economy to environment in terms of the wastes. Indeed, his model is able to differentiate the expressions for economic and ecological data (Miller and Blair, 2009, p446).

Table3.6: Victor's Model

	Commodities	Industries	Household Consumption	Total Output	Ecological Commodities
Commodities		**U**	**e**	**q**	**R**
Industries	**V**			**x**	**S**
Value added		**W**			
Total Inputs	**q'**	**x'**			
Ecological Commodities	**P**	**M**			

Econnomic sectors: **U** (inputs of industrial economic commodities), **V** (outputs of industrial economic commodities), **e** (final demand), **q** (gross output of economic commodity), **x** (industrial total outputs), **q'** (sums of **V**), **x'** (sums of **U** and **W**);

Ecological sectors: **R** (outputs of ecological commodities from final demand), **S** (industrial discharges of ecological commodities), **P** (inputs of ecological commodities in conjuction with final demand), **M** (industrial inputs of ecological commodities).

(Modified from: Miller and Blair, 2009, p446)

Leontief (1970) employed the input-output techniques to develop a pollution-abatement model (*Table 3.7*). The row vector of pollution generation stands for emissions generated from each industry during production while the column vector of pollution abatement describes emissions eliminated by the pollution abatement industries. However, the model was heatedly debated by many scholars (eg. Chen, 1973; Steenge, 1978; Qayum, 1991; Arrous, 1994, Victor, 1972), from which Victor (1972) argued that the model neglects the material balance principle and Steenge (1978) critisized the model because abatement costs might need to be reallocated if the duality between price effect and the real world crashes under externality effects.

Table3.7 Pollution-abatement Model

unit: dollar

	Manufacturing	Services	Pollution Abatement	Final Demand	Total Output
Manufacturing					
Services					
Pollution Generation					

(Modified from: Miller and Blair, 2009, p447)

Another popular application of input-output techniques is the physical input-output tables (PIOTs). In the 1990s, the statistical offices in some European countires firstly displayed input-output tables in physical terms in order to analyze the physical economic structure and comprehend the research on economy-environment relationships (Hubacek and Giljum, 2003). PIOTs has been widely applied on material flows accounting (Kratterl and Kratena, 1990; Kratena et al, 1992; Stahmer et al, 1997; Pedersen, 1999; Stahmer, 2000), energy accounting (Bullard and Herendeen, 1975; Machado et al, 2001), land use (Hubacek and Giljum, 2003), pollution diversion (Stahmer et al, 1997) and resource management (Strassert, 2001). The PIOTs record flows of all the transactions of goods and services in physical units, including both the production flows between production sectors and the material flows between economy and environment. It was developed based on the theory of material balance, which suggests that the net material accumulation should equal to the difference between total inputs and total outputs. In other words, physical inputs in a sector should equal to its physical outputs and also the consumption of households (Giljum and Hubacek, 2009). Compared with the PIOTs, monetary input-output tables (MIOTs) have played a significant role in economic policy analysis that serve as a foundation for national economic accounting system and was used widely in early works on land use (Hubacek and Giljum, 2003). The difference between MIOTs and PIOTs can be observed in *Figure 3.1* For the quadrant of intermediate transactions between industries, the two approaches are comparable except that PIOTs record the intra-industry flows in physical units. Major differences occur in the other two quadrants. PIOTs take environment into consideration by adding a source of raw materials in the primary input and a sink for residuals in the output of the economy in a way that incorporates the non-priced resource flows (Hubacek and Giljum, 2003). It is noteworthy that although the compilation of PIOTs largely follows the procedure of the monetary tables, the two tables cannot be converted two tables even if with the detailed information of prices provided because prices shown in an input-output table can be largely different from the real prices as a result of sector aggregation (Stahmer et al, 1997; Hubacek and Giljum, 2003; Giljum et al, 2004; Dietzenbacher et al, 2007). Nevertheless, PIOTs have the weakness in the use of a uniform unit, 'tons', to aggregate different qualities (Hubacek and Giljum, 2003; Suh, 2004; Giljum et al, 2004; Giljum and Hubacek, 2004). Besides, there is a lack of standardized methodology for the PIOTs compiled (Hubacek and Giljum, 2003).

MIOT (in monetary terms)	
1st quadrant	2nd quadrant
Interindustry deliveries	Final demand
3rd quadrant	
Value added Imports	

PIOT (in physical terms)	
1st quadrant	2nd quadrant
Interindustry deliveries	Final demand Residuals
3rd quadrant	
Primary inputs Imports	

(Modified from: Hubacek and Giljum, 2003)

Figure3.1 The difference between MIOTs and PIOTs

Compared with the applications of input-output techniques on energy and material flows, the applications on water-related issues tend to be fewer. Ireri and Carter (1970) appear to be the very first study that extends an interregional input-output model with water-use coefficients to evaluate the water in production flows between California and Arizona. Similary, Duchin and Lange (1994, p28) employed the water-use coefficients to assess the water embodied in production for Indonesia and for the globe, respectively. There emerges a number of studies measuring the effects on water resources from economic production and domestic demand in the late 1990s, including Yoo and Yang, 1999; Lenzen and Foran, 2001; Duarte et al, 2002; Leistritz et al, 2002 and Wang et al, 2005. One typical study can be Bouhia (2001) in which she combines a water resource allocation model based on a linear programming model with a static input-output model to construct a hydro-economic model. Water was shown in both monetary and physical terms balanced in material balance accounts. Specifically, Bouhia (2001) not only developed a set of water multipliers that allow her to assess the effects of different development scenarios of water demand but also added a column of 'change in the Natural Stock of Water' into the final demand quadrant to represent the waste water that is assumed to be deposited after the first production process and withdrawal by other sectors afterwards in order to feed back to the economic system. Meanwhile, with a different focus on water quality and water pollution, Thoss and Wiik (1974) applied a generalized input-output model on water pollution in the Ruhr. Both Ni et al (2001) and Okadera et al (2006) employed the input-output techniques to account for pollution discharge in Shenzhen and Chongqing, China, respectively.

3.3.2 Applications in Disaster Risk Studies

Earlier works on economic loss assessment of natural disasters mostly focus on the direct damages to physical infrastructure using the methods discussed in section 2.1. Assessing the disaster-induced economic disruptions merely based on direct economic impact is insufficient because it ignores the indirect economic impact (Rose, 2004). Indirect economic impacts can arise in two main ways. The first is the reduced capital and labour productivities as a result of disaster's direct damages to physical capital (in the case of 'rapid-onset' disasters) and its health impacts (in the case of 'persistent' disasters) as well as the cascading economic impacts along production supply chains due to sectoral and regional interdependencies. Imaging a region is terribly hit by floods that destroy several roads, bridges, machineries and buildings, people cannot go to work due to the traffic disruptions and destructed workplaces, and factories cannot perform productions due to the broken machines. As a result of the direct damages to these physical capital, effective working time, labour productivity and capital productivity will decrease, all contributing to the loss in economic outputs. Similarly, in the case of air pollution and heat waves, human health is severely harmed in terms of increasing mortality and hospitalization counts among respiratory and cardiovascular patients. It will inevitably induce substantial labour time loss that undermine labour productivity and economic production. The other is the impacts of production loss in a single sector on its customer ('downstream') and supplier ('upstream') sectors. Its theoretical basis is the concept of 'a circular economy' that underlines important sectoral and regional interdependencies (Leontief, 1928). Any initial impacts on a sector's production can be cascaded through such linkages and eventually spill over the remaining sectors. Therefore, indirect economic impacts can constitute a considerable share of the total socioeconomic burden of a disaster and is critical for disaster risk assessment and management. This was also approved by Hallegatte (2008) when he concluded that the ratio of total-to-direct economic loss rises with the increasing severity and magnitude of natural disaster.

A proper disaster risk assessment for systematic risk management thus requires not only to incorporate the accumulated output loss resulting from capital and labour productivity loss during economic recovery process if there is any, but also to capture the cascading economic impacts due to sectoral and regional interdependencies. This is significant for reducing vulnerability[3] while improving the resilience[2] of the affected regions (Okuyama, 2009; Rose, 2004; Veen & Logtmeijer, 2003). To cope with the industrial and regional interdependencies in disaster risk assessment, both input-output techniques and Computable General Equilibrium (CGE) model are able to capture these interdependencies regardless certain inherent

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[3] The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as the 'degree to which a system is susceptible to injury, damage, or harm' and resilience as the 'degree to which a system rebounds, recoups, or recovers from a stimulus' (Burton, Challenger, Huq, Kein, & Yohe, 2001).

limitations. The CGE model analyzes the macroeconomic context of markets by allowing instantaneous price adjustments, which can loop back into economic activities (Carrera et al, 2015). Therefore, a CGE model is often critisized by its over optimism in market flexibility regardless the various adaptive capabilities in the real world (Carrera et al, 2015; Rose, 1995). In contrast, although an input-output model contains rigidity in technological ties, it appears to be a suitable candidate to study an economy in equilibrium and thus, it is useful for analyzing disaster risks where such equilibrium and balances might be broken down by a natural disaster. With the advantages in coping with sectoral and regional interdependencies, input-output techniques have been modified and developed to overcome the rigidity problem surrounding the basic static input-output model and thereby, to be applied in a dynamic context of natural disaster. In the case studies of this thesis, the primary and initial reduction in industrial value added or final demand due to capital and labour productivity loss is referred as direct economic loss while the secondary cascading economic loss resulting from industrial and regional interdependencies is termed as indirect economic loss. The purpose of doing so is to highlight the important role of industrial and regional interdependencies in macroeconomic costs assessments.

3.3.2.1 The Inoperability Input-Output Model (IIM)

In order to assess the sectoral damages in productivity, some authors (Haimes & Jiang, 2001; Haimes et al, 2005; Santos & Haimes, 2004; Santos, 2006) introduced a concept of *'expected inoperability'* to represent the risk from natural disasters, which reflects the system risk and probability of limitation in performing the planned *natural or engineered functions*. The Inoperability Input-Output Model (IIM) was developed based on this concept by assuming a direct relation between the level of transactions and the interdependency among economic sectors. Its initial purpose lies in evaluating the propagation of perturbations and disturbances within a system of interconnected and interdependent infrastructure and sectors (Haimes and Jiang, 2001; Haimes et al, 2005). It can be applied in various fields of natural disaster, ranging from risk modelling, risk assessment to risk management for economic-based engineering systems on a large scale (Crowther and Haimes, 2005). The formula of the physical-based model is presented in *Equation 3.11*.

$$\mathbf{x}^p = \mathbf{A}^p\mathbf{x}^p + \mathbf{c}^p \Leftrightarrow \{x_i^p = \sum_j a_{ij}^p x_j^p + c_i^p\}, \forall i. \quad (3.11)$$

$\mathbf{x}^{\mathbf{p}}$: output state and the resulting vector of inoperability of various infrastructures;

$\mathbf{A}^{p}$: physical interdependency matrix that measures the interdependency between various physical subsystems within the larger system;

$\mathbf{c}^{p}$: the disturbance or perturbation input to the interconnected infrastructures in the form of natural events;

As can be seen from *Equation 3.11* that the model seems to share the similar appearance with a basic Leontief input-output model. However, Haimes and Jiang (2001) added the superscript *P* to adapt and differentiate from the Leontief model. The physical IIM improves the capacity of the basic Leontief model by enabling acurate representation of the complexity and interdependency within a physical system. Its roots in input-output analysis allow users to intuitively assess the cascading impacts on each of the remaining subsystems from a perturbation to a single subsystem (Crowther and Haimes, 2005). However, the physical model is limited by unavailability for transactional data. To cope with the data issue, the demand-reduction IIM and supply-reduction IIM were developed by Santos and Haimes (2004). A demand-reduction IIM is a system model that shows logical interdependencies between sectors and infrastructures based on the use of commodities by using equilibrium economic transactional data. In contrast, a supply-reduction IIM reflects the interdependencies from the perspectives of industrial commodity production (Crowther and Haimes, 2005). The demand-side model can be shown in *Equation 3.12* with its key elements shown from *Equation 3.13* to *Equation 3.15*.

$$\mathbf{q}=\mathbf{A}^*\mathbf{q}+\mathbf{c}^* \quad (3.12)$$

$$\mathbf{q}=[\mathrm{P}(\hat{\mathbf{x}}-\tilde{\mathbf{x}})] = \lfloor \mathrm{PAP}^{-1} \rfloor [\mathrm{P}(\hat{\mathbf{x}}-\tilde{\mathbf{x}})] + [\mathrm{P}(\hat{\mathbf{c}}-\tilde{\mathbf{c}})] = \mathbf{A}^*\mathbf{q}+\mathbf{c}^*, \quad (3.13)$$

$$\mathrm{P}=(diag(\hat{\mathbf{x}}))^{-1}$$

$$\mathbf{A}^{*}=[\mathbf{PAP}^{-1}] \Leftrightarrow \left\{a_{ij}^{*}=\frac{1}{\hat{x}_{i}}a_{ij}\hat{x}_{j}\right\}, \forall i \qquad (3.14)$$

$$\mathbf{c}^{*}=[\mathbf{P}(\hat{\mathrm{c}}-\tilde{\mathrm{c}})] \Leftrightarrow \left\{c_{i}^{*}=\frac{\hat{c}_{i}-\tilde{c}_{i}}{\hat{x}_{i}}\right\}, \forall i \qquad (3.15)$$

q: demand reduction inoperability;

A*: demand interdependency matrix, which was developed based on technical coefficient matrix **A** using the data from *Use* and *Make* matrices of the Bureau of Economic Analysis (BEA);

c*: the primary disturbance to demand

P: the transformation matrix to equate physical IIM with a demand-reduction IIM.

A supply-reduction IIM can be derived from a demand-reduction IIM by shifting the focus from users' inoperability to suppliers' inoperability. It is shown in *Equation 3.16*.

$$\mathbf{q}^{(s)}=\mathbf{A}^{(s)*}\mathbf{q}^{(s)}+\mathbf{z}^{*} \qquad (3.16)$$

$\mathbf{q}^{(s)}$: supply reduction inoperability;

$\mathbf{A}^{(s)}*$: supply interdependency mtrix, which was also developed based on technical coefficient matrix **A** using the data from *Use* and *Make* matrices of the Bureau of Economic Analysis (BEA);

z*: the primary disturbance to supply.

The approach has been applied to assess the cascading effects resulting from the disturbances to a national power outage (Crowther and Haimes, 2005). The ability of IIM to capture both interdependency and propagating effects from disturbance, Crowther and Haimes were able to assess the economic loss caused by both users' inability to receive power during the power outage, and the suppliers' inability to satisfy electricity demand (Crowther and Haimes, 2005). Alongside, they suggested that such approach can equally guide risk management policy with a focus on port security. In this respect, IIM adds insights to a more comprehensive and systematic views on potential system risks from changes in risk management policy. It has been broadly applied to critical infrastructure systems (eg. Santos and Haimes, 2004; Lian et al, 2006). It has been also extended to a multiregional level by presenting the spatially explicit concepts of intraregional and multiregional interdependency matrices, which has later applied to evaluate the geographical risk in various regions in the US (Crowther and Haimes, 2010).

Nevertheless, these models encounter several limitations due to the embodied assumptions. The first assumption lies in the fixed production procedures, suggesting constant technology and proportionality. This assumption is related with the basic assumption in the Leontief model. Secondly, supplies of raw materials are normally larger than demand while IIM ignores the overcapacity of local resources or possibility for substitutions. Thirdly, the resolution of model elements cannot exceed those from the Bureau of Economic Analysis (BEA) (Haimes et al, 2005). Indeed, Rose (2004, p25), by suggesting that "full multiplier effects are likely to take place only in short-duration hazard situations," pointed out the strictness for the duration of disturbances. On the one hand, the models do not consider possibilities for substitutions. The exclusion of substitutions can only occur when the duration of disturbances is relatively short. Otherwise, substitutions will alter the technical multipliers in the affected system. On the other hand, the duration of disturbances cannot be too short because short duration of disturbances might be easily overcome. Therefore, to fit these assumptions, a disturbance should be both short enough to avoid substitutions and long enough to take effects to the interdependent systems (Crowther and Haimes, 2005).

3.3.2.2 The Dynamics of Post-disaster Recovery

The IIM allows to assess the efficacy of risk management by measuring the economic impacts of disturbances with and without risk mitigation measures (Haimes and Chittester, 2005). However, concerning temporary and risk management evaluations, the way a particular system recovers, the costs of such recovery as well as the measures to minimize the loss during recovery process requires us to consider the dynamic nature of post-disaster economy.

To cope with the dynamic post-disaster recovery, Leontief (1986) himself extended the static basic input-output model to a dynamic input-output model (Blanc and Ramos, 2002; Miller and Blair, 2009, p2). The traditional dynamic input-output model can be shown in *Equation 3.17 and 3.18*.

$$\mathbf{x}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{Y}(t) + \mathbf{B}\mathbf{x}'(t) \qquad \text{or,} \qquad (3.17)$$

$$\mathbf{x}'(t) = \mathbf{B}^{-1}[\mathbf{I}\text{-}\mathbf{A}]\mathbf{x}(t) - \mathbf{B}^{-1}\mathbf{Y}(t) \qquad (3.18)$$

x(t): a vector of sectoral output at time *t;*

Y(t): a vector of final demand at time *t;*

B: a matrix of capital coefficients, which measures the willingness of the economy to invest in capital resources, including machines, land or software.

When the dynamic input-output model reaches an equilibrium, it will becomes a static model as shown in *Equation 3.6*. **x'**(t)=0 suggests an equilibrium. However, after revisiting *Equation 3.18*, Blanc and Ramos (2002) argued that the **B** matrix has to be negative or zero so that it can produce an economic behaviour coincided with the static Leontief model no matter what the initial situation or final demand is (Blanc and Ramos, 2002). Therefore, matrix **B** should be understood as the short-term countercyclical policy rather than long-term growth. Indeed, in the case that **B**=-**I**, what the dynamic model really describes is the adjustment level of the economic production following an imbalances between total supply and total demand at time *t* (Lian and Haimes, 2006). Facing that the dynamic process is not completely deterministic as short-term economic behaviour of sectors can be affected by myriad factors, a Dynamic Inoperability Input-Output Model (DIIM) was proposed by adding a stochastic component that describes the production adjustment rates. As an extension for the IIM, a DIIM incorporates the recovery processes of economic sectors during the aftermath of a disruptive event and describes the temporal nature of sector recoveries pursuant to a disaster based on the interdependency and resilience of the sectors (Lian and Haimes, 2006; Santos et al, 2009). The DIIM follows the *Equation 3.19*.

$$\mathbf{q}(t+1)=\mathbf{q}(t)+\mathbf{K}[\mathbf{A}^{*}\mathbf{q}(t)+\mathbf{c}^{*}(t)-\mathbf{q}(t)] \quad (3.19)$$

$\mathbf{q}(t+1)$: inoperability vector at time t+1;

$\mathbf{q}(t)$: inoperability vector at time t;

$\mathbf{K}$: resilience matrix;

$\mathbf{c}^{*}(t)$: vector of the initial disturbances.

The resilience matrix **K** plays a vital role in differentiating DIIM from IIM because it is generated from the dynamic extension to describe the recovery process of the sectors. Higher value in resilience indicates faster pace to recover and the time length needed to recover to normalcy is used as an indicator for the value in resilience (Santos et al, 2009). Despite that the DIIM has been widely applied in disaster impact analysis and economic recovery modelling (Haimes et al, 2005; Okuyama, 2007; Arkhtar and Santos, 2013; Santos, 2006; Xu et al, 2011), the assumption of economic equilibrium in the disaster aftermath is yet to be fully addressed in these models.

3.3.2.3 Post-disaster Imbalances Model

To restore the economic equilibrium appears to be the primary aim for any post-disaster recovery strategy. However, it is not an easy task because post-disaster situation is often characterized by vast disruptions and enduring disequilibrium. As I previously mentioned in section 3.2.2, the assumption of fixed proportions between primary inputs holds in a basic Leontief input-output model. Unfortunately, disproportional damages to these primary inputs always occur in the disaster aftermath, as Steenge and Bočkarjova (2007, p208) stated that “In modelling efforts, I should recall that a disaster will affect these categories differently…”. This can happen in either case that residential neighbourhoods are more physically affected than industrial and service quarters, or workers are relatively unharmed but workplaces are terribly hit by the natural disaster. In both cases, primary inputs will not be shrunk by the same proportion and the corresponding intermediate inputs cannot produce sufficient goods and services to fulfil the remaining final demand

(Steenge and Bočkarjova, 2007). Considering the disproportions between the production capacity in the 'surviving' establishments and the needs from the 'surviving' labourers, Steenge and Bočkarjova (2007) introduced a Post-disaster Imbalances Model based on a *closed* Leontief model, which enables to trace the supply and demand for each commodity and allows a set of outputs to be circulated as a set of inputs in the next round. The basic formula describing the pre-disaster economy is shown from *Equation 3.20* to *3.25*.

$$\mathbf{x}=\mathbf{A}\mathbf{x}+\mathbf{f} \tag{3.20}$$

$$L=\mathbf{l}'\mathbf{x} \tag{3.21}$$

By rearranging *Equation 3.20* and *3.21*, we can have:

$$\begin{bmatrix} \mathbf{A} & \mathbf{f}/L \\ \mathbf{l}' & 0 \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} \quad \text{or,} \tag{3.22}$$

$$\begin{bmatrix} \mathbf{A} & \mathbf{h} \\ \mathbf{l}' & 0 \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix}, \mathbf{h} = \mathbf{f}/L \tag{3.23}$$

If we designate

$$\mathbf{M} = \begin{bmatrix} \mathbf{A} & \mathbf{h} \\ \mathbf{l}' & 0 \end{bmatrix}, \mathbf{q} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} \tag{3.24}$$

Equation 3.23 will become *Equation 3.25*.

$$\mathbf{Mq} = \mathbf{q} \tag{3.25}$$

$$\begin{bmatrix} a_{11} & \cdots & a_{1n} & h_1 \\ \vdots & & \vdots & \vdots \\ a_{n1} & \cdots & a_{nn} & h_n \\ l_1 & \cdots & l_n & 0 \end{bmatrix} \begin{bmatrix} q_1 \\ \vdots \\ q_n \\ q_{n+1} \end{bmatrix} = \begin{bmatrix} q_1 \\ \vdots \\ q_n \\ q_{n+1} \end{bmatrix}$$

A: the matrix of input coefficients;

l': row vector of direct labour input coefficients;

x: vector of total output;

f: vector of final demand;

L: scalar for total employment;

M: a matrix with the Perron-Frobenius eigenvalue equal to one;

q: the corresponding positive eigenvector.

The left-hand side of *Equation 3.25* stands for the total inputs in an economy while the right-hand side is the total outputs in an economy. It essentially describes an economy's potential to be self-reproducible when sectoral capacities are at level **q** in a context of equilibrium. From *Equation 3.20* to *3.25*, Steenge and Bočkarjova (2007) have moved from a formulation based on an open Leontief model to a formulation based on a *closed* Leontief model. It is noteworthy that fixed coefficients assumption only holds in matrices **A** and **l'** while the remaining elements will change correspondingly. In other words, if **f** changes, **x**, *L* and **h** will also change.

Then, Steenge and Bočkarjova (2007) introduced (n+1) parameters $\gamma_i (0 \leq \gamma_i \leq 1)$, which can be presented as an (n+1)*(n+1) diagonal matrix in *Equation 3.26*. It shows the fraction of production capacity loss in sector *i*.

$$\Gamma = \begin{bmatrix} \gamma_1 & \ddots & 0 \\ 0 & & \gamma_{n+1} \end{bmatrix} \tag{3.26}$$

When Γ is a (n+1) dimensional zero matrix, it describes a pre-disaster situation with full employment and without idle capacity. In contrast, if Γ is not the zero matrix, post-disaster imbalances appear and *Equation 3.25* will become *Equation 3.27*.

$$\mathbf{M}(\mathbf{I} - \boldsymbol{\Gamma})\mathbf{q} \neq \boldsymbol{\Gamma}\mathbf{q} \tag{3.27}$$

In *Equation 3.27*, unless $\boldsymbol{\Gamma}\mathbf{q} = \gamma\mathbf{q}$, which indicates proportional shrink in primary inputs, proportional reduction in production capacity of primary inputs and economic output cannot be replicated. In a *closed* Leontief model, a set of outputs from the previous round will be fed back into production in the next round as a set of inputs. After a natural disaster, the possible inputs that can be circulated into the next round can be illustrated as *Equation 3.28*.

$$\mathbf{M}(\mathbf{I} - \boldsymbol{\Gamma})\mathbf{q} = \mathbf{t} \tag{3.28}$$

$$\begin{bmatrix} a_{11} & \cdots & a_{1n} & h_1 \\ \vdots & & \vdots & \vdots \\ a_{n1} & \cdots & a_{nn} & h_n \\ l_1 & \cdots & l_n & 0 \end{bmatrix} \left(\begin{bmatrix} 1-\gamma_1 & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 \\ 0 \quad 0 & & 1-\gamma_n & 0 \\ 0 \quad 0 & & 0 & 1-\gamma_{n+1} \end{bmatrix} \begin{bmatrix} q_1 \\ \vdots \\ q_n \\ q_{n+1} \end{bmatrix} \right) = \begin{bmatrix} t_1 \\ \vdots \\ t_n \\ t_{n+1} \end{bmatrix}$$

t: the column vector of the row sums of the left side of *Equation 3.28*.

It is noteworthy that *Equation 3.28* is not an input-output equation because **t** is just a matrix of row-wise addition and there is no equilibrium here. The consumption possibilities at post-shock stage with remaining capacity cannot satisfy the real remaining final demand measured by workers' real wage. To restore the pre-disaster proportions, a recovery approach that is able to modify *Equation 3.28* in order to obtain an eigenvector system suggested in *Equation 3.25* should be selected. In this respect, a Post-disaster Imbalances Model can provide a benchmark to guide post-disaster economic recovery strategy. Apart from this, their work appears to be the first that formally introduces the concept of Event Account Matrix (EAM) in the input-output modelling based on Cole et al (1993)'s initial idea in event matrix. Cole et al (1993) indicated that an event matrix should specify not only the magnitude of damage to sectoral components, but also the goal for recovery and recovery time scale. The matrix is a mathematical component that expresses the damage fraction regarding the sectoral production capacity and allows keeping track of post-disaster imbalances and possible bottlenecks.

However, Steenge and Bočkarjova (2007)'s work was developed based on fictional flooding scenarios and therefore, some practical issues are yet to be fully investigated, such as transportation, utility services and communication systems. This is based on their assumptions that substitutions of importable commodities are always available from non-affected areas regardless the remaining capacity in transportation sector. Indeed, their model cannot fully capture the dynamic nature of post-disaster economic recovery.

3.3.2.4 An Adaptive Regional Input-Output Model (ARIO)

In order to cope with the dynamic post-disaster recovery, Hallegatte (2008) proposed an hybrid modelling framework, an Adaptive Regional Input-Output Model (ARIO), to analyse the economic impacts of natural disasters and the recovery phase. His model contributes in two aspects. On the one hand, on the part of Steenge and Bočkarjova (2007), the model also considers sector production capacity as a result of the shock on the supply side and the cascading impacts resulting from sector interdependencies. On the other hand, the model introduces adaptive behaviour of producers and consumers in response to a lack of inputs. The model was designed for a regional economy, where sectors produce commodities for intermediate transactions of other sectors as well as final demand of local consumers, import commodities from outside the region and export commodities outside the region.

(a). Basic Structure of the ARIO

The original state of the pre-disaster economy can be presented as *Equation 3.29*.

$$\bar{\mathbf{X}} = \bar{\mathbf{A}}\bar{\mathbf{X}} + \bar{\mathbf{F}} \tag{3.29}$$

$\bar{\mathbf{X}}$: the vector of sectoral outputs;

$\bar{\mathbf{F}}$: the vector of final demand.

After a natural disaster, the post-disaster economy can be illustrated as *Equation 3.30*.

$$X(i) = \sum_j A(i,j)X(i) + \underbrace{LFD(i) + E(i) + HD(i) + \sum_j D(j,i)}_{TFD(i)} \tag{3.30}$$

LFD: the vector of local final demand;

E: the vector of export;

HD: reconstruction needs resulting from disaster damages to households, such as the damages to dwellings;

D: reconstruction needs from the damages to industries in terms of physical capital loss;

TFD: total final demand.

It is the first time that reconstruction needs from both damages to household dwellings and damages to industrial physical capital were incorporated into a disaster economic modelling.

Following *Equation 3.30*, the first guess production can be interpreted using *Equation 3.31*.

$$X^0(i) = (I - A)^{-1}TFD(i) = TD^0(i) \tag{3.31}$$

$TD^0(i)$: total demand of sector *i* at time 0 before the disaster's occurrence that includes both total final demand and intermediate demand from other sectors.

In a pre-disaster economy, total output can satisfy total demand, indicating a balance between supply and demand.

Then, sectoral remaining production capacity was considered by assuming the same proportional reduction in sectoral physical capital and its production capacity. X^{max} stands for sectoral production capacity. It is compared with the first-guess production TD^0 shown in *Equation 3.31.* The production of sector *i* is thus the minimum between production capacity and first-guess production from total final demand TFD, following the concept of post-disaster imbalances suggested by Steenge and Bočkarjova (2007) (*Equation 3.32*).

$$X^0(i) = MIN\{X^{max}(i); TD^0(i)\} \qquad (3.32)$$

$X^{max}(i)$: production capacity of sector *i*.

In addition, Hallegatte (2008) raised two possible situations. In the first situation, the remaining production capacity of a sector is able to satisfy its post-disaster total demand, including intermediate demand from industries, final demand of local households, demand from exports and reconstruction demand, then no problems occur. In the second situation, if the remaining production capacity of a sector is not sufficient to fulfil its total demand, then a manipulable rationing scheme takes place, which requires the sector to satisfy intermediate demand as a priority, household demand as a second, export demand as a third and reconstruction needs as an extra. However, a supply bottleneck may occur when a sector's remaining production capacity cannot even satisfy the totality of its intermediate demand. In such case, the remaining output will be proportionally distributed to other sectors according to the post-to-pre-disaster output ratio. It is also the first time that possible supply bottleneck issue and rationing scheme were raised. To present the possible bottleneck in formula, we have *Equation 3.33*.

When $X^1(j) < O^1(j)$, $O^1(j) = \sum_i A(i,j)X^1(i)$

then $X^2(i) = MIN\left\{X^1(i); for\ all\ j, \frac{X^1(j)}{O^1(j)} X^1(i)\right\}$ *(3.33)*

$O^1(j)$*:* the first guess regarding the production of sector *j* that is required to fulfil intermediate demand from other sectors;

$\frac{X^1(j)}{O^1(j)} X^1(i)$: production of sector *i* is bounded by ratio $\frac{X^1(j)}{O^1(j)}$ when a supply bottleneck occurs. Overall, production of sector *i* is constrained by the production and supply from all other sectors.

