Analysis of the embodied carbon emissions flows in China: applying a network perspective to sectors, provinces, and carbon communities within the Chinese economy

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Li Huang declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Institute for Sustainable Futures at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This thesis is the result of a Collaborative Doctoral Research Degree program with Shanghai University.

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THESIS FORMAT STATEMENT

This thesis takes the format of thesis by compilation. It is structured as a single manuscript that comprises a combination of three chapters and two published papers.

The paper *a systematic review of empirical methods for modelling sectoral carbon emissions in China* published in the *Journal of Cleaner Production* is directly used in Chapter 2 to provide a literature review of the research field.

The paper *carbon communities and hotspots for carbon emissions reduction in China* is published in the journal *Sustainablity* and is directly used in Chapter 3 for proposing a theoretical model and empirical analysis.

STATEMENT OF CONTRIBUTIONS TO THE PAPERS CONTAINED IN THE THESIS

Statement of Contributions to the Papers contained in this thesis

The following list summarizes Li Huang's particular contributions to the joint papers directly included in this thesis.

Paper	Li's Contribution
Huang, L., Kelly, S., Lv, K., & Giurco, D. (2019). A systematic review of empirical methods for modelling sectoral carbon emissions in China. *Journal of Cleaner Production*, *215*, 1382–1401. https://doi.org/10.3390/su11195508 This paper is directly used in Chapter 2.	Overall 90 %Conceptualization and formal analysis 95% Methodology 90% Data collection 100% Writing-original draft 100%
Huang, L., Kelly, S., Lu, X., Lv, K., Shi, X., & Giurco, D. (2019). Carbon communities and hotspots for carbon emissions reduction in China. *Sustainability*, *11*(19), 5508. https://doi.org/10.1016/j.jclepro.2019.01.058 This paper is directly used in Chapter 3.	Overall 90% Conceptualization and formal analysis 95% Methodology 85% Data collection 100% Writing-original draft 100%

Declaration

Li Huang's percent contributions to the above two papers have been endorsed by all the authors. Permission to include the papers into the thesis has also been granted by all the authors.

For the above two papers, Li Huang completed the original draft writing and analysis independently. Other authors contribute to the papers by having supervision or consultation meetings to improve the paper quality

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Scott Kelly	Production Note: Signature removed prior to publication.	Xunpeng Shi	Production Note: Signature removed prior to publication.
Damien Giurco	Production Note: Signature removed prior to publication.	Xuan Lu	Production Note: Signature removed prior to publication.

Two working paper arises from this thesis

Huang, L., Kelly, S., Lv, K., Xuan L., & Giurco, D. (2020). The structural roles of sectors and their contributions to carbon emissions in China: A complex network perspective.

Lu, X., Kelly, S.,**Huang, L.*** (2020). Evaluating Systemic Credit Risk in China Between the Banking Sector and the Real Economy. submitted

Abstract

With China's commitment to achieve peak emissions by 2030, emissions from different sectors of the economy are being examined. China's current carbon emissions mitigation research focus mainly on the two ends of the industrial supply chain: production and consumption. Most of the intermediate industries between these two ends are presently being overlooked. Research into the ways in which carbon emissions are transferred between sectors can provide a theoretical basis and evidence to identify the key industries and communities to achieve effective emissions mitigation.

This research combines input–output modelling and network analysis to track and examine the transfer of embodied carbon emissions between sectors and regions in China. It develops an embodied carbon emission transfer network model for such a task. In addition, empirical studies are conducted to examine the emissions transfer in China from 2007 to 2012. Network analysis is applied to clarify transmission pathways from macro, meso and micro perspectives. The role played by the structure of sectors and carbon communities are studied using a hierarchical linear model.

Network analysis metrics are used to prioritise which sectors to focus on to reduce future carbon emissions. Sectors with high out-degree, such as the electricity sector, and sectors with high in-degree, such as the construction sector, can act as a focal point for enhancing carbon emissions reduction performance. Sectors with high betweenness, such as the metallurgy sector, are shown to be hubs of the emission network, and can work as leverage points for cutting carbon-intensive inputs and hence reduce total carbon emissions along industrial supply chains.

The identification of carbon communities within which sectors engage in intensive carbon emissions exchange can help provincial governments make decisions about where they can collaborate to obtain synergistic outcomes in reducing carbon

emissions. Sectors within the same community, such as Shanghai-Zhejiang community, can strengthen their cooperation to achieve greater mitigation efficiency. Additionally, for communities which have comparatively low within-community carbon flows, such as Shanxi community, the focus should be on external connections outside the community.

'One community – one policy' is proposed for the carbon emissions mitigation work. A sector's emissions are affected both by its node level and community level structures. Therefore, to reduce the carbon emissions, the sector and its community should be considered together to achieve a synergy. In addition, the increasing size and density of carbon communities due to industrial agglomeration can have a restraining effect on the growth of sectoral carbon emissions.

Keywords: carbon emissions; industry; sector; complex network; input-output analysis; structural characteristics.

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Chapter 1 INTRODUCTION

1.1 Background

China produces more carbon emissions than any other country, and carbon emissions abatement in China has attracted worldwide attention. At the same time, China’s sustainable development is being challenged by the impacts of climate change. According to China's National Assessment Report on Climate Change (2007), the average temperature observed in China over the past 100 years has risen by between 0.5° C and 0.8° C, slightly higher than the global average. Since the 1950s, the sea level of the oceans around China has risen by between 1.4 to 3.2 mm each year, and the area of glaciers in the north-west of the country has decreased by 21%. Extreme weather events such as high temperatures, droughts, heavy rains and typhoons have become more frequent and intense. Since the beginning of this century, the direct economic losses caused by meteorological disasters have been equivalent to about 1% of GDP. This is eight times higher than the global average over the same period (Zheng, 2015). Under different representative global warming scenarios, the simulation results of various climate models show that the annual average temperature of China will continue to rise in different time periods in the future, and China's climate vulnerability to climate change impacts will remain unchanged.

China has been playing an active role in reducing greenhouse gas emissions and mitigating the trend in the future growth rate of emission. China's Thirteenth Five-Year Plan for Economic and Social Development (2016-2020) and its Five-Year Plan for Energy Development set specific climate and energy goals, showing China's determination to curb domestic carbon emissions growth. In June 2019, China reported on its policies and actions to address climate change to the Secretariat of the United Nations Framework Convention on Climate Change (UNFCCC). Between 2005 and 2016, China's carbon emissions per unit of GDP fell by 40.7%, and non-fossil energy accounted for 13.3% of total energy. Significant progress has been made in improving energy efficiency, optimising energy structure, controlling carbon emissions from non-energy activities, and increasing forest carbon sinks (Ministry of Ecology and Environment, 2019). However, even though emissions per unit of GDP have decreased, absolute emissions have continued to rise and in order to achieve the IPCC target of limiting warming to well below 2 degrees, net emissions from China would need to reduce to almost zero by 2050.

Despite this progress, there are still many challenges to efforts to achieve effective carbon emissions abatement. One of the main challenges comes from the invisible and complex transfer of embodied carbon emissions, which leads to complexity in the assessment of emissions reduction responsibilities. When the products of a sector are used by another sector, the carbon emissions produced by the first sector are transferred to the second sector in an embodied form. While the world economy and the domestic market in China have grown, the linear relationship between industries has been replaced by vertical, horizontal, and multi-lateral connections. Due to economic growth, the number of industrial connections and the quantities of goods flowing through these connections has been increasing year on year. While the sectors directly producing carbon emissions have control over their own carbon emissions, increasingly the sectors consuming the products of these sectors are being called upon to shoulder the responsibility for these emissions, because they indirectly induce them. For example, from a production perspective, the cement sector is a carbon-intensive industry. Because a large amount of cement is consumed by the construction sector, the construction sector is also deemed to be responsible for causing the emissions created in the production of concrete. Due to the intermingled supply chain relationship, it is difficult to fairly and reasonably identify the carbon emissions responsibilities of an industry or region, and this reduces the effectiveness of carbon emission reduction policies.

The production-based and consumption-based accounting methods are commonly used for identifying sectors’ responsibilities and advising solutions. Production-based accounting methods prioritise the sectors which directly produce emissions at source (Chen et al., 2016; Lin and Wang, 2015; Shan et al., 2018b; Xu et al., 2012). Policies relevant from a production perspective focus primarily on improvements to fossil fuel energy efficiency, clean energy development and substitution away from technologies with high greenhouse gas emissions. On the other hand, consumption-based accounting methods attribute all emissions in the supply chain to end-use sectors (Liu et al., 2015; Meng et al., 2011; Su and Ang, 2014; Zhang et al., 2015). Policies relevant to influencing final demand include increasing the awareness of green consumption among final consumers. In both approaches, emissions are either allocated completely to the sectors involved in production, or completely to end-use sectors. For example, in consumption-based accounting all emissions produced throughout the entire supply chain for a particular product are allocated to the final consumer of that product.

However, both the production perspective and the consumption perspective focus on the beginning and the end of the supply chain system, and there is a large number of sectors participating in the transmission of emissions that are presently overlooked. In other words, production or consumption based approaches are both addressing an accounting issue – which sector should be responsible and thus allocate the mitigation obligations. However, from an economy-wide perspective, all sectors are all responsible and contribute to the public good/bad. In order to mitigate emissions in an effective way, neither production nor consumption based approaches can provide a complete picture.

The transmission perspective, which focus on the various transfer sectors between the two ends, can offer new opportunities for policy development to reduce carbon emissions. The transmission perspective is starting to be acknowledged as an important area of investigation (Hanaka et al., 2017; Li et al., 2017; Liang et al., 2016). For example, a transmission perspective can identify the hub sectors which receive or spread emissions to other sectors in the economy. They can be targeted as new leverage points for effective emissions abatement. By looking into the details of the transmission process, all sectors can be put under the microscope. In addition, the complex connection and synergies identified in the transmission procedure can potentially help achieve higher mitigation efficiency. With relevant policy guidance, the transmission perspective is more likely to encourage the collective efforts of all the sectors in the economy on carbon emission mitigation.

1.2 Research aim and research questions

The overall research aim is to understand the characteristics of embodied carbon emissions transmission between sectors of provinces in China and provide policy suggestions for effective carbon emissions abatement. By identifying the transmission patterns and synergies among sectors of provinces in the procedure, the research aims to increase the efficiency of carbon emissions mitigation.

There are three subsidiary research questions:

1. How can embodied carbon emissions transmission between sectors in China be systematically examined?
2. Are there any patterns of transmission that can be found through this examination, and are there any leverage points for effective carbon emissions abatement? What are the policy insights for improving carbon emission abatement?

3. How do sectors' transmission-related characteristics influence emissions? How could policy better use these insights to achieve effective emissions mitigation?

1.3 Significance of the research

Research into embodied carbon emissions transmission in China is important for balancing and assigning the “common but differentiated” emission reduction responsibilities of various provinces across China. It can also play an important role in choosing and optimising regional coordinated development paths (Chai, 2015). Moreover, for the operation of the national carbon emissions trading scheme in China, this is also a foundational step in the allocation of the carbon quota(Chen Zhijian et al., 2018). Though the allocation of quota does not affect the overall economic efficiency of the ETS, the allocation does affect the distribution welfare across sectors and regions. The transmission research of the embodied carbon emissions can provide insight on the carbon quota allocation. Specific to our research, it can contribute in the following three areas.

First of all, it provides a model for systematically examining the characteristics of embodied carbon emissions transmission and identifying the complex connections, synergies and potentially real low-hanging fruits for efficient carbon emissions mitigation. Embodied carbon emissions are increasingly transmitted and accumulated in the processes of raw material extraction, production, transportation, intermediate production, packaging, and final consumption. Due to the complexity and variability involved, it is a very difficult task to evaluate the transmission process without a systematic approach. This research aims to carry out a systematic and multi-level analysis of the whole transmission process in sectors and provinces in China, and it aims to identify the key indicators and variables for such an examination.

Secondly, the research results can provide new policy suggestions for effective carbon emissions abatement at the national, provincial and sectoral levels. To ensure the sustainable development of China's economy and coordinated development among regions, and to achieve the emission reduction targets set by the central and provincial governments, it is important to: accurately grasp the spatial characteristics of emissions transfers between sectors of regions; analyse the economic spillover effect; and effectively guide the transfer of carbon emissions between regions to create a synergistic effect in China (Sun et al., 2014). For example, the research results can help identify carbon hotspots and clusters of sectors for carbon emissions reduction. In addition, because the research draws conclusions from the whole supply chain, policies can be effectively targeted to optimise the collective efforts of all the sectors.

Thirdly, the research model could be used to examine the transmission of other embodied pollutants, such as embodied atmospheric mercury emissions, at different geographical scales. To tackle global warming and promote environmental protection, efforts need to be made at different spatial resolutions including regional, country, and global perspectives. The model used in this study could be used in different geographical contexts to examine embodied pollutants transmission processes and identify the leverage points and areas for effective reduction.

1.4 Research method

1.4.1 Bibliometric analysis and knowledge mapping

Bibliometric analysis and knowledge mapping analysis were used to systematically review the papers published in the field of sectoral carbon emissions in China. Bibliometric analysis provides a quantitative analysis of the subject area, publication and citation trends. Knowledge mapping can be used to visualize the main research themes, as well as reveal the evolution of, and changes to, the frontier research areas as research is under development. The study provides a direct comparison of the main representative modelling methods, including their advantages and disadvantages, and the types of research problems they aim to solve. This analysis also explores the complementarity of various methods when they are used simultaneously to solve research problems. This study lays an important foundation for the rest of this research. It provides a comprehensive review of the literature as a basis for the selection of the research topic, the modelling methods used for the rest of the research, and the appropriate use of data and modelling variables. Moreover, the important policy-relevant areas that have significant knowledge gaps are also identified through the research.

1.4.2 The hybrid model incorporating input-output analysis and network analysis

The existing literature looking at China's carbon emissions transfers focuses mainly on either transmission between sectors at the national level or transmission between different regions. There is limited research that draws on the transmission pathways between sectors within different provinces, and which includes sectoral and geographical perspectives at the same time. The reason research is lacking in this area is mainly due to the complexity of the problem, which requires systematic analysis and substantial data processing capability.

With the development of complex network theory and the emergence of computing software with big data processing capacity, this research has become possible. Based on input-output data and complex network theory, system modelling can be used to track and examine the embodied carbon emissions between industrial sectors within regions. Input-output analysis theories and models can be used to describe the interdependence of various industries and regional economies in the Chinese economy.

Combined with complex network theory, the hybrid model can systematically examine the interdependence and interaction of carbon emissions transfer across industries and provinces. During the network modelling of the sectoral carbon emissions transfer process, network nodes represent the economic sectors in different provinces, and the edges between the nodes represent the amounts and directions of carbon emissions transferred between two sectors within a province or two provinces. Using this method, we can comprehensively and systematically model the fundamental characteristics of embodied sectoral carbon emissions transmission throughout the Chinese economy.

The interdependence and interaction of carbon emissions transfers between various industries within different provinces can be abstracted as structural characteristics of the embodied carbon emissions transfer network. Networks derived from reality often exhibit the characteristics of complex networks (Barabasi and Albert, 1999; Watts and Strogatz, 1998). For example, they are often small world, in which almost any pair of nodes can be reached within a small number of steps. Through the various metrics and algorithms of complex network analysis theory, the structural characteristics of the embodied carbon emissions network can be analysed from macro, meso and micro perspectives. These three perspectives emphasis the analysis of the transmission features of the entire industrial system, interactions between industrial groups, and interactions between sectors respectively. During the analysis, the statistical program R was used as the network construction and metrics calculation software. In addition, specialised software (Gephi and Ucinet) was used for complex network analysis to ensure the accuracy of system modelling and to provide visualisation.

1.4.3 Statistical analysis

Statistical models and analysis were used to explore the impact of carbon emission transfer network structure on sectoral carbon emissions. While a hybrid model incorporating input-output analysis and network analysis are used to analyse the static status of emissions transfer from a network structure perspective, statistical models were used to further study the network's influence on carbon emissions. In this process, by adopting a hierarchical linear model, we are able to consider, not only the effect of micro network structure (i.e. the sector of province node level), but also the meso structure (i.e. the communities of sectors). This attempt to capture the network structures at different hierarchical levels is a novel contribution of this research. Moreover, this empirical analysis also makes full use of China's interregional input-output analysis data and related data from statistical yearbooks in various related fields. To control for the ~~possibility of~~ missing data, this research used a variety of missing value processing methods to ensure the validity and reliability of the models developed.