Meanwhile, to consider that a sector producing less also demands less from other sectors, Hallegatte (2008) fed such backward impacts into Total Demand TD using *Equation 3.34.*

$$TD^1(i) = TFD(i) + \sum_j A(i,j) X^2(j) \qquad (3.34)$$

The new $TD^1(i)$ will be used in *Equation 3.32* and *3.33* until converge to $X^k(i) = 0$. During the recovery, the ARIO allows damages to industrial physical capital and household dwelling to reduce by certain amounts from reconstruction at each time stage (*Equation 3.35*). The model will continue running until $TD^{\infty} = X^{\infty}$, which suggests the final value of total demand equals to that of production and each sector is able to fulfil its total demand without any remaining reconstruction needs.

$$D(j,i) - \Delta D(j,i)\Delta t \xrightarrow{\Delta t} D(j,i) \qquad (3.35)$$

$$HD(i) - \Delta HD(i)\Delta t \xrightarrow{\Delta t} HD(i)$$

(b). Specific Supporting Equations

When considering the production capacity, Hallegatte (2008) also incorporated the factor of overproduction capacity as descried in *Equation 3.36*. The production capacity of a sector is suggested to be a function of the original production capacity, the damage fraction of production capacity and overproduction capacity.

$$X^{max}(i) = \bar{X}(i)\left[1 - \frac{\widehat{D}(i)}{\bar{K}(i)}\right]\alpha(i) \qquad (3.36)$$

$\bar{K}(i)$: sectoral production capital before the disaster;

$\alpha(i)$: sectoral overproduction capacity;

$\left[1-\frac{\widehat{D}(i)}{\overline{K}(i)}\right]$: the remaining production capacity in a sector that is assumed to be consistent with the percentage of remaining production capital.

Secondly, price sensitivity and macroeconomic condition were included in the model using *Equation 3.37*. Local final demand is a function of adapted local final demand, local macroeconomic condition and price elasticity of local final demand while exports is a function of the adapted exports and price elasticity of export demand.

$$LFD(i) = M \cdot \overline{LFD}(i) \cdot [1 - \varepsilon(p(i) - 1)] \qquad (3.37)$$

$$E(i) = \overline{E}(i) \cdot [1 - \varepsilon(p(i) - 1)]$$

$\overline{LFD}(i)$: adapted local final demand for sector *i*;

$\overline{E}(i)$: adapted export demand for sector *i*;

M: local macroeconomic indicator, measured by the current-to-pre-disaster total earning ratio;

ε: price elasticity.

In addition, as a major progress of ARIO, Hallegatte (2008) considered the adaptive behaviour in final demand from the consumers' perspectives and in intermediate consumption from the producers' perspectives. One the one hand, if the substitution for a good is available and transportable, local final demand will adapt and decrease towards zero once the production of this sector cannot fully satisfy its total demand that requires local final demand to be rationed. This is also true for demand of exports in a sector. Such adaptive behaviour can be shown in *Equation 3.38*.

$$\overline{LFD}(i) - \frac{TD^{\infty}(i) - X^{\infty}(i)}{TD^{\infty}(i)} \overline{LFD}(i) \frac{\Delta t}{\tau_{LFD}^{\downarrow}} \xrightarrow{\Delta t} \overline{LFD}(i) \qquad (3.38)$$

$$\overline{E}(i) - \frac{TD^{\infty}(i) - X^{\infty}(i)}{TD^{\infty}(i)} \overline{E}(i) \frac{\Delta t}{\tau_{E}^{\downarrow}} \xrightarrow{\Delta t} \overline{E}(i)$$

$\tau_{LFD}^{\downarrow}$, $\tau_{E}^{\downarrow}$: parameters describing the pace of adapted local final demand and adapted export demand decrease. They are the time characteristics for local consumers and importers from outside the region to leave the local producers.

Similarly, local producers will shift to imports from outside the region if a sector producing a transportable commodity cannot fulfil the total demand (*Equation 3.39*).

$$A(j,i) - \frac{TD^{\infty}(i)-X^{\infty}(i)}{TD^{\infty}(i)} A(j,i) \frac{\Delta t}{\tau_A^{\downarrow}} \xrightarrow{\Delta t} A(j,i) \quad (3.39)$$

$$I(j) + \frac{TD^{\infty}(i)-X^{\infty}(i)}{TD^{\infty}(i)} A(j,i) \frac{\Delta t}{\tau_A^{\downarrow}} \xrightarrow{\Delta t} I(j)$$

$I(j)$: imports of sector *j* from outside the region;

$\tau_A^{\downarrow}$: time characteristic that describes the pace of intermediate consumption decreases and local producers shift to imports.

In the opposite situation where local producers become able to satisfy total demand again, consumers, outsider importers and other local producers will shift back to local producers again.

Hallegatte (2008) later applied this new framework on assessing the total economic loss of Katrina's landfall in NewOrleans in 2005 and the storm surge risks under a sea level rise scenario in Copenhagen (Hallegatte et al., 2011). More recently, Wu et al (2012) employed the ARIO to evaluate the total economic loss resulting from the most destructive earthquake in China since 1949, the Wenchuan Earthquake occurred in Sichuan Province in 2008. They found that indirect loss account for over 40% of direct economic loss and the regional economy is expected to recover during 8 years. On their part, the model has been also applied to measure the ripple effects and spatial heterogeneity of total economic loss based on a scenario analysis that the Wenchuan earthquake happens in Beijing, the Capital city in China (Zhang et al, 2017). The ARIO, although can be regarded as a significant step towards dynamic disaster recovery modelling, it ignores the constraints from loss in labour productivity, either from disaster-induced health effects or from disruptions to transportation. Indeed, important imbalances and nexus between capital availabilities and labour productivity have been neglected, where disproportions between primary inputs of production might occur (Koks et al., 2016). As the assumption of fixed proportions between factor inputs holds throughout the input-output model, considering remaining production seldom based on capital degradation is a major drawback associated with the ARIO.

3.3.2.5 A Flood Footprint Model

Based on the former ARIO, Li et al (2013) laid the foundation of a *flood footprint* model by incorporating labour availability. The term '*flood footprint*' is a novel damage accounting framework that is used to describe the total socioeconomic impact that is both directly and indirectly caused by a flood event to the flooded region and wider socioeconomic systems. The model was developed as a monthly model based on dynamic inequalities in a post-disaster imbalanced economy. A series of dynamic inequalities serves as the theoretical foundation and can be interpreted in *Figure 3.2*. These inequalities occur between remaining labour production capacity and remaining capital production capacity, remaining labour production capacity and post-disaster total production, post-disaster total production and post-disaster total demand. To explain this in details, let us recall the Post-disaster Imbalances Model in section 3.3.2.3.

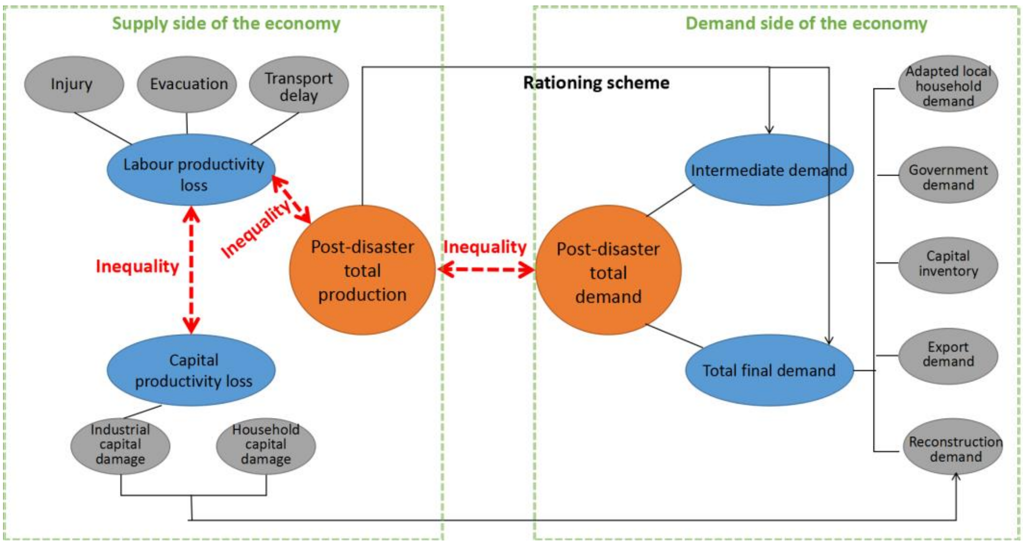

Figure3.2 Post-disaster imbalanced economy with inequalities

The diagram demonstrates the post-disaster economic inequalities occur between remaining labour production capacity and remaining capital production capacity, remaining labour production capacity and post-disaster total production, post-disaster total production and post-disaster total demand, *shown in red arrows. The left-hand side denotes the supply-side of the economy while the right-hand side shows the demand-side of the economy.*

$\mathbf{x}=\mathbf{Ax}+\mathbf{f}$

$L=\mathbf{l}'\mathbf{x}$

By introducing the labour constraints in *Equation 3.17*, we then have:

$\begin{bmatrix} \mathbf{A} & \mathbf{f}/L \\ \mathbf{l}' & 0 \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix}$ or,

$\begin{bmatrix} \mathbf{A} & \mathbf{h} \\ \mathbf{l}' & 0 \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix}, \mathbf{h} = \mathbf{f}/L$

when

$\mathbf{M} = \begin{bmatrix} \mathbf{A} & \mathbf{h} \\ \mathbf{l}' & 0 \end{bmatrix}, \mathbf{q}= \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix}$

then we have

$\mathbf{Mq} = \mathbf{q}$

A: the matrix of input coefficients;

l': row vector of direct labour input coefficients;

x: vector of total output;

f: vector of final demand;

L: scalar for total employment;

M: a matrix with the Perron-Frobenius eigenvalue equal to one;

q: the corresponding positive eigenvector.

Equations above describe a pre-disaster economy in equilibrium, which is also a closed Leontief model. After the disaster's occurrence, I introduced parameters $\gamma_i^t (0 \leq \gamma_i^t \leq 1)$ shown in *Equation 3.40,* then the demand side of the economy can be derived as *Equation 3.41 and 3.42*. It is noteworthy that this time the $\mathbf{\Gamma}$ is slightly different from the one in *Equation 3.26* as it includes time characteristics. $\mathbf{\Gamma}$ is obtained from an Event Account Matrix (EAM).

$$\Gamma = \begin{bmatrix} \gamma_1^t & & 0 \\ & \ddots & \\ 0 & & \gamma_{n+1}^t \end{bmatrix} \qquad (3.40)$$

$$\mathbf{x}_{td}^{t} \approx \mathbf{A}(\mathbf{I}-\mathbf{\Gamma}^{t})\mathbf{x}^{0}+\mathbf{f}' \qquad \text{or,} \qquad (3.41)$$

$$\mathbf{x}_{td}^{t} = (\mathbf{I}-\mathbf{A})^{-1}\mathbf{f}', (t>0) \qquad (3.42)$$

$\gamma_{\mathrm{n+1}}^{\mathrm{t}}$: damage fraction of sector n+1 at time step *t*;

$\mathbf{x}_{td}^{t}$: degraded total demand at time step *t.*

Equation 3.41 suggests that degraded total demand $\mathbf{x}_{td}^{t}$ is determined by final demand **f′** and $\mathbf{x}_{td}^{t}$ can be also understood as the total production required to fulfil such final demand over time. In contrast, *Equation 3.42* implies that $\mathbf{x}_{td}^{t}$ depends on both the intermediate demand satisfied by current production capacity and total final demand. This requires a balance between the two elements.

Now focusing on the economic supply side, with regards to labour, the degraded labour production capacity can be seen in *Equation 3.43*. Constrained by the labour, the degraded total production can be written as *Equation 3.44* because of the assumptions of fixed proportions in primary inputs (Miller and Blair, 2009, p2).

$$\mathbf{x}_{l}^{t} = \mathbf{l}_{e}^{t}/\mathbf{l},\ \mathbf{l}_{e}^{t} = (1-\gamma_{\mathrm{n+1}}^{\mathrm{t}})\mathbf{l}_{e}^{0} \qquad (3.43)$$

$\mathbf{x}_{l}^{t}$: degraded labour production capacity;

$\mathbf{l}_{e}^{t}$: total regional employment at time step *t* that is influenced by sectoral damage fraction.

$$\mathbf{x}_{tp}^{t} = L(\mathbf{I}-\mathbf{\Gamma}^{t})\mathbf{x}^{0} \qquad (3.44)$$

$\mathbf{x}_{tp}^{t}$: degraded total production.

Since the model is a closed Leontief model, the current production constrained by labour will determine the total demand of labour, that is, $\mathbf{x}_{td}^{t}$ is constrained by $\mathbf{x}_{tp}^{t}$. At each time step during recovery process, an equilibrium should be stored between total production capacity, total demand and labour production capacity and thereby, to continue recovering until it reaches a balance between the totality of inputs and totality of outputs in the economy, as shown in *Equation 3.45* and *3.46*.

$$\mathbf{q}^{(t)} = \begin{pmatrix} \mathbf{x}_{tp|td|l}^{t} \\ L_{tp|td|l}^{t} \end{pmatrix} \rightarrow \mathbf{q}^{*(t)} = \begin{pmatrix} \mathbf{x}^{*(t)} \\ L^{*(t)} \end{pmatrix} \qquad (3.45)$$

$$\mathbf{Mq}^{*(t)} = \mathbf{q}^{*(t)}, \mathbf{q}^{*(t)} = \begin{pmatrix} \mathbf{x}^{*(t)} \\ L^{*(t)} \end{pmatrix} \qquad (3.46)$$

$\mathbf{x}^{t}_{tp|td|l}$, $L^{t}_{tp|td|l}$: the balances of total output and total employment required to reach the balance between total production, total demand and labour production capacity at time step t;

$\mathbf{x}^{*(t)}$, $L^{*(t)}$: total output and total employment required to reach a balance between them;

$\mathbf{q}^{*(t)}$: a balanced total output and employment.

Similarly, Koks, et al. (2014) uses a Cobb-Douglas function to estimate the direct damages from labour and capital constraints, and the indirect damages during the recovery process through the ARIO model. The study becomes a compatible example with Li et al's study as it also incorporates restrictions in the productive capacity of labour through another approach. Incorporating labour constraints seems to be a great step towards more realistic and comprehensive disaster impact modelling, however, a major drawback is that the model treats imports as an exogenous variable by exogenously adding available imports to remaining production to fulfil both intermediate needs and final demand. Indeed, Li et al (2013) set both capital and labour recovery path exogenously that means the damage fraction of sectoral capital in next round do not really depend on the recovery from last round. This will inevitably deteriorate the applicability and practicability of his model in the real disaster cases.

3.3.2.6 A Hypothetical Extraction Method (HEM)

Focusing on the intersectoral and interregional linkages rather than the dynamic post-disaster recovery, Paelinck et al (1965) and Strassert (1968) proposed a Hypothetical Extraction Method (HEM) to measure the role of a sector in an economy typically in multisectorial models by investigating its 'keyness' in terms of economic relevance. The HEM method was first proposed to estimate the relative importance of certain sectors for the entire economy. This was done by introducing the concept of hypothetical extraction of the sector, thereby assuming that the interruption of its services could not be remedied by imports and other substitutions. The reduction in overall production level after extracting certain economic sectors gives the importance of the sector. It has been later re-formulated by Meller and Marfan (1981) and Cella (1984). Once an economic sector is hypothetically eliminated from the economic system, the HEM can be used to estimate the effects of this extraction on other sectors and on the wider economic system. Thus, the difference between the output level of the other sectors before and after the extraction reflects the linkages between the extracted sector and the rest of the economy, where these linkages can be further decomposed into backward and forward linkages[4] (Ali, 2015). Linkage analysis based on a HEM has been broadly applied on studies of water use (Duarte et al, 2004), key sector analysis (Andreosso O'Challaghan and Yue, 2004), economic importance of a wide range of sectors, including agriculture (Cai and Leung, 2004), real estate sector (Song and Liu, 2007) and construction sector (Song et al, 2006), as well as the role of energy and non-energy efficiency gains (Guerra and Sancho, 2009). In Guerra and Sancho (2009)'s work, the external interactions of energy sectors are eliminated while the external input purchases of non-energy sectors are removed at the same time. Doing so can reflect the sensitivity of non-energy sectors towards energy efficiency gains. Those sectors encountering substantial output loss are considered to have high sensitivities to efficiency gains. By using an adapted HEM, their work can not only help identify key sectors for energy efficiency policies, but also explore the origins of rebound effect from energy efficiency improvements (Guerra and Sancho, 2009). Recently, the HEM has been reformulated again by several researchers, including Dietzenbacher et al (1993), who adapted the basic HEM to measure regional linkages, as well as Dietzenbacher and Lahr (2013) and Temurshoev and Oosterhaven (2014), who extended the basic rationale underlying the HEM to a global-level analysis by considering international trade between regions and countries. In Dietzenbacher and

[4] Backward linkages refer to the linkages between a sector and other sectors that supply inputs to it while forward linkages refer to the linkages between a sector and other sector that purchase output from it (Miller and Blair, 2009, p556).

Van der Linden (1997), a whole region was hypothetically extracted within an interregional setting to examine the economic significance of the region with regards to interregional linkages. Zhao et al. (2016) investigated sectoral CO_2 emission linkages in China at the regional level by integrating the HEM with a multi-regional input-output (MRIO) model. Nevertheless, applications of the HEM on disaster risk studies seem to be fewer compared with those on environmental or resource studies. Los (2004) suggested that the HEM can be equally meaningful for the assessment of sectoral or industrial shutdown in the cases of financial crises, such as the cases for the downfall of the Dutch aircraft manufacturer Fokker and the cease of the Belgian national airline Sabena that both caused the shutdown of the whole national industry. In these cases, the HEM can be used to evaluate the economic impacts of the 'extractions' of these companies on the economic systems. One of the few studies applying HEM on disaster impact analysis is Nozaki and Oosterhaven (2014) who adopted a regional HEM to measure the economic impacts from production and infrastructure shocks on the Japanese interregional economy, including 3 aggregated sectors for each of the 9 regions. Their hypothetical scenario allows the production in the non-disaster economies not to be affected by the production shock and thus, enables the imports and exports between regions despite that the imports will change proportionally according to the change rate in regional final demand. For instances, imports in the region under infrastructure shock is expected to increase proportionally while decrease in non-disaster regions (Nozaki and Oosterhaven, 2014). In a recent paper, Oosterhaven (2017) put forward an important 'caveat' regarding the use of the HEM in disaster studies. The core of Oosterhaven's criticism concerned the use of zero's in horizontal rows of the matrix of input coefficients. These zeros can be problematic if substitution possibilities exist between domestic and foreign deliveries. In my view, this criticism, on the other hand, supports the use of the HEM in typical cases where substitution possibilities do not exist. Oosterhaven might be right in his judgment in standard cases. However, in the case of a complete shut-down of a particular sector, including its transport and transmission functions, the use of zeroes –as I have put forward- is allowed. The 'complete disappearance' of the supply-demand mechanism of the products of the sector in question were witnessed while no substitution or replacement takes place because of the special nature of the sector (see section 5.1.1). Before proceeding to the empirical part of this study, I will devote some words to the HEM.

Starting with the basic formula of the HEM, here I shall recall the basic Leontief model for an economy with n sectors (*Equation 3.47*). In the equation, the technology as represented by matrix **A** is given, final demand (**f**) is determined exogenously and output (**x**) endogenously.

$$\begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} + \begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix} \tag{3.47}$$

Now due to a major catastrophe, suppose that a sector or sectors completely or partially lose its or their backward or forward linkages with the remaining economy, a new technical matrix **A’** will be obtained as *Equation 3.48*.

$$A' = \begin{pmatrix} a'_{11} & \cdots & a'_{1n} \\ \vdots & \ddots & \vdots \\ a'_{n1} & \cdots & a'_{nn} \end{pmatrix} \tag{3.48}$$

A new final demand vector may arise when a major catastrophe alters the patterns of household and government consumption. Households may spend more on life necessities and less on luxury and entertainment while government may spend more on reconstruction and health care services. If so, a new final demand matrix **f’** can be obtained as *Equation 3.49*.

$$F' = \begin{pmatrix} f_1' \\ \vdots \\ \vdots \\ f_n' \end{pmatrix} \tag{3.49}$$

A new economy with altered technology and final demand will be obtained as *Equation 3.50*.

$$\begin{pmatrix} x'_1 \\ \vdots \\ x'_n \end{pmatrix} = \begin{pmatrix} a'_{11} & \cdots & a'_{1n} \\ \vdots & \ddots & \vdots \\ a'_{n1} & \cdots & a'_{nn} \end{pmatrix} \begin{pmatrix} x'_1 \\ \vdots \\ x'_n \end{pmatrix} + \begin{pmatrix} f'_1 \\ \vdots \\ f'_n \end{pmatrix} \tag{3.50}$$

Finally, the economic impacts of the disaster can be measured as the difference between the old and new total outputs. In a matrix notation, this can be illustrated as *Equation 3.51*.

$$\mathbf{x} - \mathbf{x}' = (\mathbf{I}\text{-}\mathbf{A})^{-1}\mathbf{f} - (\mathbf{I}\text{-}\mathbf{A}')^{-1}\mathbf{f}' \tag{3.51}$$

There are two points are particularly worth consideration when applying the HEM. Firstly, there are variants. Therefore, it is important to determine the specific variant of the HEM to be used in the study and before applying it. Following Miller and Blair (2009, p563), a column of a sector in an input-output table should be replaced by a column of zeroes if it cannot buy any intermediate inputs from other sectors; the backward linkages of this sector no longer exist. Analogously, a row of a sector in an input-output table should be replaced by a row of zeroes if it has no intermediate sales to other sectors and its forward linkages no longer exist. Both should be replaced by zeroes if both backward and forward linkages of a sector cease. Secondly, it is also crucial to decide how large a percentage of a sector’s backward and forward linkages should be reduced. In other words, whether the sector should be eliminated completely or partially and if the total capacity of the sector is put out of work. In this respect, there are two main approaches to implementing the HEM. Following the original HEM, as developed by Strassert (1968) and implemented by Schultz (1977), ‘extraction’ simply means completely removing the backward and forward linkages of a sector or replacing its row and column elements with zeros in the technical coefficient matrix. Alternatively, Cella (1984) improved the original extraction method by differentiating economic activities across all economic sectors into two categories: intermediate sales and purchases with other sectors and self-reproducible sales and purchases. Thus, an extracted sector no longer sells or purchases any intermediate products to or from other sectors, and its technical coefficients will be partially replaced with zeros while the others remain the same (Ali, 2015; Zhao et al., 2016). Although such an economic assumption seems intuitively unrealistic because all technical coefficients are dependent on each other, Dietzenbacher and Van Der Linden (1997) validated this assumption by introducing imports to sustain the original technical production process. There is another, important point with regards to Oosterhaven's negative view of the method (Oosterhaven, 2017). In his criticism, Oosterhaven points out that there is a difference between applying HEMs to backward and to forward effects. Using HEM for studying the impacts of upstream, backward effects is correct and poses no problem in terms of interpretability. However, interpreting the extraction of a row of the coefficients matrix to represent the forward, downstream impacts of the extracted sector is faulty (Oosterhaven, 2017, p8) because "it only measures the direct impacts of the complete disappearance of the demand for an industry's intermediate sales" (Oosterhaven, 2017, p8).

3.3.2.7 The Mixed Model

The mixed model can be derived from a standard demand-side input-output model but with exogenously set final demands in some sectors and gross outputs in the remaining sectors (Miller and Blair, 2009, p593). This is common in a country with planned economy, such as China, where certain amount of increase in agricultural output might be set as a target by the end of the next planning period. Therefore, the model has been broadly applied in agricultural and resource economics (Tanjuakio et al, 1996; Papadas and Dahl, 1999; Petkovich and Ching, 1978; Eiser and Roberts, 2002; Leung and Pooley, 2002).

The mixed model can be obtained by rearranging the basic Leontief model. For an economy with three sectors, the original economy can be interpreted as *Equation 3.52.*

$$(1 - a11)x1 - a12x2 - a13x3 = f1 \qquad (3.52)$$

$$-a21x1 + (1 - a22)x2 - a23x3 = f2$$

$$-a31x1 - a32x2 + (1 - a33)x3 = f3$$

a: sectoral technical coefficient;

f: sectoral final demand;

x: sectoral output.

Now assuming final demand for sector 1 and 2 (*f1, f2*) and the output level for sector 3 (*x3*) are set exogenously. By moving all exogenous variables to the right-hand side of the equations while the endogenous variables to the left, *Equation 3.52* will become *Equation 3.53*.

$$(1 - a11)x1 - a12x2 + 0f3 = f1 + a13x3 \qquad (3.53)$$

$$-a21x1 + (1 - a22)x2 + 0f3 = f2 + a23x3$$

$$-a31x1 - a32x2 - f3 = -(1 - a33)x3$$

Alternatively, it can be presented in a matrix notation as *Equation 3.54.*

$$\begin{bmatrix} (1-a11) & -a12 & 0 \\ -a21 & (1-a22) & 0 \\ -a31 & -a32 & -1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ f3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & a13 \\ 0 & 1 & a23 \\ 0 & 0 & -(1-a33) \end{bmatrix} \begin{bmatrix} f1 \\ f2 \\ x3 \end{bmatrix} \qquad (3.54)$$

Let $\mathbf{M} = \begin{bmatrix} (1-a11) & -a12 & 0 \\ -a21 & (1-a22) & 0 \\ -a31 & -a32 & -1 \end{bmatrix}$ and $\mathbf{N} = \begin{bmatrix} 1 & 0 & a13 \\ 0 & 1 & a23 \\ 0 & 0 & -(1-a33) \end{bmatrix}$,

The endogenous variables can be solved based on the exogenous variables as:

$$\begin{bmatrix} x1 \\ x2 \\ f3 \end{bmatrix} = \mathbf{M}^{-1}\mathbf{N} \begin{bmatrix} f1 \\ f2 \\ x3 \end{bmatrix} \qquad (3.55)$$

Indeed, apart from determining the endogenous variables from set targets in some exogenous variables, the mixed model can also help evaluate, for example, the potential impacts of a rise in the output in a sector on the output or final demand of the remaining sectors (Miller and Blair, 2009, p593).

3.3.3 Research Gap in Disaster Risk Analysis

Regardless the hybrid models shown in section 3.3.2 in existing disaster risk studies, they largely focus on 'rapid-onset' disasters, such as floods and hurricanes, in which case the accurate estimation will heavily depend on the quantification of industrial physical capital damages, from which the loss in industrial production capacity loss can be inferred based on an Event Accounting Matrix (EAM). However, they tend to neglect two critical points. On the one hand, each 'rapid-onset' disaster can take different forms with distinctive characteristics and affect physical and human capital differently. Damages to physical capital do not necessarily happen in a natural disaster. In such a case, existing disaster modelling frameworks that mainly rely on assessment of industrial physical capital damage might lose its efficacy. On the other hand, some natural disasters persist longer and take longer to realize their effects on the society and economy, such as air pollution and heat waves, which have rarely discussed in current disaster risk studies. The possible reason is that these disasters normally cause little damage to physical infrastructure but substantial health impacts on human beings. To quantify these 'invisible' effects impose a challenge for disaster risk analysis. However, considering the health impacts on human is equally important because they constitute principle factor inputs during production as labourers. As a result, the degradation in labour productivity and capacity can equally impede economic activity. Indeed, as a disaster may affect physical and human capital differently, there may exist disproportional shrinks between physical and labour production capacity. As the assumption of fixed proportion in primary inputs holds throughout an input-output model, disaster-induced health impacts may result in imbalances between post-disaster labour and capital production capacity, which constrain the total post-disaster production. Therefore, incorporating these impacts appears to be equally important for disaster risk assessment and management, as well as post-disaster recovery strategies to restore the balances.

Chapter 4: Development and Implications of a Disaster Footprint Framework

After summarizing the research gaps in existing health costs assessment and disaster risk studies, this chapter develops an interdisciplinary approach that combines environmental or meteorological studies, epidemiological studies and macroeconomic analysis. The economic part of the approach is constructed based upon input-output techniques and thus, it is able to capture the cascading indirect economic impacts resulting from industrial and regional interdependencies. The approach introduces a new concept of '*disaster footprint*' that denotes total economic loss measured by total reduction in aggregated production resulting from a natural disaster with a specific focus on the cascading indirect economic loss along economic production chains. The total economic loss incorporate not only the industrial initial reductions in both supply of primary inputs (value added) and final demand, but also the cascading indirect economic loss as a result of backward and forward linkages between interconnecting economic sectors within the economic system. By utilizing the interdisciplinary approach, health impacts can be integrated into disaster risk studies and industrial interdependency analysis through the lens of labour with additional consideration on disaster characteristics of either 'rapid-onset' or 'persistent' natural disasters. The specific tasks for this chapter are:

1. To sketch the overall methodological framework of the '*disaster footprint* model';
2. To introduce the main components of the model as well as details in specific methods or equations from environmental/meteorological, epidemiological and macroeconomic studies that bridge these three fields;
3. Regarding the macroeconomic part of the approach, to propose several possible ways to feed health impacts into the input-output based economic models that can successfully reflect the macroeconomic implications from

these health impacts. For each method, the rationale, basic equation, data requirements, advantages and disadvantages will be provided together with a simple numerical example based on fictive scenario.

4.1 Overall Methodological Framework

Figure 4.1 portrays the overall methodological framework of the interdisciplinary *'disaster footprint'* model that is able to bridge environmental and meteorological studies (box in red), epidemiological studies (box in blue), industrial impact analysis (box in grey) and macroeconomic analysis (box in orange). Key elements belonging to one particular study are shown in the same colour as small circles shown in the right of the diagram. They are connected with labelled arrows that represent the detailed methods employed to actualize certain specific objectives displayed in the small circles. It can be observed from the diagram that the developed methodological framework constitutes a flow, which originates from environmental or meteorological studies that help identify a particular natural disaster event, which can be either 'rapid-onset' or 'persistent'. Thereafter, it has been separated into two directions. On the one hand, if the disaster under investigation is a 'persistent' disaster, either $PM_{2.5}$ air pollution or heat waves, the next step will evaluate the resulting clinical health and sub-clinical impacts based on developed exposure-response relationships or findings from existing epidemiological studies, from which the productive working time loss can be estimated and possible impacts on final demand and industrial value added can be examined depending on whether a demand-driven or supply-driven input-output model will be pursued to trace the cascading indirect economic loss along economic production chains. On the other hand, if the disaster is 'rapid-onset', both industrial physical capital damages and injuries or deaths among labour should be analyzed, depending on the distinctive characteristics of the disaster in consideration, based on which potential balances or imbalances between post-disaster remaining capital production capacity and labour production capacity can be detected. The loss of connection with other sectors for the affected sectors will be inferred based on loss in overall production capacity loss. The loss in connections with other sectors will be further regarded analogously as the extraction of this sector from the economic system for a certain period by using a Hypothetical Extraction Method (HEM) to trace the economic impacts on the remaining sectors and economy. The chosen four case studies employ selective input-output based approaches that are most appropriate for the distinctive characteristics of each case. However, I also propose several other approaches based on input-output techniques to facilitate more analysing angles and modelling options. Eventually, the model is expected to provide useful macroeconomic implications for disaster-induced total economic loss, including both direct and indirect economic loss. The following sections tend to specifically explain detailed methods incorporated in each environmental and meteorological studies, epidemic studies, industrial impact analysis and macroeconomic analysis.

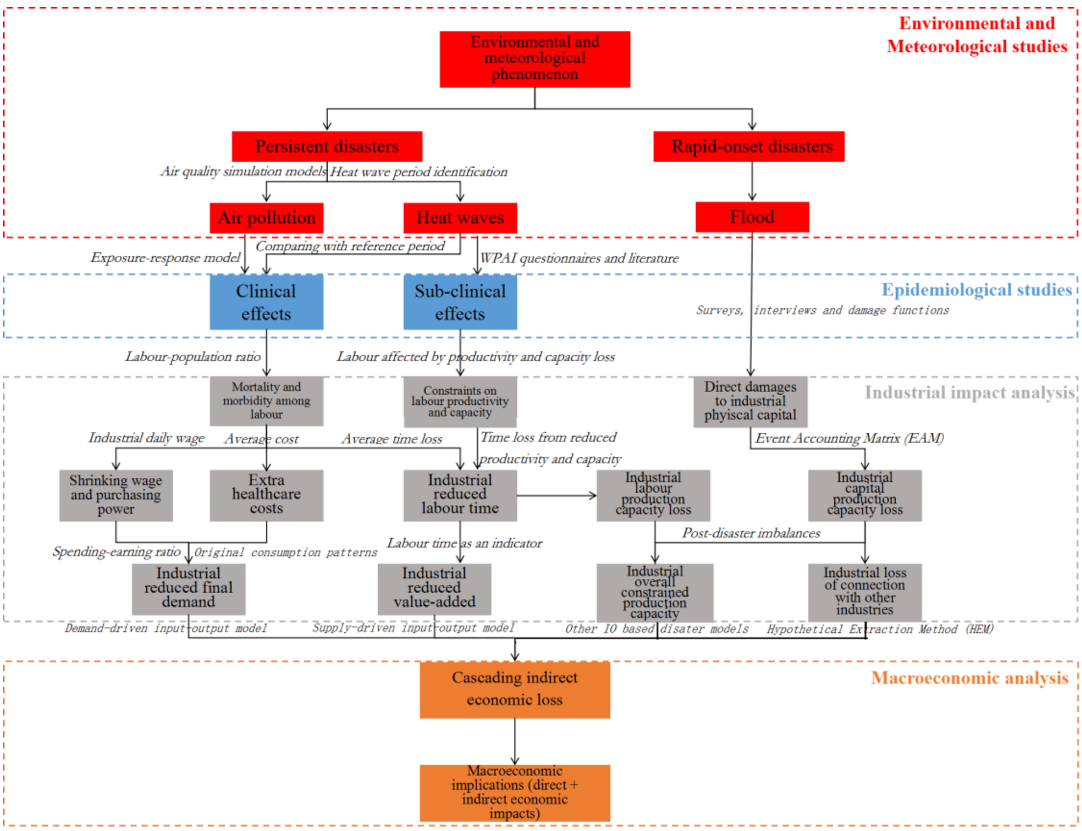

Figure4.1 Overall methodological framework

Figure 4.1 portrays the overall methodological framework of the interdisciplinary 'disaster footprint' model that is able to bridge environmental and meteorological studies (box in red), epidemiological *studies (box in blue), industrial impact analysis (box in grey) and macroeconomic analysis (box in orange). Key elements belonging to one particular study are shown in the same colour as small circles shown in the right of the diagram. They are connected with labelled arrows that represent the detailed methods employed to actualize certain specific objectives displayed in the small circles.*

4.2 Environmental and Meteorological Studies

4.2.1 Air Quality Simulation Models for Assessing $PM_{2.5}$ Concentrations

For $PM_{2.5}$ air pollution, air pollutant emission inventories were used to estimate the provincial $PM_{2.5}$ concentration levels among 30 Chinese provinces using air quality simulation modelling. The anthropogenic emissions for China were obtained from the Multi-resolution Emission Inventory for China (MEIC), which is a technology-based and bottom-up air pollutant emission inventory used in China since 1990 and has been continuously updated by Tsinghua University in China. The inventory initially contained the anthropogenic emissions for 10 types of air pollutants and greenhouse gases emissions from over 700 emission sources. More recently, it has further refined and updated by incorporating unit-based emissions data for power plants, cement and high-resolution vehicle emission at a national level (Xia et al, 2016). Air quality simulation models used include the offline-coupled Weather Research and Forecasting (WRF) model (v.3.5.1 http://www.wrf-model.org/) and Community Multi-scale Air Quality (CMAQ) model (v5.0.1, http://www.cmascenter.org/) with 14 layers' vertical resolution from the surface to tropopause in which the height of first layer is 38m. The CMAQ model was invented by the US Environmental Protection Agency (EPA) and its domain includes the 127 × 172 East Asia grid cells that cover the entire China by 36 km × 36 km grid squares. It is a three dimensional (3D) Eulerian air quality model system for simulating various pollutants at different scales from local to continental. Simulations were run for the four model months (January, April, July and October) in the study to obtain the annual $PM_{2.5}$ concentration while the meteorological fields at 36 km horizontal grid spacing were generated by WRF with 23 vertical layers using the reanalyzed data from the US National Centers for Environmental Prediction (NCEP). The initial and boundary conditions were derived from the final NCEP analysis data (FNL) and were used to drive the CMAQ model. The land-use/land-cover and topographical data were obtained from the default WRF input dataset. The anthropogenic and natural source emission inputs were derived from MEIC and MEGAN (Model of Emissions of Gases and Aerosols from Nature) (Xia et al, 2016).

4.2.2 Heat Wave Period Identification

There are various ways to define a heat wave. It is suggested that the definition of a heat wave tends to have considerable impacts on its added effects (Chen et al, 2015). The length of heat wave can be completely different under distinct heat wave definitions (eg. Anderson and Bell, 2011; Son et al, 2012; Tian et al, 2013; Peng et al, 2011; Huang et al, 2010, etc). For consistency, this paper defines a heat wave as a period of at least 3 consecutive days with daily maximum temperature beyond 35℃, daily average temperature beyond 31.3℃ and daily average temperatures exceed 97th percentile during the study period. Certain length of heat wave periods can be identified with this definition. For comparison purpose, especially in analyzing the heat impact on excess deaths and hospitalization, selecting a near-term summer reference period for each identified heat wave to control potential time-varying confounding effects appears to be crucial for epidemic studies in the next step. The selected reference period should have the same duration and distribution of days of the week (DOW) as each corresponding heat wave and excludes the days immediately after the heat wave (Basu and Samet, 2002; Ma et al, 2011). The data on daily temperature for Nanjing during 2013 and Shanghai during 2007 were obtained by Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing from Nanjing meteorological monitoring station and Shanghai Baoshan meteorological monitoring station, respectively.

4.3 Epidemiological Studies

4.3.1 Health Endpoints of $PM_{2.5}$ Air Pollution

Epidemic studies on $PM_{2.5}$-induced health outcomes have linked $PM_{2.5}$ air pollution with various health endpoints by using exposure-response relationships. They describe the changes in effect on an organism resulting from different levels of exposure to a risk factor after certain length of exposure time, which can be applied on either individuals or the whole population (Burnett et al, 2014). For $PM_{2.5}$ pollution, I specifically focus on its impacts on mortality, hospital admissions and outpatient visits for certain disease types. I referred to an integrated exposure-response (IER) model developed by Burnett et al (2014) that could describe several patterns in relative risks (RRs) which are considered as *a prior* applicable to exposure-response models. The model takes the similar shape with several burden assessment models as log-linear and linear (Cohen et al, 2004) and a power function (Pope et al, 2011b) to estimate the RRs for $PM_{2.5}$-induced mortality, hospital admissions and outpatient visits.

For disease-induced mortality, an IER model captures concentration-response relationships with a specific focus on ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD) and lung cancer (LC). The RRs for the mortality estimation function for the four diseases are shown in *Equation 4.1.*

$$\text{For } z<z_{cf} \qquad RR_{IER}(z) = 1 \qquad (4.1)$$
$$\text{For } z\geq z_{cf} \qquad RR_{IER}(z) = 1+\alpha\ \{1-exp[-\gamma(z-z_{cf})^{\delta}]\ \}$$

z : the $PM_{2.5}$ exposure in micrograms per meter cubed;

z_{cf} : the counter-factual concentration level below which no additional health risk is assumed;

δ: the strength of $PM_{2.5}$ and γ is the ratio of RR at low-to-high exposures.

For morbidity risk, I calculated cardiovascular and respiratory hospital admissions and outpatient visits for all causes using a log-linear response function and the RRs for each category of morbidity was calculated using *Equation 4.2*.

$$RR = e^{\beta x} \tag{4.2}$$

β : the parameter that describes the depth of the curve. They are the exposure-response coefficients to quantify the relationship between different levels of $PM_{2.5}$ exposures and the resulting health outcomes.

Then, the calculated RR was then converted into a population attributable fraction (PAF) by using *Equation 4.3* that measures the proportional decrease in mortality or morbidity counts that will occur once exposure to a risk factor decreased to an alternative ideal exposure scenario (WHO, 2017).

$$AF = \frac{RR - 1}{RR} \tag{4.3}$$

Thereafter, excess counts of $PM_{2.5}$ disease-induced mortality, hospital admissions and outpatient visits were calculated using *Equation 4.4*.

$$E = AF \times B \times P \tag{4.4}$$

E: $PM_{2.5}$-induced mortality and morbidity counts;

B: the national level incidence of a given health effect, which was applied for all provinces because of limited data;

P: the size of the exposed populations.

4.3.2 Health Endpoints for Heat Waves

To assess the health endpoints of heat waves, I referred to Ma et al (2011) in calculating excess hospital admissions and excess deaths. By assuming little changes occurred in population and socioeconomic structures of the cities under analysis, same duration and DOW distribution between each heat wave and each corresponding reference period enable the ratio comparison between two periods to reflect the relative impact of the heat wave. For the heat-induced excess deaths, all-cause mortality were considered and were calculated as the difference in number of mortality between heat wave period and its corresponding reference period, while the heat-induced hospital admissions, mainly for cardiovascular and respiratory admissions, were calculated as the difference in numbers of hospital admissions between the two periods. The heat-induced outpatient visits were calculated based on Sun et al (2014). I also calculated The RRs for heat-induced mortality, cardiovascular admissions and respiratory admissions were calculated by dividing the number of mortality/admissions during heat wave (study period) by number of mortality/admissions during corresponding reference period with the 95% confidential intervals (CIs) for the RRs. The calculation process can be interpreted in *Equation 4.5* to *4.8*.

$$M_{heat} = M_s - M_r \qquad (4.5)$$

M_{heat}: the heat-induced excess number of non-accidental mortalities;
M_s: the number of mortalities during the heat wave;
M_r: the number of mortalities during the reference period.

$$RR_{heat-mortality} = \frac{M_s}{M_r} \qquad (4.6)$$

$$RR_{heat-admissions} = \frac{H_s}{H_r} \qquad (4.7)$$

$RR_{heat-mortality}$: the rate ratio for heat-induced mortality;
$RR_{heat-admissions}$: the rate ratio for heat-induced admissions of a certain disease.

$$RR_{95\%\,CIs} = [\exp\,(LnRR \pm 1.96\sqrt{\frac{1}{s} + \frac{1}{r}})] \qquad (4.8)$$

s: the numbers of mortality or disease-specific admissions during heat wave (study period);
r: the number of mortality or disease-specific admissions during the reference period (Rothman et al, 2008; Ma et al, 2011).

Then, the counts of heat-induced death, hospital admissions and outpatient visits were estimated using *Equation 4.2* and *4.3* in section 4.3.1.

$$AF = \frac{RR - 1}{RR}$$

$$E = AF \times B \times P$$

AF: the population attributable fraction that measures the fraction of the affected population that can be attributed to extreme heat;

RR: the rate ratios for a particular health endpoint in investigation;

‘1’: the counterfactual risk ratio using a theoretical-minimum-risk exposure distribution. In this case, it reflects the temperature level below which there is no additional health risks;

E: the total affected counts of a particular health endpoint that are attributable to extreme heat;

B: the national level admission incidence of a given health effect;

P: the exposed population (WHO, 2017).

The daily counts of death data were obtained from the China Information System of Death Register and Report of Chinese Center for Disease Control and Prevention (China CDC). The causes of death were coded by China CDC according to the International Classification of Diseases, Tenth Revision (ICD-10): non-accidental disease (A00-R99), cardiovascular disease (I00-I99) and respiratory disease (J00-J99).

4.4 Industrial Impact Analysis

4.4.1 Mortality and Morbidity Counts among Labour

Mortality and morbidity counts were scaled down to mortality and morbidity counts among labour using employment-population ratio. It can be presented in *Equation 4.9* to *4.11*.

$$E_{motality,L} = E_{mortality} * \frac{L}{P} \qquad (4.9)$$

$$E_{admissions,L} = E_{admissions} * \frac{L}{P} \qquad (4.10)$$

$$E_{outpatients,L} = E_{outpatients} * \frac{L}{P} \qquad (4.11)$$

$E_{motality,L}$, $E_{admissions,L}$, $E_{outpatients,L}$: counts of mortality, hospital admissions and outpatient visits among labour;

L: Total employment;

P: Total population.

For $PM_{2.5}$ air pollution, 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 suggested by 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 (Xia et al, 2016). However, due to the data unavailability for occupational disease incidence rates for heat, mortality and morbidity counts among labour were assigned to industries using industry-total employment ratios.

4.4.2 Sub-clinical Effects on Labour Productivity and Capacity

Sub-clinical effects on productivity and capacity were considered only for heat waves. For heat-induced productivity loss due to mental distraction or reduced cognitive skills, due to the lack of a quantitative relationship between heat exposure and the resulting productivity loss, a 12% reduction (Bux, 2006) was assumed in productive working time for workers working indoors with light work intensity (Zander et al, 2015). Meanwhile, for heat-induced work capacity loss due to workplace safety standards, assumptions were made according to the real summer average humidity in Chinese cities, which requires a 45 minutes' relief time per hour for outdoor workers with high work intensity (Occupational Health and Safety, 2010).

4.4.3 Industrial Reduced Labour Time

All labourers in China were assumed to work 8 hours a day and 250 days per year. Each death will result in a total 250 working days lost regardless different disease types. Each cardiovascular admission will result in 11.9 working days lost while each respiratory admission causes 8.4 working days lost (National Bureau of Statistics of China, 2016). 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 and frequency of outpatient visits in China, the previous assumptions were made based on the current status of Chinese medical system where no pre-booking and follow-up services are available. I believed the use of a daily 4 hours can provide a conservative prediction in model results considering time for queueing, inquiry and medical treatment. It is noteworthy that no holiday that might be potentially embodied in the working days lost was considered.

After this, working time lost from all mortality, admissions and outpatient visits were summed up to obtain the total time loss for these health endpoints, which was further compared with the original working time without any disaster-induced health impacts to calculate the percentage reductions in industrial working time (*Equation 4.12*).

$$\sigma = \frac{250 * E(i)_{mortality} + 11.9 * E(i)_{cardio} + 8.4 * E(i)_{resp} + 0.5 * E(i)_{outpatients}}{250 * L(i)} \tag{4.12}$$

$E(i)_{mortality}$, $E(i)_{cardio}$, $E(i)_{resp}$, $E(i)_{outpatients}$ *:* counts of mortality, cardiovascular admissions, respiratory admission and outpatient visits in industry *I;*

$L(i)$*:* Total employment in industry *i;*

σ*:* percentage reductions in productive working day in industry *i.*

4.4.4 Shrinking Wage and Extra Health-care Expenditure

As a result of disaster-induced health impacts, on the one hand, loss in labour productive time indicates a loss in disposable wage and purchasing power if no compensatory behaviour was accounted. On the other hand, extra expenditure on health-care services can induce a ‘crowd-out’ effect on the consumption by households and government as the cost burden was partially borne by patients (20%) and partially by Chinese government (80%).

Considering the constraining effects of health outcome on disposable wage, the industrial labour day loss calculated in the last section 4.4.3 were multiplied by industrial daily salary in that year to estimate the reduction in workers’ earnings in each sector, where the results were summed up and eventually multiplied by household expenditure-earnings ratio to reflect the 'real' reduction in households' final demand. Sectoral daily wage was calculated by dividing sectoral annual average compensation from National Statistical Yearbook by 250 days (*Equation 4.13*).

$$\omega(\downarrow) = [\sum_i \sigma * 250 * L(i) * w(i)] * \frac{X}{W} \qquad (4.13)$$

$\omega(\downarrow)$: the overall reduction in households' purchasing power;

$w(i)$: the wage rate in industry *i;*

$\frac{X}{W}$: expenditure-earnings ratio.

Considering the crowd-out effects of medical cost burden on the consumption of household and government, total extra medical expenditure should be firstly estimated as shown in *Equation 4.14*. The costs of each cardiovascular, respiratory admission and outpatient visits were obtained as 6413.3, 3042.8 and 211.0 Yuan[5], respectively from China's Health and Family Planning Statistical Year and China Health Statistical Yearbook (National Bureau of Statistics of China, 2016). The total extra medical expenditure was partially borne by both government (80%) and partially by patients/households (20%). Medical costs for any heat-induced mortality were not considered in the current study.

$$C = c_{cardio} * E_{cardio,L} + c_{resp,L} * E_{resp,L} + c_{outpatient} * E_{outpatients,L} \qquad (4.14)$$

C: total extra health-care expenditures;

c_{cardio}, $c_{resp,L}$, $c_{outpatient}$: costs of each cardiovascular, respiratory admission and outpatient visits;

$E_{cardio,L}$, $E_{resp,L}$, $E_{outpatients,L}$: counts of cardiovascular admissions, respiratory admissions and outpatient visits among labour. Counts in each category outside the labour market were not considered because it is the wage for labourers that generate the final demand and their consumption.

From above, reducing household purchasing power and crowd-out effects of rising medical burden will both shrink households and government's consumption on

[5] Yuan is a monetary unit for Chinese RenMinBi and it is equivalent with 0.15 USD and 0.11 GBP (2017).

other commodities or public services with disproportional reductions in final consumption of other sectors according to the original consumption patterns of households and government, which suggest the adverse ranking in their original consumption or investment with an underlying assumption that commodities occupying large proportions of final consumption are considered as necessities and is less likely to reduce in the face of decreasing disposable wage and constrained budgets.

4.5 Input-Output Based Macroeconomic Analysis

Another major limitation of existing approaches for health costs assessment, such as HCA and CVA, is their similar focus on patients' economic burden at microeconomic level (Wan et al, 2004 & 2005; Nam et al, 2010). I suggest that same attention should be attached on impacts on wider economic systems at macroeconomic level in health costs assessment, with additional emphasis on inter-industrial and interregional linkages. The seven proposed input-output based methods (shown in yellow in *Figure 2.1* from section 2.2.2) are able to capture these crucial industrial and regional interdependencies. In this respect, the Leontief input-output framework is an effective way to capture the inter-industrial relationships but a great challenge here is how to incorporate the disaster-induced health effects, which are generally measured in the numbers of people affected, into an input-output model or its modified forms. This would require the translation of health outcome into suitable inputs for an input-output model, such as loss in labour productive working time or induced changes in households' real wages. The remaining of this section provides details on several methods developed based upon input-output techniques to understand the macroeconomic implications of disaster-induced health impacts as well as the resulting labour capacity and productivity loss. A simple numeric example will be provided with the basic or modified forms of equations, data input requirements, preliminary results, advantages, disadvantages and policy implications to help interpret each proposed method. Differences in estimation results regarding the macroeconomic impacts in terms of economic output can be observed from these methods.

Let us start with a simple numerical example. Suppose that a simple economy with only two sectors 1 and 2 with technical coefficient matrix $\mathbf{A}=\begin{bmatrix}0.25 & 0.4\\ 0.14 & 0.12\end{bmatrix}$, final demand matrix $\mathbf{f}=\begin{bmatrix}55\\ 30\end{bmatrix}$ and total output matrix $\mathbf{x}=\begin{bmatrix}100\\ 50\end{bmatrix}$. *Table 4.1* presents the basic input-output table for such 2-sector economy. Without any disaster-induced health effects, all labourers in this economy are assumed to be healthy and work for 8 hours a day and 250 working days a year as full-time with full productivity.

Table4.1 Standard Input-Output Table for a 2-Sector Economy

Standard Input-Output Table for a 2-sector Economy				
Sector	Intermediate transaction Z		Final demand f	Output X
	1	2		
1	25	20	55	100
2	14	6	30	50
Value added V	61	24		
Total input X'	100	50		

4.5.1 Constrained Production for Final Demand

Firstly, the problem can be examined from a relatively straightforward perspective of constrained production for final demand.

Underlying rationale: Considering an arbitrary case that all labours are suffered from severe health impacts from a natural disaster that induce a 50% loss in their productive time, as the input-output model assumes fixed proportion in input investment during production, it can be inferred that the loss of productive working time will cause the same proportional reduction in the output level. Thus, this reflects a decrease of 50% in the output level, which will further trigger the output available for final consumption, which is a key indicator for social benefits measured by the reduced economic outputs available for household consumption.

<u>Basic equation</u>**:**

$$\begin{aligned} \mathbf{x} &= \mathbf{Lf} \\ \Delta\mathbf{x} &= \mathbf{L} * (\Delta\mathbf{f}) \end{aligned} \tag{4.15}$$

$\Delta\mathbf{x}$**:** changes in industrial output level;

L: Leontief inverse for this 2-sector economy;

$\Delta\mathbf{f}$: changes in final consumption available for households.

<u>Preliminary results</u>:

$\mathbf{x}' = \begin{bmatrix} 50 \\ 25 \end{bmatrix}$ and $\mathbf{f}' = \begin{bmatrix} 22.5 \\ 15 \end{bmatrix}$

x': new output level;

f': new final consumption.

<u>Advantages:</u> This method is able to directly reflect the impacts of disaster-induced health impacts on productive time loss and social benefits in terms of total economic outputs available for consumption for households.

<u>Disadvantages:</u> Main uncertainties exist in the assumption of same proportional reductions in productive time and output level. Such linear relationship does not necessarily hold in real case where other factor inputs also exist, such as land and physical capital, possible substitution of factor inputs is possible and sick labour may be replaced by someone else to maintain the same production level.

<u>Policy implications</u>: As final consumption is the only source for social benefits, the constrained production for final demand therefore refers to a loss in social benefits, measured by the reduced economic outputs available for household consumption. The policy implication in this respect is that loss in production for final consumption can be understood as a loss in social benefits as the inter-industrial sales are assumed to have no 'welfare' at all and all social benefits come from final consumption while social costs come from the use of labour (Dofman et al, 1958).

4.5.2 Changes in Real Wages

Secondly, the problem can be considered from the perspective of a closed Leontief model where labour income as a source for generating household consumption (Steenge and Bočkarjova, 2007).

<u>Underlying rationale</u>: Health effects might induce changes in labours' real wages in terms of final demand available and cause changes in final consumption per head. For example, all workers in sector 1 have suffered from degraded health status and 50% loss in their productive working time, in order to achieve the original production level x_1, it now needs doubled number of unhealthy labour because two unhealthy workers whose productivity have become halved can produce the same amount of output as a healthy worker. In this respect, there are two possible outcomes depending on the changes in their compensations. If each gets half of their original nominal wage as productive working time has reduced by 50%, total real wages will remain the same and nothing changes. However, if due to some social protection policies, the employer has to keep their nominal wages at the original level, total real wages will then become halved because the number of employed workers has been doubled now and economic surplus is insufficient to pay out. The shrinking final demand can be traced backwards along production chains to estimate the cascading indirect economic impacts from this initial changes in final demand.

<u>Basic equations</u>:

$$\begin{aligned} \mathbf{x} &= \mathbf{L}\mathbf{f} \\ \Delta\mathbf{x} &= \mathbf{L} * (\Delta\mathbf{f}) \end{aligned} \quad \text{and} \quad \mathbf{f}' = \begin{bmatrix} 22.5 \\ 30 \end{bmatrix} \text{due to halved real wages.} \qquad (4.16)$$

<u>Preliminary results</u>:

$$\mathbf{x}' = \begin{bmatrix} 52.65 \\ 42.47 \end{bmatrix}$$

<u>Advantages</u>: This method allows to investigate the cascading effects of shrinking real wages and constrained household final demand on the production chains from a

demand-driven perspective. It is able to detect how changes in dollar value of final demand in a single sector or several sectors affect the gross production of the economy. Without the replacement of workers or compensatory behaviour, the nominal wage will become less due to labour time loss resulting from sickness, which suggests a shrink in their purchasing power. Meanwhile, extra health-care expenditure will also exert crowd-out effect on consumptions with fixed budget. Both of them will constrain households' final demand, which turns to be similar with the case described above.

Disadvantages: Uncertainties firstly exist in social protection policies that determines the changes in workers' real wages. Indeed, to truly reflect changing in household final demand from changes in their real wages requires to consider macroeconomic variables, such as propensity to consume as well as consumption behaviour and preference. Additionally, a Leontief input-output model has several basic assumptions of a partial equilibrium model, including the determinant role of industrial output to industrial intermediate transactions, a fixed relationships between a sector's input and output as well as fixed proportions among industrial inputs (Miller and Blair, 2009, p2). Although such partial equilibrium model may not fully reflect the real-world economic phenomena, it is still powerful to study equilibrium in constricted markets.

Policy implication: This method sheds lights on the effects of possible changes in labour's real wage on their final demand and in turn, on the entire economic system through the backward linkages. However, to analyze how changes in labour real wages will actually affect their consumption behaviour requires to precisely evaluate macroeconomic multipliers, price elasticity, marginal propensity to consume and so forth, which might be subject to data unavailability.

4.5.3 A Supply-driven Input-Output Model

The impacts of disaster-induced productive time loss on the economy can be also analyzed from a supply-driven perspective by capturing the forward linkages along production supply chains. The supply-driven input-output model takes an alternative representation of traditional input-output model by using a Ghosh-type coefficient matrix to describe the output allocation of a particular sector across all the other sectors. The model is an example of an input-output modification for calamity modelling, although it does not include a discussion of the essence of perturbations.

Underlying rationale: In this method, percentages reduced in industrial .productive time due to various health endpoints is perceived as an indicator for percentages reductions in industrial value added, which can be further fed into a supply-driven input-output model. Assuming that labour in sector 1 lose 20% of working time due to disaster-induced health effects, an equivalent 20% decrease can be thus expected in value added of sector 1 since human capital is a major components of sectoral value added. The new value added will be $v = \begin{bmatrix} 48.8 \\ 24 \end{bmatrix}$.

Basic equations:

$$\mathbf{x}' = \mathbf{v}'(\mathbf{I}\text{-}\mathbf{B})^{-1}, \mathbf{G} = (\mathbf{I}\text{-}\mathbf{B})^{-1} \quad \text{with} \quad \mathrm{v}_{\mathrm{new}} = \begin{bmatrix} 48.8 \\ 24 \end{bmatrix} \qquad (4.17)$$

$\mathbf{x}' = \mathbf{v}'\mathbf{G}$ or $\mathbf{x} = \mathbf{G}'\mathbf{v}$

B: matrix of allocation coefficients;

x: the output matrix;

v: the value added matrix.

G, **G'**: output/Ghosh inverse and the element g_{ij} indicates the value of each unit of primary inputs in sector i that enters sector j.

Preliminary results:

$$\mathbf{x}' = \begin{bmatrix} 82.2252 \\ 45.9603 \end{bmatrix}$$

Advantages: A supply-driven input-output model provides a solution for the major drawback of conventional input-output model, which input-output model is rigid and limited to demand driven type. It provides flexibility to allow an input-output model to be supply driven by considering supply constraints incurred endogenously during model stimulations. Besides, the model provides a chance to view productive time loss as an indicator and feed the degraded labour due to natural disasters back to production processes by using industrial value added decreases to detect the overall drop in output within the wider economic system.

Disadvantages: A fundamental problem in the model is that according to Ghosh model, any primary input increase in a single sector will be transmitted to output increases in all its downstream sectors without corresponding increases in primary inputs in these sectors (Oosterhaven, 1988 & 1989). Both Dietzenbacher (1997) and Oosterhaven (1996) reinterpreted the model as a price model by fixing quantity in order to overcome its implausibility, in which **Δv** reflects changes in costs of primary inputs while **Δx** shows changes in values of outputs. In this respect, the model will become analogous with a cost-push input-output model.

Policy implications: The method is able to perceive productive time loss as an indicator for degradation in factor input of labour in value added that can trace forward to estimate the cascading indirect economic effects along the production supply chain. Therefore, 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.

4.5.4 The Post Disaster Imbalances Model

When regarding health problem as a consequence of particular types of disasters that affect more on the human capital than physical capital, the post-disaster imbalances model can be used to detect the output changes when an economy reaches a new equilibrium (Steenge and Bočkarjova, 2007).

Underlying rationale: This approach was developed based on a closed Leontief model with equilibrium by introducing labour factor into a standard Leontief equation. Any disastrous event will break the balances in the economy and cause changes in labour real wages and their final demand for instances. Thereafter, the economy will restore to a new equilibrium with new output level (Steenge and Bočkarjova, 2007).

Basic equations:

$$\begin{bmatrix} \mathbf{A} & \mathbf{f}/L \\ \mathbf{l}' & 0 \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} \quad \text{or} \qquad (4.18)$$

Mq = q

L: value of total employment

l': direct labour coefficient matrix. Fixed coefficient assumption only applies to the matrices **A** and **l'** in **M.** The left hand-side of the equation refers to the total inputs required in the production while the right hand-side refers to the total outputs. The equation describes an economy in perfect equilibrium and If consumption preference **f** changes, **x** and *L* will change correspondingly to achieve a new equilibrium (Steenge and Bočkarjova, 2007).

M: a n*n matrix of input coefficients and its Perron-Frobenius eigenvalue is equal to unity, suggesting that the economy needs all inputs to be self-reproducible and it has no surplus for consumption without endangering the capacity of reproducing (Steenge and Bočkarjova, 2007).

In the original situation, *L* = 260 and $\mathbf{l}' = \begin{bmatrix} 0.8 & 3.6 \end{bmatrix}$ so that the basic equation can be written as *Equation 4.19*.

$$\begin{bmatrix} 0.25 & 0.4 & 0.21154 \\ 0.14 & 0.12 & 0.11538 \\ 0.8 & 0.36 & 0 \end{bmatrix} \begin{bmatrix} 100 \\ 50 \\ 260 \end{bmatrix} = \begin{bmatrix} 100 \\ 50 \\ 260 \end{bmatrix} \qquad (4.19)$$

If the reduced productive working time has induced a rise in technical coefficient because more inputs are required to produce the original level of outputs now due to degraded productivity and slight reduction in final demand in both sectors because of possible changes in labour's real wages and their final demand (can be seen in section 5.3.2), then two parameters *α*=1.5 and *β*=0.876 can be introduced into the equation **M.** The new equation at equilibrium will be shown as *Equation 4.20,* from which new output levels for industry 1 and 2 can be resolved.

$$\begin{bmatrix} 0.25 & 0.4 & 0.21154\beta \\ 0.14\alpha & 0.12 & 0.11538\beta \\ 0.8 & 0.36 & 0 \end{bmatrix} \begin{bmatrix} x_1' \\ x_2' \\ 260 \end{bmatrix} = \begin{bmatrix} x_1' \\ x_2' \\ 260 \end{bmatrix} \qquad (4.20)$$

<u>Preliminary results:</u>

$$\mathbf{x'} = \begin{bmatrix} 91.89 \\ 51.80 \end{bmatrix}$$

<u>Advantages:</u> This method provides a mathematical based solution for evaluating the effect of disaster-induced imbalances on gross output of the economy, which might be caused by degradation in labour productivity, availability and direct labour coefficients. Indeed, it uncovers how changes in industrial technical coefficient, direct labour coefficient, employment or final demand will affect the gross output. Reversely, the approach can be also used to explore changes in these variables that are required to restore new economic balances.

<u>Disadvantages:</u> Major challenges lie in the precise values for parameters α and β. Besides, the use of a closed Leontief input-output model that assumes labour income as the only source for generating household final demand may not fully consistent with real economic phenomenon (Steenge and Bočkarjova, 2007).

<u>Policy implications:</u> In a relatively longer term, this method provides useful guidelines and solid mathematical evidence for the recovery process of post-disaster economy, especially in restoring the economic balances. If degraded labour health have induced changes in direct labour coefficients and technical coefficients, or changes in real wages result in changes in consumption behaviour, this method can serve as a mathematical foundation to trace the overall output loss by introducing different values of α and β.

4.5.5 Hypothetical Extraction Method (HEM)

The impacts of a sector's hypothetical extraction from an economic system on other sectors can be evaluated by the HEM, which prominently focuses on industrial interdependencies.