1.5 Key terms

As this research is conducted in the context of China, some terms might not be readily accessible to readers. In addition, some terms may not have agreed definitions. Table 1.1 provides a summary of the key terms and their interpretation for easy reference, although all the terms are explained as they arise.

Table 1.1 Summary of key terms

Key terms	Interpretation
sector	This research aims to examine the embodied carbon emissions flows among the sectors of the whole Chinese national economy. In the officially published *Industrial Classification for National Economic Activities* in China, the whole economy is classified into 97 major industrial sectors. Due to data availability of sectors' carbon emissions and the multi-regional input-output table, the 97 major industrial sectors were merged into 30 major industrial sectors in this research. Therefore, the sector in this research means the one of the 30 major industrial sectors which together represent the whole Chinese national economy.
province	In the Chinese political geography system, provinces, autonomous regions, municipalities, special administrative regions make up the first level of political divisions. For ease of expression, autonomous regions, municipalities and special administrative regions are also taken as provinces in this research. In addition, China is divided into 23 provinces, 5 autonomous regions, 4 municipalities, and 2 special administrative regions. Together 30 provinces are included in the research, except for Tibet, Taiwan, Hong Kong and Macau due to data limitation.
sub-sector	The embodied carbon emission transmitted at sectors of provinces are examined in the thesis. For ease of expression, sub-sector is used to refer to a sector of a province in the thesis.
network analysis	Network analysis provides a set of metrics and algorithms derived from network theory to depict relations among actors in a network and analyse the structures emerge from the relations recurrence (Chiesi, 2001; Smiraglia, 2015).
carbon emissions transfer network	When the products of a sector are used by another sector, the carbon emissions produced by the first sector are transferred to the second sector in an embodied form. In order to examine the embodied carbon emissions flows between sectors within provinces in the whole economy, the embodied carbon emissions transfer process is modelled as an embodied carbon emissions transfer network.
node	In the embodied carbon emissions transfer network, a node represents a sector within a province in China.
edge	In the embodied carbon emissions transfer network, a directed edge between two nodes represent the amounts and directions of carbon emissions transferred between two sectors of the same province or two different provinces.
carbon community/cluster	Carbon cluster and carbon community have similar meaning, both of which refer a group of sectors where carbon emissions flows are much more intensive within the group than outside. These two terms are

Key terms	Interpretation
	interchangeable. In addition, community is more frequently used in network analysis, while cluster is used more frequently in input-output analysis.
community detection	A community in the network is defined as a group of nodes such that those within a group interact with each other more frequently than with those outside the group. Community detection is the process of discovering those cohesive groups in the network applying methodologies from numerous forms of sciences based on the measurement of similarity or distance.
production-based accounting method**s**	The production-based accounting methods calculate the amount of carbon emissions directly produced by each sector.
consumption-based accounting methods	The consumption-based accounting methods attribute all emissions embodied in the supply chain to the end-use sectors.
carbon emission intensity	carbon emission intensity refers to each sector's direct production based carbon emission per monetary unit of its total output
emission trading scheme (ETS)	The emission trading scheme (ETS) is a regulatory tool that is aimed at reducing greenhouse gas emissions (i.e. carbon dioxide) cost-effectively and at the same time minimizing the cost of compliance for the industry. ETS is a market in which the traded commodity is particulate matter emissions.
bibliometric analysis	The bibliometric analysis provides a quantitative analysis of the subject area, publication, and citation trends. It is the key method to be informed of the development of research themes.
knowledge mapping	Knowledge mapping can be used to visualize the main research themes, as well as reveal the evolution of, and changes to, the frontier research areas as research is under development.
CiteSpace	CiteSpace is a popular choice for conducting knowledge mapping. It is developed based on bibliometric analysis, data mining algorithms and visualization methods.
multi-region input-output (MRIO) table	MRIO table is widely used to analyse the economic interdependence among sectors of regions in an economy. In these models, the relationships between sectors in an economy are represented by technical coefficient matrix A, reflecting the direct input requirements of sectors' outputs from other sectors. Consequently, the Leontief inverse matrix $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$ reflects the direct and indirect input requirements of sector's outputs from other sectors.

Key terms	Interpretation
environmentally extended input-output model	The environmentally extended input-output model is extended from the standardized input-output analysis by integrating “environmental-related” information from physical accounting, such as emissions, primary (natural) resource use, land use, energy or material use, or pollution. Environmentally extended input-output model tables bring together economic and environmental data in a consistent, related sectoral framework.
backbone of the network	The backbone of the network is the most important connections in a weighted network after removing the noise or redundant links/connections. The extraction of the backbone of the network can be divided into three main categories: coarse-graining, filtering/pruning and statistical models (as used in this paper).
backbone detection algorithm	The backbone detection algorithm is the algorithm used to detect the backbone of the weighted network. The most frequently used ones are (1) the application of a global threshold, (2) minimum/maximum spanning tree, (3) the method using a global null model preserving both the network topology and the weight distribution of the system.
modularity	Modularity in network theory is the measurement describing the strength of the division of a network into communities. It is used as the object to be maximized in optimization methods for detecting communities. The higher the modularity is, the denser connections between the nodes within the community are and sparser connections between nodes in other communities.
degree centrality	In network theory, the degree of a node of a network is the number of edges that are incident to the node. Degree centrality assigns an importance ranking based simply on the number of links held by each node.
strength centrality	In network theory, the strength of a node of a network is the sum of the weights of all the edges linked to the node. Strength centrality assigns an importance ranking based on the summed weights held by each node.
betweenness centrality	In network theory, the betweenness of a node is defined as the amount of information (which is simply proportional to the number of shortest paths) passing through this node. It measures the influence a node has over the spread of information through the network. Betweenness centrality assigns an importance ranking based on the betweenness of each node.
IPCC Sectoral Approach	IPCC sectoral approach is a systematic framework and practical guidance suggested by IPCC to produce an accurate estimate of CO2 emissions from fuel combustion. It is published in “IPCC Guidelines for national greenhouse gas inventories (Institute for Global Environmental Strategies (IGES), 2006)”.

Key terms	Interpretation
hierarchical linear model	The hierarchical linear model (HLM) or multilevel linear model is a regression-based model that considers the hierarchical structure of the data. Hierarchically structured data is the data where groups of units are clustered together in an organized fashion. The classic I.I.D. assumption of data, which is independent and identically distributed, is violated because the communities or clusters of observations are not independent of each other. HLM models estimate the coefficient on each level of the model specified. The number of levels in HLM can be two or more.
intraclass correlation (ICC)	In the hierarchical linear model, the intraclass correlation is the measurement of the proportion of variation in the outcome variable that occurs between groups versus the total variation present. It ranges from 0 (no variance among clusters) to 1 (variance among clusters but no within-cluster variance). The higher the ICC is, the more necessary and valid the application of the hierarchical linear model is.

1.6 Organisation of the thesis

The thesis, including publications, is structured into five chapters that address gaps in theory and research on sectoral carbon emissions mitigation in China (Figure 1.1). Two of the five chapters have been accepted in peer reviewed climate change and sustainability journals. These two self-contained journal articles have been incorporated as Chapters 2 and 3 of this thesis. While Chapter 2 is a literature review paper, Chapter 3 constructs the network model of embodied sectoral carbon emission transmission and conducts an empirical study of emissions transmission among 30 sectors within 30 provinces in China in 2012. Chapter 4 follows the traditional thesis style and studies the influence of transmission network structure on sectors' emissions based on three years' data for China in 2007, 2010 and 2012. Chapter 5 includes a final discussion of the research results and concludes with policy suggestions and suggestions for future research.

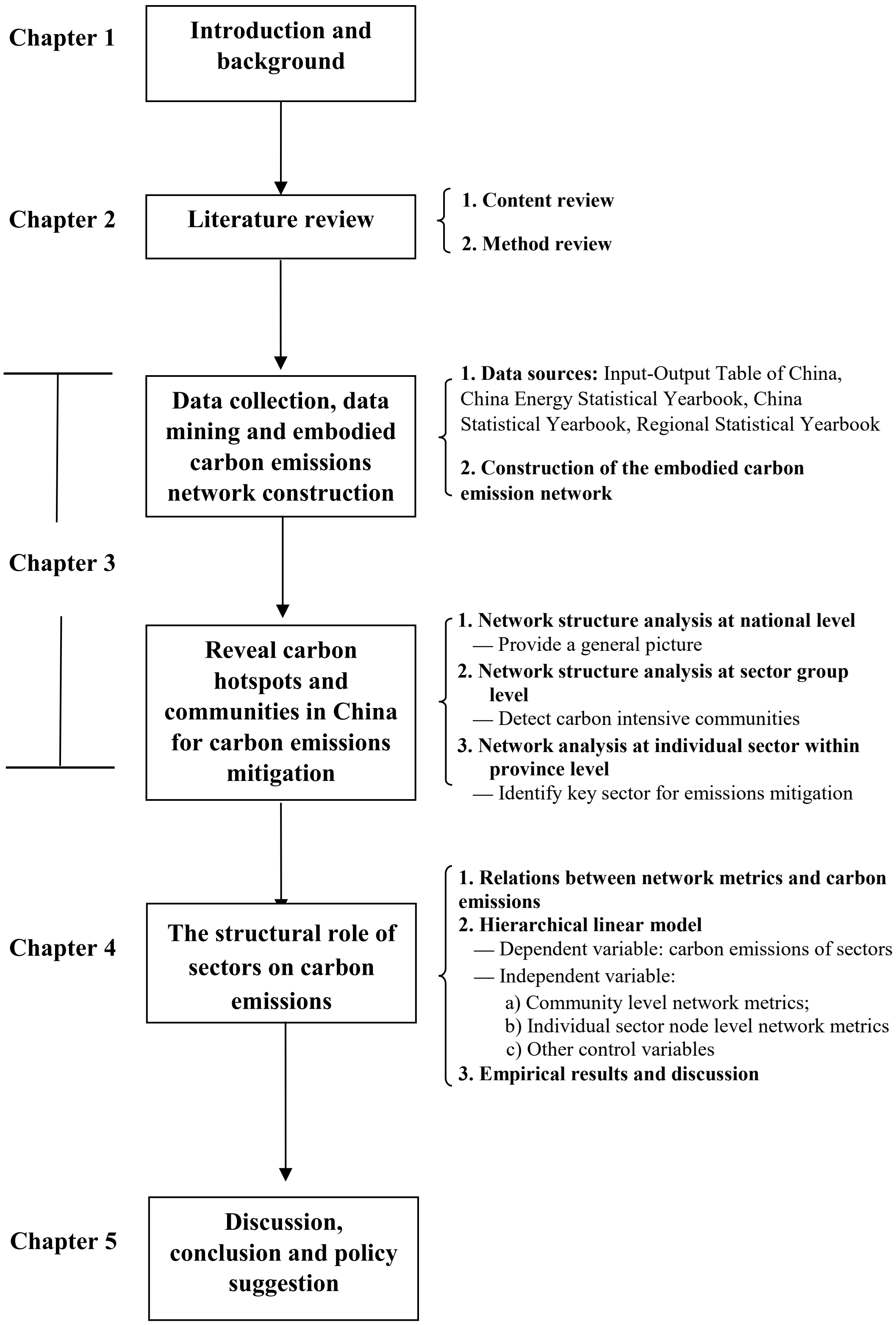

Figure 1.1 Outline of thesis

Chapter 2 provides a systematic literature review of China's sectoral carbon emissions research. This research field has been very active since 2015, with hundreds of peer-reviewed papers published every year. While the research has been approached from distinct perspectives, a number of modelling methods have also been used or developed for different research purposes. In this chapter, on the basis of the 807 SSCI and SCIE indexed papers published from 1997 to 2017, bibliometric analysis and knowledge mapping were used to visualise the research topics and development paths in the field. In addition, the review has identified the families of methods that are commonly used to develop models, and their advantages and disadvantages are compared directly. This chapter develops the foundation and methods used for the rest of the research.

Chapter 3 constructs the backbone transmission network of embodied sectoral carbon emissions in China and adopts network analysis metrics to identify the hotspots and communities in the network. This research combines input–output modelling and network analysis to track the embodied carbon emissions among thirty sectors of the thirty provinces in China in 2012. On the basis of the network, network centrality metrics and community detection algorithms are used to assess each individual sectors' roles, and to reveal the carbon communities. Detailed analyses are conducted at both the sector and community levels to formulate targeted policy suggestions for local and central governments.

Chapter 4 is structured as a traditional thesis chapter and analyses the effect of the carbon emission network structure on each sector's emissions. While the performance of a network is determined by its structure, each sector's carbon emissions are also influenced by the structure of the embodied carbon emissions network. By applying a hierarchical linear model, this study is able to consider, not only the effect of network structure at the node and community levels, but also the interactive effects of the two levels on each other. Based on three years of data from China, the empirical study quantitatively examines the network structure's effect at the sector, province and community levels.

Chapter 5 synthesises previous chapters on findings, conclusion and policy suggestion, discusses the contribution made by the research, and concludes with suggestion for future research.

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Chapter 2 LITERATURE REVIEW

Preface

The text for this chapter is reproduced from paper *a systematic review of empirical methods for modelling sectoral carbon emissions in China*, published in Journal of Cleaner Production. The purpose of this thesis is to contribute to mitigating sectoral carbon emissions in China. To achieve this, it is necessary to have a clear picture of the progress in this field of research before moving on to specific thesis research questions. However, due to the rapid growth of the literature and the diverse modelling methods adopted in the field, as well as the lack of existing literature review papers, it was very challenging to conduct a comprehensive literature review. For example, 807 papers in more than 12 research fields were published in SSCI- and SCIE-indexed journals from 1997 to 2017. This chapter fills a research gap by providing a comprehensive review of progress in the field of modelling carbon emissions in China. The review critiques different research methods and provides a summary of the strengths and weaknesses of these methods for answering different types of research questions. This chapter also discusses the emerging trends on the use of different research methods. The results of this literature review can help scholars quickly identify and compare different methods for addressing specific research problems. This review lays the foundations for investigating the research questions for this thesis.

A systematic review of empirical methods for modelling sectoral carbon emissions in China

Abstract

A number of empirical methods have been developed to study China's sectoral carbon emissions (CSCE). Measuring these emissions is important for climate change mitigation. While several articles have reviewed specific methods, few attempts conduct a systematic analysis of all the major research methods. In total 807 papers were published on CSCE research between 1997 and 2017. The primary source of literature for this analysis was taken from the Web of Science database. Based on a bibliometric analysis using knowledge mapping with the software CiteSpace, the review identified five common families of methods: 1) environmentally extended input-output analysis (EE-IOA), 2) index decomposition analysis (IDA), 3) econometrics, 4) carbon emission control efficiency evaluation and 5) simulation. The research revealed the main trends in each family of methods and has visualized this research into ten research clusters. In addition, the paper provides a direct comparison of all methods. The research results can help scholars quickly identify and compare different methods for addressing specific research questions.