Underlying rationale: The HEM allows to follow the hypothetical extreme case by either completely or partially extracting a single or a group of sectors by extracting the backward, forward or both linkages relating to a sector. Now assuming that sector 1 ceases as a result of severe health impact induced by a natural disaster, all its labour, as assumption in fixed proportions between inputs holds in Leontief input-output model, this means that sector 1 will be completely extracted from the economy and it will no longer has intermediate transactions with other sectors (both backward and forward linkages will be eliminated). The final consumption of both sectors are assumed to be unchanged as relatively short period in consideration appears to be insufficient for either households or government to react immediately and adapt their consumption behaviour.

Basic equations:

$$\mathbf{x - x' = (I\text{-}A)^{-1}f - (I\text{-}A')^{-1}f' = Lf - L'f'} \qquad (4.21)$$

A': new technical coefficient matrix after extraction of certain sectors (*Table 4.2*);

x': new output matrix;

f': new final demand matrix (assume the same in our case).

Table4.2 New Technical Coefficient Matrix following an Original HEM

Technical Coefficient Matrix for a 2-sector Economy		
Sector	1	2
1	0	0
2	0	0.12

Preliminary results:

$$\mathbf{x}' = \begin{bmatrix} 55 \\ 34.09 \end{bmatrix}$$

Advantages: An HEM allows to detect the influence from the extraction of a certain sector, either completely or partially, on the production level of the remaining sectors and the entire economy.

Disadvantages: Firstly, it is challenging to determine the specific variant of the HEM to be used in the study and before applying it. Whether it should be eliminated by a row, a column or all together from the original technical coefficient matrix will depend on the distinctive disaster characteristics and damage fractions in industrial production capacity. Secondly, it is difficult to decide the precise percentage of a sector's backward and forward linkages should be reduced that can truly reflect the real economic phenomenon. As it is challenging to estimate the percentage of extraction from a single indicator, such as productive time loss in our case of heat waves, it is difficult to derive the new technical coefficient matrix and final demand matrix. Indeed, the model does not consider the ripple effect of changing demand on price once changes in final demand occur. As have been discussed in section 3.3.2.6, Oosterhaven (2017) put forward an important 'caveat' regarding the use of the HEM in disaster studies with specific criticism on the use of zero's in horizontal rows of the matrix of input coefficients. He argued that these zeros can be problematic if substitution possibilities exist between domestic and foreign deliveries. This criticism, nevertheless, supports the use of the HEM in typical and some extreme cases where substitution possibilities do not exist.

Policy implications: The method can not only detect the linkages between sectors but also determine sector with key significance by identifying the impact of its hypothetical extraction on an economy's total output. Besides, in the case of disasters, it can help estimate the effects of reducing backward or forward linkages of a sector on the remaining economy if percentages reduction can truly reflect the post-disaster economy. Therefore, the HEM is useful in key sector identification, disaster risk assessment, preparation and adaptation.

4.5.6 The Mixed Model

The mixed model can be derived from the standard Leontief equation through a set of mathematical rearrangements and it is useful to measure the required output level for certain final demand level that is set exogenously by government in order to sustain the minimum level of social benefits (Miller and Blair, 2009, p593).

Underlying rationale: The mixed model is particularly useful when final demand of certain sectors or gross output level of certain sectors are set exogenously with the highlights on industrial interdependencies under some policy targets. The situation can also happen when the output of a particular sector is fixed at certain amount on hand at warehouses, awaiting transportation and delivery to buyers (Miller and Blair, 2009, p594). Here, it helps to calculate the endogenous gross output level required to meet the final demand level exogenously set by government.

Basic equations:

$$\begin{cases} (1 - a_{11})x_1 - a_{12}x_2 = f_1 \\ - a_{21}x_1 + (1 - a_{22})x_2 = f_2 \end{cases} \qquad (4.22)$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \mathbf{M}^{-1}\mathbf{N}\begin{bmatrix} f_1 \\ f_2 \end{bmatrix}$$, where **M** = $\begin{bmatrix} 1 - a_{11} & -a_{12} \\ -a_{21} & 1 - a_{22} \end{bmatrix}$ and **N** = $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

f_1 and f_2 are set exogenously according to a minimum level of social benefits as $f' = \begin{bmatrix} 40 \\ 20 \end{bmatrix}$ while the remaining are endogenous, the equations can be rearranged as *Equation 4.22* above, where all endogenous variables are assigned to the left while all exogenous variables to the right.

Preliminary results:

$$\mathbf{x'} = \begin{bmatrix} 71.52 \\ 34.11 \end{bmatrix}$$

Advantages: The mixed model is particularly effectively in determining the required amount of endogenous variables, such as gross output, when final demand of certain sectors or gross output level of certain sectors are set exogenously with the highlights on industrial interdependencies under some policy targets.

Disadvantages: The mixed model is more useful to determine the required output level for certain exogenously set final demand target and thereby, it is meaningful for target-setting during post-disaster economic recovery. However, it provides little information regarding the real magnitude of health impacts on production supply chain where no clear government target exists.

Policy implications: Using mixed model, endogenous variable can be related with exogenous variables so that it is able to estimate the required amounts in endogenous gross output levels in both sectors from the exogenous targets in final demands. In the case of natural disasters, there might be a large drop in final demand of both sectors if the real wages have been altered substantially by reducing productive time. In order to maintain a minimum level of social benefits, the government now decides to impose basic lines for final demand. In this respect, mixed model can be used to estimate the amounts of gross outputs required so that the targets of final demand can be met.

4.6 Data Sources and Input-Output Table

Data on air pollutant emissions were obtained from the Multi-resolution Emission Inventory for China (MEIC) while data on city-level daily temperature were obtained from local meteorological monitoring stations. For data on household consumption, industrial output and employment at a local or national level, I referred to Office for National Statistics for the UK dataset and Provincial and National Statistical Yearbook in relevant years in China. For required time for certain health endpoints and their average expenditures, data were gathered from the Health Statistical Yearbook in study years. The data on counts of mortality and morbidity were acquired from the China Information System of Death Register and Report of Chinese Center for Disease Control and Prevention (China CDC). The causes of death were coded by China CDC according to the International Classification of Diseases, Tenth Revision (ICD-10): non-accidental disease (A00-R99), cardiovascular disease (I00-I99) and respiratory disease (J00-J99). I also referred to the relevant recent epidemiological studies, the WHO reports and the Bureau of Labour Statistics in the US to collect data on the relative risks for certain disease, the national level incidence of a given health effect and occupational disease incidence rates, respectively when the specific data for China were not available. The input-output tables used in the case studies from Chapter 5, 6 and 7 were acquired either from Bureau of Provincial Statistics regarding the provincial input-output tables, or from Mi et al (2017) for the multiregional input-output table in China during 2012. Each table contains detailed vectors in final demand, including rural and urban household consumption, government expenditure, fixed capital formation, capital inventory changes and exports whereas in value added, including labour compensations, net production tax, fixed capital depreciation and operation profit. They describe the inter-industrial and interregional relationships for a total of 42 industries in a single province (single regional input-output table) or 900 industries across 30 Chinese provinces in 2012, respectively (multiregional input-output model). All model calculations were conducted using MATLAB R2003a (The MathWorks, Inc., Natick, Massachusetts, United States).

The next three chapters will employ suitable methods from those proposed above with respects to the characteristics of real cases in assessing the macroeconomic impacts from both ‘rapid-onset’ and ‘persistent’ natural disasters happened either in the UK or China at different points in time. By applying the interdisciplinary approach in real cases, cascading indirect economic impacts from industrial and regional interdependencies can be evaluated and distinctive disaster characteristics can be considered. Chapter 5, 6 and 7 apply the disaster footprint model to assess the cascading indirect economic impacts from both 'rapid-onset' and 'persistent' natural disasters happened either in the UK or China at different points in time. They are the results chapters that totally encompass four cases studies using selective input-output based models from those that have been introduced in Chapter 4 to represent various types of natural disasters, including one study on floods occurred around Christmas time in York, UK, 2015; one studies on air pollution in China, 2012; and two studies on heat waves in two Chinese cities, Shanghai and Nanjing during 2007 and 2013, respectively. Due to the distinctive characteristics of each natural disaster, each case study will present with a background, a distinctive methodology, findings and a summary with policy implications, embodied assumptions and sensitivity analyses. The methodology of each case study is neatened from the principle disaster footprint framework with additional consideration regarding the unique characteristics of the nature disaster under investigation. The specific tasks of the following three chapters are:

1. To assess the macroeconomic impacts from the shutdown of IT services sector due to floods on local economy of York in 2015;
2. To evaluate the health impacts among 30 Chinese cities in 2012 due to $PM_{2.5}$ air pollution and the resulting macroeconomic loss along production supply chain and compare with those from 2007 (Xia et al, 2016);
3. To examine the cross-regional economic impacts due to industrial and regional interdependencies resulting from the pollution-induced health impacts in China, 2012;
4. To identify the health impacts of heat waves in Shanghai, 2007 and the resulting macroeconomic loss along production supply chain;
5. To measure the health impacts of heat waves in Nanjing, 2013 and the resulting macroeconomic loss along production supply chain;
6. To conduct sensitivity analysis for selective case studies in order to verify the accuracy and variance regarding model results.

Chapter 5: Application of a Disaster Footprint Framework for Cascading Indirect Economic Impacts of UK Urban Flood, 2015

The case below focuses on floods in urban areas. Studying such floods is relatively new. Floods have a number of characteristics and can vary widely in scale and scope. In many cases a substantial part of infrastructure is lost, which means that modelling efforts may become very complex, having to focus on impact and reconstruction at the same time. Some floods, however, are different. In this study, I focus on one of those cases, the 'Christmas' flood in York (UK), 2015.

This case is special in the sense that little infrastructure was lost or damaged, while one sector (IT services) was knocked out for a limited time. These characteristics cause the standard modelling techniques not to be appropriate anymore. An alternative, however, is provided by the hypothetical extraction method, or HEM, which has earlier been tested in studies to identify so-called key sectors. There, however, is the restriction in that the HEM only performs satisfactorily in cases where no realistic substitutes exist for inputs from sectors that have been hit. This was the case in the York flood and that the HEM performs very well.

The empirical part of this case study shows that a three days' shutdown of the IT services caused a £3.24m loss in York, which is equivalent with 1% of the monthly GVA of York city (£396m). The services sector (excluding IT services) sustained the greatest loss at £0.80m, caused by business support sector which was predominantly hit. It is also the first time to apply a HEM in this type of flood on a daily basis in this type of risk analysis.

5.1 Background

Flooding was widespread in the UK during the 2015 Christmas season, putting thousands of roads, railways, houses and buildings at risk. The most severe flooding occurred on the night of Christmas Day (25 December 2016) and lasted till Boxing Day (27 December 2016) (BBC, 2015). The city of York was hard hit by the flood, where especially homes and businesses in the city centre experienced severe flooding after the banks of the River Ouse burst (BBC, 2015). The flooding led to a broad IT service shutdown. The flood knocked out the power to BT's York exchange while the broadband cables were damaged by flood water in the York BT exchange. As a consequence, thousands of York homes and businesses experienced phone and broadband services outage (The Guardian, 2015). Shops could not accept card payments and cash machine services from Natwest, Lloyds and Yorkshire Bank were out of order (The Guardian, 2015). As broadband services are usually physical products that are mostly provided by local service carriers, they cannot readily/straightforwardly be substituted by services from elsewhere. As a result, the IT outages disrupted almost all commercial transactions and economic activities within York for three days during Christmas and Boxing Day; a newsman described York during those days vividly as a 'ghost town' (The Guardian, 2015).

Traditional ways of flood and disaster modelling become less useful here due to several reasons. Most important is that existing flood and disaster modelling (such as approaches based on the recently presented adaptive models) heavily rely on quantifying the damages to infrastructures as a direct and tangible consequence of flooding. However, there was not much damages to infrastructure in the York flood, which makes it difficult to implement standard ways of disaster modelling. Instead, the flood induced substantial indirect and intangible costs from the IT service shutdown, where no direct alternatives were available. As York is a core commercial hub of the region Yorkshire and the Humber, an IT service blackout can seriously affect upstream and downstream sectors that rely on those services to sustain their business activities, particularly so during the busy Christmas season where the timing of the flooding undoubtedly exacerbated its economic impact. The flood knocked out the IT services in York for exactly three days, without any adaptive processes being available as substitutes. Both points imply the need for a more appropriate approach to better fit the distinctive characteristics of the York flood.

Here the so-called HEM was applied by perceiving the three days' IT shutdown as the 'extraction' of IT services sector from the York economy for three days. An HEM is able to measure the overall reduction in the production level after extracting selected economic sectors from the economy. For flood and disaster researches, the method becomes an option when some sectors partially or completely lose their connections to other sectors or if the sector inputs must be adapted due to technology change or market development. The HEM was applied in the context of the York flood in 2015 to determine the total indirect economic loss. The HEM was structured on a daily basis because the flood induced exactly three days' of shutdown of the IT services sector in York. Such approach is able to quantify the economic impact on the gross output level when a sector/sectors is/are hypothetically extracted from the economic system. Therefore, for a York-type of flood, the HEM actually provides an excellent way to assess total economic loss.

5.2 Methodology

(a). A Basic Leontief Input-Output Model

Let me recall the traditional input-output model that is based on the assumption of a one-to-one relationship between a sector and its characterizing product. Starting from:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}$$

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

A: the $n \times n$ matrix of technical coefficients;

x: the output matrix for *n* sectors;

f: the final demand matrix for *n* sectors;

$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$: the Leontief inverse matrix.

(b). The Hypothetical Extraction Method (HEM)

The technology under a basic Leontief model is represented by matrix **A** as given, final demand (**f**) is determined exogenously and output (**x**) endogenously. The pre-disaster economy can be shown as *Equation 5.1*.

$$\begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} + \begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix} \qquad (5.1)$$

Suppose now that sector 1 ceases production due to a major catastrophe. Consequences can be modelled if I follow the HEM concept to completely extract sector 1 from the economy. This then means that there will be no longer any intermediate transactions with the other sectors. This extraction can be achieved by simply removing its backward and forward linkages with other sectors. Thus, the extracted n x n matrix turns into a new technical coefficient matrix **A'** with first row and first column equal 'zero' (*Equation 5.2*).

$$A' = \begin{pmatrix} 0 & \cdots & \cdots & 0 \\ \vdots & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & a_{n2} & \cdots & a_{nn} \end{pmatrix} \qquad (5.2)$$

A new final demand vector may arise when a major catastrophe alters the patterns of household and government consumption. Households may spend more on life necessities and less on luxury and entertainment while government may spend more on reconstruction and health care services. However, the current study considers neither changes in the final demand vector nor imports because: Firstly, the time period in consideration is relatively short-term and is insufficient for consumers and government to react in a way that changes their consumption behaviour. Secondly, although outages of some products can sometimes be compensated from imports, IT services are generally provided by local carriers in York. Therefore, I assume that there is no immediate import available for IT services during the 3-day outage. The new economy after shock can be interpreted as *Equation 5.3*.

$$\begin{pmatrix} x_1' \\ \vdots \\ \vdots \\ x_n' \end{pmatrix} = \begin{pmatrix} 0 & \cdots & \cdots & 0 \\ \vdots & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & a_{n2} & \cdots & a_{nn} \end{pmatrix} \begin{pmatrix} x_1' \\ \vdots \\ \vdots \\ x_n' \end{pmatrix} + \begin{pmatrix} f_1' \\ \vdots \\ \vdots \\ f_n' \end{pmatrix} \qquad (5.3)$$

where x' is the new output level while f' is the new final demand for the correspondingly reduced final-demand vector (see Miller and Blair, 2009, p563).

In matrix notation, the difference in total output then can be obtained *by Equation 5.4.*

$$\mathbf{x} - \mathbf{x}' = (\mathbf{I}\text{-}\mathbf{A})^{-1}\mathbf{f} - (\mathbf{I}\text{-}\mathbf{A}')^{-1}\mathbf{f}' \qquad (5.4)$$

(c). Deriving a City-level Input-Output Table from a National Table

Firstly, due to the lack of city-level technical coefficients, the regional technical coefficients of Yorkshire and the Humber was derived from the UK national table using the Flegg and Webber scaling-down approach (Miller and Blair, 2009, p475). Then, the regional technical coefficients were applied to York in the current study by assuming the city of York has the same technical coefficients as Yorkshire and the Humber region. [6] This study uses the Augmented Flegg Location Quotients (AFLQ) technique to obtain the regional coefficients matrix for Yorkshire and The Humber from the national statistics. The technique seeks to correct the national technical coefficients to obtain the regional technology. Regional economies, clearly, can substantially differ from national economies in terms of trading relationships. Also, intermediate purchase from other regions should be regarded as a leakage under a regional economy but as domestic production under a national economy. For this purpose, data on industrial employment of the regional economy is used to re-scale the national coefficients to better reflect the regional economic structure of Yorkshire and the Humber. The process consists of adjusting the national coefficients to the regional scale, by measuring the relative size of each industry for the regional

[6] Input-output tables are traditionally developed at the national level by the relevant statistical bureaus. This also is the case for the UK where Supply and Use tables, the building blocks of IO tables, are produced yearly by the Office for National Statistics.

economy, in relation to the relative size of the same industry for the national economy; adjusting by certain parameters to consider the commercial traffic between the regional economy and other regions, and the possible specialization of an industry within the region. Then, the regional technical coefficient, r_{ij}, is derived from the national technical coefficients, a_{ij}, when re-sized by a regional-economy parameter or *location quotient*, lq_{ij}, like in *Equation 5.5*.

$$r_{ij} = lq_{ij} * a_{ij} \tag{5.5}$$

$$lq_{ij} = \begin{cases} FLQ_{ij} * [log_2(1 + SLQ_j] & for\ SLQ_j > 1 \\ FLQ_{ij} & for\ SLQ_j \leq 1 \end{cases}$$

where r_{ij} is the amount of input from industry *i* needed to produce one unit of output in industry *j*. Here I apply one of the most widely used location quotients, lq_{ij}, the AFLQ. I start from the so called simple location quotients (SLQ), to assess the relative importance of each regional industry *i*, as described in *Equation 5.6*.

$$SLQ_i = \frac{RE_i / TRE}{NE_i / TNE} \equiv \frac{RE_i}{NE_i} * \frac{TNE}{TRE} \tag{5.6}$$

where TRE is total employment in the region, TNE is total employment in the country, REi employment in the supplying region, while NEi accounts for national employment in the same sector.

Then, the cross-industry LQ (CILQ) has been derived from the SLQ to assess the relative importance of a supplier industry *i*, regarding the purchasing industry *j* as shown in *Equation 5.7*.

$$CILQ_{ij} = \frac{RE_i / NE_i}{RE_j / NE_j} \equiv \frac{SLQ_i}{SLQ_j} * \frac{TNE}{TRE} \tag{5.7}$$

As intermediate sales between regions were often treated as domestic production in the CILQ, it will underestimate the regional imports. In a later contribution, Flegg and Webber (1997) refined the regionalization in the Flegg LQ (FLQ) to correct for the persistence of underestimation of regional imports in the CILQ through the parameter $\lambda = \left[1 + TRE / TNE\right]^{\delta}$ to obtain the FLQ. Including the parameter δ allows to refine $\log_2 = \left[1 + \mathrm{TRE} / TNE\right]$ by changing its degree of convexity and with 0 ≤ δ < 1 (Flegg and Webber, 1997). An increasing δ indicates an increasing allowance for interregional imports while δ = 0 occurs when $FLQ_{ij} = CILQ_{ij}$. Finally, in the AFLQ (*Equation 5.8*), one last parameter was added to cover the possibility of regional specialization in some sectors, $\log_2(1 + SLQ_i)$. The effect of applying the logarithmic transformation to SLQ_j is that a larger region is more likely to have a bigger allowance for regional imports than a smaller region (Round, 1978).

$$AFLQ_{ij} = CILQ_{ij} * \lambda * [\log_2(1 + SLQ_j)] \qquad (5.8)$$

Secondly, the data of final consumption for the 46 sectors in Yorkshire and the Humber were scaled down to city-level data for York based on the city-to-regional gross value added (GVA) ratio in 2015, which was calculated as 4.7%. Based on the final consumption in York, I derived the city-level input-output table for York by assuming it has the same technical coefficient with York and the Humber region. Then, the data of the aggregated final consumption for the 46 York sectors were divided by 365 to obtain the daily value of each sector's final consumption, and the results were multiplied by three to calculate the sectors' total final consumption during the three-day shutdown period of the IT services sector. I assumed that final consumption did not change during the flooding because of the relatively short time period for households and the government to react.

(d). Developing a Hypothetical Extraction Model for York in 2015

In view of the above, the IT service sector can be treated as a 'key' sector in the economy of York when considering its domestically supplied inputs (Miller and Blair, 2009, p563). Given that the sector's output can hardly be replaced with imports during the severe flood, I proposed a 100% extraction of the IT service sector's linkages with other sectors under the original HEM. As a result, in current study, both the backward and forward linkages of the IT services sector were eliminated (set to ‘0’) in the technical coefficient matrix, representing a complete blackout of IT services. Then, the newly obtained technical coefficient matrix—with a ‘0’ column and row for the IT services sector and data for three days’ worth of sector final consumption in York—was used in *Equation 5.1* to calculate the new sector output level required to support three days’ final consumption. Finally, this new output level, without IT service support, was compared with the original output level for satisfying three days’ of final consumption with IT services in place.

In order to consider the excessive transaction volumes during the Christmas shopping period, an upper bound for the results was provided following the same methods but employing different values for final demand during the three-day IT outages. Due to the lack of daily sales data for York, I assumed the same monthly trend in household expenditure as the UK. According to data from Office for National Statistics (2016), household expenditure on food, drink and tobacco, clothing and footwear and other household goods during December are 16%, 42% and 31% higher than those of other non-Christmas months during 2015. Therefore, I adjusted in this way the original three days’ final demand that was calculated from the input-output table.

5.3 Results and Discussions

(a). Total Economic Loss

After a three-day shutdown of IT services, the proposed HEM revealed total economic loss of £3.24 million, of which the IT services sector suffered the largest part, £1.83 million (56.48%); the remaining £1.41 million (43.52%) in loss were distributed among the remaining 44 economic sectors. The results re-emphasize the importance of considering indirect economic loss in disaster risk assessment, as over 40% of the economic loss in the present case resulted from the cascading effects of sectoral inter-dependencies.

(b). Sectoral Economic Loss

As pointed out above, excluding the IT services sector, the remaining sectors suffered a total of £1.41 million in economic loss due to the three-day shutdown of the IT sector. This substantial indirect loss resulted from the many interdependencies between these sectors and the IT services sector. Thus, unsurprisingly, the services sector suffered the greatest economic loss among the 3 broad sectors (£0.80 million), accounting for 57% of the total economic loss (not including direct loss suffered by the IT services sector) (*Figure 5.1*).

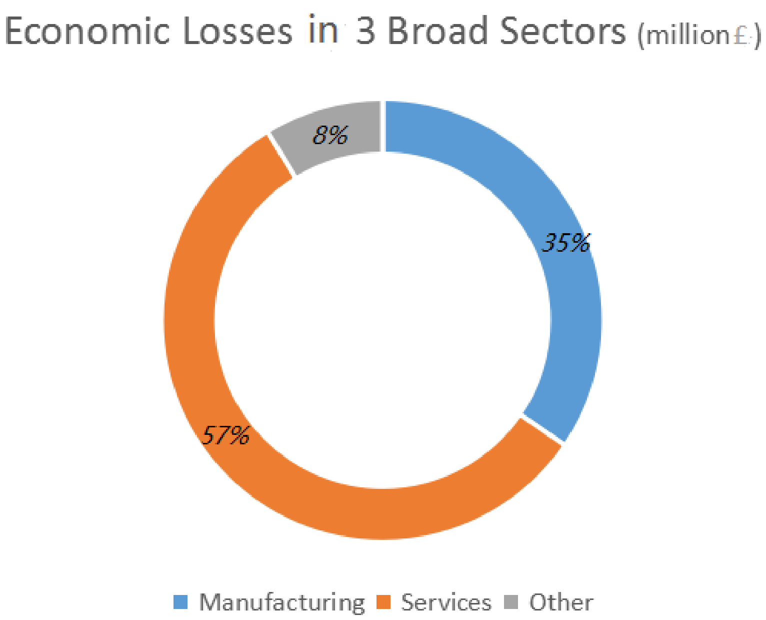

Figure5.1 Economic loss in 3 broad sectors

The pie chart shows the proportions of economic loss in 3 broad sectors, namely, manufacturing, services sectors and other (agricultural and mining, energy supply and construction). Percentages are displayed inside the circle.

According to the 2011 Census in the city of York from Neighbourhood Statistics (Office for National Statistics, 2011), the local economy is mainly led by the service sector including Wholesale and Retail Trade, Human Health and Social Work Activities, Education and Accommodation and Food Service Activities, while Agriculture, Forestry and Fishing, Mining and Quarrying as well as Manufacturing occupy only a small portion of the economy. Therefore, I specifically focus on the economic loss occurred in the service sector in the city of York. Among the 25 industries in that sector, the business support services sector sustained the greatest indirect economic loss from the IT service shutdown (£0.18 million), followed by other professional services sector (£0.09 million) (*Figure 5.2*). Additionally, the financial and insurance (£0.075 m), architectural (£0.076 m), legal and accounting (£0.054 m), warehousing and postal (£0.049 m), wholesale trade (£0.045 m) and head offices and management (£0.036 m) sectors were also negatively affected by the IT service shutdown.

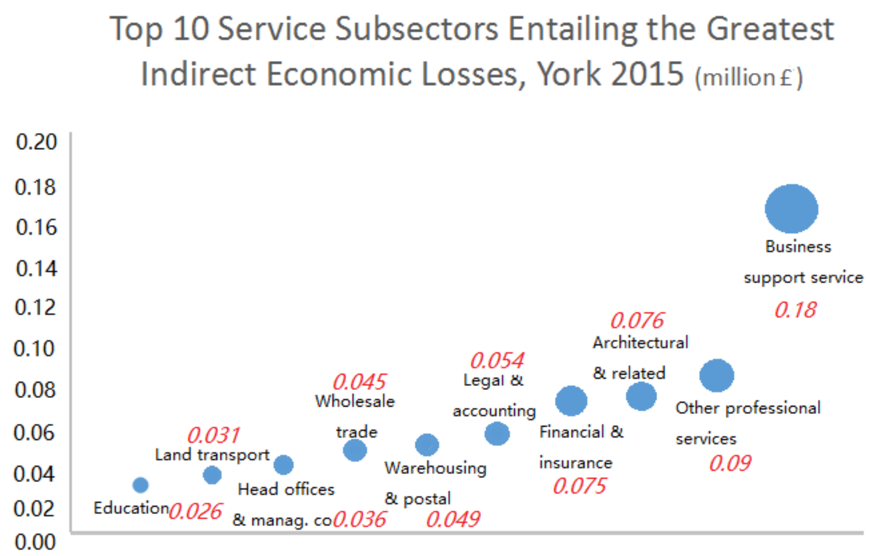

Figure5.2 The top 10 service sub-sectors suffering the greatest indirect economic loss in York, UK in 2015

The scatter diagram shows the 10 service sub-sectors suffering the greatest economic loss among the 45 total sectors in York, UK in 2015 due to the three-day IT service shutdown resulting from the 2015 York flood. The different sectoral indirect economic loss originate from their different levels of dependency on the IT services sector. The y-axis shows the value of economic loss measured in millions of dollars and the spot sizes represent the different magnitudes of economic loss in each sector.

Notably, findings suggest that a number of manufacturing sub-sectors were also affected by the shutdown of the IT services, with an overall loss of £0.49 million, accounting for 35% of the total non-IT services sector economic loss (*Figure 1*). Among the 15 manufacturing industries, the computer sector, likely due to its close relationship to IT services, suffered the greatest economic loss (£0.09 m), followed by other manufacturing (£0.063 m), metals (£0.055 m) and non-metallic (£0.053 m) sectors. Other sectors, including agricultural and mining, energy supply and construction sectors totally occupy some 8% of the total economic loss. These results are in line with the recent remarkable growth in IT outsourcing in the UK. Miozzo and Grimshaw (2005) reported that large service firms, client organizations and manufacturing companies in the UK have outsourced IT services to multinational technology and computer services suppliers. The technical and social division of labour during manufacturing production has largely inspired the rise of knowledge-intensive business services (KIBS) (Miozzo and Soete, 2001), which tend to be IT-intensive and based on social and institutional knowledge (Miozzo and Grimshaw, 2005). Meanwhile, products from the traditional professional services, computer, R&D and engineering services sectors are mostly intangible services that require continuous interaction with both customers and suppliers (Miles, 1993). As a result, firms in the manufacturing and services sectors have become increasingly reliant on IT services, which explains why industries in both the manufacturing and services sectors in York suffered severe economic when the IT services sector was made non-functional due to the flooding.

5.4 Recapitulation, Conclusions and Uncertainties

This case study has dealt with modelling the impact of floods in urban areas. Focusing on this type of flood is a relatively new area. Partly this is to be explained from the fact that many cities lie in delta-area which may even be below sea-level, which signals a higher risk for flooding. Modelling floods in cities also poses new challenges from a modelling point of view. Today’s models have to address three main issues, i.e. 1) the loss of infrastructure, 2) the rise of various new or alternative processes because many sectoral connections have been interrupted, manifesting itself in newly appearing adaptation and substitution processes and 3) the reconstruction issues. For cities these issues can be formidable, see e.g. Hallegatte (2008) or Li et al (2013).

However, there are exceptions. Sometimes the type of flood can be such that little infrastructure is lost or damaged. This can, e.g. be due to the time profile of the flood. Also, it may be that various substitution processes were not put in place because time was limited, or for technical or organizational reasons. For these types of disasters, the standard adaptive models cannot be used. One important reason here is that many parameters have to be newly calibrated, or 'neglected', which severely affects the performance of the model. In such a case, an alternative method may be available, the hypothetical extraction method or HEM, for short. The HEM has been used extensively in key sector analysis where the importance of a particular sector is determined by hypothetically removing this sector from the available tables or models. Because a severe flood disconnects many parts of an economy, applying this concept (i.e. 'removing' a sector) to disaster analysis may provide an alternative. Here, however, is a problem. This is related to the fact that the services of a sector which is severely hit, and therefore cannot deliver to its customers, can be replaced by substitutes, from other areas. This makes applying HEM questionable and has led to severe criticism of the method.

However, certain floods have characteristics that are different from the standard cases. One such flood was the 'Christmas' flood in York (UK), 2015. The flooding lasted three days, while little infrastructure was lost. The IT services sector was completely knocked out, while other sectors were relatively unhurt. The services in question were such that within the relevant time span no alternatives could be offered. This meant that the conditions were right for applying the HEM to estimate the loss involved. Because input-output tables at city level were not available, I used the Flegg and Webber 'scaling down' method as a first approximation. The outcomes were that a three-day shutdown of IT services caused £3.24 million in economic loss in York during 2015; of these loss, the IT services sector itself accounted for £1.83 million, and the remaining 44 sectors suffered £1.41 million of the total economic loss. The services sector (excluding IT services sector) bore most of the economic loss (£0.80 million) due to its heavy reliance on IT services. Within the services sector, the business support services sector, other professional services sector and financial and insurance sector suffered the greatest reductions in output out of all the sectors, as firms in these fields are more likely to outsource IT services for KIBS (Miozzo and Grimshaw, 2005).

Further research along this line is certainly required. First, the present study utilized an original HEM approach, which means that both backward and forward linkages of a sector were simply removed from the economy. This was motivated above in terms of the sector in question (IT) being for a limited time and to a very large degree isolated from the rest of the economy (thereby bringing HEM use in line with recent criticism). Nonetheless, there can be a further differentiation between a sector’s internal and external linkages, as suggested by Cella (1984). Second, possible changes in final demand were not considered in the present study due to the relatively short time period of the outage. It is equally important to model the changes in consumer behaviour in risk assessments of more ‘persistent’ disaster events. Additionally, due to the lack of daily data on household expenditure in York, I could not specifically detect the exact value of sales during the three-day IT outages. In this respect, the current study opens up new research avenues when applying the HEM onto flood research and disaster risk studies once more accurate data on daily household consumption or city-level input-output table become available.

5.5 Sensitivity Analysis

Due to data unavailability, the averaged daily final demand was used in calculating the economic loss of three days’ IT service shutdown by employing an HEM. However, considering that large volumes of transaction should have involved in the special Christmas period during which the floods occurred, this sensitivity analysis refers to the data on the monthly trend on consumption value of the York city to test the variation range of model results. By using alternative dataset on final demand, the total economic loss resulting from three-day shutdown of IT services in York is expected to rise to £4.23 million when considering the excessive volumes of transactions during the Christmas season.

Chapter 6: Application of a Disaster Footprint Framework for Cascading Indirect Economic Impacts of Air Pollution, China, 2012

Serious haze has put China under international spotlight. It can cause various contaminant diseases that further induce substantial labour time loss along production supply chain. It is associated with cardiovascular and respiratory diseases and high mortality and morbidity, which could be translated to reduced labour availability and time. In assessing the disease burden of $PM_{2.5}$ pollution, health studies rarely consider such macroeconomic impacts by capturing industrial interlinkages while disaster studies seldom involve air pollution and the resulting health impacts. The following case study adopted a supply-driven input-output model to estimate the monetary value of total output loss resulting from reduced working time caused by diseases related to air pollution across 30 Chinese provinces in 2012. Before that, the provincial concentration levels of $PM_{2.5}$ pollution were utilized to investigate the health impacts that are attributable to air pollution. The developed input-output model is able to cope with the indirect cascading effects along interregional production supply chains. Results show the total economic loss of 398.23 billion Yuan[7] with the majority comes from Eastern China (39%) and Mid-South (30%). The total economic loss is almost equivalent with 1% of China's GDP in 2012 with a totality of 82.19 million affected labourers. Changes can be observed at provincial economic loss from the early study in 2007 (Xia et al, 2007) as Henan and Jiang become two provinces entailing the greatest loss with largest $PM_{2.5}$-induced mortality and morbidity counts. Study on 2012 also examines the cross-regional economic impacts in order to underline the important role of indirect

[7] Yuan is a monetary unit for Chinese RenMinBi and it is equivalent with 0.15 USD and 0.11 GBP (2017).

economic loss. Mid-South, North China and Eastern China account for the majority of indirect economic loss across all regions at 24.65, 16.99 and 12.17 billion Yuan, respectively, where it indicates that geographical distance plays a role in determining interregional trade and regional interlinkages. Given that the majority of economic loss originate from secondary industry, it also specifically analyzes the key sub-industries in secondary industry that account for the greatest proportions in both direct and indirect economic loss in each great region in China. In North China, Northwest and Southwest, a considerable part of their indirect economic loss are originated from Manufacturing industries outside the region. The second largest source in these three regions that accounts for economic loss from secondary industries in other regions is Energy, with the greatest amount occurs in North China at 2.32 billion Yuan. In contrast, Coal and Mining accounts for the majority of indirect loss from secondary industries outside the region for Eastern China, Mid-South and Northeast at 37.4% (10.83 billion Yuan), 33.4% (3.65 billion Yuan) and 24.4% (1.30 billion Yuan), respectively, which might be caused by the different economic structures and dependences between North China, Northwest, Southwest and Eastern China, Mid-South, Northeast. When turning to the economic loss from secondary industry inside the region, Regions show heterogeneity. Coal and Mining accounts for the largest part of inner-regional economic loss in North China and Northwest at 42.4% and 43.8%, respectively, Equipments and Energy are two major sources for inner-regional economic loss Eastern China and Southwest, while Metal and Non-metal and Manufacturing constitute considerable proportions in inner-regional economic loss from secondary industries in Mid-South.

The proposed interdisciplinary modelling approach provides an alternative method for health-cost measurement with additional insights on inter-industrial and interregional linkages along production supply chains, thereby, it highlights the importance of integrating interdependency analysis into health costs assessment and air pollution into disaster studies from a health-impact perspective. By doing so, future policymakers and researchers could obtain an alternative macroeconomic tool to better conduct cost-benefit analysis in any environmental or climate change related policy design, and to comprehend health costs studies in its macroeconomic side.

6.1 Background

Millions of people in China frequently breath toxic air substances, which has become one of the most serious topics in environmental issues in China by resulting in widespread environmental and health problems, including increasing risks for heart and respiratory diseases, stroke and lung cancer (LC) (Greenpeace, 2017). As air pollution has long-term health impacts that evolves gradually over time, understanding the health and socioeconomic impacts of China’s air pollution requires continuous efforts.

Serious air pollution in China has largely inspired epidemic studies that examine specific health outcomes from air pollution, as well as health costs assessments that translate health outcomes into monetary loss. Existing epidemic studies simulate a exposure-response relationships between Particulate Matter (PM) concentration levels and relative risks (RRs) for a particular disease while health costs assessments frequently stem from patients’ perspective at microeconomic level, by evaluating either their willingness-to-pay (WTP) for avoiding disease risk or the potentially productive years of life loss (PPYLL). However, when perceiving unhealthy labourers as degradation in labour input, macroeconomic implications for production supply chains lack investigation. Meanwhile, as the health effects of air pollution are built up slowly over time which implies the lasting nature of air pollution, it has been rarely studied in current disaster risk literature. Differing from rapid-onset disaster analysis (flood, hurricane, earthquake, etc) that normally reply on quantifying damages to physical capital, air pollution affect more human capital than physical capital and the resulting health impacts are relatively invisible and unmeasurable. As a result, linking PM concentrations with health endpoints and further with macroeconomic impacts require an interdisciplinary approach that integrates all the three elements into one.

6.2 Methodology

(a). Methodological Framework

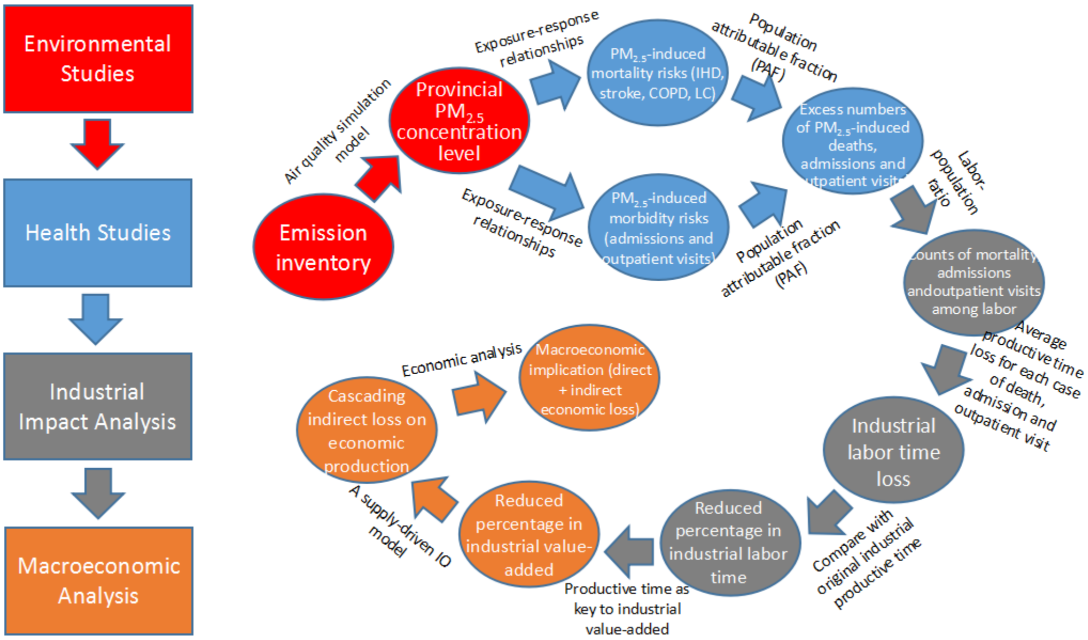

Figure6.1 Methodological framework

Figure 6.1 illustrates the overall methodological framework developed. 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 were shown above the arrows.

$PM_{2.5}$ concentration levels for 30 provinces of China were first identified from emission inventory using air quality simulation model. The relative risks (RRs) for $PM_{2.5}$-induced mortality (IHD, Stroke, COPD and LC), hospital admissions (cardiovascular and respiratory diseases) and outpatient visits (all causes) were estimated using an Integrated Exposure-Response (IER) model, based on which population attributable fraction (PAF) can be calculated to estimate counts of $PM_{2.5}$-induced deaths, admissions and outpatient visits. Additionally, counts of mortality, hospital admissions and outpatient visits for 2012 were further translated into productive working time loss that was compared with the industrial original working time without any $PM_{2.5}$-induced health effects (full employment and full productivity) to derive the percentages reduction in industrial value added. Moreover, reductions in industrial value added served as an input in the supply-driven input-output model to measure the total indirect economic loss incurred along the production supply chain, which is measured as the total loss in output level. Finally, macroeconomic implications regarding industrial and provincial economic loss can be obtained from my model results.

(b). Estimating Provincial $PM_{2.5}$ Concentration Levels

To estimate the provincial $PM_{2.5}$ concentration levels, air pollutant emission inventories were used to predict provincial $PM_{2.5}$ concentration levels among 30 Chinese provinces using air quality simulation modelling. The anthropogenic emissions for China were obtained from the Multi-resolution Emission Inventory for China (MEIC), which is a technology-based and bottom-up air pollutant emission inventory used in China since 1990. The inventory initially contained 10 types of air pollutants and more recently, it has incorporated cement and high-resolution vehicle emission at a national level (Xia et al, 2016). Air quality simulation models used include the offline-coupled Weather Research and Forecasting (WRF) model and Community Multi-scale Air Quality (CMAQ) model with 14 layers' vertical resolution. The CMAQ model domain includes the 127 × 172 East Asia grid cells that cover the entire China by 36 km × 36 km grid squares. Simulations were run for the four model months (January, April, July and October) in the study year to obtain the annual $PM_{2.5}$ concentration while the meteorological fields at 36 km horizontal grid spacing were generated by WRF with 23 vertical layers. The initial and boundary conditions were derived from the final NCEP analysis data (FNL) and were used to drive the CMAQ model. The land-use/land-cover and topographical data were obtained from the default WRF input dataset. The anthropogenic and natural source emission inputs were derived from MEIC and MEGAN (Model of Emissions of Gases and Aerosols from Nature) (Xia et al, 2016). I also referred to Chinese provincial $PM_{2.5}$

concentration levels estimated by Geng et al (2015), where the authors improved the method for estimating long-term surface $PM_{2.5}$ concentrations using satellite remote sensing and a chemical transport model to assess the provincial $PM_{2.5}$ concentration levels in China during 2006-2012. The model domain includes a map of surface $PM_{2.5}$ concentrations at 0.1° × 0.1° over China using the nested-grid GEOS-Chem model with the most updated bottom-up emission inventory and satellite observations from MODIS and MISR instruments (Geng et al, 2015).

(c). Estimating Health Impacts from $PM_{2.5}$ Concentration Levels

Epidemic studies on $PM_{2.5}$-induced health outcomes have linked $PM_{2.5}$ air pollution with various health endpoints by using exposure-response coefficients. The case studies focus on the impacts of $PM_{2.5}$ pollution on mortality, hospital admissions and outpatient visits. I referred to an integrated exposure-response (IER) model developed by Burnett et al (2014) to estimate the relative risks (RRs) for $PM_{2.5}$-induced mortality (IHD, Stroke, COPD, LC), hospital admissions (cardiovascular and respiratory diseases) and outpatient visits (all causes).

For disease-induced mortality, an IER model captures concentration-response relationships with a specific focus on ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD) and lung cancer (LC). The relative risks (RRs) for the mortality estimation function for the four diseases were shown in *Equation 6.1.*

$$\text{For } z<z_{cf} \qquad RR_{IER}(z) = 1 \qquad (6.1)$$
$$\text{For } z\geq z_{cf} \qquad RR_{IER}(z) = 1+\alpha \ \{1-exp[-\gamma(z-z_{cf})^{\delta}]\ \}$$

z : the $PM_{2.5}$ exposure in micrograms per meter cubed;

z_{cf}: the counter-factual concentration level below which no additional health risk is assumed;

δ: the strength of $PM_{2.5}$ and γ is the ratio of RR at low-to-high exposures.

Then, the calculated RR was then converted into an attributable fraction (AF) in *Equation 6.2*. The attributable fraction measures the proportional decrease in disease or mortality population that will occur once exposure to a risk factor decreased to an alternative ideal exposure scenario (WHO, 2017).

$$AF = \frac{RR - 1}{RR} \qquad (6.2)$$

Additionally, excess counts of $PM_{2.5}$ disease-induced mortality were estimated in *Equation 6.3*.

$$E = AF \times B \times P \qquad (6.3)$$

E: $PM_{2.5}$-induced mortality counts;

B: the national level incidence of a given health effect, which was applied for all provinces because of limited data;

P: the size of the exposed populations.

For morbidity, I calculated cardiovascular and respiratory hospital admissions and outpatient visits for all causes using a log-linear response function and the RRs for each category of morbidity was calculated using *Equation 6.4*.

$$RR = e^{\beta x} \qquad (6.4)$$

β : the parameter that describes the depth of the curve and was listed in *Table 6.1*. They are the exposure-response coefficients to quantify the relationship between different levels of $PM_{2.5}$ exposures and the resulting health outcomes. Counts of $PM_{2.5}$-induced hospital admissions and outpatient visits were analogously estimated using *Equation 6.2* and *6.3*.

Table6.1 Concentration-response Coefficients for Morbidity

Health impacts	Coefficient	References
Cardiovascular HA	0.0009059	Health risks of air pollution in Europe – HRAPIE project
Respiratory HA	0.001882	Health risks of air pollution in Europe – HRAPIE project
Outpatient visits	0.000389241	Xu et al. (1995)

(Modified from: Xia et al, 2016)

(d). Estimating Industrial Labour Time Loss

Each labourer is assumed to work 8 hours every day and 250 days during 2012. For $PM_{2.5}$-induced mortality, each death will result in a total 250 working days lost regardless different disease types. For $PM_{2.5}$-induced morbidity, each cardiovascular admission will result in 11.9 working days lost while each respiratory admission causes 8.4 working days lost (Health Statistical Yearbook, 2016). Meanwhile, 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 and frequency of outpatient visits in China, such assumption was made based on the current status of Chinese medical system where no pre-booking and follow-up services are available. Then, provincial mortality, hospital admissions and outpatient visits counts were scaled down to counts among labour according to labour-population ratios across all the 30 provinces during the year (Provincial Statistical Yearbook, 2008 & 2013). I further distributed provincial mortality, admissions and outpatient counts into 30 industries. It is worth noting that 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% (Bureau of Labour Statistics, 2007). However, the data follows the US sector categorization. As a result, 30 industries in China were re-categorized into four large sectors suggested by 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 (Xia et al, 2016). Differentiating the disease incidence rates for various occupations is important because workers in different sectors normally have different working environment with different exposures to $PM_{2.5}$ pollution. Additionally, labour time loss for each case of mortality, admission and outpatient visit were multiplied by industrial counts of mortality, admission and outpatient in each province respectively, where the results were summed up to derive the industrial total labour time loss due to $PM_{2.5}$-induced mortality and morbidity for 2012. Moreover, I compared the industrial total labour time loss with the original labour time with full employment and labour productivity when there is no $PM_{2.5}$-induced health impacts.

The results show the percentage reductions in industrial working time, which were used as an indicator for percentage reductions in industrial value added for 2012 in a supply-driven input-output model by considering labour as the major component for industrial value added (Xia et al, 2016).

(e). Estimating Indirect Economic Loss on Production Supply Chain

I employed a supply-driven input-output model to evaluate the indirect economic loss due to $PM_{2.5}$-induced mortality and morbidity along production supply chain for both years. A supply-driven input-output model was derived from a traditional Leontief input-output model by rotating the view of the basic model. The basic model is:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}$$

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

A: the $n \times n$ matrix of technical coefficients;

x: the output matrix for *n* sectors;

f: the final demand matrix for *n* sectors;

$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$: the Leontief inverse matrix.

A supply-driven input-output model takes a rotated view of Leontief input-output model that shows an opposite influencing direction between sectors. It suggests that production in a sector can affect sectors purchasing its outputs as inputs during their production processes and it has a supply-side focus. A supply-driven input-output model is used to calculate the impact of changes in primary inputs on sectoral gross production. The basic structure of a supply-driven model is shown in *Equation 6.5* and *6.6*.

$$\mathbf{x'} = \mathbf{v'}\ (\mathbf{I}\text{-}\mathbf{B})^{-1} \quad (6.5)$$

$$\mathbf{x'} = \mathbf{v'}\ \mathbf{G},\ \mathbf{G} = (\mathbf{I}\text{-}\mathbf{B})^{-1} \quad (6.6)$$

B: the allocation coefficient (direct-output coefficient) matrix that is calculated by dividing *Zi* by *Xi*. It refers to the distribution of sector *i*'s outputs in sector *j*. Assumption of fixed allocation coefficients in the economy also holds for a supply-driven input-output model;

V: the industrial value added matrix, including capital and labour input;

G: the Ghosh inverse matrix, which measures the economic impacts of changes in a sector's value added on other sectors' output level (Miller and Blair, 2009, p543).

6.3 Results and Discussions

Firstly, regarding the total number of affected labour and total economic loss, the total economic loss resulting from $PM_{2.5}$-induced health outcomes in China 2012 is 398.23 billion Yuan, which corresponds to almost 1% of national GDP in 2012. The total number of affected labour in China is 0.80 million for $PM_{2.5}$-induced mortality, 2.22 million for $PM_{2.5}$-induced hospital admissions and 79.17 million for $PM_{2.5}$-induced outpatient visits (*Figure 6.2*). *Figure 6.2* presents the provincial counts of $PM_{2.5}$-induced mortality, hospital admissions, outpatient visits and economic loss with least severe and most severe situation shown from green to red. For total populations of $PM_{2.5}$-induced mortality and morbidity, among 30 provinces, Henan and Shangdong province have the largest total counts of $PM_{2.5}$-induced mortality and morbidity, which is consistent with the findings in 2007 study (Xia et al, 2016). Guangdong province has the greatest counts of $PM_{2.5}$-induced hospital admissions at 291 thousands, where a substantial increase can be observed at 175 thousands compared with results in 2007 (Xia et al, 2016). It almost doubles its provincial count of outpatient visits and triples its mortality counts. Meanwhile, increase can be observed in both counts for Northwest region, including Shanxi, Gansu, Qinghai, Ningxia and Xinjiang provinces. Specifically, the count of hospital admissions in Shanxi province in 2012, 100 thousands, also doubles that of 2007, which was at 50 thousands (Xia et al, 2016). Even sharper increase of admission counts can be seen in Xinjiang province, where the number is almost 7 times of that from 2007 (Xia et al, 2016).

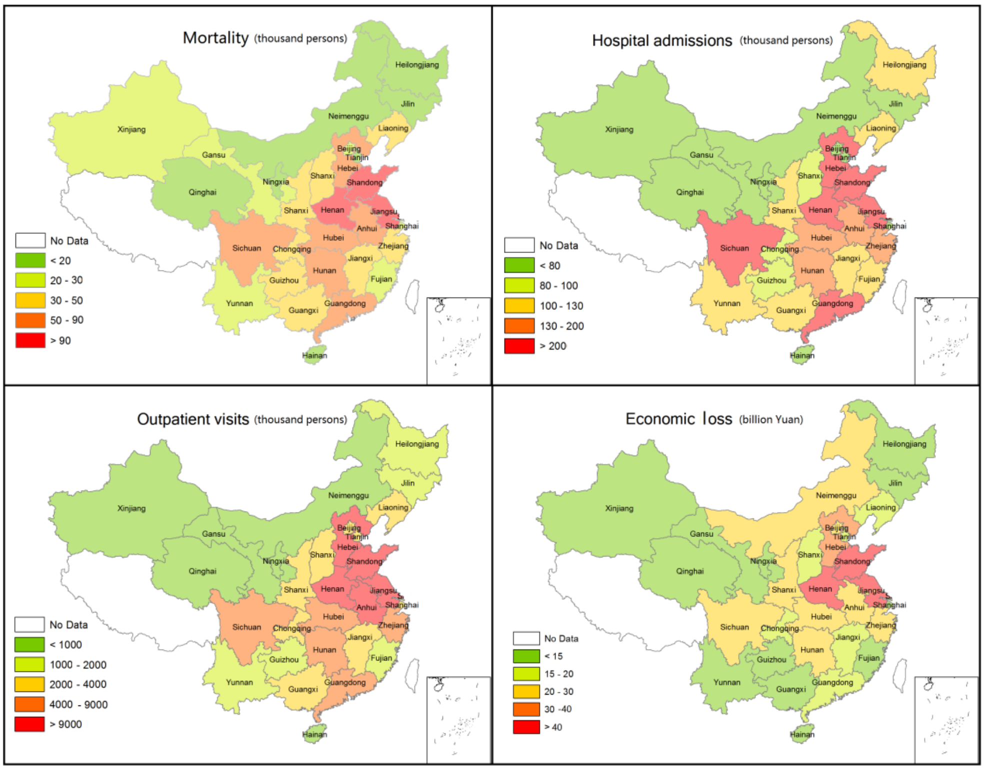

Figure6.2 Provincial counts of $PM_{2.5}$-induced mortality, hospital admissions, outpatient visits and economic loss in China, 2012

Figure 6.2 presents the provincial counts of $PM_{2.5}$-induced mortality, hospital admissions, outpatient visits and economic loss with least severe and most severe situation shown from green to red.

Secondly, concerning economic loss by provinces, regions and industries, at the provincial level (*Figure 6.2*), economic loss of Henan province exceeds that of Jiangsu province in 2007 (55.90 billion Yuan) and becomes the province suffering the greatest economic loss at 56.37 billion, accounting for 14% of the total economic loss in China. This is followed by Jiangsu province at 45.32 billion Yuan and Shangdong province at 43.23 billion Yuan. This is because all the three provinces have the largest counts of $PM_{2.5}$-induced mortality and morbidity, which result in substantial provincial labour time loss. I also calculated the economic loss in six China's great regions. Eastern China and Mid-South appear to be the two regions suffering the greatest economic loss that amount at 153.39 and 119.21 billion Yuan and account for 39% and 30% of total economic loss in China, 2012. It is in line with the findings from 2007 study (Xia et al, 2016), where the economic loss of these two regions are 115.33 and 80.88 billion Yuan respectively. Therefore, there has been a remarkable rise in economic loss for Mid-South region. Meanwhile, economic loss by three industries is displayed in *Figure 6.3*. Primary industry includes agriculture and fishing, where the economic loss is 19.12 billion Yuan. Secondary industry includes all manufacturing sectors, energy and construction and it entails the greatest proportion of economic loss at 320.06 billion Yuan (80% of total economic loss). Tertiary industry accounts for the remaining 15% of total economic loss at 59.05 billion Yuan.

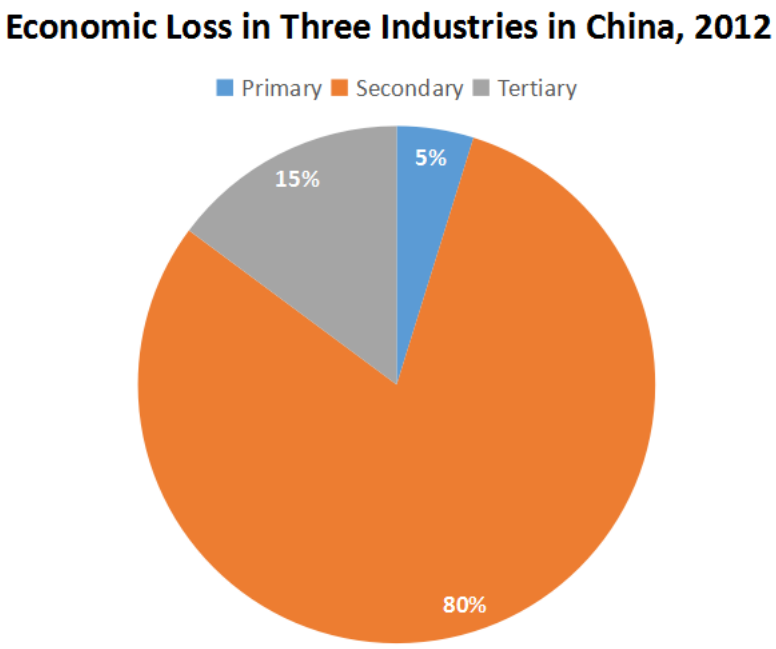

Figure6.3 Economic loss in three industries in China, 2012

Figure 6.3 presents the proportions of economic loss by three industries, where secondary sector suffered the greatest percentage of economic loss due to air pollution.

Additionally, this case study also examined the cross-regional economic losses between six Great Regions in China. As one significant advantage for input-output model is to capture the industrial and regional interdependencies, it is effective to measure the propagating disaster-induced indirect economic loss along production supply chain. I traced the cross-regional economic loss due to their interlinkages, such as interregional trade, as shown in *Figure 6.4*. The diagram demonstrates the interregional economic impacts due to their interdependencies. The left-hand side shows the regional indirect economic loss while the right-hand side denotes the sources for these indirect economic loss. The proportion of regional indirect loss among regional total economic loss is displayed next to each region's name on the left-hand side. Although the majority of regional economic loss come from the direct economic loss occurred within the region across almost all the six regions, Northeast, Eastern China and Northwest still entail great indirect economic loss from other regions, which occupies 31%, 21% and 30% of the total regional economic loss, respectively. In Northeast, a totality of 18% of its total regional economic loss is originated from North China and Mid-South, including 1.84 billion Yuan from North China and 1.85 billion Yuan from Mid-South. Similarly, Mid-South is responsible for 9% of the economic loss in Eastern China at 13.36 billion Yuan. It accounts for even larger proportion of regional economic loss in Northwest at 13%. Meanwhile, Eastern China also accounts for another 8% of the total regional economic loss in Northeast, which amounts at 1.66 billion Yuan. Overall, Mid-South accounts for the largest amount of indirect economic loss in other Chinese regions at 24.65 billion Yuan, which is followed by North China and Eastern China at 16.99 and 12.17 billion Yuan, respectively. This finding highlights the increasing significance in capturing the industrial and regional interdependencies and indirect economic loss in disaster risk analysis because such interdependencies can largely raise the overall economic loss far beyond the direct economic loss and constitute a noticeable component of total economic loss.

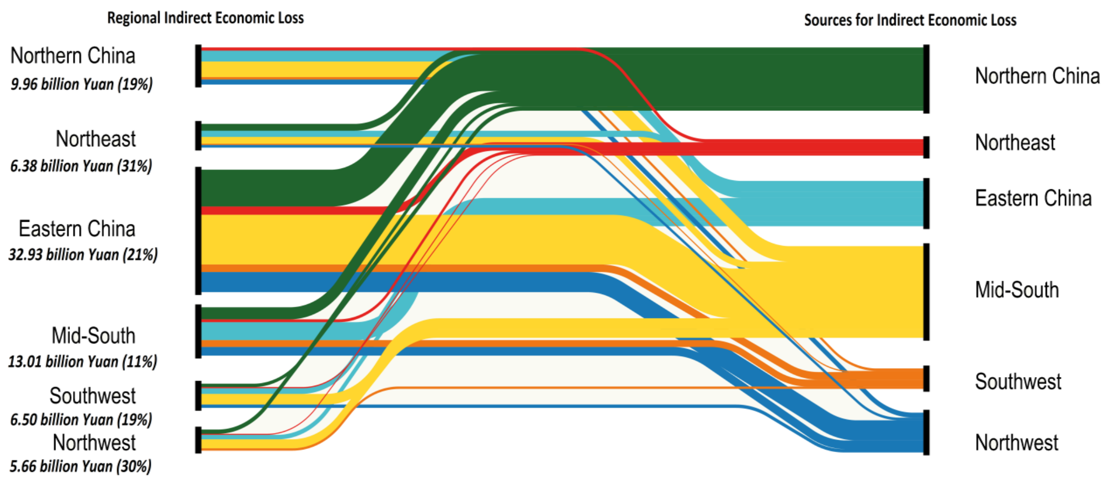

Figure6.4 Cross-regional economic loss

The esankey diagram shows the cross-regional economic loss analysis that focus on regional indirect economic loss only. The left-hand side measures the regional indirect economic loss while the right-hand side stands for the sources for indirect economic loss across six China's great regions.

Moreover, as secondary industry plays a vital role in Chinese economy and entails greatest economic loss among the three industries, I specifically analyzed the regional economic loss that are directly and indirectly resulting from secondary industries both inside and outside a region. Focusing on secondary industry, *Figure 6.5* illustrates both direct and indirect economic loss originating from each region and outside the region. The inner ring denotes the direct economic loss originating from secondary industry inside the region while the outer ring stands for the indirect economic loss from secondary industries in other regions. Percentage shown on the inner ring shows the proportion of direct economic loss regarding total regional economic loss and percentages shown on the outer ring are the proportions of indirect loss from other region relative to total regional indirect economic loss resulting from all outside secondary industries. As can be seen from the diagram, despite that the majority of economic loss resulting from secondary industry are originated from inside the region for all the six great regions in China, in Northwest and Northeast, economic loss attributed to secondary industries outside the region still constitute a considerable share due to industrial and regional interdependencies. Secondary industries in the Mid-South, Eastern China and North China become three major sources for indirect economic loss across all the six regions. For instances, in Northwest, economic loss from secondary industries in Mid-South, Eastern China and North China account for 14%, 6% and 6% of total regional indirect loss from secondary industries outside the region, at 2.20, 0.99 and 0.90 billion Yuan, respectively. Similarly, in Northeast, economic loss from secondary industries in these three regions occupy 10%, 8% and 9% of total regional indirect loss from secondary industries outside the region, at 1.66, 1.33 and 1.46 billion Yuan, respectively. This is resulting from their geographical distance to Mid-South, Eastern China and North China, as well as close trade relationships with these three regions. The significant roles of Mid-South and Eastern China in interregional trade have been early confirmed by Sun and Peng (2011), where they pointed out the export-oriented nature for trades in Eastern China and Mid-South, and their close trade relations with Northwest regions with respects to imports of raw materials. Likewise, it is noticeable that indirect economic loss is more likely to come from neighbour-regions, which highlights the possibility that short geographical distance might accelerate interregional trade and strengthen regional interlinkages.