Keywords: climate change; carbon emissions; China; knowledge mapping; literature review; modelling

List of abbreviations

Abbreviation	Description
ABM	agent-based model
ARIMA	autoregressive integrated moving average model
CBE	consumption-based emissions
CGE	computable general equilibrium
CSCE	China's sectoral carbon emissions
DEA	data envelopment analysis
DMU	decision-making unit
EE-IOA	environmentally extended input-output analysis
ELC	environmental learning curve
ETS	emissions trading scheme
FDI	foreign direct investment
GIS	geographic information system
GMM	generalized method of moments
GPS	Global Positioning System
IAM	integrated assessment models
IDA	index decomposition analysis
IOA	input-output analysis
IO-LCA	input-output life cycle assessment
IPAT	Impact = Population × Affluence × Technology
IPCC	Intergovernmental Panel on Climate Change
LCA	life cycle assessment
LLR	log-likelihood ratio
LMDI	logarithmic mean Divisia index
MRIO	multi-region input-output
MRIO-LCA	multi-region input-output models and their integration with life-
MSIO	multi-scale input-output tables
PBE	production-based emissions
SCE	sectoral carbon emissions
SD	system dynamics
SDA	structural decomposition analysis
SRIO	single-region input-output
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and
WoS	Web of Science

2.1 Introduction

Interest in formulating and applying analytical or modelling techniques to understand carbon emissions has profoundly increased since the Kyoto Protocol was introduced in 1997. In China the largest source of CO_2 emissions comes from intermediate production processes, which are attracting the attention of policy makers, researchers and the international community wishing to curb growth in emissions. Several commentators have also given China the title as the “factory of the world” owing to the significant proportion of global manufactured goods originating in China (Liu and Diamond, 2005; X. Tang et al., 2015; Zhang et al., 2016). Given the growing importance of full life-cycle accounting and the associated embodied emissions in products – particularly for products consumed in developed countries that were manufactured in emerging markets – China’s national emissions inventory is continuing to attract global attention. The need to understand and operationalise emissions reductions targets is demonstrated by the wide range of methods and approaches that are being embraced and developed in the rapidly growing number of published research papers looking at China’s Sectoral Carbon Emissions (CSCE). This has been particularly evident since 2007 when China became the largest carbon emitting country in the world. Today, around one-third of global sectoral carbon emissions (SCE) research focuses on emissions generated in China. A number of novel modelling techniques have been developed and deployed to address complex SCE issues specific to the Chinese context.

Tackling the CSCE problem is complex and requires diverse research approaches. While several attempts have been made to review specific methods in their own contexts, few, if any, research papers have provided an analysis of the main research methods that provide an overall picture of the multiple methods that have been developed to answer different research questions. For example, in one family of methods under the broad umbrella of CSCE, the method known as environmentally-extended input-output analysis (EE-IOA) was reviewed by Hoekstra (Hoekstra, 2010) and updated by Hawkins et al. (Hawkins et al., 2015). In another, a total of 80 papers were reviewed using index decomposition analysis (IDA), by Xu and Ang (Xu and Ang, 2013). Data envelopment analysis (DEA) was reviewed by Meng et al. (Meng et al., 2016) who compared five widely used DEA efficiency methods. In addition, in papers that review or apply to a specific method or family of methods, it is rare for authors to explain why they chose a particular method to address their research problem.

While scholars from particular fields are naturally familiar with one method or another, such as economists using econometrics, scholars would be in a much better position to approach the problem if they were aware of, and could compare, the strengths and weaknesses of the main methods that have been used to answer similar research questions. This review paper addresses this problem through a direct comparison of the strengths and weaknesses of each of the main research methods. It also highlights the relationships between methods and research themes, recent trends, the popularity of different methods as well as research gaps and opportunities for further research. This paper aims to fill an important gap by providing an analysis of all major CSCE-related methods so that scholars and policymakers can quickly identify and compare different methods for answering their research needs.

Instead of focusing on the detailed techniques or models that are used in a particular method, we outline the main methods that have been applied and the types of research questions that each method can answer. We use bibliometric analysis and knowledge mapping with the software CiteSpace to create an overall picture of the ongoing activity in CSCE research, and to assess the similarities and differences between the adopted methods. The paper reviews five families of methods that are commonly used to model and assess carbon emissions, and it examines the pros and cons of each method. The families of methods identified include: (1) environmentally extended input-output analysis (EE-IOA), (2) index decomposition analysis (IDA), (3) econometrics, (4) carbon emission control efficiency evaluation and (5) simulation. While we draw on carbon emissions research in China, the findings can be applied to carbon emissions research worldwide.

The rest of this paper is structured as follows. Section 2 (Methods) describes the boundaries of the literature reviewed and how the research papers were analysed using bibliometric analysis and knowledge mapping. Section 3 (Review of methods) describes each of the representative methods and discusses the pros and cons for each of them. Section 4 (Bibliometric analysis) provides a quantitative analysis which compares the main trends and approaches for each family of methods. Section 5 (Knowledge mapping) presents a number of graphical visualisations of the main research themes and summarizes the main points of comparison between the methods. This section also identifies key milestone papers in the development of the CSCE field over the last 20 years. Section 6 (Discussion) critiques the representative methods and explores what can be done to further develop and grow CSCE research. Finally, Section 7 (Conclusion) summarizes the gaps in the present literature and the main findings and limitations.

2.2 Method

2.2.1 Search strategy and selection of papers

A systemic review of the literature was undertaken using Thomson Reuters's Web of Science (WoS) database. The WoS database covers approximately 12,000 leading journals worldwide. It includes the Science Citation Index Expanded, the Social Sciences Citation Index, and the Arts and Humanities Citation Index databases. The quality and quantity of papers included are therefore sufficient for conducting a systemic review.

We searched for papers in the CSCE field using the following steps. Papers were filtered using key words “China”, “carbon emission*” and “indust* OR sector*” in titles, abstracts or indexing terms. The period selected for this analysis was from 1997 to 2017 because of the growing importance of CSCE since the introduction of the Kyoto Protocol in 1997. The most recent paper was published on 20 July, 2017. In total 1,057 papers were identified under the CSCE umbrella published between 2001 and 2017. The number of papers was reduced to 807 by filtering by document type to only include articles and reviews and exclude proceedings papers, book chapters, reprints, meeting abstracts, editorial material and retracted publications.

The five families of methods listed in the introduction to this paper were identified after we manually reviewed the 807 papers. When we searched for articles that use a particular family of methods such as environmentally extended input-output analysis, we would add relevant method descriptions in the search terms such as “input-output analysis”, “IOA” or “SDA”. For more information about the search terms for each method, see Table 2.1.

Table 2.1 Search terms for the representative methods

Method		Topic Search Terms
Environmentally Extended Input-Output Analysis		IO *OR* input-output *OR* embodied *OR* “structural decomposition” *OR* SDA
Index Decomposition Analysis		LMDI *OR* “index decomposition” *OR* “Logarithmic mean divisia index” *OR* decoupling
Econometrics		Regression *OR* “panel data” *OR* econometrics *OR* correlation *OR* STIRPAT *OR* IPAT *OR* statistics
Carbon emission control efficiency evaluation		DEA *OR* “data envelopment analysis” OR Malmquist
Simulation	Computable General Equilibrium	CGE *OR* “computable general equilibrium”
	Integrated Assessment	“integrated assessment” *OR* “integrated-assessment” *OR* IAM
	System Dynamics	“system dynamic” *OR* “system-dynamic” *OR* SD
	Agent-Based	“agent-based model” OR “agent-based modelling” *OR* ABM
	Optimization	Optimization
	Multi-Criteria	“multi criteria” OR “multi-criteria”
	Techno-Economic	“techno economic” OR “techno-economic”

2.2.2 Methods used for bibliometric analysis and knowledge mapping

Bibliometric analysis and knowledge mapping were used to analyse the search results. The bibliometric analysis revealed subject areas as well as publication and citation trends for each of the five families of methods. In the literature, knowledge mapping is commonly used to uncover and visualise groups of similar ideas or unusual features and trends by showing how knowledge within a field has evolved over time in a comprehensive and transparent manner (X. Li et al., 2017). Compared with bibliometric analysis, which mostly focuses on providing a general understanding of the field by undertaking a descriptive analysis, knowledge mapping aims to reveal structural and dynamic aspects of studies by charting, mining, analysing, sorting, and displaying knowledge (Shiffrin and Börner, 2004).

The software used for this analysis, CiteSpace, is a popular choice for conducting knowledge mapping. Chen (2004) developed this software based on bibliometric analysis, data mining algorithms and visualization methods. We used CiteSpace in this paper to visualize research clusters and detect milestone developments in CSCE research. To this end, CiteSpace was used to explicitly establish the intellectual base for each research method and track its evolution based on co-citation network. The co-citation network was derived using graph-theories, in which the vertices represent the reference papers of the 807 papers, on the basis of the CSCE search results from the WoS database. If two papers were cited in a third paper, they were co-cited, and a link was formed in the co-citation network. The co-citation network was further clustered by using the expectation maximization algorithm (Chen, 2014) based on a series of attributes, including citation frequency, first author, year of publication and the source of the publication. See Figure 1.1 for the conceptual framework of the co-citation network. The clustering analysis provided insights into the underlying knowledge structure by detecting fundamental and distinctive research papers in the field. In addition, CiteSpace uses Kleinberg's (2003) burst-detection algorithm[1] for identifying sharp increases of interest in a particular topic, thereby providing insights on the critical evolving paths in a timely manner.

Previous literature review papers published in the CSCE field have usually been expert-dependent, and such papers cannot avoid subjectivity and individual preferences. Our analysis using CiteSpace was driven by bibliometric data, and no subjective preferences were involved in the clustering and visualisation process for identifying unique research groups.

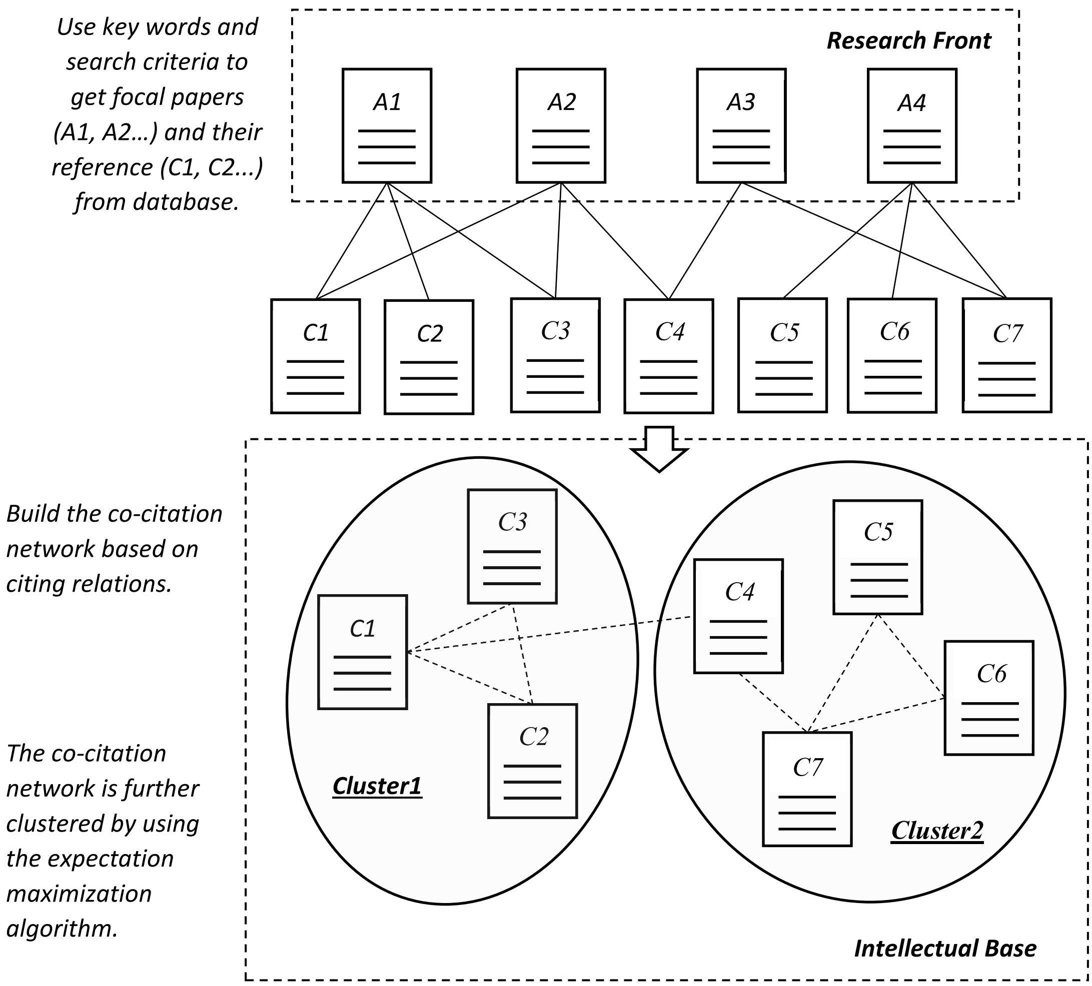

Figure 2.1 The conceptual frame work of the co-citation network

[1] The burst-detection algorithm is used to find features which have high intensity over a period of time and then fade away through analysing document streams arriving continuously (Kleinberg, 2003). The 'bursty' event which is uncharacteristically frequent, and the corresponding time period can be identified by using this algorithm.

2.3 Review of methods

In this section, five families of methods within the CSCE field are reviewed. For each method, we provide a brief introduction to show how it has been applied, followed by a short discussion of its pros and cons.

2.3.1 Environmentally extended input-output analysis (EE-IOA)

Over the last ten years EE-IOA has been increasingly used to study the regional and sectoral effects of carbon emissions in China. It allows for the assessment of carbon emissions from both a production and a consumption perspective (Leontief, 1970). EE-IOA is particularly useful for examining the embodied carbon flows of industries both within China and internationally (Liu et al., 2012; Su and Ang, 2014) and provides a good foundation for “common but differentiated” responsibilities for tackling carbon abatement.

Within EE-IOA, both the direct and indirect effects of economic activities on the environment are examined in the entire supply chain and production system. The influence of changes to production, technology and final demand on China’s carbon emissions are frequently examined through multiplier effect analysis (Su and Ang, 2014; W. Zhang et al., 2015) and structural decomposition analysis (SDA) (Shan et al., 2018a; Su and Thomson, 2016). It is straightforward to integrate EE-IOA with other methods to provide more solutions to research problems in the CSCE field. For example, the integration of EE-IOA with life cycle assessment (LCA) enables a much more detailed account of total life-cycle carbon emissions, and makes it possible to adopt a cradle-to-grave approach for industries and regions (Bilec et al., 2010; Thiesen et al., 2008).

Although EE-IOA offers several benefits, it also has several limitations. The data used to construct EE-IOA tables is variable and depends on the assumptions and data collection methods used. Significant differences can arise simply from the accounting and collection methods that are used. For example, estimates of consumption-based carbon emissions for China varied from 1,841 Mt to 4,030 Mt in 2012 with a 54% difference rate (Zhang et al., 2017). Moreover, due to the large datasets required to conduct EE-IOA at high sectoral and regional resolution, there is a significant time lag between each new release of input-output data tables.

2.3.2 Index decomposition analysis

Index decomposition analysis (IDA) has been used to examine the driving forces of carbon emissions in China over time. IDA starts with the macro-variable of carbon emission change (Ang, 2004). It is commonly decomposed into "activity effect" indicators such as GDP, the "structure effect" indicators such as industrial structure, and the "intensity effect" indicators such as carbon emissions per unit of GDP (Liu et al., 2007). Through an "ideal decomposition" process (i.e. there is no residual term), such as the logarithmic mean Divisia index (LMDI) decomposition approach (Ang and Choi, 1997), IDA produces a deterministic result to trace the effect of each indicator used in the analysis.

The popularity of this method can be attributed to its minimal data requirements, and the ease of application and result interpretation. The data sources available for conducting IDA are relatively abundant, as only aggregate sector-level data are required. In China, such data is readily available and is provided on an annual basis at high spatial resolution by regional and national bureaus of statistics. IDA has proven to be flexible in problem formulation and is generally easy to apply. Using this method it is possible to work with both multidimensional and multilevel emissions data over both time and space (Su and Ang, 2012). For example, the latest publications in the field cover an analysis time span of over twenty years and range from the city to the international level, and they can incorporate data from specific industry sectors and economy-wide emissions trends (Zhao et al., 2016; Zhen et al., 2017).

One limitation of this method is that it fails to represent the linkages between industries and it is therefore unable to capture the spill-over effects of changing demand across different industry sectors (Hoekstra and van der Bergh, 2003). Another limitation is that IDA is only able to reveal changes to macro-variables owing to the limited number of predefined factors. Because IDA requires factors to be introduced that cancel each other out, it is not easy to incorporate new variables such as weather into the analysis. Moreover, because IDA looks at change over time for specific macro-variables, it is generally necessary to have a time-series over the period of interest.