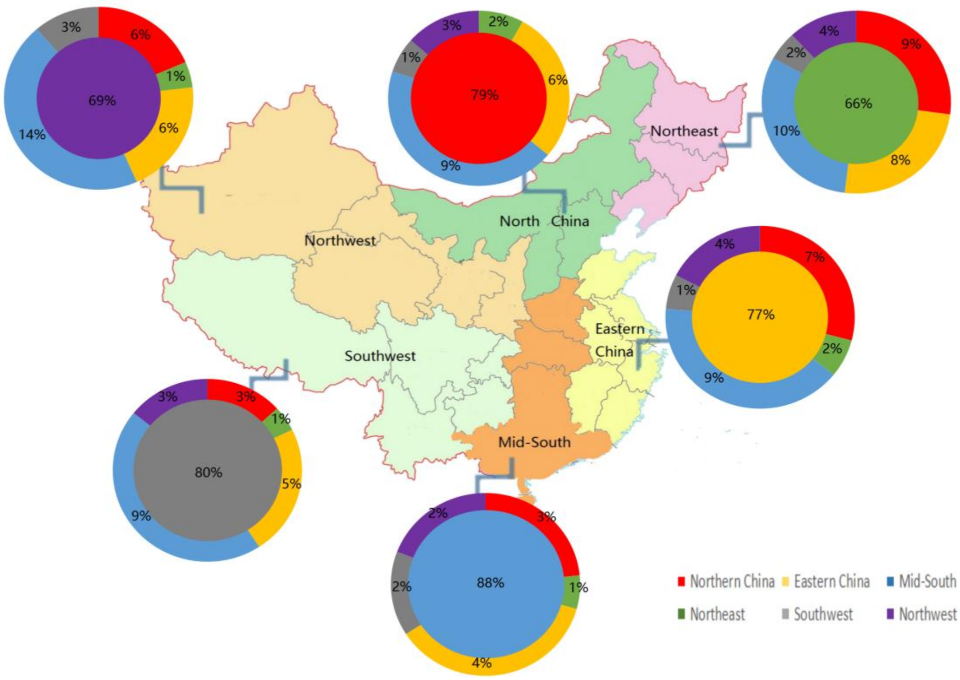

Figure6.5 Regional direct and indirect economic loss from secondary industry

Figure 6.5 illustrates both direct and indirect economic loss originating from each region and outside the region. The inner ring denotes the direct economic loss originating from secondary industry inside the region while the outer ring stands for the indirect economic loss from secondary industries in other regions. Percentage shown on the inner ring shows the proportion of direct economic loss regarding total regional economic loss and percentages shown on the outer ring are the proportions of indirect loss from other region relative to total regional indirect economic loss resulting from all outside secondary industries.

Furthermore, the secondary industry was also broken down into 7 sectors in order to examine the major economic loss sources among secondary industries inside and outside the region. They include Coal & Mining, Manufacturing, Fuel processing & Chemicals, Metal & Non-metal, Equipments, Energy and Constructions as displayed in *Figure 6.6*. The inner circle shows the economic loss from secondary industry inside the region. The size of the inner circle stands for the different proportions of inner-regional economic loss relative to total regional economic loss. Colours demonstrate economic loss from 7 sectors in secondary industry inside the region. Meanwhile, the outer circle indicates the economic loss from secondary industries outside the region. Economic loss resulting from 7 sectors are shown in black and white. Percentages shown on the outer circle are the proportions of indirect loss from other regions relative to total regional indirect economic loss. In North China, Northwest and Southwest, most of their indirect economic loss from secondary industries outside the region comes from Manufacturing with 27.0%, 26.7% and 22.2%, respectively. The second largest source in these three regions that accounts for economic loss from secondary industries in other regions is Energy, with the greatest amount occurs in North China at 2.32 billion Yuan, followed by Northwest at 1.29 billion Yuan and Southwest at 1.26 billion Yuan. In contrast, Coal and Mining accounts for the majority of indirect loss from secondary industries outside the region for Eastern China, Mid-South and Northeast at 37.4% (10.83 billion Yuan), 33.4% (3.65 billion Yuan) and 24.4% (1.30 billion Yuan), respectively. One possible underlying reason is that economies in Northwest, North China and Southwest are mainly dominated by Coal and Mining but relying on imports of Manufacturing products from other regions, whereas Eastern China, Mid-South and Northeast have more prosperous Manufacturing industries but tend to heavily depend on imports of raw materials from Coal and Mining industries in Northwest, North China or Southwest. With regards to the economic loss from secondary industry inside the region, it shows diversified patterns across six great regions. Coal and Mining accounts for the largest part of inner-regional economic loss in North China and Northwest at 42.4% and 43.8%, respectively, Equipments and Energy appear to be two major sources for inner-regional economic loss Eastern China and Southwest, while Metal and Non-metal and Manufacturing constitute considerable proportions in inner-regional economic loss from secondary industries in Mid-South, which reach 21.86 billion Yuan and 21.61 billion Yuan, occupying 27.4% and 27.1%, respectively.

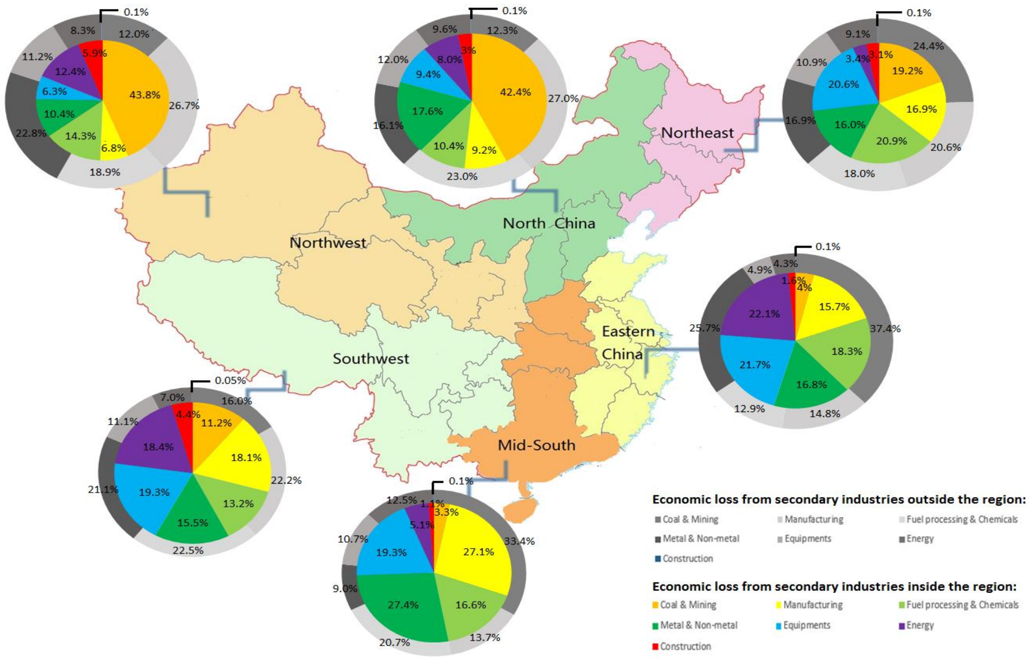

Figure6.6 Economic loss from 7 sectors in secondary industry inside and outside the region

The diagram measures the economic loss originating from 7 subsectors in secondary industry inside and outside each of the six great regions. The inner circle shows the economic loss from secondary industry inside the region. The size of the inner circle stands for the different proportions of inner-regional economic loss relative to total regional economic loss. Colours demonstrate economic loss from 7 sectors in secondary industry inside the region. Meanwhile, the outer circle indicates the economic loss from secondary industries outside the region. Economic loss resulting from 7 sectors are shown in black and white. Percentages shown on the outer circle are the proportions of indirect loss from other regions relative to total regional indirect economic loss.

6.4 Policy Implications, Conclusions and Uncertainties

International newspaper headlines have been frequently occupied by China's serious $PM_{2.5}$ pollution with terrifying photos. $PM_{2.5}$ has seriously undermined human health by inducing contaminant diseases, such as IHD, Stroke, COPD and LC. These diseases have resulted in increasing numbers of mortality and morbidity that cause little physical capital damages but substantial labour degradation in terms of productive working time loss along production supply chain. Indeed, as the industrial and regional interconnectedness have become unprecedentedly tightened under globalization, the cascading indirect economic loss of degraded labour time can be considerable due to these interdependencies. Therefore, there is a growing need to explore the macroeconomic implications of $PM_{2.5}$-induced health effects that can also capture industrial and regional interdependencies. However, existing health costs studies using HCA and CVA assess the health costs at microeconomic level without an investigation over these linkages on the production supply side. Meanwhile, existing disaster risk studies rarely involve $PM_{2.5}$ pollution as a disaster that harm human capital more than physical capital. Thus, the situation described in the current case study differs from that in Chapter 5 because labour constraints from pollution-induced health impacts need to be incorporated here. Methods focusing on the damages to infrastructure seem to be inefficacious here when measuring the 'damages' to human health, such as the ARIO (section 3.3.2.4) and Flood Footprint Model (section 3.3.2.5). For an approach is able to cope with the macroeconomic impacts from 'invisible' health impacts, it should firstly, consider both labour constraints and industrial and regional interdependencies; secondly, integrate risk analysis, impact analysis and interdependency analysis because it is significant for key sector identification to strengthen post-disaster economy recovery strategies and develop more sustainable policies (Xia et al, 2016).

The current case study applies the interdisciplinary approach by combining environmental, epidemiological and macroeconomic studies to assess the macroeconomic impacts of $PM_{2.5}$-induced health effects in China during 2012. In the model, environmental phenomenon was related with health endpoints using an integrated exposure-response model, reduction in labour time were estimated based on the pollution-induced mortality and morbidity counts, and industrial reducing labour time was perceived as an indicator for industrial reducing value added, which was further fed back into a supply-driven input-output model. By doing so, health studies can be integrated into impact evaluation and interdependency analysis.

The results are threefold. Firstly, the total economic loss from China's air pollution during 2012 amount at 398.23 billion Yuan with the majority comes from Eastern China (39%) and Mid-South (30%). The total economic loss is equivalent with 1.0% of

China's GDP in 2012 and the total number of affected labourers rises to 82.19 million. Compared with study in 2007 (Xia et al, 2016), although secondary industry remains the industry encountering the most economic loss (80%), changes can be noticed for economic loss at provincial level. Henan and Jiangsu become two provinces that suffering the greatest economic loss at 56.37 and 45.32 billion Yuan respectively, followed by Shangdong province with total economic loss at 43.23 billion Yuan. Henan and Shangdong provinces also have the largest numbers of $PM_{2.5}$-induced mortality, hospital admissions and outpatient visits. Secondly, the study highlights the cascading indirect economic loss triggered by industrial and regional interdependencies in health costs assessment. In 2012, indirect economic loss constitutes a significant part of total regional economic loss in Northeast, Eastern China and Northwest, which occupies 31%, 21% and 30% of the total regional economic loss, respectively. Overall, Mid-South accounts for the largest amount of indirect economic loss in other Chinese regions at 24.65 billion Yuan, which is followed by North China and Eastern China at 16.99 and 12.17 billion Yuan, respectively. Additionally, the study specifically focuses on 7 sectors in secondary industry and differentiates economic loss from these sectors inside the region from those outside the region. In Northwest and Northeast, economic loss attributed to secondary industries outside the region still constitute a considerable share due to industrial and regional interdependencies at 31% and 34% of total regional economic loss, respectively. Secondary industries in the Mid-South, Eastern China and North China become three major sources for indirect economic loss across all the six regions. Indeed, I also suggest that indirect economic loss is more likely to come from neighbour-regions, which highlights the possibility that short geographical distance might accelerate interregional trade and strengthen regional interlinkages. In North China, Northwest and Southwest, most of their indirect economic loss are originated from Manufacturing industries outside the region with 27.0%, 26.7% and 22.2%, respectively. The second largest source in these three regions that accounts for economic loss from secondary industries in other regions is Energy, with the greatest amount occurs in North China at 2.32 billion Yuan. In contrast, Coal and

Mining accounts for the majority of indirect loss from secondary industries outside the region for Eastern China, Mid-South and Northeast at 37.4% (10.83 billion Yuan), 33.4% (3.65 billion Yuan) and 24.4% (1.30 billion Yuan), respectively. Such distinctive compositions of outer-regional economic loss might be due to the different economic structures and dependences between North China, Northwest, Southwest and Eastern China, Mid-South, Northeast. Turning to the economic loss from secondary industry inside the region, Regions show heterogeneity. Coal and Mining accounts for the largest part of inner-regional economic loss in North China and Northwest at 42.4% and 43.8%, respectively, Equipments and Energy are two major sources for inner-regional economic loss Eastern China and Southwest, while Metal and Non-metal and Manufacturing constitute considerable proportions in inner-regional economic loss from secondary industries in Mid-South.

There are some final remarks for policymakers and researchers here from this typical air pollution issue. On the one hand, given that the prosperous interregional trade, policymakers are required to conscientiously consider these increasingly strengthened industrial and regional linkages in climate change mitigation and adaptation policy design based on a better understanding of implications resulting from any climate change-induced health issues at both micro and macroeconomic levels. Meanwhile, sufficient adaptation measures are required to be implemented along with the climate change mitigation strategies in operation. The purpose of this is to expand the economy beyond the regional geography and natural endowment, and to release the current reliance of economy on labour-intensive sectors (Mauricio Mesquita, 2007). On the other hand, researchers on epidemic studies should actively integrate these interdependencies into future health costs evaluation while researchers on disaster risk analysis should not lose sights on ‘persistent’ disasters as described in this study, which affect more human capital and may imply degradation in production factor inputs.

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, p543). 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.

6.5 Sensitivity Analysis

This section provides a sensitivity analysis for the case 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.

6.5.1 Timed Required for Each Cardiovascular Hospital Admission

In the case study of this chapter, 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 6.2*. 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.

Table6.2 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**

6.5.2 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 6.3*. 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.

Table6.3 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**

6.5.3 Equal Distribution of Mortality and Morbidity Counts in Industries

Another assumption in this case 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.

6.5.4 Distribution of Mortality and Morbidity Counts based on Industrial Exposure Rates

I 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 4 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 6.4*. 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.

Table6.4 Occupational Exposure to Harmful Substances or Environment

Occupational Exposure to Harmful Substances or Environments	
Occupation	**Exposure**
Agriculture, forestry, fishing, hunting	35
Coal ming	17
Oil, gas wells	8
Metal ore mining	17
Nonmetal mineral mining, quarrying	17
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
Non-metal 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
Natural gas distribution	4
Electric power generation, transmission, distribution and water, sewage, other systems	15
Transportation	37
Wholesale trade, retail trade	23
Accomodation and food service	11
Financial activities, rental, leasing	13
Professional scientific, technical service	5
Other service	10
Construction	182

Natural resources&mining
Services-providing
Manufacturing
Construction

(Source: US Bureau of Labour Statistics)

Chapter 7: Application of a Disaster Footprint Framework for Cascading Indirect Economic Impacts of Heat Wave, China

The southeast region of China is frequently affected by summer heat waves, such as Nanjing and Shanghai, two metropolitan cities in China, have been frequently affected by summer heat waves. 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. There are two possible ways to understand the macroeconomic implications from these health impacts in the economic system, focusing on the production supply side and demand side, respectively. On the one hand, 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. By perceiving labour as a key primary input, industrial reducing labour time can be an indicator for industrial reducing value added so that it can be fed into a supply-driven input-output to trace all cascading indirect economic loss triggered by industrial and regional interdependencies. Following this, the developed approach is similar with the one in Chapter 5 but to combine meteorological, epidemiological and economic analyses rather than environmental studies on emission inventory or pollutant concentrations. On the other hand, the degraded labour productivity and productive working time also indicates a loss in disposable wage and purchasing power when moving labourers from the production supply side to consumers on the production demand side. Meanwhile, increasing hospital admissions and outpatient visits will raise the economic burden of health-care services for both households and government. With budget constraints, rising health-care expenditure will impose ‘crowd-out effects’ on consumption and investment on other commodities and services by households and government. Reducing productive working time was used as an indicator for loss in disposable wage and purchasing power of households and extra expenditure on health-care services as an indicator for the 'crowd-out' effects that both cause a shrink in final demand category of the economy. Following a demand-driven input-output model, the initial net impact on final demand can be traced along the production chains to evaluate all cascading indirect economic impacts resulting from these backward linkages.

The following context contains two cases studies on Nanjing and Shanghai, using the distinctive approaches as discussed above. Regardless the focus on different linkages, they have the same root in '*a circular economy*' and are actually two sides of the same coin. They attempt to describe the impacts from a macroeconomic scope through two different angles.

The first study, by adopting a supply-driven input-output model, the results show a total economic loss of 27.49 billion Yuan[8] 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 input-output model to capture indirect economic loss, the 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. In contrast, the second study utilizing a demand-driven input-output model to assess the economic loss from heat waves in Shanghai during 2007. Instead of focusing on the production supply-side, the approach evaluates the economic impacts resulting from industrial backward linkages by perceiving health impacts as an indicator for reducing labour wage and extra expenditure on health-care services by households and government that both lead to a shrinking final demand. The second study concludes that a ten days' heat wave has caused a

[8] Yuan is a monetary unit for Chinese RenMinBi and it is equivalent with 0.15 USD and 0.11 GBP (2017).

total economic loss of 323.71 million Yuan with 845 thousands affected labourers in which the majority of economic loss come from the tertiary sector at 157.35 million Yuan, accounting for almost half of the total economic loss in Shanghai. At a sectoral level, Agriculture and Technological service sectors ranked among the top ten sectors suffering the greatest direct, indirect and total economic loss, highlighting a need for special key sector protection in disaster preparation and adaptation. Besides, huge gaps between direct and indirect economic loss can be observed from Finance and Wholesale and Retailing sectors, which reemphasizes the significant role of cascading indirect economic loss due to industrial and regional interdependencies.

7.1 Assessment of the Economic Impacts of Heat Waves: A Case Study of Nanjing, China – A Supply-driven Approach

7.1.1 Background

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 (Field, 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 programs. 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 (Miller and Blair, 2009, p2). 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 because their 'invisible' damages to human health can invalidate existing disaster modelling frameworks that heavily focus on quantifying the physical capital loss, such as the ARIO (section 3.3.2.4) or Flood Footprint Model (section 3.3.2.5). Therefore, the current study specifically focuses on the heat wave event happened in Nanjing, Jiangsu Province, China, in 2013. The interdisciplinary approach integrates meteorological, epidemiological and macroeconomic analyses to assess the total indirect economic impacts on the production supply chain of Nanjing city from heat-induced diseases, productivity losses due to mental distractions under extreme heat, and capacity losses with occupational work safety regulations. The employed supply-driven input-output model allows productive working time losses due to the degradation of health, productivity and capacity to be perceived as an indicator for potential changes in the value added of the economy that will be traced along the supply chain to detect the total cascading indirect economic loss due to industrial interdependencies.

7.1.2 Methodology

(a). Methodological Framework

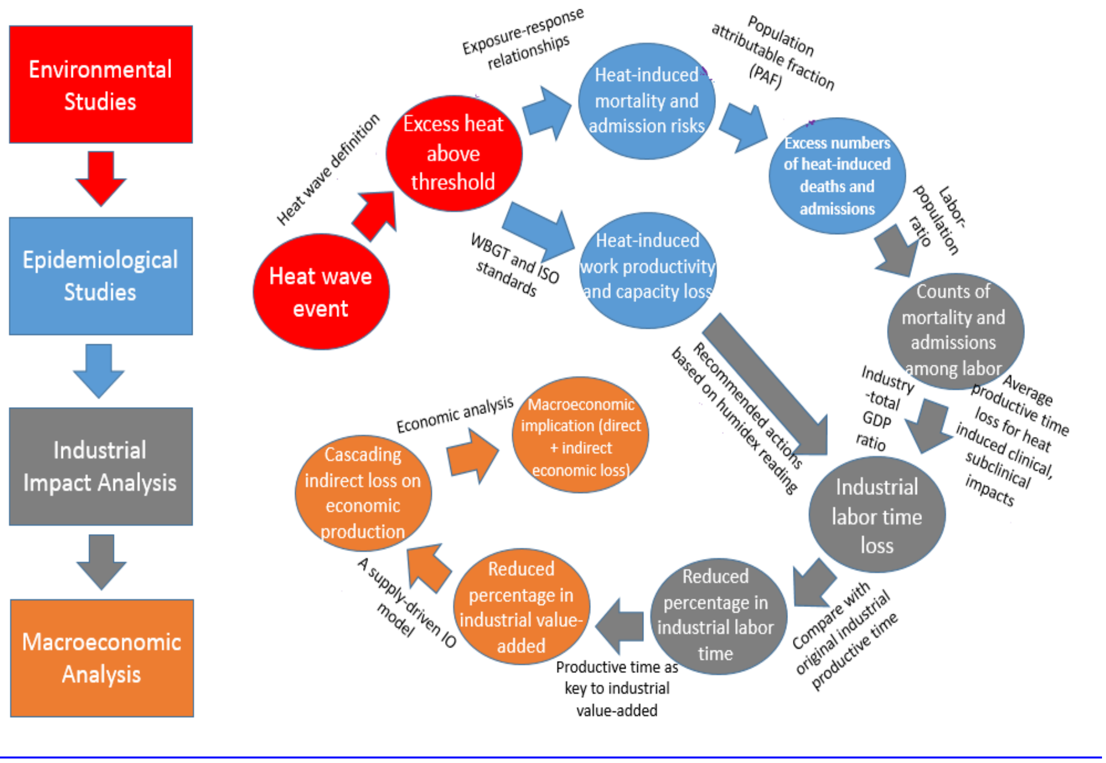

Figure7.1 Methodological framework

Figure 7.1 is analogous with Figure 6.1 in section 6.2 (a) but accommodates to the distinctive characteristics of heat waves. It 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. 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. 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. Additionally, heat-induced mortality, morbidity, productivity and capacity loss were translated into productive working time loss, which was further compared with the original working time without the heat effect to derive the percentage reduction in industrial value added. Moreover, the reduction in value added serves as an input in the supply-driven input-output model to measure the total indirect economic loss incurred along the production supply chain, which is measured as the total loss in output. Finally, macroeconomic implications can be obtained from our model results.

(b). Identify Heat Wave Period

There are various ways to define a heat wave. In this study, I 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 ℃ 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 as shown *Figure 7.2* and Table *7.1.*

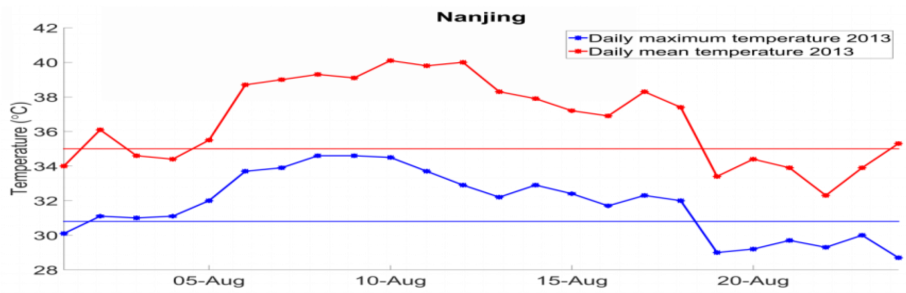

Figure7.2 Identified heat wave period in Nanjing, 2013

5/8–18/8/2013 was identified as the heat wave in Nanjing in 2013.

Table7.1 Observed Temperature from Stations in Nanjing, 2013

Station	97th percentile	T_{mean}	T_{max}
	℃	℃	℃
Xu zhou	29.5	32.7	37.0
Nan jing	30.8	33.1	38.4
Dong tai	29.5	31.8	36.4

(c). Heat-induced Mortality and Morbidity in Nanjing

For heat-induced mortality in Nanjing, I 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 using *Equation 7.1*.

$$M_{heat} = M_s - M_r \qquad (7.1)$$

M_{heat}: the heat-induced excess number of non-accidental mortalities;
M_s: the number of mortalities during the heat wave;
M_r: 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, I considered excess hospital admissions for respiratory and cardiovascular diseases. Because of a lack of records and data for Nanjing, I had to refer to similar episode studies on heat-induced morbidity in other cities. I 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 I therefore assumed that the populations would have similar vulnerabilities to heat exposure.

The RRs for the two diseases were used in *Equation 7.2* to calculate the population attributable fraction (PAF) and were further used in *Equation 7.3* to estimate the population counts affected by a particular health endpoint.

$$AF = \frac{RR - 1}{RR} \tag{7.2}$$

$$E = AF \times B \times P \tag{7.3}$$

AF: the population attributable fraction that measures the fraction of the affected population that can be attributed to extreme heat;

RR: the rate ratios for a particular health endpoint in investigation;

'1': the counterfactual risk ratio using a theoretical-minimum-risk exposure distribution. In this case, it reflects the temperature level below which there is no additional health risks;

E: the total affected counts of a particular health endpoint that are attributable to extreme heat;

B: the national level admission incidence of a given health effect;

P: the exposed population (WHO, 2017).

The RRs for cardiovascular and respiratory hospital admissions are 1.08 (95% CI) and 1.06 (95% CI), respectively (Ma et al, 2011).

(d). Productivity and Capacity Loss

For heat-induced productivity loss due to mental distraction or reduced cognitive skills, I 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, I 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, I 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. I 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 7.3*; 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)

Figure7.3 Humidex-based heat response plan (humidity range and corresponding relief time required are highlighted in red box)

(e). Productive Working Time Loss

I 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. I did so by considering labour as a major component of industrial value added.

(f). A Supply-driven Input-Output Model

A supply-driven input-output model was derived from a traditional Leontief input-output model with the rotated view. 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. Recall the traditional Leontief model:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}$$

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{f} \;,\; \mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$$

A: the $n \times n$ matrix of technical coefficients;

x: the output matrix for *n* sectors;

f: the final demand matrix for *n* sectors;

$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$: the Leontief inverse matrix.

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 input-output model is used to calculate the sectoral gross production changes caused by changes in the amount of primary inputs, including capital and labour. It has been mentioned in section 6.2 (e) regarding *Equation 6.5* and *6.6*. Let us revisit the equations for a supply-driven input-output model.

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

B: the allocation coefficient (direct-output coefficient) matrix that is calculated by dividing *Zi* by *Xi*. It refers to the distribution of sector *i*'s outputs in sector *j*. Assumption of fixed allocation coefficients in the economy also holds for a supply-driven input-output model;

V: the industrial value added matrix, including capital and labour input;

G: the Ghosh inverse matrix, which measures the economic impacts of changes in a sector's value added on other sectors' output level (Miller and Blair, 2009, p543).

Because there is no city-level input-output table for Nanjing, I scaled down the provincial input-output 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.

7.1.3 Results and Discussions

(a). 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 7.4*). 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 7.4*).

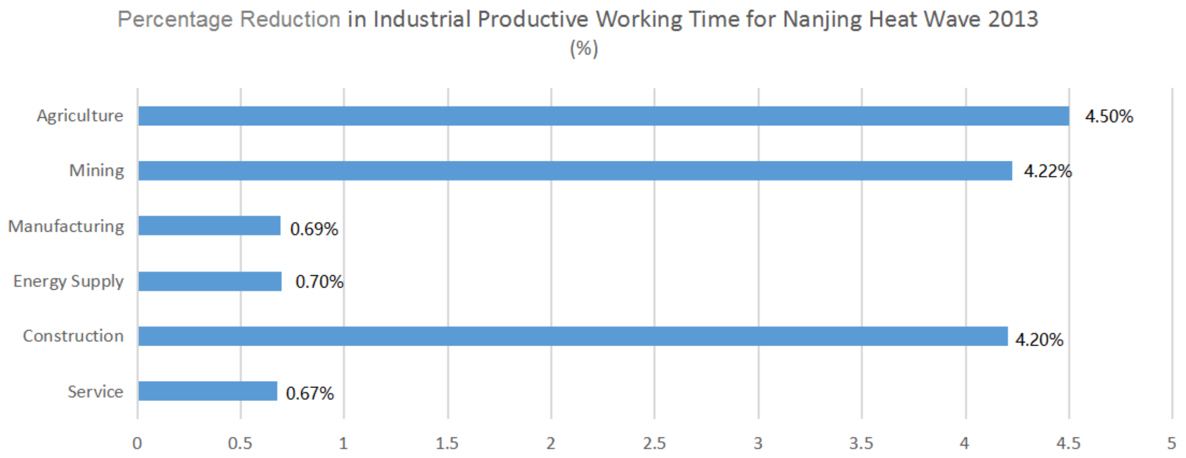

Figure7.4 Percentage reduction in industrial productive working time for Nanjing heat wave 2013

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.

(b). 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 input-output model, the 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 7.5*), 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 7.5*). 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.

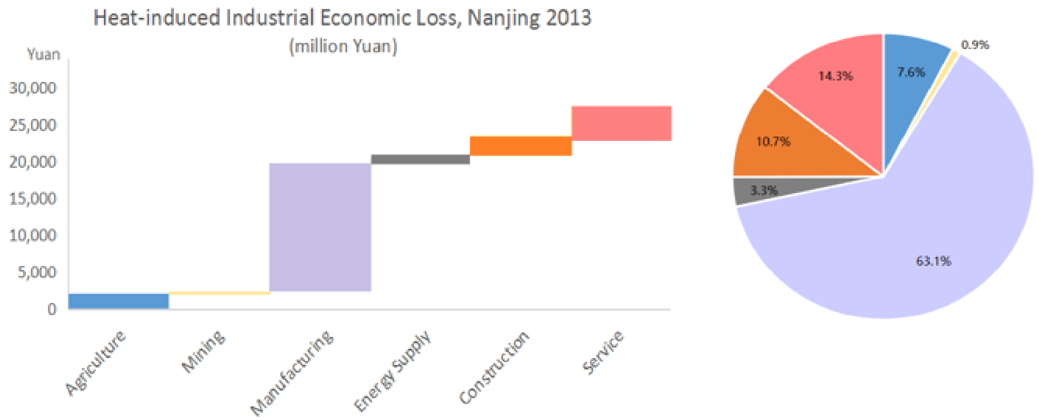

Figure7.5 Heat-induced industrial economic loss, Nanjing 2013

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).

(c). Direct and Indirect Impact Analysis

The direct and indirect impact analysis highlights the significance of industrial interdependencies. As shown in *Figure 7.6*, 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.

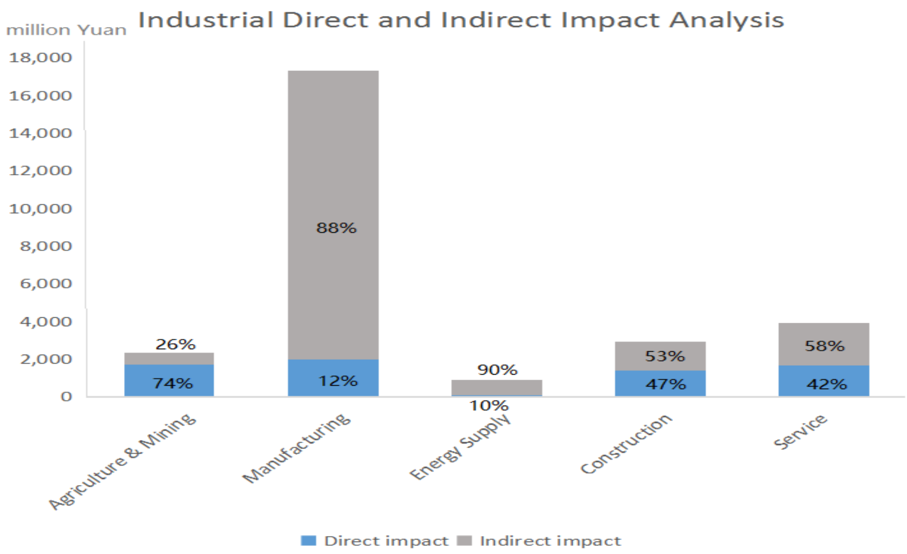

Figure7.6 Direct and indirect impact analysis

The bar chart shows the direct and indirect impact analysis across five broad industries. 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.

7.1.4 Policy Implications, Conclusions and Uncertainties

Given the increasing frequency of heat waves and their severe impacts on human beings, there are a growing number of studies examining heat-induced health impacts on mortality and morbidity as well as translating the heat-induced health impacts into monetary units in terms of health cost assessments. However, I found that 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. Considering all of the above, this study 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 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, this 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 input-output model's ability to capture indirect economic losses, the 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 study contributes to filling the four research gaps described above among existing studies on heat epidemiology, health cost assessments and disaster risk analyses.