2.3.3 Econometrics

Econometrics is used as an analytical tool to describe the contributions of multiple factors or policies to carbon emissions. Most of the econometrics models in the field of CSCE research are derived from STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) framework. Based on the estimated relationship, STIRPAT also serves as a starting point to simulate carbon emissions under different scenarios (Y. Liu et al., 2015; Wang et al., 2013). For a more precise specification of the sensitivity of the carbon emissions to the driving factors, researchers have attempted to improve this approach, by using different model specifications or by adding more variables of interest.

Panel data is the most frequently used econometrics method in CSCE. It attempts to provide quantitative evidence of the connections between carbon emissions and influencing factors across different industries in the observed period. Several changes have been introduced in an attempt to enable more precise measurement. Firstly, to avoid multicollinearity issues among socioeconomic variables, partial least squares or ridge estimation procedures are widely applied (D. Yan et al., 2017). Secondly, the Tobit model has been adopted to analyze the factors affecting energy-environment efficiency (Yang et al., 2014). Thirdly, because economic behavior exhibits some continuity, it is essential to introduce the lagged level of carbon emissions to ensure that the model coefficients are calculated consistently and effectively (Omri and Nguyen, 2014). To solve the endogeneity problem causing by the dynamic lag term of the explained variables, the generalized method of moments (GMM) using a set of instrumental variables is applied to estimate the dynamic panel data model (Guo, 2017; Zhang and Xu, 2017).

A key advantage of econometrics is its versatility due to the wide variety of methods and techniques that can be used. For example, spatial econometrics has introduced the concept of 'economic distance' into carbon emissions research to provide a new perspective on the impact of geospatial factors (Conley and Ligon, 2002). In addition, many other previously less-discussed variables have been incorporated into the econometric analysis, such as financial development (Mahdi Ziaei, 2015; Zhang, 2011), urbanization (Ding and Li, 2017; Xu and Lin, 2015), climate change (Cai et al., 2017; Hao et al., 2016), the relationship between CO_2 and other pollutants (Li et al., 2015), land use and distribution (Zhang and Xu, 2017; Zhou et al., 2015). Moreover, due to the versatility of econometrics, it is relatively straightforward to find the data required to answer the research question of interest.

The disadvantages of econometrics can be categorized according to the analysis procedure undertaken. In the data gathering phase, it is sometimes difficult to observe some variables, such as financial development and proxy data is often chosen, such as the amount of foreign direct investment (FDI). This may result in concerns about validity and reliability. In addition, owing to the complexity of this type of analysis, it is challenging to choose the most appropriate method and conduct the right statistical tests. Even when the same data is used for analysis, the magnitude of an effect can vary depending on the method and the variables used. For example, Hang and Tu (2007) found that energy prices had a significant impact on energy efficiency in China, while Zhao et al. (2014) reached the opposite conclusion. In some cases, it can be difficult to explain why certain variables are significant, and it can be difficult to interpret the effects of different coefficients. While most of these issues can be well-handled with proper econometrics, the key disadvantage remains the challenge to adequately model linkages, synergies and spill-overs across sectors or regions.

2.3.4 Carbon emission control efficiency evaluation

Measuring the efficiency of carbon emission control measures has been an active research topic in recent years, according to the publication and citation record in Figure 2.4. The aim is to improve productivity at levels ranging from the micro to the macro. Methods of efficiency evaluation can be divided into two groups: non-parametric, including Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH)) methods, and parametric efficiency method, including Stochastic Frontier Approach (SFA) and Distribution-Free Approach (DFA). For the parametric method, the researchers must first set up the specification of the technology, efficiency frontier, the exact functional form between inputs and outputs, and the composition of error terms. In the context of carbon emissions mitigation research, it is hard to have that knowledge or information in advance due to the complex relations among multiple inputs and outputs. Therefore, non-parametric efficiency methods are preferred in this field of research.

The most common approach is data envelopment analysis (DEA). DEA models can be classified according to their reference technologies and efficiency measures (see

Figure 2.2 for details). It investigates and compares the CO_2 emissions across regions and sectors and across time (Li and Lin, 2015; Meng et al., 2016). For regions in China, most studies focus on measuring the carbon emission efficiency of 28–30 provinces and regions. For sectors, DEA either investigates specific sectors, usually energy intensive sectors, or adopts a comprehensive perspective which includes all the main sectors. The research spans the period from 1992 to 2012, especially the 2000–2010 period.

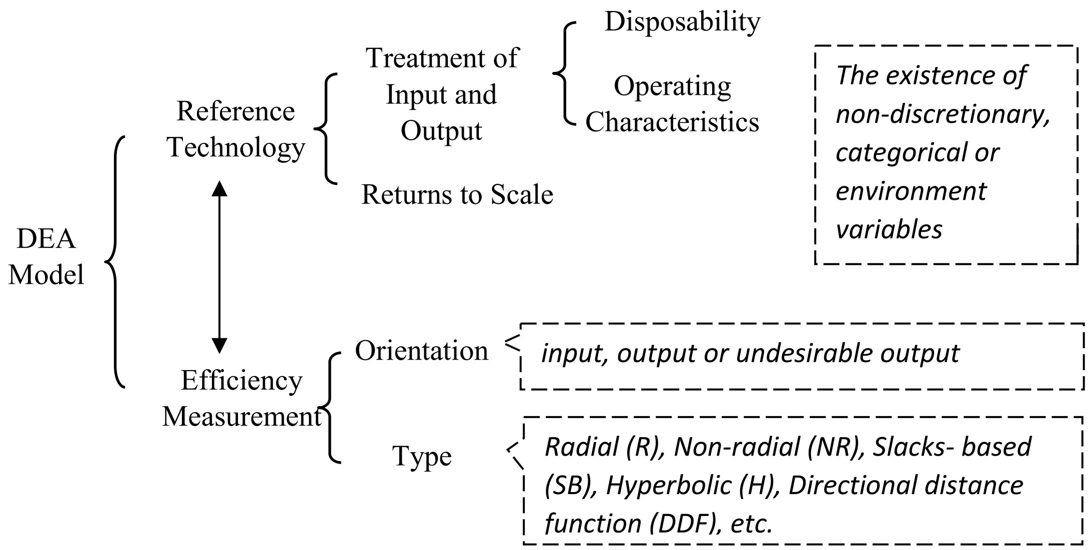

Figure 2.2 The general structure of a DEA model adapted from (Zhou et al., 2008)

DEA is a non-parametric method and does not assume the production 'technology' function determining the relationship between inputs and outputs of each decision-making unit (DMU) (Seiford and Thrall, 1990; Zhou et al., 2008). Instead, it takes each DMU as a whole, without considering the detailed internal production procedures (Kao, 2014). The method therefore allows hidden relationships to be uncovered.

In regard to disadvantages, the model selection and choice of variables can affect the results dramatically. Meng et al. (2016) reviewed 18 studies using DEA to estimate carbon emission efficiency in China from 2006 to 2015. The analysis showed that there are five main model types and several variable schemes available. Meng et al. found substantial differences in the outputs due to different choices of models and variables. In addition, due to the unspecific production function, the end result of DEA is an efficiency index rather than an estimate of carbon emissions. When the scope of the research changes, the efficiency values also change.

2.3.5 Simulation and other methods

In the context of CSCE, simulation is usually employed to predict carbon emission trends when policies, technologies, or other influential factors change. This paper identifies the following simulation methods: computable general equilibrium models (CGEs), integrated assessment models (IAMs), system dynamics (SD), agent-based modeling (ABM), optimization and multi-criteria optimization, and techno-economic models. These methods are adopted worldwide to address carbon emission abatement problems.

2.3.5.1 Computable general equilibrium models and integrated assessment models

Computer general equilibrium models (CGEs) and integrated assessment models (IAMs) come from the same family of economic optimization models. They use real data and rely on a series of equations that are either empirically or theoretically derived to determine projections from the present state to some future equilibrium state where the system has been optimized. While CGE models describe the sectoral interrelationships of the whole economy with a focus on cost optimization, IAMs are more integrated and include not only socio-economic activities, but also the physical relationships that drive climate change (Parson, 1995). CGEs and IAMs are frequently used to predict how carbon emissions and economies will react to emissions trading schemes (Babatunde et al., 2017), carbon taxes (Tang et al., 2017), low-carbon policies (Cheng et al., 2016), technology diffusion (Hübler, 2011) and energy consumption (Chi et al., 2014), in order to find the 'optimal' option.

The primary advantage of IAMs and CGEs is their ability to incorporate the complex relationships between the world economy and environmental policy to tackle climate change mitigation problems. When the effect of a specific policy is evaluated, the effects of 'exogenous' variables on economic, social and environmental systems can also be considered (Cantore, 2009). By providing simulation results based on different scenarios, the consequences of policy choices are presented in a clear and easy to understand way.

A key output of IAMs and CGE models is forecasts of model variables under very specific conditions and assumptions. These models are often criticized for their unrealistic assumptions, such as homogenous products or services and full employment of labor (Böhringer and Löschel, 2006). Different models may therefore give contrasting simulation results, due to different modeling assumptions. In addition, for IAMs, because the physical mechanisms underlying climate change are complex and partly unknown, it is difficult to set convincing parameter values with a sound theoretical or empirical foundation (Pindyck, 2013).

2.3.5.2 System dynamic models

While CGE and IAM produce scenario analysis results as snapshots, system dynamics (SD) models reflect the dynamic evolution of systems. SD models take several simulations over a given period of time (Anand et al., 2005). The dynamic of system consists of two components: a causal loop diagram and a flow diagram. The causal loop diagram is developed by incorporating various subsystems, such as socio-economic factors, energy consumption, technologies, and other factors associated with industries which produce CO_2 emissions. They reveal the interactive and reinforced causality relationships among the subsystems and influential factors. Research into the factors driving carbon emissions focus mainly on energy consumption (Feng et al., 2013), population and economic growth (Du et al., 2018), energy and economic structure upgrades (Mao et al., 2013), technological progress (Lai et al., 2017), and policies (Xiao et al., 2016). Based on the causal loop diagram, a flow diagram is created to demonstrate the measurable elements in each subsystem and the intricacies of the interacting processes.

One advantage of SD models is their capacity to explicitly model dynamic feedbacks. The two-way relationships among the driving factors in subsystems provide a holistic cause-and-effect interpretation of the evolving trend of sector carbon emissions and their changes under different polices and social and economic conditions. Another advantage is that system dynamics models are easy to use for policy analysis. Researchers can directly identify the direction and magnitude of carbon emission changes due to policy changes from causal and flow diagrams. However, the evolution ability of SD models depends on the variations in the values used in feedback loops and equations. Once the input values of all parameters and constants are fixed, the feedback mechanism itself cannot change. This creates difficulties in the interpretation of research results. For example, the marginal impact of a technology upgrade on carbon emissions will fluctuate in response to changes in market competition or governmental subsidies, but, such impacts are usually modeled as fixed auxiliary variables. This leads to biased estimates when simulations of more than ten years are conducted.

2.3.5.3 Agent-based models

IAM, CGE, and SD models estimate carbon emissions and identify the factors driving them from a macroscopic perspective by dealing with aggregated variables and parameters. Agent-based models (ABMs), on the other hand, focus on the dynamic behavior at the individual or “agent” level. In agent-based models, final aggregate carbon emissions emerge as a result of the dynamic interactions of those agents. These interactions are considered to occur at each simulation step according to predefined decision-making rules. In the context of sector carbon emissions, agent-based models are most frequently used in research about strategy and mechanism design for carbon emissions trading. The main purpose is to understand how carbon emissions at an aggregate level change from the bottom up.

Agent-based models are defined using two main components: (1) the selection of agents, and (2) the interactions between agents which lead to emergent outcomes. Firms, industries and governments, as carbon trading scheme participants, are the most common agents chosen (Jiang et al., 2016; L. Tang et al., 2015). Firms and industries usually aim at profit maximization. Governments, on the other hand, set carbon prices, allocate emissions quotas and ensure fair trade by imposing penalties and subsidies. From these interactions between these agents, researchers can examine how total carbon emissions emerge from micro-level behavior.

The main advantage of agent-based models lies in their ability to capture dynamic decision-making process which involve adaptive and evolutionary learning. This provides a more realistic representation of the behaviors of bounded rational firms and governments, because the preferences and strategies underpinning their decision-making can change when new information is obtained. Another advantage is that no prior knowledge about the macro interdependencies and dynamics is required. However, the interactions in agent-based models sometimes cannot always be easily articulated to reflect reality (Bonabeau, 2002). Moreover, the granular information fed into the model implies that if the number of parameters involved is large, this may introduce sensitivities to the emergent outcomes at an aggregated level (Filatova et al., 2013). This calls for vigorous validation with respect to the soundness of model construction.

2.3.5.4 Optimization and multi-criteria optimization models

Optimization is defined as finding universal solutions of a function that minimizes or maximizes its value while being subjected to constraints (Banos et al., 2011). Optimization can be categorized as being either single- or multiple objective problems. The latter is sometimes called a multi-criteria optimization model, which more likely deals with several conflicting objectives (Odu and Charles-Owaba, 2013). When it comes to sectoral carbon emissions, optimization models are most frequently used to formulate carbon mitigation policies (Chang et al., 2017), design carbon trading systems, compare different taxing strategies (Wei et al., 2014), upgrade and optimize industrial infrastructure (L. Chen et al., 2016), and analyze the mechanisms of inter-regional carbon emissions transfer (Sun et al., 2017).

The optimization or multi-criteria optimization models require the specification of objective functions and constraints to which the objective function is being subjected. Minimizing the total production costs, minimizing carbon emissions, and maximizing economic growth are the most frequent but conflicted objectives (Chang, 2015). In addition, several other constraints, such as: meeting energy demand; reaching energy and emission control targets; energy resource availability; and manufacturing and construction budgets are also identified as constraints across different research themes. For example, to find the best carbon mitigation policy, Zhang et al. (2012) take three distinct carbon tax policies as constrains for scenario analysis.

Optimization or multi-criteria optimization models rely on the capacity to provide an optimal pathway to achieve carbon emission targets under different sets of assumptions about technologies, the economy, and energy systems. However, the establishment of the optimization system requires detailed prior information on the functions and parameters which are used. In addition, it is sometimes not feasible to find a solution for the optimization function.

2.5.5 Techno-economic model

Rather than estimate sectoral carbon emissions directly, techno-economic models use a decision-making process to compare available technological options, especially for CO_2 reduction and carbon capture technologies (Cormos and Cormos, 2017; Klemeš et al., 2007). Techno-economic models approach research problems from both a technical and an economic perspective. From the technical perspective, productivity performance is assessed with reference to different configurations with and without applying new CO_2 reduction and capture technologies under predefined operational parameters (Pettinau et al., 2017). The technical assessment aims to evaluate the extent to which the new technologies improve productivity or reduce energy consumption. From an economic perspective, potential benefits and costs, including investment, operation and maintenance, are quantified for the life of the technology (Huang et al., 2010). Techno-economic models employ sensitivity analysis of the key factors included in the model, such as fuel costs, technological growth and environmental impacts, to provide uncertainty bounds on the final estimation. The economic assessment aims to ensure that profits can be achieved.

For estimating sector carbon emissions, the primary advantage of techno-economic models is that assessing new technologies from two independent perspectives enables researchers to evaluate their benefits in a more practical and objective manner. However, the full implementation of a techno-economic model is a major undertaking. Significant effort is required to evaluate existing and future technical options, and to work out meaningful parameters. Moreover, techno-economic models rely on the synthesis of technological and economic expertise, which is usually very challenging for researchers.

2.4 Bibliometric analysis

As indicated in Figure 2.3, since China overtook the USA as the largest carbon emitter in 2007, CSCE research has attracted increasing attention. Over the last six years, the annual number of CSCE publications has increased from 14 in 2010 to 230 in 2016, with an average annual growth rate of 63%. The annual number of citations has also increased markedly, growing from 97 in 2010 to 2,716 in 2016, equating to an average annual growth rate of 47%. Though the number in 2017 only covers seven months of the year, the increasing trend for both publications and citations is evident. This compares with an estimated average annual growth rate of 8%–9% in global scientific output since the end of WWII, making CSCE research a very active area of research which is growing four times as fast (McKerlich et al., 2013).

CSCE research attracts scholars from a diverse range of disciplines. The number of published subject areas has increased from 2 in 1997 to 25 in 2017. While the disciplines of environmental science, energy, engineering and technology have dominated the CSCE field, research in economics, meteorology, atmospheric sciences, thermodynamics, water resources and public management has increased significantly. Initially, CSCE research was primarily conducted in science subjects, but it is increasingly being conducted in fields such as urban studies, government, law and international relations.