The current study makes several assumptions and thus is subject to uncertainties that open up new research directions for future studies. First, heat-induced productivity loss due to mental distractions was assumed to induce a 12% loss of daily productive time during the heat wave period. I 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. Second, it was 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. There is no differentiation between indoor and outdoor workers within the same industry, which might lessen the accuracy of the results. Third, because of the lack of quantitative relationships or records on heat admission and heat outpatient visits for Nanjing, a heat admission study conducted in Shanghai in 2011 (Ma et al, 2011) was referred in this study without considering 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. Finally, the current study employed a supply-driven input-output model by perceiving labour as a key primary input and reduced productive time as an indicator of reduced value added. Therefore, the current study provides a way to incorporate health impacts into disaster risk analyses using the input-output 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 compensation for working during the hot days and the resulting positive effects on economic activities due to rising wages.

7.1.5 Sensitivity Analysis

This section 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.

7.1.5.1 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 7.2.* 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.

Table7.2 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**

7.1.5.2 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.

7.1.5.3 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 7.3.* Compared with figures in *Table 7.2*, 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.

Table7.3 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**

7.1.5.4 Timed Required for Each Cardiovascular Hospital Admission

Finally, the study also makes assumption on time required for each cardiovascular admission. Thus, I 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 7.4*. The results only change slightly, suggesting that model results are not sensitive towards changes in time required for each cardiovascular hospital admission.

Table7.4 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**

7.2 Assessment of the Economic Impacts of Heat Waves: Shanghai Case – A Demand-driven Approach

7.2.1 Background

Global warming has become unprecedentedly severe since the 1970s that can be mainly attributable to anthropogenic activities (Parry et al, 2007). The world economic expansion during the past decades largely rely on fossil fuel consumption that dramatically increased greenhouse gasses (GHGs) emission and exacerbated global warming. The Intergovernmental Panel on Climate Change (IPCC) also anticipates a 1.4-5.8℃ rise in world average temperature by 2100 (Smithson, 2002). Meanwhile, anthropogenic related global warming seriously affect human health in return through more frequent heat waves and cold spells. Heat waves in Europe during August, 2003 caused over 15,000 excess deaths only regarding France (Roklöv and Forsberg, 2008). As developed countries, developing countries such as China, has also suffered noticeable climate change and is more frequently impacted by heat waves in summer during the last decade (China National Development and Reform Commission, 2007). Heat waves can influence an economic system through the resulting health outcomes on human capital. On the one hand, it is suggested that heat waves are positively related with non-accidental mortality and morbidity (hospital admissions and outpatient visits), especially for cardiovascular and respiratory diseases (Ma et al, 2011). As labour is a key productive factor during production process, such health outcomes will degrade labour productivity by reducing productive working time that further indicates a loss in disposable wage and purchasing power if there is no compensatory behaviour. On the other hand, increasing hospital admissions and outpatient visits raise the economic burden of health-care services for both households and government. With budget constraints, rising health-care expenditure will impose ‘crowd-out effects’ on consumption of other commodities and services and investments by households and the government, respectively. From an economic perspective, heat waves, health outcomes and its socioeconomic impacts are interacting and thus, should be integrated as a whole in analyses. However, most existing health studies on heat waves in China focus on either heat-induced mortality or heat-induced morbidity instead of investigating both in the study. The analyses mainly stem from an epidemiological perspective without considering the economic impacts of the resulting health outcomes. Even though methods have been developed for health costs assessment (eg. Human Capital Approach, Contingent Valuation Approach), they tend to provide insights on patients’ economic burden (Wan et al, 2004; 2005) without much information on the cascading indirect economic loss that is resulting from sectoral/regional interdependencies (Xia et al, 2016). Given such interdependencies, reduction in a single sector due to the health-related loss in labour productivity can affect sectors that purchase inputs from / sell outputs to it. The initial effects of heat-induced health outcome on sectoral production will ultimately spill over the unaffected sectors, regions and the entire economic system through such interdependencies.

Alongside, heat waves can be also perceived as a physical hazard (Basu and Samet, 2002) which however have been rarely analysed in disaster risk studies. It is analogous to flood and hurricane in the sense that it can also disrupt the economic functioning by exerting substantial impacts on human capital rather than physical capital. Focusing on the heat wave in Shanghai during 2007, this study employs a demand-driven input-output model to assess the macroeconomic impacts of the heat-induced mortality and morbidity on the local economy of Shanghai. With the emphasis on backward linkages, the proposed method is able to uncover how indirect economic loss is cascaded and accumulated from the initial reduction in final demand category. In the model, reducing productive working time resulting from heat-induced health impacts is used as an indicator for loss in disposable wage and purchasing power of households. It also provides an alternative approach for health risk assessment through the angle of labour productivity at macroeconomic level that emphasizes the interdependencies along production supply chains. Meanwhile, the interdisciplinary framework enables to integrate health costs assessment and economic impact evaluation simultaneously into disaster risk studies. For policymakers and government, such framework can not only establish more solid scientific ground for risk and impact assessment of heat waves, but also provides vivid evidence for potential benefits in improving health status of population as well as constructing health care and protection schemes, climate change mitigation and adaptation strategies.

7.2.2 Methodology

(a). Methodological Framework

Figure 7.7 presents the methodology framework used to estimate socioeconomic impacts of heat-induced mortality and morbidity in Shanghai for heat wave year during 2007. The framework involves six components to incorporate health effects of heat waves into an input-output analysis.

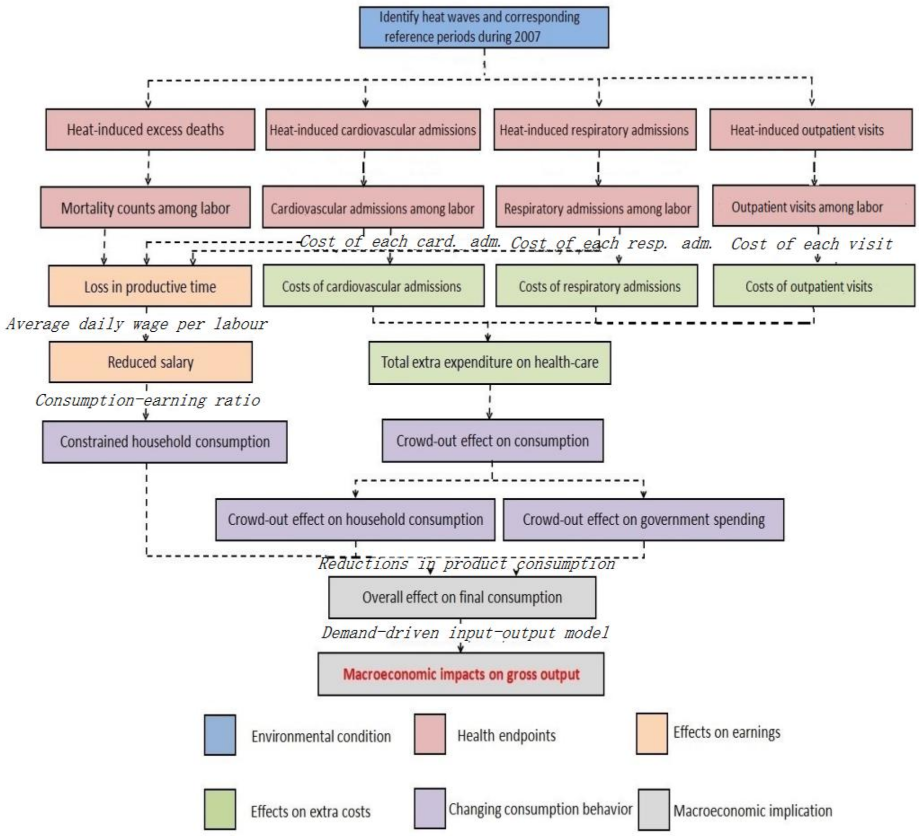

Figure7.7 Methodology framework

Figure 7.7 presents the methodology framework used to estimate socioeconomic impacts of heat-induced mortality and morbidity in Shanghai for heat wave year during 2007. The framework involves six components to incorporate health effects of heat waves into an input-output analysis, which will be explained in details in the following section (b) to (f).

(b). Identifying Heat Waves and Reference Periods in Shanghai during 2007

There are various ways to define heat waves and Chen et al (2015) suggested considerable impacts of heat wave definitions on added effects. The length of heat wave can be completely different under distinct heat wave definitions (eg. Anderson and Bell, 2011; Son et al, 2012; Tian et al, 2013; Peng et al, 2011; Huang et al, 2010, etc). For consistency, this study defines a heat wave as a period of at least 3 consecutive days with daily maximum temperature over 35°C, daily average temperature over 31.3°C and daily average temperatures exceed 97th percentile during the study period. With this definition, 24th July to 2nd August in 2007 was identified as a heat wave with a totality of ten days. I also chose a near-term summer reference period for each identified heat wave to control potential time-varying confounding effects. The selected reference period has the same duration and distribution of days of the week (DOW) as each corresponding heat wave and excludes the days immediately after the heat wave (Basu and Samet, 2002; Ma et al, 2011). The reference period is 10th to 16th July and 7th to 9th August, 2007. The data on daily temperature during 2007 were obtained by Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing from Shanghai Baoshan meteorological monitoring station.

(c). Heat-induced Mortality and Morbidity in Shanghai

For identified heat wave during 2007, I followed the same way of Ma et al (2011) in calculating excess hospital admissions and excess deaths in Shanghai. The assumption of little changes in Shanghai population and same duration and DOW distribution between each heat wave and each reference period enable the ratio comparison between two periods to reflect the relative impact of the heat wave. The heat-induced excess deaths (all causes) were calculated as the difference in number of mortality between heat wave period and its corresponding reference period, while the heat-induced hospital admissions (cardiovascular and respiratory admissions) as the difference in numbers of hospital admissions between the two periods. The heat-induced outpatient visits were calculated based on Sun et al (2014). Let us recall the *Equation 7.1* that have been introduced in section 7.1.2 (c).

$$M_{heat} = M_s - M_r$$

M_{heat}: the heat-induced excess number of non-accidental mortalities;
M_s: the number of mortalities during the heat wave;
M_r: the number of mortalities during the reference period.

The rate ratios (RRs) for heat-induced mortality, cardiovascular admissions and respiratory admissions were calculated by dividing the number of mortality/admissions during heat wave (study period) by number of mortality/admissions during corresponding reference period (*Equation 7.4 and 7.5*).

$$RR_{heat-mortality} = \frac{M_S}{M_r} \qquad (7.4)$$

$$RR_{\ heat-admissions} = \frac{H_s}{H_r} \quad (7.5)$$

$RR_{\ heat-mortality}$: the rate ratio for heat-induced mortality;
$RR_{\ heat-admissions}$: the rate ratio for heat-induced admissions of a certain disease. We also calculated the 95% confidential intervals (CIs) for the RRs by *Equation 7.6*.

$$RR_{\ 95\%\ CIs} = [\exp\ (LnRR \pm 1.96\sqrt{\frac{1}{s} + \frac{1}{r}})] \quad (7.6)$$

s: the numbers of mortality or disease-specific admissions during heat wave (study period);
r: the number of mortality or disease-specific admissions during the reference period (Rothman et al, 2008; Ma et al, 2011).

Then, the counts of heat-induced death, hospital admissions and outpatient visits were estimated using *Equation 7.2* and *7.3* in section 7.1.2 (c).

$$AF = \frac{RR - 1}{RR}$$

$$E = AF \times B \times P$$

AF: the population attributable fraction that measures the fraction of the affected population that can be attributed to extreme heat;

RR: the rate ratios for a particular health endpoint in investigation;

'1': the counterfactual risk ratio using a theoretical-minimum-risk exposure distribution. In this case, it reflects the temperature level below which there is no additional health risks;

E: the total affected counts of a particular health endpoint that are attributable to extreme heat;

B: the national level admission incidence of a given health effect;

P: the exposed population (WHO, 2016).

The daily counts of death data were obtained from the China Information System of Death Register and Report of Chinese Center for Disease Control and Prevention (China CDC). The causes of death were coded by China CDC according to the International Classification of Diseases, Tenth Revision (ICD-10): non-accidental disease (A00-R99), cardiovascular disease (I00-I99) and respiratory disease (J00-J99).

(d). Constraining Effects of Health Outcomes on Household Purchasing Power

In order to translate health impacts of heat into suitable input for a demand-driven input-output model, I suggest two types of impacts of health outcome on the consumption of households and government. Firstly, as all workers are also consumers for final consumption, the resulting health outcomes will cause substantial loss in labour productive time, which further constrain their disposable wage and purchasing power. Secondly, excess numbers of hospital admissions and outpatient visits indicate an increasing cost burden for medical treatment that is partially borne by patients (20%) and partially by Chinese government (80%). With budget constraints, extra health-care costs will crowd out consumption of households and government on other commodities and public services. I assumed that the disproportional reductions in consumptions of other products will depend on the original consumption pattern across those sectors excluding health-care services sector.

Considering the constraining effects of health outcome on disposable wage, I started by converting health outcome into labour productive time loss. I first scaled down the numbers of mortality, hospital admissions and outpatient visits to the numbers among labour using employment-population ratio in Shanghai during each study year (Shanghai Statistical Yearbook). Heat-induced mortality, hospital admissions and outpatient visits among labour were further distribute into 42 economic sectors according to sector-city output ratio. I assumed that each employee works 8 hours per day and 250 days, each case of mortality will result in 250 working days' loss, each case of cardiovascular admissions will cause 11.9 working days lost and each case of respiratory admissions will cause 8.4 working days lost and each outpatient visit require 4 hours (National Bureau of Statistics of China, 2016). These assumptions remain unchanged throughout 2007. Weekends during the working day lost are not considered in the current study due to lack of data. We multiplied work day lost for each case of mortality, hospital admissions and outpatient visits by numbers of mortality, hospital admissions and outpatient visits in each sector to obtain the sectoral productive time loss. I further multiplied sectoral working day loss by sectoral daily salary in that year to estimate the reduction in workers' earnings in each sector, where the results were summed up and eventually multiplied by household expenditure-earnings ratio in Shanghai during the year to reflect the reduction in households' purchasing power. Sectoral daily wage was calculated by dividing sectoral annual average compensation (National Bureau of Statistics of China, 2016) by 250 days.

(e). Crowd-out Effects of Extra Medical Costs on Household and Government Consumption

Considering the crowd-out effects of medical cost burden on the consumption of household and government, I firstly estimated total extra medical expenditure by multiplying the averaged costs of each admission case and each outpatient visit by the number of hospital admissions and outpatient visits among labour. The costs of each cardiovascular, respiratory admission and outpatient visits were obtained from China's Health and Family Planning Statistical Year and 2007 China Health Statistical Yearbook (National Bureau of Statistics of China, 2016). For those years with missing data, I estimated the costs by yearly average inflation rate during that year. The missing data on 2007 was estimated by adjusting the costs in 2006 with yearly average inflation rate in 2007, 4.82% (inflation.eu, 2016). The costs of each cardiovascular, respiratory admission and outpatient visit during 2007 can be thus calculated as 6413.3, 3042.8 and 211.0 Yuan, respectively. I assumed the total extra medical expenditure is borne by both government (80%) and patients/households (20%), which also holds constant throughout 2007. Medical costs for any heat-induced mortality were not considered in the current study.

From above, reducing household purchasing power and crowd-out effects of rising medical burden will both shrink households and government's consumption on other commodities or public services. I suggest disproportional reductions in final consumption of other sectors according to the original consumption patterns of households and government. On the one hand, the aggregate loss in household purchasing power was distributed into 42 industries (including health-care services sector) based on the adverse ranking in industrial-total ratios of household final consumption with an underlying assumption that commodities occupying large proportions of final consumption are considered as necessities and is less likely to reduce in the face of decreasing disposable wage. On the other hand, extra medical costs borne by household and government were added into the household final consumption and government expenditure on health-care services sector, respectively whereas the equivalent amounts were deducted from expenditures on other sectors' commodities and public services using the same approach as shrinking disposable wage. Lastly, households' constrained consumption in all 42 industries due to wage loss and the crowd-out effect of increasing medical costs on household and government final consumption in other sectors were summed up to obtain the net impacts on the final demand of 42 sectors during that year, which would serve as an input in the demand-driven input-output model at next step. We assumed each economic sector only produces one distinct product. Data on final consumption were obtained from Shanghai Input-output Table (42 sectors) in 2007.

(f). A Demand-driven Input-Output Model

The calculated reductions in final demand serve as an input for a demand-driven input-output model to trace the cascading effects resulting from initial reductions in final demand. The Leontief model assumes that outputs of interacting industries in an economic system are used for both final consumption and intermediate transactions. Recalling the equations for Leontief model,

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}$$

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

A: the $n \times n$ matrix of technical coefficients;

x: the output matrix for *n* sectors;

f: the final demand matrix for *n* sectors;

$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$: the Leontief inverse matrix.

7.2.3 Results and Discussions

(a). Heat-induced Mortality and Morbidity Counts in Shanghai, 2007

Table 7.5 demonstrates the heat-induced excess numbers of death, hospital admissions for two diseases and all-cause outpatient visits that were calculated based on the counts in each category during heat wave period and the reference period. The number of cardiovascular admissions is 4 times of the number of respiratory admissions while the relative risk for heat-induced outpatient visits appears to be the highest among the four categories.

Table7.5 Excess Counts in Mortality and Morbidity due to Heat Wave in Shanghai, 2007

	Heat wave period	Reference period	Excess counts	Relative risks（*RR*）（95%CI）
Mortality	1334	1243	91	1.07（0.99，1.16）
Cardiovascular admissions	4051	3752	299	1.08（1.05，1.11）
Respiratory admissions	1361	1289	72	1.06（1.00，1.11）
Outpatient visits			1243631	1.10（1.07，1.13）

(b). Economic Loss through Backward Linkages

By evaluating the macroeconomic impacts of heat wave-induced health impacts in Shanghai during 2007, results suggest that the 10 days' heat wave has affected a totality of 845 thousands labourers in Shanghai in terms of excessive mortality, hospital admissions and outpatient visits, which occupy 16.9% of the total employment in Shanghai. When perceiving these health impacts as degradation in labour availability and productive working time, these health impacts can be translated into a 0.035% reduction in the productive labour year in Shanghai during 2007. The reducing wage as a result of working time loss and the crowd-out effect as a result of extra health-care expenditure by government and households have caused the final demand to shrink measured as 'direct economic loss' here. Such direct economic loss amounted at 227.17 million Yuan (except the extra expenditure on health-care services). The initial decrease in final demand was further triggered by industrial interdependencies that raised the total economic loss to 323.71 million except Chemicals, Transportation, Construction, Neighbourhood service and

Health-care service sector, where the reductions in final demand led to an increase in their output level due to their close industrial interconnectedness with Health-care or medical services. I therefore only focused on the sectors that suffer economic loss. The backward linkages between sectors have resulted in a totality of indirect economic loss at 96.54 million Yuan, accounting for almost 30% of the total economic loss. Among three major industries, tertiary industry entailed the most substantial economic loss at 157.35 billion Yuan, which encompasses 69% as direct economic loss at 109.31 billion Yuan while the remaining 31% as indirect economic loss at 48.05 million Yuan. This was followed by secondary industry that accounted for 30% of the total economic loss in Shanghai, 2007. Secondary industry encountered a greater proportion of indirect economic loss than tertiary industry for 46% that valued at 44.51 million Yuan *(Figure 7.8). Figure 7.8* illustrates the economic loss in 3 major industries in Shanghai, 2007 with details on the proportions of direct and indirect economic losses.

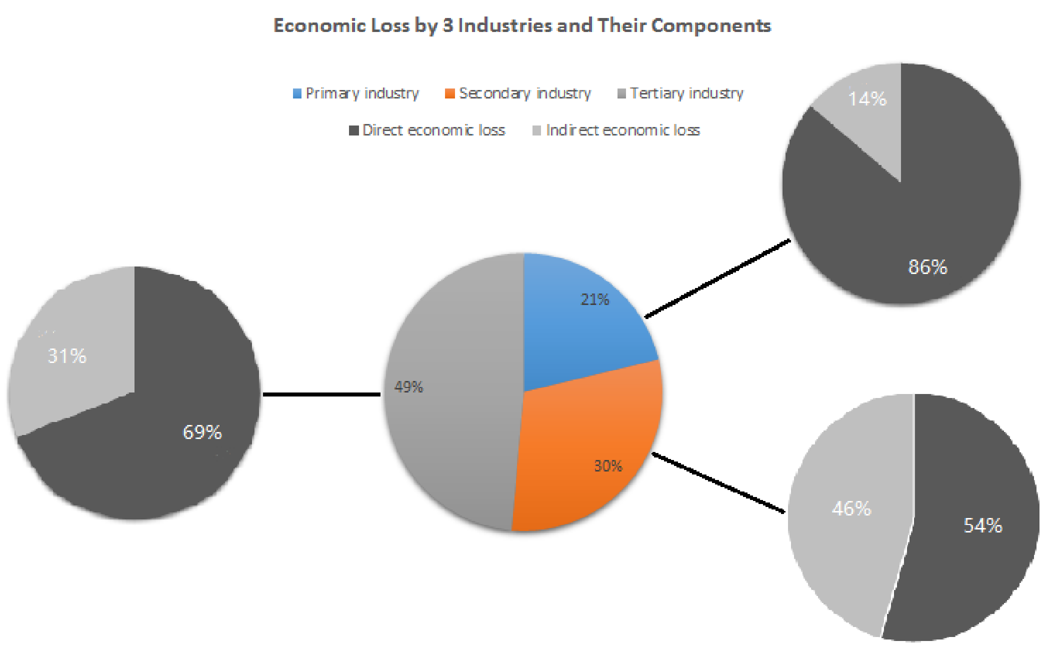

Figure7.8 Economic loss by 3 industries and their components

Figure 7.8 illustrates the economic loss in 3 major industries in Shanghai, 2007 with details on the proportions of direct and indirect economic losses in three grey and black pie charts.

Focusing on specific sectors, *Figure 7.9* presents the top ten sectors that were most severely hit in terms of direct, indirect and total economic loss due to heat wave in Shanghai, 2007, measured in million Yuan. Agriculture sector suffered the greatest direct economic loss at 59.23 million Yuan in terms of value reduced in sectoral final demand, followed by Technological service sector and Public infrastructure sector at 43.65 and 21.66 million Yuan, respectively. They are also the three sectors that encountered the greatest total economic loss. Turning to indirect economic loss, Technological service sector become the one entailing the greatest loss at 13.46 million Yuan, which is followed by Transportation and Food manufacturing sectors that suffered a loss of 10.08 and 10.07 million Yuan, respectively. The top ten sectors suffering the greatest direct economic loss accounted for over 83% of the total direct economic loss while those entailing the most substantial total economic loss also constituted a considerable share of the total economic loss at 73%. It is noteworthy that Agriculture and Technological service sectors have been both listed on all of the three economic loss rankings, indicating the sensitivity of these two sectors towards heat-induced final demand shrink from the perspectives of backward linkages. In disaster preparation and adaption for future disaster events in Shanghai, the local government should take particular cautiousness in protecting these ‘key’ sectors in order to prevent further economic loss.

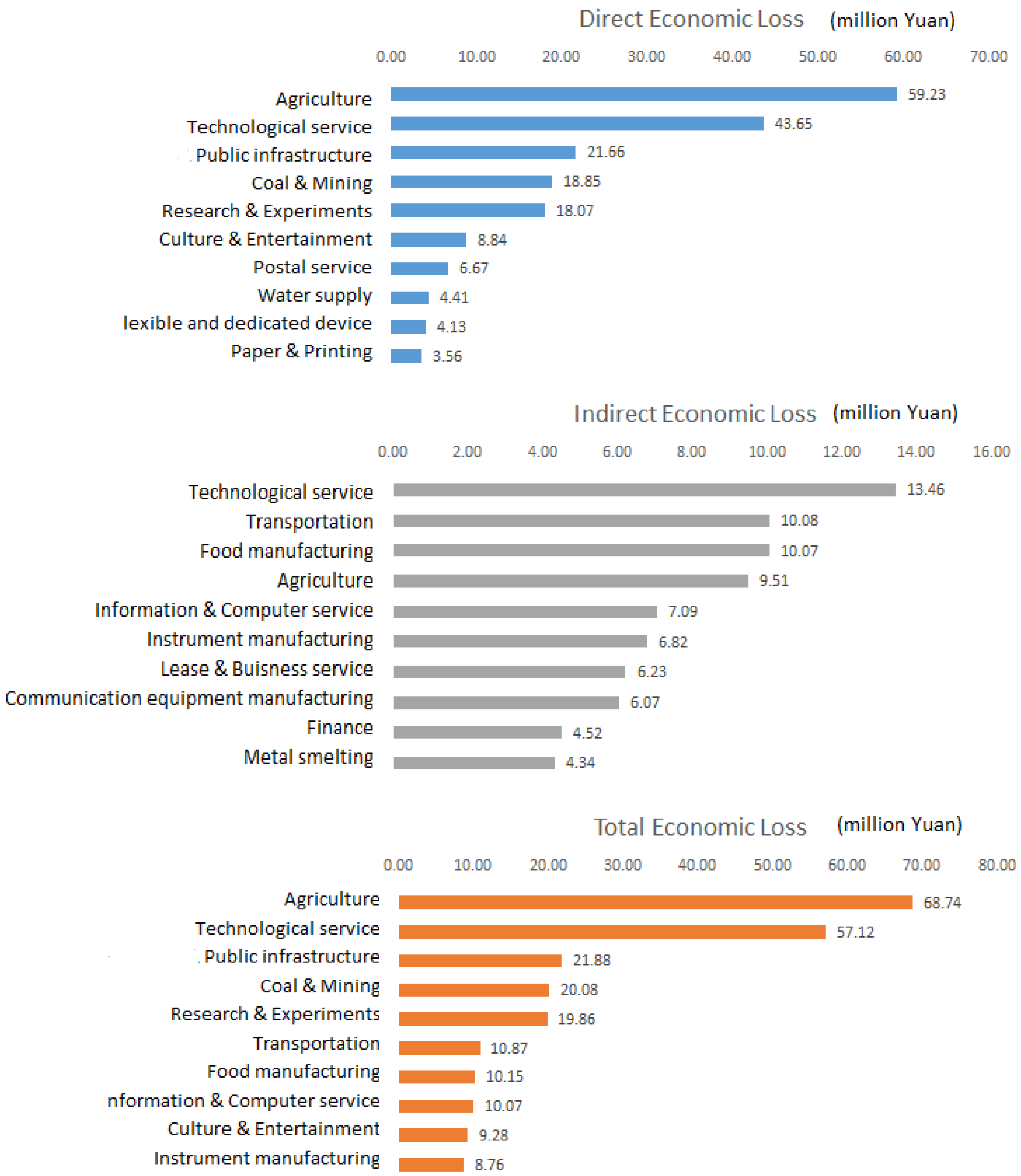

Figure7.9 Top 10 sectors suffering the greatest direct, indirect and total economic loss

Figure 7.9 presents the top ten sectors that were most severely hit in terms of direct, indirect and total economic loss due to heat wave in Shanghai, 2007. Agriculture and Technological service sectors have been both listed on all of the three economic loss rankings.

As the tertiary sector accounted for the majority of total economic loss, the following analysis compares direct and indirect economic loss with a specific emphasis on the tertiary sector. *Figure 7.10* shows the direct and indirect economic loss for all service sectors. The x axes stands for the indirect economic loss while the y axes is the direct economic loss and both are measured in million Yuan. The size of each circle differentiates the total economic loss of these sectors. It can be observed that the direct and indirect combinations vary across sectors with the largest gap between direct and indirect economic loss for Public infrastructure and Education sectors, where direct economic loss both occupy 99% of the total economic loss. On the contrary, the indirect economic loss entailed by Finance and Wholesale and Retailing sectors significantly outweigh the direct economic loss, accounting for 92% and 83% of their total economic loss, respectively. Such direct and indirect impact analysis appears to be meaningful to identify sectors suffering more direct economic loss and those encountering greater indirect economic loss. In disaster preparation schemes, particular key sector protection strategies should be designed and implemented in order to prevent degradation in final demand of those sectors suffering direct loss while prevent cascading indirect loss resulting from the tightened inter-industrial backward linkages of those largely entailing indirect loss.

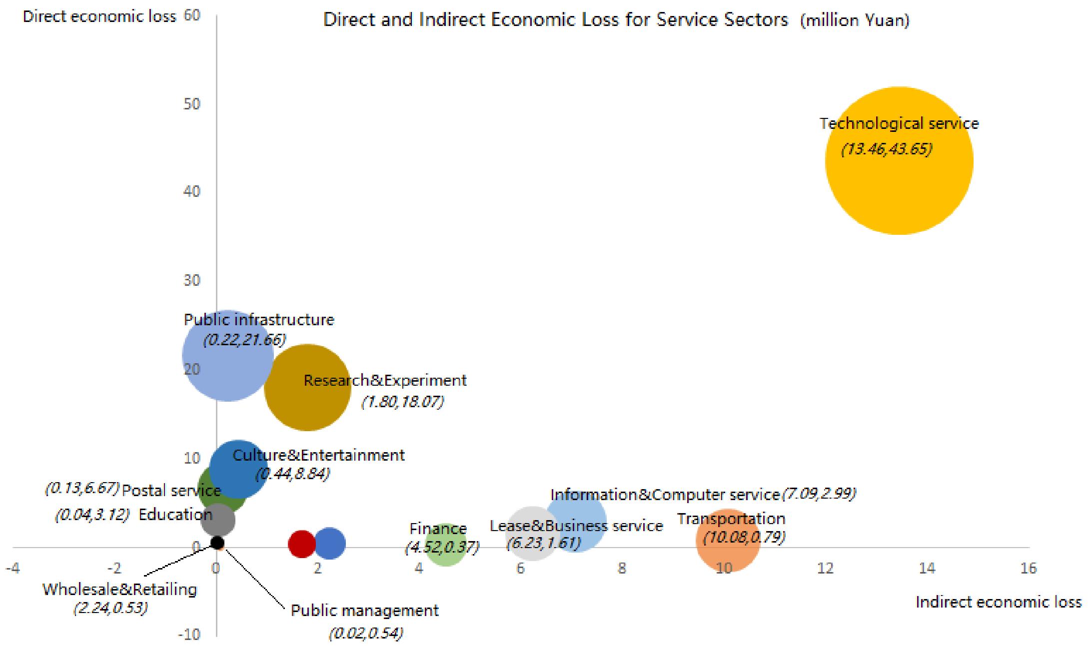

Figure7.10 Direct and indirect economic loss for service sectors

Figure 7.10 shows the direct and indirect economic loss for all service sectors. The x axes stands for the indirect economic loss while the y axes is the direct economic loss and both are measured in million Yuan. The size of each circle differentiates the total economic loss of these sectors.