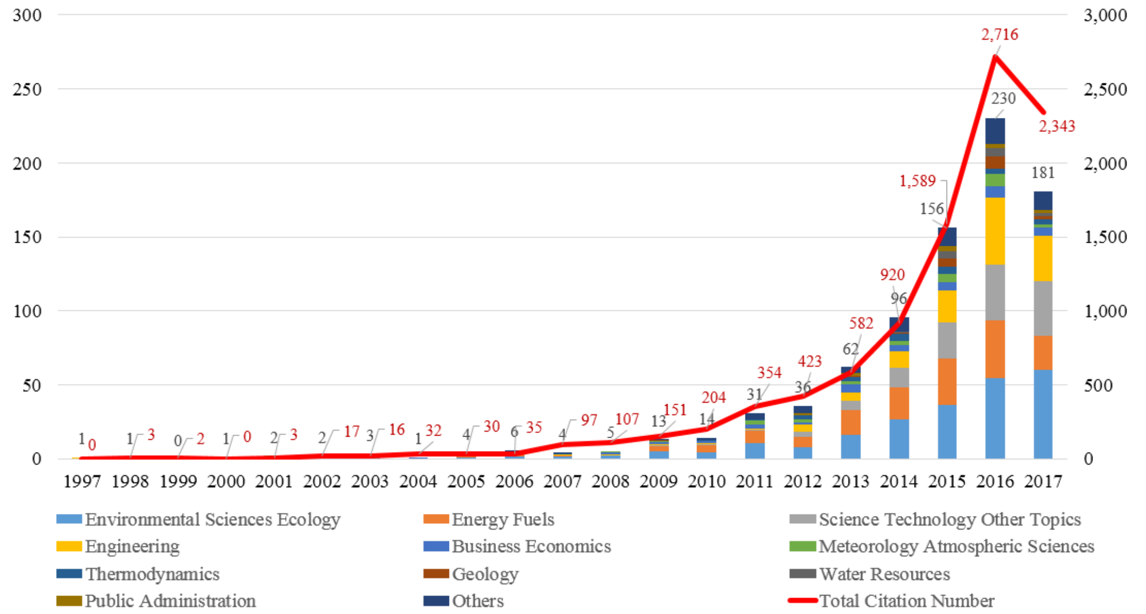

Figure 2.3 Publications and citations of papers published from 1997 to 2017

Notes:
1. The data for 2017 only covers the first 7 months of the year.
2. Because one paper can belong to more than one subject area, the stacked column shows the relative proportion for each subject. It does not indicate the publication or citation number for each subject.

Table 2.2 indicates that IOA, IDA and econometrics are the three main methods adopted in the CSCE field. Around 50% of CSCE papers cite at least one of these three methods

Table 2.2 Percentages of published CSCE journal papers using each method

Method		WoS search results	Percentage
Environmentally extended input-output analysis		182	22.55%
Index decomposition analysis		121	14.99%
Econometrics		135	16.73%
Data envelopment analysis		35	4.34%
Simulation and other methods	Computable general equilibrium	38	4.71%
	Integrated assessment	10	1.24%
	System dynamics	6	0.74%
	Agent-based	3	0.37%
	Optimization	6	0.74%
	Multi-criteria	1	0.12%
	Techno-economic	1	0.12%

Note: More than one method may be used in the same CSCE paper.

Figure 2.4 (publications) and Figure 2.5 (citations) show the increasing use of the main methods applied in the CSCE field. Between 2010 and 2016, the number of publications grew at an average annual rate of 85%, with the number of citations growing at an average annual rate of 68%. For 2017, only papers that were published before 20th July were included in the analysis. However, the trend is still evident. In addition, while IOA, IDA and Econometrics are still the dominant methods in this research field, DEA, IAM and CGE methods have become increasingly popular, taking up a larger share of the total percentage.

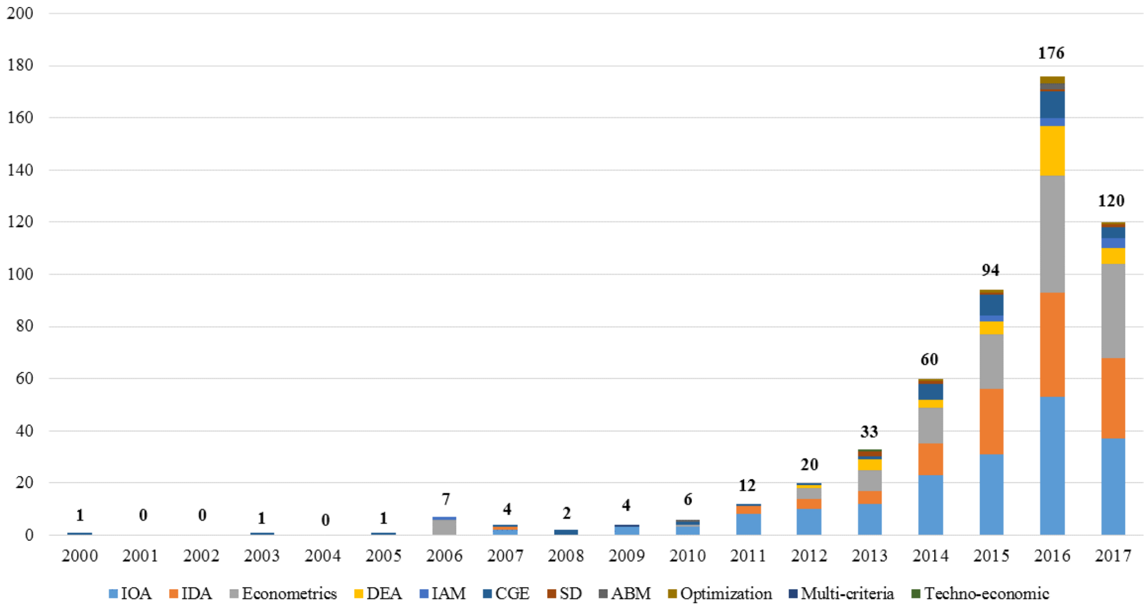

Figure 2.4 Publication per method from 1997 to 2017

Note: The stacked columns show the relative proportion of each family of methods in each year.

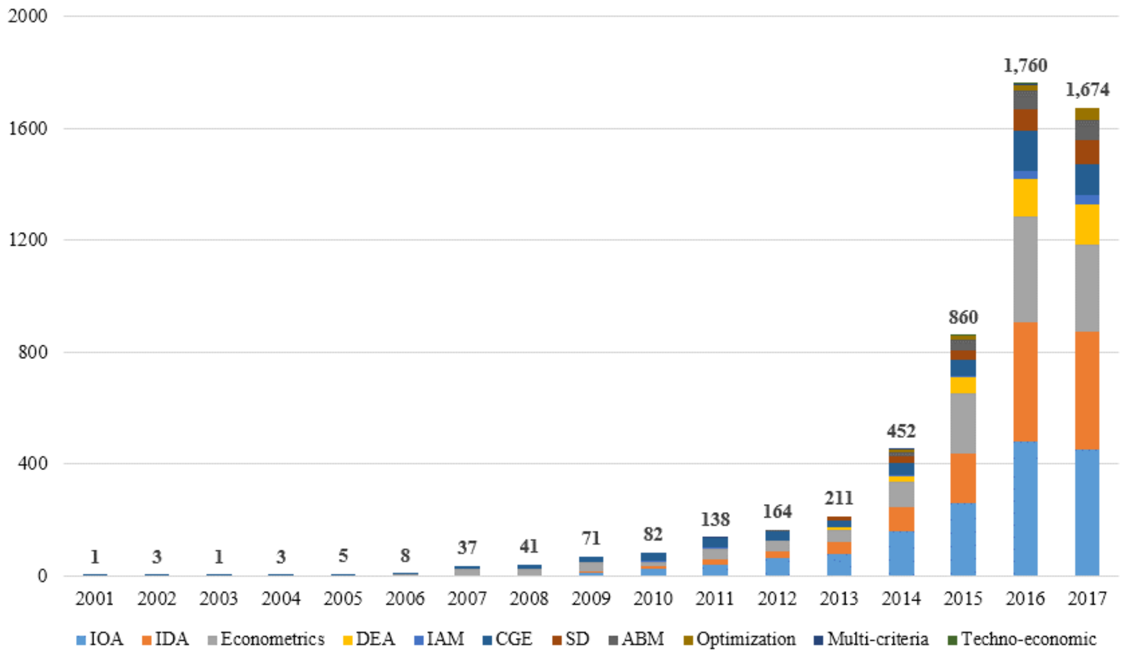

Figure 2.5 Citation per method from 1997 to 2017

Note: The stacked columns show the relative proportion of each family of methods in each year.

2.5 Knowledge mapping through CiteSpace

Figure 2.6 presents a landscape view of the CSCE field, generated by CiteSpace. It is based on 807 papers and 24,744 citations between 2001 and 2017. The top 50 most-cited publications in each year are used to construct a network of citations for that year. Each individual network is then synthesized so that each node on the map represents a cited paper, and the node size represents the number of citations for that paper. If two papers are both cited in a third paper, there is considered to be a link connecting the two cited papers. The assumption is that if two papers are cited together, the two references are associated in some ways (Chen et al., 2012). The nodes with red tree-rings are references with "citation bursts", which indicate dramatic increases in their citations over one year or multiple years. These bursts were detected using Kleinberg's (2003) algorithm. The colour of the cluster areas indicates the time when co-citation links in one area of research appeared for the first time (Chen, 2017). Areas in green were generated earlier than areas in yellow.

We used CiteSpace to cluster references that are commonly cited in CSCE research. Each cluster corresponds to an underlying research speciality. The co-citation network was found to have a high modularity Q of 0.7799. Modularity Q measures the extent to which a network can be grouped into clusters with distinct boundaries (Chen et al., 2010; Martin III, 2012). The high modularity Q suggests that the specialties of the CSCE network are clearly defined in terms of co-citation clusters.

While the cited papers in the reference provide the knowledge base, citing papers present the frontier of certain subjects. In other words, the paper which cites the papers in a cluster reveals the latest research topic of the underlying research speciality. The clusters were labelled using terms in the titles of citing papers and a log-likelihood ration (LLR) weighting algorithm (Chaomei Chen et al., 2010). LLR algorithms are used to create labels for clusters by identifying the core concepts in the cluster using keywords and phrases from the titles of papers. In order to better reveal the focus of each cluster, we have adjusted the labels according to the titles and abstracts of the citing papers as shown in Figure 2.6.

In Figure 2.6, it can be seen that Cluster 4 is distinct from the other clusters. Cluster 4 concentrates on organic and black carbon emissions, while all other clusters focus on carbon dioxide emissions, which comprise 81% of greenhouse gas emissions (United States Environmental Protection Agency, 2018). Organic and black carbon emissions are components of particulate matter, produced by the incomplete combustion of carbonaceous fuels (Chow et al., 2012). They have a different effect on the climate, and they are studied using different research methods. In addition, Clusters 9 and 10 are less connected with other clusters due to their distinct research interests. The rest of the clusters are closely connected, with some areas of overlap.

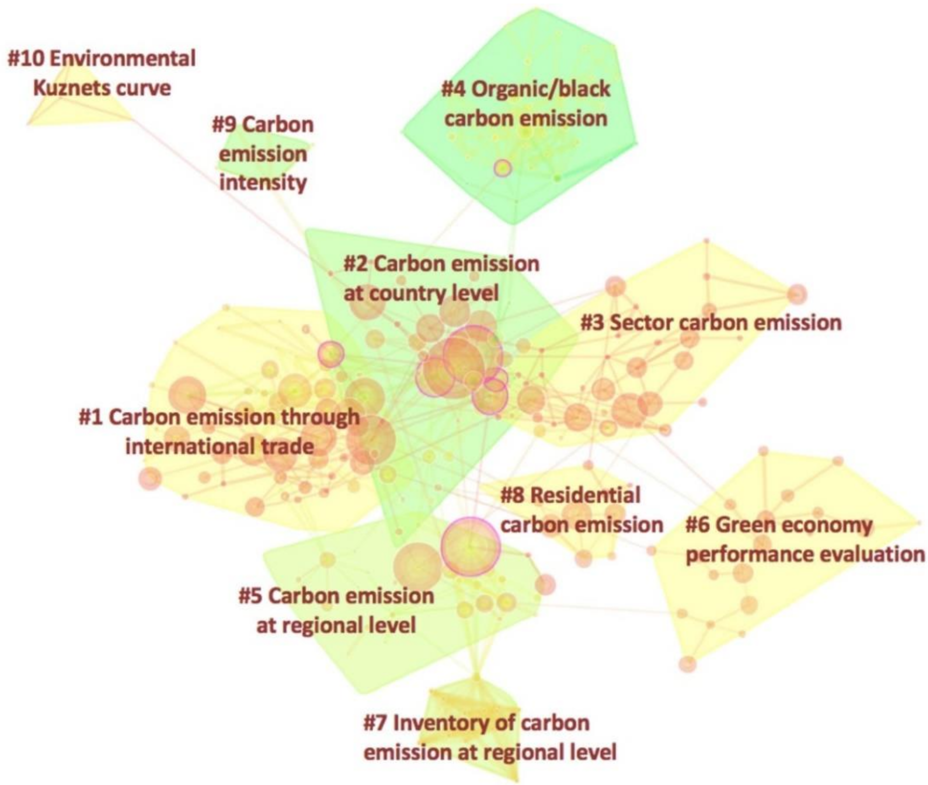

Figure 2.6 A landscape view of the co-citation network from 1997 to 2017

In Table 2.3, a 'silhouette score' is calculated for each cluster to measure the quality of a cluster as indicated by its homogeneity and consistency (Chen et al., 2010; Rousseeuw, 1987). The closer the silhouette score is to 1.0, the more homogeneous the cluster is thought to be. As indicated in Table 2.3, the silhouette scores for most of the largest ten clusters are above 0.78. These high scores suggest that the content of each paper is well matched to its own cluster, and poorly matched to neighbouring clusters. In addition, the Mean (Cite Year) column in Table 2.3 is the average year of publication within a single cluster, indicating whether a cluster generally comprises old or recent papers (Chen, 2014). It can be seen that Clusters 2, 4 and 9 are relatively old clusters that contain papers with an average year of publication of 2007 or 2008. Clusters 3, 6, 8 and

10 are relatively new clusters that contain papers with an average year of publication of 2012 or later.

Table 2.3 Summary of the largest 10 clusters

Cluster ID	Size	Silhouette score	Cluster Label	Mean (Cite Year)
1	54	0.883	Carbon emissions through international trade	2010
2	44	0.775	Carbon emissions at country level	2008
3	36	0.788	Sector carbon emission	2012
4	35	0.988	Organic/black carbon emission	2007
5	31	0.807	Carbon emissions at regional level	2009
6	20	0.933	Green economy performance evaluation	2012
7	14	0.983	Inventory of carbon emission at regional level	2009
8	10	0.963	Residential carbon emissions	2012
9	5	0.994	Carbon emission intensity	2008
10	4	0.977	Environmental Kuznets curve	2014

Size: The number of reference that a cluster contains

Figure 2.7 presents the timeline of co-citation clusters. The clusters are arranged according to size. The clusters, “carbon emissions through international trade”, “carbon emissions at country level” and “sector carbon emissions”, are the most active clusters, and they have been active for more than 10 years. In addition, there have been continuous breakthrough achievements in these clusters. This can be seen from the large nodes in red indicating ‘bursts in citations’. The clusters, “carbon emissions at regional level”, “green economy performance evaluation” and “residential carbon emission” were formed later but are now active clusters.

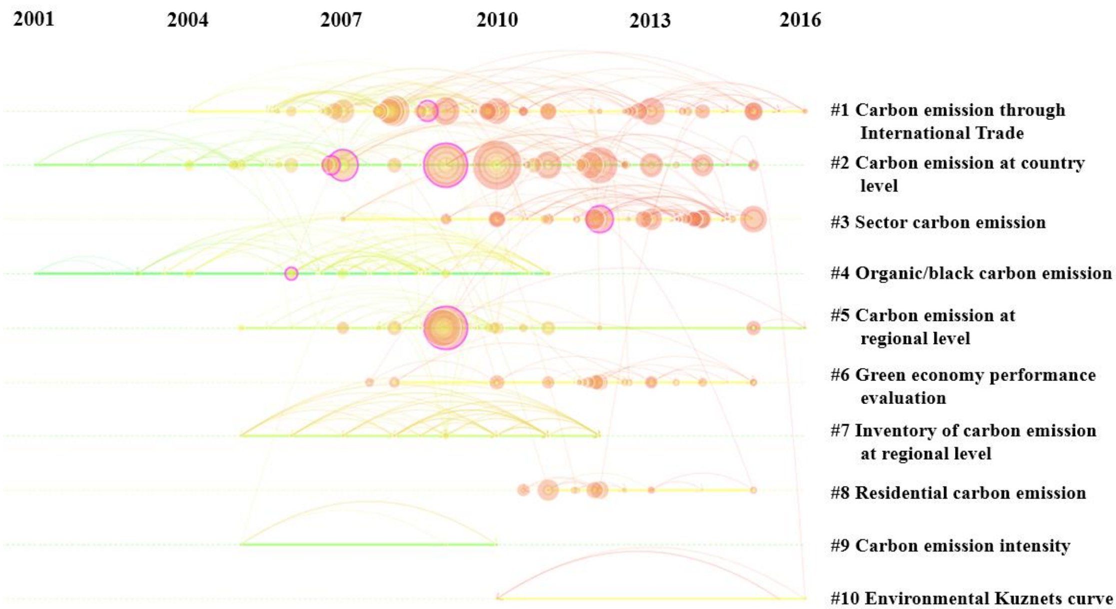

Figure 2.7 The timeline of co-citation clusters from 1997 to 2017

In Table 2.4 below, the main methods adopted in each cluster are identified by manually reviewing the top 20 citing papers in each cluster. Co-citation analysis has been criticized for not being able to identify whether a citation gives supportive arguments or offers a critique (Cheng, 2016; Kunz and Hogreve, 2011). Through a manual review, the potential bias of co-citation analysis is minimized. Each cluster is reviewed to confirm the research focus and identify the main analysis methods used, creating a more precise presentation of CSCE field.

The clusters are arranged in order according to the average year of publication of the cluster. The three clusters ‘carbon emissions at country level’, ‘organic/black carbon emissions’ and ‘carbon emissions intensity’ are the earliest clusters, with average publication years of 2007 and 2008 respectively. The initial research interest was in carbon emissions at the country level. A bottom-up inventory method was adopted to produce the direct carbon emissions inventory, and there have been many efforts to improve its accuracy. In addition, the effect of the main influencing factors, especially carbon emissions intensity, on national carbon emissions, has attracted significant interest. IOA, IDA and econometrics were all used for the impact analysis. Some comparative analysis was also conducted to compare the different impact factors across countries and across regions in China. Based on the inventory and impact factors research, some simulation models, such as the environmental learning curve (ELC) model, were developed to predict trends in carbon emission activities.

The research focus moved to the regional level around 2009 due to concerns about the large size and imbalanced development of the Chinese economy. The ‘Inventory of carbon emissions at regional level’ cluster and the ‘Carbon emissions at regional level’ cluster focus on this topic. Similar methods were used to construct emissions inventories, analyse impact factors and predict future trends. In addition, this area of research also looks at carbon footprints across different regions and the spatial distribution of carbon emissions using lifecycle and spatial analysis. For the emissions inventory, analysis went beyond direct emissions to create an embodied carbon emissions inventory based on input-output tables. The examination of linkages between different regions has grown in popularity.

Research on embodied carbon emissions due to international trade has emerged as an important area of study which is clarifying the role that China should play in mitigating global carbon emissions. Although China has been the largest carbon emissions country since 2007, as a world factory, much of these carbon emissions are induced by demand from other countries. While input-output databases serve to construct embodied carbon emissions, IOA and IDA techniques and models are frequently used to analyse the relevant impact factors.

Research interest was gradually drawn to the sector level around 2012. Although embodied emissions inventory construction and impact analysis are still at the core of sector-level research, much of the discussion has shifted to providing policy suggestion for curbing future emissions. Policies discussed have included establishing a carbon tax and constructing an emissions trading scheme (ETS). CGE models are frequently used to forecast the impact of these policies in different contexts.

The green economy performance evaluation cluster is distinct in terms of its research content and methods. The main aim of studies in this cluster is to assess the performance and efficiency of the carbon emission control policies of regions, industries or countries. DEA, Malmquist index analysis, directional distance function or their hybrids are usually used to assess efficiency levels and to measure green total factor productivity. In addition, econometrics are used to analyse the impacts of particular factors on carbon emission efficiency.

A growing area of research is attempting to model residential carbon emissions, due to the constantly increasing amounts of emissions produced by residents. In this line of research, two new research topics are being used. One draws on the behaviour of residents using survey methods and the other uses network analysis models to examine urban carbon emissions. The reason for this growing interest in residential emissions is that the control of emissions is more complete when the residential sector is considered.

Network analysis could provide a new perspective for considering both the linkages between industries and final demand using a residential model.

The most recent research cluster focuses on analysing the factors impacting carbon emissions by investigating the existence of environmental Kuznets curves.[2] This is a relatively small cluster, formed around 2014. The research content itself is not new, but the cluster provides a new perspective based on the use of the Kuznets curve.

[2] The environmental Kuznets curve (EKC) proposes an inverted-U relationship between pollution and economic development (Grossman and Krueger., 1995). In other words, pollution increases with economic development to a certain income level, and after that it declines.

Table 2.4 Methods used by the top 20 citing papers for each cluster

Cluster ID	Adjusted label	Mean (Year	Research focus	Main Method					
				IOA	IDA	Econometrics	Simulation	Efficiency	Others
1	Carbon emission through international trade	2010	1) Inventory of embodied carbon emissions through international trade at industry, region and country level 2) Analysis of impact factors on the embodied carbon emissions through international trade	✓ IOA/SDA: construct the embodied inventory; analyse impact factors	✓ analyse impact factors on embodied carbon emission through international trade				1) Hybrid between SDA and IDA: to clarify the effect of impact factors on embodied carbon emissions through international trade
2	Carbon emissions at country level	2008	1) National carbon emissions inventory and accuracy improvement 2) Analysis of impact factors on carbon emissions in China at region and industry level 3) Comparative analysis of factors impacting carbon emissions across countries/regions in China 4) Prediction for future scenarios	✓ IOA/SDA: analyse the impact factors on carbon emission	✓ IDA / LMDI: analyse the impact factors on domestic carbon emission	✓ Econometrics/ STIRPA: analyse the impact factors on domestic carbon emission	✓ Environ-mental learning curve (ELC) model: predict carbon intensity reduction potentials		1) Bottom-up inventory: to construct direct emissions inventory at country level using official statistical data, latest emission factor, collected activity data and emissions sources 2) Path analysis model: to analyse the impact factors on domestic carbon emission 3) Comparative analysis: to compare the different emission amounts and impact factors in different regions 4) Use Individual sector prices indices used instead of one general GDP deflator for improvement in decomposition analysis

Cluster ID	Adjusted label	Mean (Year	Research focus	Main Method					
				IOA	IDA	Econometrics	Simulation	Efficiency	Others
3	Sector carbon emission	2012	1) Inventory of each industry's carbon emissions 2) Analysis of impact factors on each industry's carbon emissions 3) Development of emissions trading scheme (ETS), including the allocation of carbon emissions among industries, the impact of ETS on certain industries	✓ construct the emissions inventory of industries	✓ IDA / LMDI: analyse the impact factors on each industry's carbon emission		✓ CGE/IAM/ Optimization/System Dynamic/ ABM To provide policy suggestion for ETS design, carbon tax and examine its impact		1) Literature review: to provide policy suggestion for ETS design
4	Organic/black carbon emission	2007	1) Emissions inventory of black carbon emissions at city, region and country levels 2) Prediction of black emission amounts				✓ Monto Carlo simulation model, global chemical transport model, MOZART-4 model		1) Bottom-up inventory: To construct emissions inventory of black/organic carbon using official statistical data, latest emission factor, collected activity data such as vehicle activity data, and major emission sources in cities
5	Carbon emission at regional level	2009	1) Carbon footprint through different industrial spaces 2) Impact factor analysis at city level 3) Spatial analysis 4) Prediction for future scenarios of low-carbon cities		✓ IDA / LMDI: analyse the impact factors on regional carbon emission	✓ analyse the impact factors on regional carbon emission	✓ Long-Range Energy Alternatives Planning model and others: predict future scenarios of cities		1) Life-cycle model: to simulate the carbon emissions, amount of fossil energy and rural biomass energy of different regions of China 2) Spatial analysis: to analyse the spatial distribution of carbon emissions

Cluster ID	Adjusted label	Mean (Year	Research focus	Main Method					
				IOA	IDA	Econometrics	Simulation	Efficiency	Others
6	Green economy performance evaluation	2012	1) Assessment of carbon emissions performance at industry, city, province and country levels 2) Measure China's green total factor productivity (TFP) growth 3) Analysis of impact factors on carbon emission levels in different stages and regions			✓ Econometrics/STIRPAT/SEM: analyse impact factors on carbon emission efficiency in different regions/ development stages		✓ DEA/ Malmquist index/ DDF: compare carbon emission performance of industries or regions	1) Hybrid among DEA, Malmquist index and DDF: to estimate the changes in carbon emission performance as well as their driving forces at industry and whole economy level, such as the meta-frontier non-radial Malmquist CO2 emissions performance index model
7	Inventory of carbon emissions at regional level	2009	1) Carbon emissions inventory of cities	✓ construct the embodied inventory at city level					1) Bottom-up inventory: to construct direct emissions inventory at city level using official statistical data, latest emission factor, collected activity data and emission sources
8	Residential carbon emission	2012	1) Emissions inventory of the residents 2) Analysis of impact factors on the carbon emissions of the residents 3) Prediction for future scenarios of residential carbon emission 4) Analysis of residential carbon emission behaviour 5) Mitigating urban carbon emissions through network perspective	✓ construct the embodied inventory of residents		✓ Econometrics/STIRPAT: analyse impact factors on the carbon emissions of residents	✓ AIM (Asia-Pacific Integrated Model)/End use model/others: predict future scenarios of residential carbon emission		1) Bottom-up inventory: to construct direct emissions inventory of residents using official statistical data, latest emissions factor, collected activity data and emission sources 2) Divisia index decomposition method: to analyse impact factors on the carbon emissions of residents 3) Survey study: to investigates the energy consumption behaviours of households

Cluster ID	Adjusted label	Mean (Year	Research focus	Main Method					
				IOA	IDA	Econometrics	Simulation	Efficiency	Others
									4) Network analysis: to mitigate carbon emissions in a holistic way
9	Carbon emissions intensity	2008	1) Analysis of impact factors on carbon emission intensity change		✓ IDA / LMDI				
10	Environmental Kuznets curve	2014	1) Analysis of factors impacting carbon emissions through investigation of the existence of an environmental Kuznets curve			✓ Econometrics/STIRPAT/GMM: analyse impact factors on the carbon emissions from various angles			

Important milestone papers in the development of CSCE research can be identified from the list of references with citation bursts (Table 2.5) and they reflect the dynamics of the field. A citation burst means that the reference it is associated with has received a sharp increase in the number of citations over a year or multiple years. The detection of citation bursts in CiteSpace is based on Kleinber's algorithm (Kleinberg, 2003). The size of the increase in citations is indicated by the strength of the citation burst, which takes account of both the number of citations and the length of the period over which the citations occur. From 1997 to 2017, there were 37 reference papers with citation bursts in CSCE research. Table 2.5 lists the 10 references with the largest citation burst strength values. The table is arranged according to the strength of the citation bursts. The colour along the timeline from 1997 to 2017 indicates the number of citations the paper received. The stronger the colour, the greater the number of citations. The red part represents the period when the citation burst happened.

As can be seen from the method column, four out of five families of methods have been adopted as the main methods by the top 10 papers. The earliest two bursts, which started in 2009 and ended in 2012, focused on decomposing carbon emission changes at the national level with IDA (Ang, 2004) and particularly with LMDI (Wang et al., 2005). Subsequently, two other bursts from 2014 to 2015 addressed consumption-based national emissions inventory construction with input-output databases and the analysis of the forces driving carbon emissions using SDA (Peters et al., 2007). From 2015 to 2017, researchers focused on: decomposing carbon emissions changes in the cement and transportation industries using LMDI (Wang et al., 2011; J.-H. Xu et al., 2012); constructing residential carbon emissions inventories and analysing impact factors with IOA (Zhu et al., 2012); examining total factor carbon emissions performance with DEA (Zhu et al., 2012) and Malmquist index analysis (Zhou et al., 2010); and predicting the impact of household consumption patterns on carbon emissions with CGE (Dai et al., 2012)

Table 2.5 Top 10 papers with the strongest citation burst

Strength of burst	Burst start	Burst end	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
7.1695	2015	2017		2012	Xu J., Fleiter T., Eichhammer W., and Fan Y.	Energy consumption and CO2 emissions in China's cement industry: A perspective from LMDI decomposition analysis	Energy Policy	IDA/ LMDI	83
5.8507	2009	2012		2004	Ang B.W.	Decomposition analysis for policymaking in energy: which is the preferred method?	Energy Policy	IDA	543
5.6039	2014	2015		2008	Peter G.P.	From production-based to consumption-based national emission inventories	Ecological Economics	IOA	327
5.4458	2015	2017		2012	Zhu Q., Peng X., and Wu K.	Calculation and decomposition of indirect carbon emissions from residential consumption in China based on the input–output model	Energy Policy	IOA	38
4.9897	2009	2012		2005	Wang C., Chen J., and Zou J.	Decomposition of energy-related CO2 emission in China: 1957–2000	Energy Policy	IDA/LMDI	222
4.8829	2014	2015		2007	Peters G. P., Weber C., Guan D., and Hubacek K.	China's Growing CO2 Emissions - A Race between Increasing Consumption and Efficiency Gains	Environmental Science and Technology	IOA/SDA	263
4.7592	2015	2017		2012	Wang Z., Zeng H., Wei Y. and Zhang Y.	Regional total factor energy efficiency: An empirical analysis of industrial sector in China	Applied Energy	DEA	194
4.7592	2015	2017		2012	Dai H., Masui T., Matsuoka Y., and Fujimori S.	The impacts of China's household consumption expenditure patterns on energy demand and carbon emissions towards 2050	Energy Policy	CGE	41
4.6897	2015	2017		2011	Wang W. W., Zhang M., and Zhou M.	Using LMDI method to analyse transport sector CO2 emissions in China	Energy	IDA/LMDI	71
4.4166	2015	2017		2010	Zhou P., Ang B.W., and Han J.Y.	Total factor carbon emission performance: A Malmquist index analysis	Energy Economics	Malmquist index analysis	174

2.6. Discussion

2.6.1 Critique of methods

Methods cannot be discussed in isolation from the research questions they are used to address. As indicated in Table 2.4, different methods were adopted in different clusters. However, although the research was conducted from distinct perspectives ranging from the residential sector to international trade, there are three common topics: the emissions inventory, impact analysis, and predictions for carbon emission trends. The five families of methods are discussed below, in relation to these three common topics. In addition, there are special topics for some clusters, such as carbon trading schemes in the 'sector carbon emissions cluster'. The relevant methods shall also be discussed.

2.6.1.1 Carbon emissions inventory

For the carbon emissions inventory topic, the two main methods used are the bottom-up approach and input-output analysis. Emissions inventories have been constructed at the household, industry, city, province, country and international trade levels. The bottom-up approach is generally used for calculating direct carbon emissions, using official statistical data, the latest emission factors, collected activity data and information about major emissions sources. Input-output analysis, and more specifically the databases of MRIO, SRIO and MSIO, are used to calculate the embodied carbon emissions of industry sectors and regions. In addition, the IOA database is frequently used in conjunction with other methods, such as life-cycle assessment, computable general equilibrium, and network analysis. While the direct carbon emissions inventory can be updated on an annual basis, the embodied inventory is updated less frequently, due to the large data requirement. Inventory construction provides support to clarify the responsibilities of regions and countries for carbon emissions from both a production and a consumption perspective. Inventory construction could also be used to make decisions about how to allocate the initial quotas of certificates for an emissions trading scheme (ETS) in China, and how to share responsibilities for emissions reduction internationally.