7.2.4 Policy Implications, Conclusions and Uncertainties

Under the background of climate change, the globe has been affected by extreme heat and summer heat more frequently. Examples are the heat waves in Europe during 2013, which resulted in over 20 thousands deaths. The South China is also suffered from heat waves. However, the heat protection infrastructure and mechanisms in the developing countries are generally less developed compared with those in the developed world that exacerbate the vulnerability of populations in developing countries during heat waves. The relationships between extreme heat and the relative risks of mortality and morbidity due to several diseases have been well documented in existing epidemic studies with a particular focus on respiratory and cardiovascular diseases. Altogether, the increasing frequency and intensity of heat waves have inspired studies on revealing the heat-health-economy nexus in a number of developing countries. Unfortunately, established methods in health cost assessment studies mostly ignore the possible cascading economic impacts resulting from industrial and regional interdependencies at a macroeconomic level. To reflect the macroeconomic impacts of a heat wave event on the economic system more comprehensively, the above study has linked meteorological, epidemiological and economic studies to build up an interdisciplinary framework based on a demand-driven input-output model that is able to incorporate heat waves and the resulting health impacts into disaster risk analysis and simultaneously, capture the industrial and regional interdependencies. The developed approach was applied on a real heat wave case happened in Shanghai during 2007. Compared with a supply-driven input-output model, the demand-driven model considered heat-induced health impacts as an indicator for both reducing labour wage and extra health-care expenditure by households and government that both constrained the final demand. Using the demand-driven input-output model allows to trace the shrinking final demand backwards along the industrial backward linkages so that the induced cascading indirect economic loss can be effectively evaluated. The study results unfold that the ten days' heat wave has resulted in a total economic loss at

323.71 million Yuan in Shanghai during 2007 with 845 thousands affected labourers in terms of health impacts. Almost half of the economic loss came from the tertiary sectors at 157.35 million Yuan. On the one hand, focusing on sectors, Agriculture sector suffered the greatest direct economic loss at 59.23 million Yuan in terms of value reduced in sectoral final demand, followed by Technological service sector and Public infrastructure sector at 43.65 and 21.66 million Yuan, respectively. They are also the three sectors that encountered the greatest total economic loss. Meanwhile, Technological service sector become the one entailing the greatest loss at 13.46 million Yuan, followed by Transportation and Food manufacturing sectors that suffered a loss of 10.08 and 10.07 million Yuan, respectively. Agriculture and Technological service sectors both ranked among the top ten sectors entailing the greatest direct, indirect and total economic loss that underlines their needs to be protected in disaster protection and preparation schemes. On the other hand, focusing on the sectors from the tertiary industry, sectors like Education and Public infrastructure and Education sectors, direct economic loss both occupy 99% of the total economic loss. On the contrary, the indirect economic loss entailed by Finance and Wholesale and Retailing sectors significantly outweigh the direct economic loss, accounting for 92% and 83% of their total economic loss, respectively. The direct-indirect combinations in sectoral total economic loss show heterogeneity across sectors, which provide local government in Shanghai insightful implications regarding key area protection for these critical sectors.

The study is subject to uncertainties to certain degrees, which mostly are surrounding data unavailability issue. Firstly, in calculating the productive working time loss from various health endpoints, the study made assumption on required time for each outpatient visit due to a lack of systematic statistics on outpatient visits. The assumption was made in line with several characteristics embodied in current Chinese medical system in which no pre-booking or follow-up services are available. Secondly, heat-induced mortality and morbidity counts into industries were assigned to industries according to industry-total employment due to a lack of occupational heat-induced disease incidence rates in China. Provided with more comprehensive dataset, the model results will be more accurate by better reflecting the real situation where some workers working outdoors may be more directly exposed to heat and thus, tend to have higher disease incidence rates than those who work indoors with better cooling systems. Thirdly, no compensatory behaviour was considered in estimating the labour time loss from various health endpoints. This is also consistent with the fact that no extra pay will be made for overtime work in China. Moreover, the costs required for each case of admissions and outpatient visits were an average because the study did not tend to differentiate case by case and the estimation was based on an averaged situation. Furthermore, in predicting the consumption behavioural changes for households and government, due to the lack of relevant data, assumptions were made based on their final demand data shown in the 2007 Shanghai input-output table. Lastly, no macroeconomic variables, such as the price elasticity of demand, inflation or market deficiency was considered in the current study as a basic Leontief input-output model describes an economy in equilibrium.

7.2.5 Sensitivity Analysis

This section shows a sensitivity analysis for the case study on Shanghai heat wave during 2007 to test the impacts of alternative data or assumptions on the model results by considering different time required for each cardiovascular hospital admission, different time required for each outpatient visit and same proportional shrinks among commodities in the face of reducing wage and extra health expenditure regardless the initial consumption/investment patterns of households and the government.

7.2.5.1 Time Required for Each Cardiovascular Hospital Admission

The variation range of model results was tested when each cardiovascular admission takes 30, 60 and 90 working days. The results for these alternatives required time can be observed from *Table 7.6*. The variation range of the results is small with rising time required for each cardiovascular hospital admission.

Table7.6 Varying Working Day Lost for Each Cardiovascular Admission

Sensitivity Analysis - cardiovascular hospital admission time	
Number of working days lost	Output Loss (millionYuan)
30	324.58
60	326.03
90	327.47

7.2.5.2 Time Required for Each Outpatient Visit

4 hours assumption also holds for the case study as a result of the lack of data on the required time for each outpatient visit in China. Therefore, the impacts on the modelling results will be tested using different time required for each outpatient visit, 2, 6 and 8 hours. The results are shown in *Table 7.7*. With the increasing time required for each outpatient visit, the total output loss rise from 273.86 million Yuan at 2 hours' loss per outpatient visit, to 424.69 million Yuan at 8 hour' loss per outpatient visit, suggesting that the total economic loss is relatively sensitive to timed required for each outpatient visit, which might be resulting from relatively large counts of heat-induced outpatients.

Table7.7 Varying Time Required for Each Outpatient Visit

Sensitivity Analysis - time required for each outpatient visit (hour)	
Hours Lost	Output Loss (millionYuan)
2	273.86
6	373.98
8	424.69

7.2.5.3 Same Proportional Shrinks among Commodities

An important assumption in the study is the shrinks among commodities are disproportional and largely depend on the original consumption or investment patterns of households and the local government. Therefore, I tested the total economic loss resulting from an alternative way of shrink, which implies same proportional reductions across all industrial commodities despite of the initial consumption or investment pattern. With the same proportional shrinks, the total economic loss along the demand side of the economy in Shanghai becomes 340.24 million Yuan, which tends to be similar with the results shown in the case study.

Chapter 8: Conclusions and Achievements

By focusing on one of the global threats, natural disasters, this thesis comprehends existing modeling tools and explores new opportunities for quantitative research on disaster risk analysis by proposing an interdisciplinary methodological framework – *Disaster Footprint Framework* – that bridges environmental/meteorological, epidemiological and macroeconomic studies to access the cascading indirect economic loss resulting from industrial and regional interdependencies along economic production chains. The developed approach respects distinctive characteristics of natural disasters by differentiating 'persistent' natural disasters from 'rapid-onset' ones with regards to the different impacts on physical and human capital. On the one hand, the approach provides alternative ways to evaluate the total economic loss for a special case of 'rapid-onset' disaster where existing disaster modelling tools lose efficacy due to the damages to 'soft' services without substitution possibilities. On the other hand, the approach explores new opportunities to reveal the disaster-health-macroeconomic implications nexus for 'persistent' natural disasters. The macroeconomic part of the interdisciplinary framework is built on input-output techniques, which not only enables to capture industrial and regional interdependencies but also allows one to incorporate labour constraints as a result of disaster-induced health impacts. This chapter firstly recapitulates the cases studies in Chapter 5, 6 and 7, followed by an overview of overall methodological contribution of this PhD thesis to both health costs studies and disaster risk analysis. The chapter ends with presenting the limitations surrounding the proposed methodological framework and case studies, which on the other hand, illume research directions for future studies.

Finally, the thesis arrives at several vital remarks from the case studies. Firstly, disaster risk studies should attach equal significance to loss in capital productivity and labour productivity. Then, air pollution and heat waves should be perceived analogously as a natural disaster that affects human capital more than physical capital and thus, they should be investigated more deeply in disaster risk studies. In addition, disaster risk modelling should be conducted with additional attention on disaster characteristics. Moreover, 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. In this respect, the input-output techniques and its modified forms are able to provide more modelling options for disaster risk assessment and management. Further, the developed interdisciplinary approach can successfully bridge environmental or meteorological studies, epidemiological studies and macroeconomic analysis. It also allows to consider the distinctive feathers of natural disasters, to understand and incorporate the health impacts through an angel of reducing labour availability and productive time, and to capture the cascading indirect economic loss triggered by industrial and regional interdependencies. Last but not least, the estimation based on such interdisciplinary model can be more accurate and effective once more comprehensive and sophisticated datasets become available, such as those on the occupational disease incidence rates and required time for each outpatient visit.

8.1 Concluding Remarks on Case Studies

In the background of climate change, the increasing frequency and intensity of natural disasters have put the globe and the world population in danger by resulting in substantial damages to physical infrastructure and numerous deaths and injuries. These natural disasters can take different forms, either 'rapid-onset' with terrifying destructive impacts to the society and without any warnings in advance, or 'persistent' with considerable 'invisible' health effects that persist over time. As capital and labour are two principle factor inputs during economic production, the damages to either of them can impede economic activities and functioning. It is until recently that the tricks in potential post-disaster imbalances between remaining capital and labour production capacity have drawn more attention by disaster risk studies with particular focuses on cascading indirect economic impacts from interconnecting economic sectors and post-disaster economic reconstruction process. However, existing disaster risk modelling tends to attach greater weights to the evaluation of capital production capacity based on accurate quantification of physical capital damages resulting from 'rapid-onset' disasters, such as floods, earthquakes and hurricanes. To quantify the intangible health impacts from persistent environmental or meteorological phenomenon where minimal physical capital loss can be observed exert great challenges for existing disaster risk assessment and management. Indeed, even for 'rapid-onset' disasters, the tangible capital damages do not necessarily occur as a result of wide variety in disaster time length and resulting impacts on infrastructures and humans. On the other hand, early health studies on 'persistent' environmental phenomenon, such as air pollution and heat waves, generally conclude with specific health endpoints in epidemiological analysis, or microeconomic implications in studies on health costs assessment. Both of them stem from the perspectives of patients and thus, cannot fully reflect the potential health impacts on an entire economic system at a macroeconomic level. Due to difference in scope, a distinctive instructional method should be provided to serve as a scientific tool for assessing the total economic impacts of health endpoints on a national economy.

Focusing on a special case of urban floods in York during the Christmas period in 2015, Chapter 5, by applying an HEM that was widely utilized in linkage analysis, indicates that a three-day complete shutdown of IT services can induce a £3.24m loss in York, which is equivalent with 1% of the monthly GVA of York city, where almost half of the total economic loss at £1.41m are entailed by other sectors excluding the IT service sector itself as a result of sectoral interdependencies. The case study proves with solid evidence that the HEM is an effective method that can be equally applied on disaster risk analysis, especially for such situations that no specific physical capital damages can be detected but certain ‘soft’ services are completely ceased due to the disaster event. Turning to a ‘persistent’ natural disaster, Chapter 6 examines the total economic loss resulting from China’s $PM_{2.5}$ pollution in 2012 that amounts at 398.23 billion Yuan with substantial health impacts on 82.19 million Chinese labourers, where nearly two thirds of the total loss can be attributed to indirect economic loss resulting from industrial and regional interdependencies. The results highlight the significance of capturing indirect cascading economic impacts in disaster risk assessment. Alongside, the case study approves that a supply-driven input-output model provides a chance to integrate disaster-induced health effects into macroeconomic analysis by perceiving labour as a key primary input during industrial production, degrading health status as an indicator for productive time loss, and productive time loss as a sign for reducing industrial value added. With the same focus on ‘persistent’ disasters, Chapter 7 conducts two case studies to estimate the economic loss from a different type of ‘persistent’ disaster – heat waves – in Nanjing 2013 and Shanghai 2007 by using a supply-driven input-output model and a demand-driven input-output model, respectively. For the Nanjing heat wave case, the study examines the economic loss from both heat-induced clinical health impacts and sub-clinical impacts in terms of productivity loss due to mental distractions and capacity limits constrained by occupational safety standards. Both effects can result in substantial labour time loss, which again, are viewed as indicators for reductions in value added and fed back into a supply-driven model. Results show that the 14 days’ heat wave caused a totality of 27.49 billion Yuan loss for Nanjing in 2013, which is equivalent to 3.43% of the city’s gross value of production in 2013. Health impacts, productivity loss and capacity constraints can considerably reduce productive working time by an overall 2.50%. In the case study on Shanghai heat wave, health impacts and extra required expenditure on medical services are perceived as a sign for reducing labour wage and shrinking consumption on other commodities because of the crowd-out effect from extra medical expenses. Both of them can further induce a shrink in final demand, which are fed into a demand-driven model to evaluate the propagating economic loss along industrial backward linkages from the initial shrinks in final demand. Results suggest that the 10 days' heat wave has affected almost 17% of total labourers in Shanghai by inducing excessive mortality, hospital admissions and outpatient visits. These health impacts can be translated into a 0.035% reduction in the productive labour year in Shanghai during 2007. Direct economic loss in terms of initial reductions in final demand is evaluated at 227.17 million Yuan, which are further triggered by industrial interdependencies that raised the total economic loss to 323.71 million. By following a demand-driven input-output model, the case study illumes an alternative way to understand and measure the macroeconomic loss from disaster-induced health impacts through a lens of shrinking final demand.

8.2 Research Contributions

This PhD thesis constructs a *Disaster Footprint Methodological Framework* based on input-output techniques to investigate and incorporate the resulting damages to physical capital and health impacts, output loss caused by the reductions in capital and labour productivity, as well as their cascading macroeconomic impacts along economic production chains resulting from sectoral and regional interdependencies into disaster risk assessment. By linking up environmental or meteorological study, epidemiological study and macroeconomic analysis, the proposed approach not only allows one to feed the disaster-induced damages to physical capital and human health into a macroeconomic model so that the cascading economic loss along the production chains can be assessed, but also enables to accommodate according to the distinctive characteristics of either 'rapid-onset' (eg. Floods) or 'persistent' natural disasters (eg. Air pollution, heat waves) in the real cases that occurred worldwide at different points in time. Main methodological achievements are summerized as follows:

1. The Concept of *Disaster Footprint*

The developed methodological framework introduces a new concept of '*disaster footprint*' to denote total economic loss resulting from a disaster event. This includes the initial reduction in supply of industrial primary inputs or industrial final demand as a result of disaster-induced loss in capital and labour productivity; and the cascading indirect economic loss resulting from sectoral and regional interdependencies. The economic loss is measured by total reductions in aggregated production resulting from a natural disaster with a specific emphasis on the cascading indirect economic loss along economic production chains. The approach refers direct economic loss of a natural disaster as the physical damages to basic infrastructures, deaths and injuries, as well as the primary changes in industrial value added and final demand as a result of both capital and labour production capacity loss, and differentiates it from the indirect economic loss propagating along the economic production chains. The total economic loss therefore should incorporate not only the industrial initial reductions in both supply of primary inputs (value added) and final demand due to the loss in both capital and labour production capacity, but also the cascading indirect economic loss as a result of backward and forward linkages between interconnecting economic sectors within the economic system. In this respect, the proposed approach comprehends existing understanding of total economic impacts from a natural disaster by providing a new measurement as an instruction for disaster impact analysis.

2. Industrial and Regional Interdependencies in Health Costs Studies

Existing approaches in health costs assessment can provide useful microeconomic information about the potential monetary benefits of any reductions in health effects or the economic burden for healthcare sectors due to their standpoints of patients. Apart from a relatively aggressive indicator of labour salary used in HCA and limited applicability of CVA, especially in developing countries, a common problem for both approaches appears to the ignorance of important industrial and regional interdependencies. A national economy consists of a number of interconnecting economic agents. Production in a particular sector can affect other sectors in the economy through production supply and demand chains. This implies that changing production in a single sector can influence both sectors that provide its primary inputs and purchase its outputs as inputs during their production processes. In the face of globalization, such relationships between industries, sectors and regions have become unprecedentedly tightened, highlighting the significance of considering industrial and regional interdependencies in the assessment of disaster-induced macroeconomic impacts on national GDP. In this respect, the proposed interdisciplinary approach, by rooting in an input-output model, is able to evaluate the cascading indirect economic impacts on national economy as a result of these interdependencies. Specifically, the approach allows one to loop any health impacts and endpoints predicted by epidemiological studies into a macroeconomic input-output based framework by perceiving labour as a principle for economic activities and the diminishing labour time as a consequence of health impacts.

3. Health Impacts and '*Persistent*' Natural Disasters in Disaster Risk Studies

Despite that numbers of hybrid models have been developed in existing disaster risk studies, most of them largely depend on accurate quantification of industrial physical capital damages and the estimation of industrial loss in capital production capacity, which are normally the case for 'rapid-onset' natural disasters that arrive rapidly with few days or without warnings and whose destroying impacts is observable immediately after the disaster's occurrence (Development Workshop, 2017). However, exceptions always exist when a 'rapid-onset' disaster takes different forms with distinctive characteristics from in which there is little or even no damage to physical capital but serious interruptions of the local-provided 'soft' services. In such cases, the root of traditional disaster modelling frameworks that mainly rely on assessment of industrial physical capital damage will be shaken. Indeed, some natural disasters persist longer and take longer to realize their effects on the society and economy, regardless their substantial harms on human health, they are yet to be thoroughly investigated in disaster risk analysis because quantifying these 'invisible' effects is a challenge. Incorporating these health impacts on human is equally important because labour constraints and changing consumption behavior can equally deteriorate economic functioning. As a disaster may affect physical and human capital differently, there may exist disproportional shrinks between physical and labour production capacity, which both contribute to a shrinking total post-disaster production. Therefore, incorporating these impacts appears to be equally important for disaster risk assessment and management, as well as post-disaster recovery strategies to restore the balances. In this respect, the proposed interdisciplinary approach bridges environmental/meteorological, epidemiological and macroeconomic studies and provides several feasible ways to incorporate disaster-induced health impacts into economic impact assessment according to various disaster characteristics. Following this, the approach carried out in this thesis enriches current disaster risk analysis by enabling to incorporate epidemic studies into disaster impact analysis and economic interdependency analysis. Focusing on the health impacts, it considers not only the physical health endpoints in terms of disease-induced mortality and morbidity, but also the sub-clinical effects in terms of mental distractions and capacity constraints from a natural disaster that can equally degrade labour availability. Besides, the framework will be further applied onto selective empirical cases that are yet to be investigated in current disaster literature. The four chosen case studies include both ‘rapid-onset’ and ‘persistent’ natural disasters that occurred in the UK and China at different points in time to measure and contrast the cascading indirect economic impacts from different types of natural disasters. By doing so, the validity of the framework can be tested in real cases and future disaster risk studies can leapfrog to a more comprehensive risk assessment and management system with macroeconomic views. Meanwhile, by focusing the case studies in the UK and China, the research is expected to contribute to the disaster preparation and management in both developed and developing countries, especially for the developing world, where the disaster protection mechanisms appear to be less developed and population are thus more vulnerable.

8.3 Limitations and Direction for Future Research

Being an interdisciplinary approach that covers three divergent fields, assumptions and uncertainties turn to be inevitable for such brand new galaxy. Results in each case study from the results chapters (Chapter 5, 6 and 7) are subject to uncertainties and limitations to certain degree, which have been already discussed and tested through sensitivity analysis at the end of each case study in Chapter 5, 6 and 7. These limitations and uncertainties are mostly resulting from the data unavailability in which assumptions have to be made. The following firstly revisited broader sets of limitations and uncertainties relative to assumptions and results from sensitivity analysis. Secondly, it provides readers with ideas and speculations to further extend based on these uncertainties.

The first case on York floods during 2015 Christmas time utilized an original HEM approach with both backward and forward linkages of IT services being eliminated for three days. This is largely inspired by the unique characteristics of the York case where IT service sector being for a limited time and to a very large degree isolated from the rest of the economy and no substitutions are available because the services is provided locally. To apply the approach on other types of natural disaster thus requires researchers to be cautious in determining the exact percentages to be extracted from backward, forward or both linkages and even to differentiate internal and external linkages of a sector as suggested by Cella (1984). Besides, the study does not consider possible change in final demand by assuming that three days are too short to respond by households. In future research, such changes can happen when the disaster under investigation lasts longer enough for adaptive consumption behaviour. Moreover, due to the lack of exact daily data on household expenditure in York and the city-level input-output table, the exact value of sales during the three-day IT outages cannot be calculated while the city-level table is obtained using the Augmented Flegg Location Quotients (AFLQ) technique. Therefore, new research opportunities would emerge once more accurate data on daily household consumption or city-level input-output table become available.

The second case on China's air pollution during 2012 adopted a supply-driven input-output model by regarding labour time loss as an indicator for reduction in value added and thereby, looping the value added changes into the model. A supply-driven input-output model is frequently criticized as it neglects 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 in the case 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. It can be corrected by considering the model as a price model (Miller and Blair, 2009, p551). Besides, some major assumptions lie in the allocations of mortality and morbidity counts among industries and time required for each outpatient visit due to a lack of systematic data on occupational disease-specific incidence rates and average time for outpatient visit. As a result, the study referred to the US occupational disease incidence rates and made assumption on time required for each outpatient visit based on current status of Chinese medical system. A sensitivity analysis was also conducted to test the model results for alternative assumptions, which suggests that model results tend to be more sensitive to changes in outpatient visit time than the way to assign mortality and morbidity counts across industries. Therefore, researchers should be dedicated to developing a more comprehensive dataset regarding these information for China based on which the accuracy of model estimation can be further improved in future studies.

The third case on Nanjing heat wave in 2013 also employed a supply-driven input-output model. It also encounters uncertainties from the assumptions on percentage reduction in labour time due to heat effect on productivity; number of labour hours lost from capacity constraints; type of labour affected by productivity and capacity degradation; and no compensatory behaviour after recovery. Due to a lack of quantitative relationship between heat exposure and productivity loss as well as occupational exposure levels, the study made assumption based on Bux (2006) and the normal summer meteorological condition in Nanjing. Accuracy of model results can be further improved once such data become available for China because indoor and outdoor workers might encounter different heat exposures as a result of distinctive working environment. From the sensitivity analysis, study results tend to be more sensitive towards the extent of productivity loss than to the level of capacity loss. Thus, future studies on global heat waves should specifically focus 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.

The final case on heat wave in Shanghai during 2007 utilized a standard demand-driven input-output model in which potential impacts from heat-induced health effects on final demand was traced back along the demand-side of the economy. Although the model is good for analyzing an economy in equilibrium, it is subjects to uncertainties due to the lack of a comprehensive dataset, especially on occupational heat-induced disease incidence rates to distribute mortality and morbidity counts into industries and the consumption behavioural changes for households and government in estimating the disproportional shrinks among commodities in the face of reducing wage and extra medical expenditures. Besides, no macroeconomic variables, such as the price elasticity of demand, inflation or market deficiency were considered in the current study as a basic Leontief input-output model describes an economy in equilibrium. However, in this thesis, I have tried best to predict consumption behaviour changes from the original consumption/investment patterns of households and the government suggested in the final demand categories in the input-output model, which appears to be a relatively reliable estimation with current data availability. This, on the other hand, opens up new research avenue for future scholars in specifying industrial heat exposure, industrial disease incidence rates and more accurate track of post-disaster consumption patterns.

Meanwhile, there is other limitations surrounding the input-output model. Firstly, 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 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. Secondly, an input-output model 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. Additionally, 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.

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Appendices

Appendix A – 1 Observation on Heat Wave from Xuzhou Meteorological Station

Xuzhou **No. 58027**	Daily average temperature ℃	Daily max temperature ℃	Daily average temperature from 9am-9pm ℃
5 Aug 2013	31.5	35.4	33.9
6 Aug 2013	32.9	37.0	35.3
7 Aug 2013	33.6	37.6	35.7
8 Aug 2013	32.6	36.2	34.5
9 Aug 2013	32.1	36.5	34.8
10 Aug 2013	32.1	37.1	35.1
11 Aug 2013	34.4	38.3	36.8
12 Aug 2013	32.6	35.9	34.2
13 Aug 2013	32.9	37.6	35.1
14 Aug 2013	32.2	37.1	35.1
15 Aug 2013	33.6	38.3	36.1
16 Aug 2013	33.1	36.9	35.3
17 Aug 2013	33.2	38.2	35.6
18 Aug 2013	31.6	35.3	33.1

Appendix A – 2 Observation on Heat Wave from Nanjing Meteorological Station

Nanjing **No. 58238**	Daily average temperature ℃	Daily max temperature ℃	Daily average temperature from 9am-9pm ℃
23 July 2013	31.2	36.2	34.2
24 July 2013	32.5	36.9	34.9
25 July 2013	32.5	36.6	35.0
26 July 2013	32.3	37.3	35.1
27 July 2013	32.7	36.6	34.5

28 July 2013	32.3	36.2	34.5
29 July 2013	32.7	36.3	34.9
30 July 2013	33.2	37.2	35.7
31 July 2013	31.9	37.7	32.0
5 Aug 2013	32.0	35.5	34.4
6 Aug 2013	33.7	38.7	36.7
7 Aug 2013	33.9	39.0	37.2
8 Aug 2013	34.6	39.3	37.6
9 Aug 2013	34.6	39.1	37.2
10 Aug 2013	34.5	40.1	35.6
11 Aug 2013	33.7	39.8	37.0
12 Aug 2013	32.9	40.0	35.0
13 Aug 2013	32.2	38.3	35.5
14 Aug 2013	32.9	37.9	35.7
15 Aug 2013	32.4	37.2	34.3
16 Aug 2013	31.7	36.9	34.3
17 Aug 2013	32.3	38.3	35.5
18 Aug 2013	32.0	37.4	35.1

Appendix A – 3 Observation on Heat Wave from Dongtai Meteorological Station

Dongtai No. 58251	Daily average temperature ℃	Daily max temperature ℃	Daily average temperature from 9am-9pm ℃
5 Aug 2013	31.1	36.2	33.7
6 Aug 2013	32.9	36.9	35.2
7 Aug 2013	32.8	37.2	35.1
8 Aug 2013	33.3	37.2	35.6
9 Aug 2013	33.4	37.5	35.8
10 Aug 2013	32.8	36.3	34.0
11 Aug 2013	32.1	37.3	34.5
12 Aug 2013	31.5	36.5	34.1

13 Aug 2013	30.9	35.7	33.8
14 Aug 2013	31.5	36.3	34.2
15 Aug 2013	31.6	35.9	34.1
16 Aug 2013	30.7	35.4	33.5
17 Aug 2013	30.9	36.2	33.9
18 Aug 2013	30.3	35.6	32.8

Appendix A – 4 Observation on Heat Wave from Lyusi Meteorological Station

Lyusi No. 58265	Daily average temperature ℃	Daily max temperature ℃	Daily average temperature from 9am-9pm ℃
23 July 2013	32.7	37.0	35.3
24 July 2013	32.8	37.0	35.2
25 July 2013	33.3	37.8	34.7
26 July 2013	32.4	37.0	33.9
27 July 2013	32.0	36.1	33.7
28 July 2013	33.0	36.8	35.0
29 July 2013	33.3	37.5	35.3
30 July 2013	33.6	37.6	35.6
6 Aug 2013	33.0	38.6	35.7
7 Aug 2013	32.6	38.0	34.9
8 Aug 2013	33.3	38.1	35.5
9 Aug 2013	33.3	37.7	35.2
10 Aug 2013	32.1	37.6	34.4
11 Aug 2013	30.5	35.9	32.8
12 Aug 2013	30.3	35.8	32.3

(Data from Chinese Academy of Sciences, 2013)

Appendix B – Observed Excess Deaths from Respiratory and Cardiovascular Diseases during 2013 heat waves in 20 Chinese Cities

City name	Total excess deaths	**City name**	Total excess deaths
Shenyang	155	Hefei	333
Beijing	98	Chengdu	412
Tianjin	565	Wuhan	23
Yinchuan	35	Hangzhou	69
Taiyuan	6	Chongqing	379
Jinan	189	Ningbo	35
Zhengzhou	161	Changsha	444
Shanghai	531	Fuzhou	64
Xian	167	Guiyang	26
Nanjing	656	Kunming	26

(Data from China CDC, 2017)

Appendix C – Definitions for Terminologies

Natural disaster: any catastrophic event resulting from the natural processes of the earth, examples include floods, hurricanes, tornadoes, earthquakes, tsunamis and other geologic processes that only happened to populated areas. In this thesis, we also treat $PM_{2.5}$ air pollution as a natural disaster that could cause substantial damages to human health because it has been included in the Beijing Municipal Meteorological Disaster Prevention Statute as a ‘meteorological disaster’.

Rapid-onset disaster: natural disasters that arrive rapidly with few days or without warnings, such as floods and earthquakes.

Persistent disaster: natural disasters that persist longer and whose effects will be gradually realized over time.

Disaster footprint: Total economic loss resulting from a disaster event in terms of the total reduction in aggregated production. This includes the initial reduction in supply of industrial primary inputs or industrial final demand as a result of disaster-induced loss in capital and labour productivity; and the cascading indirect economic loss resulting from sectoral and regional interdependencies.

Direct economic loss: the primary and initial reduction in industrial value added or final demand due to capital and labour productivity loss.

Indirect economic loss: the secondary cascading economic loss resulting from industrial and regional interdependencies.

Backward linkages: the linkages between a sector and other sectors that supply inputs to it.

Forward linkages: the linkages between a sector and other sector that purchase output from it.

Upstream industries: sectors that sell outputs to a sector.

Downstream industries: sectors that purchase a sector’s output as input for their production processes.

Health endpoints: occurrence of a disease, symptom, sign or labouratory abnormality that constitutes one of the target outcomes of the trial.

Morbidity: disease-induced hospital admissions and outpatient visits.

Relative risk: the ratio of the probability of an event happening in an exposed group to the probability of the event happening in a non-exposed group.

Population attributable fraction: the proportional decrease in mortality or morbidity counts that will occur once exposure to a risk factor decreased to an alternative ideal exposure scenario.

Exposure-response relationship: changes in effect on an organism resulting from different levels of exposure to a risk factor after certain length of exposure time.

Appendix D – List of Underlying Assumptions

Case 1:

1. No possible change in final demand because three days are too short to respond by households;
2. Daily household final demand follows the averaged level instead of considering the excessive transaction volume during Christmas period;
3. Technical coefficients for the city of York are same with those for the Yorkshire and Humber region.

Case 2:

1. The allocation of mortality and morbidity counts among industries follows the US occupational disease incidence rates, that is 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%;
2. Each Chinese labourer works 8 hours a day and 250 days a year;
3. Each mortality will cause a whole working year loss, each cardiovascular admission will cause 11.9 working days' loss, each respiratory admission will cause 8.4 working days' loss and each outpatient visit will lead to 4 hours working day loss;
4. No replacement of sick labourers are available;
5. No compensatory working behaviour are considered;
6. No overproduction capacity are considered;
7. No change in price and technological status.
8. Labour time is a direct indicator for industrial value added.

Case 3:

1. Extreme heat during heat wave will cause a daily 12% reduction in labour time for indoor self-paced workers for the heat wave period;
2. Outworkers will require 45 minutes' relief time per hour of working time during heat wave period due to working safety regulations, and this is termed as work capacity loss;
3. Workers from Agriculture, Mining and Construction sectors are outdoor workers and affected by work capacity loss while workers from manufacturing and services sector are indoor workers and affected by work productivity loss due to mental distractions;
4. Each mortality will cause a whole working year loss, each cardiovascular admission will cause 11.9 working days' loss, each respiratory admission will

cause 8.4 working days' loss and each outpatient visit will lead to 4 hours working day loss;

5. Each Chinese labourer works 8 hours a day and 250 days a year;
6. No compensatory behaviour after recovery;
7. No overproduction capacity are considered;
8. No change in price and technological status;
9. Labour time is a direct indicator for industrial value added.

Case 4:

1. The allocation of mortality and morbidity counts among industries follows industrial labour proportions;
2. Consumption behavioural changes after shrinking wage and crowd-out effect are based on the original consumption patterns of households and government;
3. Each mortality will cause a whole working year loss, each cardiovascular admission will cause 11.9 working days' loss, each respiratory admission will cause 8.4 working days' loss and each outpatient visit will lead to 4 hours working day loss;
4. Each Chinese labourer works 8 hours a day and 250 days a year;
5. No compensatory behaviour after recovery;
6. No macroeconomic variables, such as the price elasticity of demand, inflation or market deficiency were considered
7. No overproduction capacity are considered;
8. No change in price and technological status.