In addition, it is important to note the large fluctuation in both production-based emissions (PBE) and consumption-based (CBE) emissions. Zhang et al. (2017) compared ten PBE and CBE results for 1995, 2000, 2002 and 2005. They found significant differences in the quantities of carbon emissions and the differences tended to increase over time. Such discrepancies may result from the different assumptions that are associated with the different methods being used. These methods include single-region input-output models, bi-regional input-output models, as well as multi-region input-output models and their integration with life-cycle assessment models (MRIO-LCA).

The different data sources on which these models are based also contribute to differences in results. For example, Guan et al.'s (2012) research on China concluded there was a gigatonne gap between the national carbon dioxide inventory and the summation of provincial inventory data between 1997 to 2010. More transparency is therefore urgently needed for data collection, processing and validation of statistical procedures. In addition, the data collected by statistical bureaus and agencies within China is only as reliable as the sources of the data, and these sources are susceptible to political pressure. Statistical agencies and bureaus are frequently pressured to conceal data to achieve a political goal, which further reduces the quality of the data being collected. However, with increasing awareness about data accuracy due to commentary by domestic and international critics, attempts have been made by the Chinese government and scholars to address the problem. For instance, research by Z. Liu et al. (2015) refined carbon emissions inventories with independently assessed activity data and two new sets of measured emission factors for Chinese coal based on 602 coal samples.

2.6.1.2 Impact analysis

In the process of impact analysis, the methods of input-output analysis, index decomposition analysis and econometrics all come into play. The main advantage of IOA techniques lies in the examination of system-wide effects, including the direct and indirect effects on the entire supply chain. However, in contrast to its wide application in emissions inventory construction, input-output analysis techniques were only used frequently in carbon emissions research at the country (Cluster 1) and international trade (Cluster 2) levels. Two lines of research are adopted for assessing the impacts of the factors which affect carbon emission levels. The first approach is based on the assumption that there is a stable technological structure. When the flow of outputs in any part of the system is altered, this changes the input requirements in all sectors in fixed proportions, leading to a multiplier effect across the economy (Su and Ang, 2014; W. Zhang et al., 2015). The second approach, known as structural decomposition analysis (SDA), relaxes the assumption of fixed technology coefficients and allows the sensitivity of changes to technical coefficients to be explored to assess their relative impacts (Tarancon and Del Río, 2012; J. Yan et al., 2017). Using SDA, it is possible to apply a disaggregated comparative statistical approach to both final demand and technological structure (Cellura et al., 2012; Su and Thomson, 2016).

Index decomposition analysis has been used extensively for impact analysis at various levels of carbon emissions, including at the industry, city, province, country and international trade levels. IDA produces deterministic results through an "ideal decomposition" with no residual term. With the development of several extensions of the

LMDI method such as LMDI-I, the number of pre-defined factors is increased from five to eleven, and the application areas are expanded from specific industry sectors to economy-wide energy trends (Ang and Wang, 2015). In addition, various decomposition schemes have been proposed to satisfy a range of different macro-level variables, with corresponding formulas to carry out the decomposition (Ang, 2005; Su and Ang, 2012).

IDA is especially useful for examining the effects of changes in carbon emissions intensity on carbon emission levels. Moreover, in the international trade research cluster, IDA is used in conjunction with SDA methods, such as multiplicative SDA, to clarify the roles of different impact factors. The popularity of IDA comes mainly from its ideal decomposition and annually updated data resources. Because there is no residual term in the formula, it is easy to interpret results. However, while IDA works well at macro and meso levels of analysis, it is rare for attempts to be made to use IDA at micro levels, such as the firm and household levels.

Econometrics has increasingly been used in almost all the research clusters due to its versatility. Apart from impact factor analysis at the macro and meso levels, econometrics is also used for micro-level analysis, including at the firm and household levels. Moreover, for research evaluating green economy performance (cluster 6), econometrics is also used to investigate the driving forces behind changes to carbon emissions control efficiency. The Kuznets curve cluster, focusing primarily on research that analyses the Kuznets curve, also takes economics as its main method.

An important development in using econometrics in CSCE is to take the regional spillover effect and the heterogeneity of provinces into consideration. It is particularly evident in the research about carbon emissions at the country level (cluster 2) and regional level (cluster 5). The spatial autoregressive model (Zhang and Xu, 2017), spatial lag model (Chuai et al., 2012), and exploratory spatial data analysis (Chuai et al., 2012) are usually the starting points for this approach. Those models assume the carbon emissions in one place manifest an increased likelihood of emissions in neighboring places. They capture the spillover effect by adding the spatial lag of the dependent variable, namely carbon emissions. In addition, considering that the determinants of carbon emissions such as population, income and technology are also directly affected by neighboring places, The Spatial Durbin Panel Data Model (Liu et al., 2016; Y. Liu et al., 2014) was adopted to add the spatial autocorrelation coefficients of the explanatory variables. This kind of random coefficient geographically weighted regression model effectively captures both nonstationary and spatial heterogeneities by relaxing the assumption of global estimators of invariant parameters (Brunsdon et al., 1996). However, it is applicable only when high-solution and balanced data is available. The spatial correlation effect is statistically significant across all research, which indicates a remarkable spillover effect existing in China's sectoral carbon emissions processes.

In addition, the provincial heterogeneity is also considered for impact factor analysis in recent studies. Given China has a vast territory with significant provincial differences in resources distribution and economic growth, the relationships between socioeconomic variables and carbon emissions is nonlinear, and this may result in a biased estimation (Lin and Wang, 2015). Quantile regression was attempted to solve the problem and this line of research demonstrated that the effects of explanatory variables are not constant across the spectrum of the dependent variable (carbon emission). For example, Lin and Benjamin (2017) found that urbanization was only significant at the tail ends (10^{th} percentile and 90^{th} percentile respectively) of the carbon emissions distribution while the gross domestic product, energy intensity, carbon intensity was statistically significant across the entire spectrum of carbon emissions. However, for the factors exerting consistent impacts across all the carbon emission groups, the magnitude of effects would be biased at the tail ends. This calls for better understanding for how the effects of explanatory variables are different across the distribution.

2.6.1.3 Predictions for carbon emission trends

The prediction of carbon emissions is active in national carbon emissions research (Cluster 2), sectoral carbon emissions research (cluster 3), regional carbon emissions research level (Cluster 5), and residential carbon emissions research (Cluster 8). Apart from the prediction methods reviewed in part 3.5 simulation, more models and techniques within IOA, IDA and econometrics, which are not traditionally used for predictions, have been developed for forecasting. Take the increasingly used time-series econometrics models for example. They focus more on the simulation or prediction of carbon emissions under different scenarios, including GM (1,1) grey model (Tang et al., 2016), autoregressive integrated moving average model (ARIMA) (L. Liu et al., 2014) and the vector-error correction model (Zheng and Luo, 2013). Although time series models are helpful for understanding the long-term trend of sectoral carbon emissions, historical data lasting more than two decades are required to obtain a robust estimation. Data availability is another challenge in this group of study. In addition, in consistent with the impact analysis research, IOA, IDA and econometrics usually predict carbon emissions under the impact of final demand, population, economic growth, technology progress, energy consumption, industrial structural change.

The influence of ETS, carbon tax and other low-carbon policies on future carbon emissions have attracted much attention. CGE, IAM, SD and ABS are mainly adopted to evaluate these initiatives based on forecast analysis. CGE, IAM and SD take a top-down approach. While CGE and IAM focus on scenario analysis results, SD focuses on the dynamic evolution of the system. The dependency and dynamics among economic, social and environmental systems are assumed from macro perspective. Correspondingly, the parameters of equations are predefined according to existing literatures, empirical evidences, expert judgements, or intuitive assumptions. While the research results are straightforward, which is easy for interpretation, it is challenging to set appropriate and convincing parameters. On the other hand, ABM takes a bottom-up approach from a micro perspective, and several simulations were taken over a given period of time to reflect the dynamic. It focuses on the interaction at individual level, such as firms and industries, and approaches the changes in carbon emissions as an aggregated result from bottom up.

The adoption of IAM and Tech-economic models encourages multi-disciplinary research. Apart from examining the influence of socio-economic activities, IAM considers the physical relationships that drive climate change while the techno-economic model considers the productivity performance of newly introduced technology. These integrated models make prediction from a more comprehensive perspective and yield a more convincing result. However, it is very extensive undertaking. In addition, drawing on data simulation based on different model assumptions, IAMs seek to provide information on climate change policy choices, rather than advancing the understanding for knowledge's sake (Kolstad, 1998).

2.6.1.4 Carbon control efficiency measurement

The green economy performance evaluation cluster is distinct from other clusters. The common methods used in this cluster include DEA, the Malmquist index and the directional distance function. Econometrics is usually used in conjunction with the above methods for efficiency assessment. Hybrid approaches and econometrics are increasingly being used to estimate the changes in carbon emissions performance and to identify the driving forces at the industry and whole economy levels. The meta-frontier non-radial Malmquist CO_2 emissions performance index model is a good example of this (Lin and Tan, 2016).

2.6.1.5 Method summary

Table 2.6 summarises the key features of the main methods that have been reviewed in this paper. Apart from these primary methods, several other less popular methods have been introduced for fulfilling different research purposes. For example, Moran I is has been introduced to analyse the spatial distribution of carbon emissions. The use of surveys was introduced to investigate the energy consumption behaviours of households, and network analysis was introduced to study carbon emissions control in a more holistic way.

Table 2.6 Comparison of the main methods in CSCE field

	IOA	***IDA***	***Econometrics***	***DEA***	***IAM/CGE***	***SD***	***ABM***	***Optimization***	***Tech-Economic***
General and specific purpose	Carbon emissions inventory; influencing factor analysis	Influencing factor analysis	Influencing factor analysis	Efficiency evaluation	Simulation for forecast	Simulation for forecast; Influencing factors analysis	Simulation for forecast; ETS design	Simulation for forecast; Policies making	Simulation for forecast; Evaluation of new technology
Type of variables	Production effect variables, such as GDP; technology change variables in terms of intermediate input structure or carbon emissions intensity; final demand variables	Activity effect variables such as GDP; Structure effect variables, such as industrial structure; intensity effect variables such as carbon emissions per unit GDP	Various social economic variables, including population, GDP, GDP per capital, technology, energy structure, industrial structure, energy price, geography, urbanisation, financial development	Major input variables: labour force, capital stock and total energy consumption Major output variables: GDP and CO_2	Various Social economic variables and physical variables driving climate change	Energy consumption, population, economic growth, energy and economic structure upgrading, technologies progress, policies	Rules or strategies used for interaction among the agents Adaptive learning mechanism of agents	Energy demanding, energy and emissions control targets, energy resources availability, manufacture and construction budget, carbon tax policies	Predefined operation parameters of new technologies, measurement of productivity efficiency Cost and benefit components

	IOA	***IDA***	***Econometrics***	***DEA***	***IAM/CGE***	***SD***	***ABM***	***Optimization***	***Tech-Economic***
Key assumptions	Input-output linkages among the industries can be quantified	Total effects can be decomposed into several influencing factors without residuals	High accuracy of variables measurement; the relationship between dependent and independent variables are correctly quantified by the selected models	Optimal productivity frontier exists	Globally Pareto equilibrium exists	Whole system can be represented by subsystems with causal and feedback loops	Autonomous and heterogenous agents with adaptive learning ability exist	Global optimal solution can be reached under nonlinear constraints	Changes if applying new technologies are measurable
Analytical approach	Top-down	Top-down	Top-down	Top-down	Top-down	Top-down	Bottom-up	Top-down	Top-down
Mathematical approach	Linear algebra, statistics	System decomposition, partial derivative	Statistics, econometrics	Envelopment analysis	Simultaneous equations	Differential equations	Statistics and differential equations	Convex optimization and nonlinear programming	Statistics
Geographical Coverage	Global, national, regional, local	Global, national, regional, local	Global, national, regional, local, project	Global, national, regional, local, project	Global, national, regional, local	National, regional, local	Local	National, regional	Local
Sectoral coverage	High	High	High	Medium	High	High	Low	Medium	Low
Time horizon	Short	Short	Short	Medium	Long-term	Long-term	Short	Medium	Short
Data requirement	High	Medium	Medium	Low	High	Medium	Medium	Medium	High
Static analysis	Yes	No	Yes	Yes	No	No	No	No	N/A
Time-series	No	Yes	Yes	Yes	N/A	N/A	N/A	N/A	N/A

	IOA	***IDA***	***Econometrics***	***DEA***	***IAM/CGE***	***SD***	***ABM***	***Optimization***	***Tech-Economic***
High Geo spatial	Medium	Low	High	Medium	Medium	Low	Low	Medium	N/A
Residual terms	No	No	Yes	No	No	No	N/A	No	N/A
Integration with other methods	✓✓✓	✓✓	✓✓✓	✓✓	✓✓	✓	✓✓	✓	N/A
Prediction	✓	✓	✓✓✓	✓	✓✓✓	✓✓✓	✓✓	✓	N/A
Flexibility to incorporate variables	✓✓	✓✓	✓✓✓	✓	✓✓✓	✓✓	✓✓✓	✓✓	✓
Parametric	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Main Limitations	High resolution data requirement; limited flexibility to incorporate new variables	Overlook systemic effect; limited flexibility to incorporate new variables	Hardly avoidable bias in parameter calculation; overlook systemic effect	Non-parametric	Based on logically inconsistent assumptions to some extent	Structured equations with limited evolving capacity	Interactions hardly be articulated to reflect the reality; Highly sensitive to parameters	Detailed prior information required; End up as a NP-hard problem	Heavily relies on the synthesis of technologies and economic expertise
Future directions	Improve data quality and update frequency of database; prediction techniques development; hybrid model	Prediction techniques development; hybrid model	Incorporate more impact factors; overcome bias	Hybrid model; more consideratio n about the international structure of DMU	Improve scenario forecast accuracy	Integrate more meaningful subsystems with more accurate measurements	Vigorous validation with respect to the soundness of model constructions	Integrate more micro-level constraints	Modular-based design of evaluation process

2.6.2 Emerging trends and gaps for method usage in CSCE field

The emerging trends and gaps can be summarized according to the three common research topics of carbon emissions inventory, impact analysis and predictions.

For carbon emissions inventory construction, there have been continuous improvements in data quality and update frequency, partly driven by the dramatic 'big data' capture and analysis that has evolved over recent years. The data sources used by these models have also become increasingly diversified. For example, Ma et al. (Ma et al., 2015) used an activity survey and a geographical information system (GIS) based on land use data to compile data on emissions from work and non-work trips. Global positioning system (GPS) data and GIS data are used to analyse the spatial-temporal features of emissions from taxis (Luo et al., 2017). Remote-sensing data is increasingly used to monitor and verify carbon emissions in factories and workplaces in real time, for example by monitoring carbon that is released from burning coal (Jiang et al., 2017).

There have also been recent attempts to improve the resolution and accuracy of carbon emissions data. For bottom-up research relating to direct emissions, efforts are being made to improve and update the important factors for calculation, including emissions factors, oxidation rates and the quality of fossil fuels. The variations of these factors within and among provinces need to be considered for a comprehensive and accurate understanding. Liu et al. (Z. Liu et al., 2015) found that the IPCC default emissions factor for coal is on average 40 percent higher than Chinese coal, based on on-site sampling from Chinese coal mines. For the MRIO database relating to embodied carbon emissions, scholars have been increasing the update frequency and data resolution. Wang et al. (Wang et al., 2014) demonstrated a new approach to constructing time series data from an MRIO database for China from 1997 to 2011 covering 30 provinces and 135 industries, as well as linkages to 185 countries. In addition, the introduction of multi-scale input-output tables (MSIO) (Shao et al., 2016) also serves as an efficient tool when MRIO data is not available.

For impact analysis a multi-disciplinary perspective is needed for advancing the understanding of climate change and identifying more relevant variables accordingly. The ultimate goal of carbon emissions abatement is to mitigate climate change. The CSCE research is a multi-disciplinary field. The knowledge sharing among scholars will bring out more relevant variables and make better use of the increasingly rich data. For example, sectoral carbon emissions reduction is closely connected with social and economic development. More socioeconomic and governance information can provide extra value, such as income inequity, financial development, low carbon awareness of residents, regional economic collaboration, development concepts bearing by municipal governments and geopolitics around China. Moreover, the climate and geographic information are another source of variables to be considered.

In addition, the development of techniques within each family of methods provides new perspectives to tackle impact analysis problems, and to improve the validity and veracity of model results. Benefiting from its versatility, econometrics is increasingly being used to include these new variables. In addition, there is also a trend for IDA to be decomposed into more factors. Though IOA is frequently used as a database, the IOA analysis techniques should be valued more for examining the systemic effect of variables. In addition, the gap between IOA and IDA with regards to decomposition methods has been narrowed. For example, multiplicative decomposition used to only be used by IDA, but is now being increasingly used by SDA (Su and Ang, 2012). DEA and LMDI are integrated to better assess energy efficiency (Olanrewaju et al., 2012). Several new methods and techniques have been introduced in the CSCE filed. For example, network analysis has recently been combined with IOA to track and control embodied carbon flows (Chen and Chen, 2016; Wang et al., 2017).

For prediction, within the family of simulation, more efforts could be made to bridge the gap between micro- and macro-level analysis. From the comparison of the main methods in CSCE field (see table 2.6), it is found that most of the methods are undertaken at the macro-level. To understand the micro-meso-macro pipeline of CSCE, further research is called for linking microscopic behaviours modelled by agent-based models with macroscopic emission patterns modelled by the ones such as econometrics, IAM/CGE, and system dynamics, by learning from other disciplines (Eppstein et al., 2011; Geertman and Stillwell, 2009; LeBaron, 2012; Miller et al., 2004).

For other families of methods, more techniques can be also introduced for the prediction of emissions. While IOA and IDA are traditionally adopted to analyse past developments, the trend is to do more prospective analysis. For example, the sensitivity analysis of IOA, sometimes combined with other techniques such as Monte Carlo, is increasingly used for future scenario analysis (Cao et al., 2017; Tarancon and Del Río, 2012). This trend is even more obvious for IDA. The projections can be based either on retrospective analysis or on different quantifications of the underlying drivers (Ang, 2015). IDA can also be used to analyse how reduced emissions can be realized through decomposing the difference between the projected emission levels and the business-as-usual scenario (Ang, 2015; Smit et al., 2014).

From an overall perspective, an integration of multiple methods could play a crucial role in enhancing research developments of all the CSCE clusters. For example, building a hybrid estimation model by integrating econometrics with hierarchical clustering techniques, machine learning, induced ordered weighted harmonic averaging operator and LMDI are some of the new endeavours (Bai et al., 2016; Y. Liang et al., 2016; Song et al., 2014). Yet another area of ongoing research activity combines spatial and geographic modelling that use computer vision techniques with deep learning methods, which offer additional insights by analysing the images from a meteorological satellite system.

The integration of EE-IOA with other methods is another good example. It is now possible to integrate EE-IOA with life cycle assessment, including input-output life cycle assessment (IO-LCA) (Bilec et al., 2010; Thiesen et al., 2008) and hybrid life cycle assessment (hybrid LCA) (Finnveden et al., 2009; Suh et al., 2004). The use of hybrid approaches enables a much more detailed account of total life-cycle carbon emissions and makes it possible to adopt a cradle-to-grave philosophy for industries and regions. By incorporating the strengths of bottom-up approaches that use LCA, and of top-down approaches offered by IOA, the benefits of both approaches can be maximised. Recently there have been several attempts to fuse IOA with index decomposition analysis (IDA) (Hoekstra and van der Bergh, 2003; Su and Ang, 2012), scenario analysis (Hubacek and Sun, 2001; Liu et al., 2010; Xuan and Yue, 2017), computable general equilibrium (CGE) (Dervis et al., 1982; Guo et al., 2014) and network analysis (Chen and Chen, 2016; Wang et al., 2017) to achieve different complementary purposes where I-O analysis on its own would not have given the solution required.

From a research content perspective, while the carbon emissions at a national and provincial level dominated CSCE research for almost a decade, a recent trend has been a focus on the role played by cities, firms and residents in carbon emissions reduction. To estimate embodied carbon emissions, the industrial connections between provinces/cities, rather than connections at a regional level, have begun to be the focus of attention in the search for opportunities to reduce carbon emissions. While the Chinese government has demonstrated its determination to curb carbon emissions, more discussion on relevant policies, such as a carbon emissions trading scheme and carbon tax, provide another important area for future research.

The transmission of the embodied sectoral carbon emissions starts to be acknowledged as an important area of investigation. Most of the representative methods deal with a sector's carbon emissions in isolation from other sectors in the economy, overlooking its spill-over effect and interconnections. Though input-output analysis uses Leontief inverse matrix to reflect the economic sectoral connections, while all the rich information is hidden in the matrix, it is very challenging to understand how sectors interact with each other to transfer embodied carbon emissions and how sectors' transmission-related characteristics can influence emissions. Methods are in need to examine the emissions transmission systematically for a synergistic mitigation effect. Some attempts were already made to adopt network analysis to identify the hub sectors which receive or spread emissions to other sectors in the economy (Hanaka et al., 2017; Liang et al., 2016). More methods will be adopted and developed to look into the details of the transmission process, in the hope of identify the leverage points and optimise the collective efforts of all the sectors on carbon emissions mitigation.

2.7 Conclusions and recommendations

China has been playing a leading role in tackling climate change in recent years. China's 13th Five-Year Plan for Economic and Social Development (2016-2020) and its 13th Five-Year Plan on Energy Development, set specific climate and energy targets, which demonstrate China's determination to curb carbon emissions within the country. The national carbon trading scheme launched in 2017 is a good example of putting policy into action. In addition, the Three-Year Action Plan for Winning the Blue Sky, released in 2018 by China State Council, asked for a reduction in carbon emissions in coordination with a reduction in emissions of pollutants. The CSCE research is important for tackling global climate change and has still been an active research field.

This paper presents a systematic and objective review of the main research methods adopted in CSCE field through a survey of 807 papers published from 1997 to 2017. It compares five primary 'families of methods' and assessed their pros and cons. In addition, the knowledge mapping exercise undertaken for this study clarifies where the methods sit within different research clusters. The five families of methods have different focuses and they complement each other to solve the current and future research problems under different research themes. The CSCE field is a very active cross-disciplinary research area. All the methods have been modified and improved through problem solving in realities. From the analysis, all the methods aim to answer three fundamental problems. They are (i) carbon inventory construction, (ii) analysis of carbon emissions influencing factors and (iii) future trend prediction. The research results provide relevant Chinese departments with practical methods for carbon emissions trend prediction, low-carbon path design and environmental innovation. In addition, they also offer reference to similar research in other countries and regions.

When it comes to identifying the most suitable method for assessing carbon emissions, each method has its strengths and weaknesses. For conducting sectoral based analysis of carbon emissions, several methods are suitable depending the research question being asked. If the researcher wishes to understand embodied carbon flows, then IOA is the most appropriate method. For estimating the major contributing factors to sectoral emissions then IDA is the most important. If the researcher wishes to optimise emissions based on different constraints, then Optimisation methods are the recommended approach. DEA is recommended when the research focus is on evaluating the efficiency frontier over regions and sectors.

For predicting or simulating future emission trends by sector then several methods are suitable depending on data availability and the research question. For example, SD methods are most appropriate for assessing stocks and flows and when the dynamic evolution of systems affecting future carbon emission is the primary research interest. ABM methods are most appropriate when a researcher wishes to simulate future outcomes and emergent properties from the system. IAMs are used when the relationship between the economy and environmental outcomes can be described by theory. Techno-economic simulation models are usually used to assess the impacts of new technologies, and finally, econometrics can be used when the user has access to historical time-series data and wishes to achieve a rigorous statistically significant result.

Although CSCE studies have made great progress in many disciplines over the last two decades, there are still substantial gaps that urgently need to be filled. First, the quality of the fundamental data needed for CSCE research have to be improved constantly. GPS, GIS and remote-sensing data technology, as well as onsite surveys could be employed to collect real-time, accurate and high-resolution raw data. In addition, some new approaches need to be developed for constructing MRIO at higher resolutions and with higher update frequencies. Second, the iteration of data and new research results can help modify models and construct dynamic optimization models.

At the same time, the research needs of CSCE based researchers has been changing. While researchers in the past were happy to apply historically collected data, the current trend is to use dynamic real-time data for analysis purposes. While in the past data was sampled, the current tends is to use complete data. In addition, models are increasingly being integrated and adapted, benefiting from the advantages of increased computing power and advances in new methods such machine learning, deep learning, Monto-Carlo and agent-based models. Recent developments aim to improve carbon emissions efficiency measurement and low-carbon policy design through analysing large-scale complex relationships among different driving factors for carbon emissions.

The focus of research methods used for CSCE has been gradually moving away from technological development, to innovation in social governance systems. For example, new research trends are increasingly incorporating (i) the establishment of environmental policies; (ii) the analysis of adjustments to industrial structure, energy structure and transportation structure; and, (iii) the analysis of constructing efficient low-carbon energy system. In addition, while the CSCE used to be approached from national and provincial perspective, it has now expanded into regional economic zones which cross several administrative divisions. From regional perspective, the research focus is on the carbon emissions transfer caused by urbanisation, trade and population immigration, and its influence on optimizing the industrial structure and recognizing carbon abatement responsibilities. Moreover, it is a complex environmental problem to reduce carbon emissions. Efficient response mechanism needs to be formed to deal with problems at different levels, from non-disciplined enterprise-level emissions to large-scale excessive regional carbon emissions. Lastly, the emissions trading scheme (ETS) as well as research and innovation in carbon tax, carbon efficiency improvement and low-carbon policy should be further enhanced to form a solid foundation for reducing greenhouse gases as quickly as possible.

This research was impacted by several limitations. First, this it is limited to the Web of Science database of English peer-reviewed journal papers. The grey literature and non-English journal articles could add another layer of insights to this paper. In addition, while this paper focuses on method review, other knowledge mapping visualisation techniques or methods could be combined to explore and explain developments from other perspectives, such as the author collaboration network and more qualitative or policy-focused analysis.

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Chapter 3 CARBON COMMUNITIES AND HOTSPOTS FOR CARBON EMISSIONS REDUCTION IN CHINA

Preface

The text for this chapter is reproduced from paper *carbon communities and hotspots for carbon emissions reduction in China* published in Sustainability. This chapter proposes a theoretical model to examine embodied carbon emissions transfer between sectors of regions in China. It adopts network analysis metrics and algorithms to clarify emissions transmission patterns and identify the leverage points for effective carbon emissions abatement. Through the literature review in Chapter 2, the importance of mitigating carbon at both the regional and sector levels are active areas of research, and that there is a trend to adopt hybrid methods for complementary research purposes. In this chapter, drawing on input-output analysis and network analysis theory and models, the study constructs a theoretical model of carbon emissions transfer networks amongst sectors and regions. In addition, a two-step network reduction algorithm is proposed to extract the multi-level network structure to deal with the challenges posed by the redundant intricacy and large number of edges in the raw network. Using empirical data, the 2012 embodied sectoral carbon emissions network is constructed. It is used to demonstrate how network analysis can examine embodied carbon emissions flows from micro, meso and macro perspectives. Policy suggestions are also proposed on the basis of the research results for carbon emissions mitigation.

Carbon communities and hotspots for carbon emissions reduction in China

Abstract

With China's commitment to peak its emissions by 2030, sectoral emissions are under the spotlight due to the rolling out of the national emission trading scheme (ETS). However, the current research focuses either on production or consumption while the majority of sectors falling between are overlooked. This research combines input–output modelling and network analysis to track the embodied carbon emissions among thirty sectors of thirty provinces in China. Based on the large-data resolution network, a two-step network reduction algorithm is used to extract the backbone of the network. In addition, network centrality metrics and community detection algorithms are used to assess each individual sector's roles, and to reveal the carbon communities where sectors have intensive emission links. The research results suggest that sectors with high out-degree, in-degree or betweenness can act as leverage points for carbon emissions mitigation. In addition to the electricity sector, which is included in the national ETS, the study found that the metallurgy and construction sectors may also have the potential to leverage the efforts for emissions reduction from national and local levels from transmission perspective.. However, the hotpots are different across provinces and thus provincial specific targeted policies should be formed. Moreover, there are nineteen carbon communities in China with unique features, providing future direction for provincial governments' external policy collaboration for synergistic effects.

Keywords: China; carbon emissions; network analysis; input–output analysis; climate change; policy

3.1 Introduction

The importance and urgency of reducing sectoral carbon emissions in China is widely recognized (Andersson, 2018; Bai et al., 2019; Mi et al., 2017; Su and Thomson, 2016; Wang et al., 2018; Zhou et al., 2014). However, there are many challenges in dealing with the problem efficiently due to the complex supply chain relationships between sectors. For carbon intensive sectors, a large percentage of sectoral outputs are used as intermediate inputs in other sectors of the economy. The intermingled sectoral connections make it challenging to differentiate each sector's responsibility for carbon emissions and where to target carbon emission reduction strategies.

In the current practice of identifying sector's responsibilities and advising policy to mitigate emissions, emissions are either allocated completely to the sectors involved in production (the production approach) or completely to those sectors involved in consumption (the consumption approach). The production-based accounting methods prioritize the sectors which directly produce emissions when at source (Chen et al., 2016; Lin and Wang, 2015; Shan et al., 2018b; Xu et al., 2012). On the other hand, consumption-based accounting methods attribute all emissions in the supply chain to end use sectors (Liu et al., 2015; Meng et al., 2011; Su and Ang, 2014; Zhang et al., 2015). The argument for adopting a production perspective for the allocation of sectoral carbon emissions include the ease of estimating emissions at the source of emissions. For example, the total carbon emissions for a sector can be directly estimated from the quantity of fossil fuels that are purchased and consumed by a sector, multiplied by known emissions factors for different fuel types. In contrast, when estimating consumption-based emissions, a second step is required that allocates emissions from across the supply chain to final consumers. The argument for using a consumption-based approach is that ultimately it is final consumers who induce demand for goods and services in the economy and thus ultimately it is end users who are responsible for the emissions being produced.

However, both the production perspective and the consumption perspective disregard the transmission of carbon emissions through the economy. While the majority of analysis to date has ignored the transmission perspective, it is beginning to be acknowledged as an important area of investigation (Hanaka et al., 2017; Li et al., 2017; Liang et al., 2016). For example, a transmission perspective can identify the sectors which interact directly with the original source of emissions and the final consumers of end products. The transmission sectors therefore provide a bridge between the producers and consumers and could provide new opportunities for policy development to reduce sectoral carbon emission flows through targeting industrial sectors that are neither responsible for consuming fossil fuels directly from a production perspective nor are they the final consumer of any of these products. By looking into details at the transmission sectors connecting the source of emissions to final consumers, all sectors are put under the microscope and their roles in transmitting carbon through the economy are examined.

This research fills the gap by analyzing data from an environmentally-extended input–output (EE-IOA) table using network analysis to track the embodied carbon emission flows among 30 sectors of 30 provinces in China. An embodied carbon emission network is developed and analyzed using network analysis metrics. More specifically, by examining the roles of sectors through community detection, degree centrality, strength centrality, and betweenness centrality, the carbon intensive communities and hotspots of sectors along the transmission pathway are revealed.

Our research regarding the importance of the transmission perspective is novel and contributes to the literature in the following ways. First, our embodied carbon emission network has a large data resolution, consisting of 30 sectors of 30 provinces, and a two-step network reduction algorithm is adopted to extract the backbone of the network. Therefore, the noise in our network is considerably reduced and the network can reveal the transmission pattern more clearly at a meso level. Secondly, when network metrics is applied to such an adjusted large-resolution network, new insights can be provided. For example, our analysis suggests that the 30 sectors of Beijing are divided into six communities with other province sectors. This structure cannot be identified using other methods where Beijing is taken as a single entity (Meng et al., 2011; Mi et al., 2017; Sun et al., 2016). Thirdly, our research findings are connected with policy development goals. Specific policies options arising from the findings are proposed at national, provincial and sectoral level.

The paper is structured as below. The next section presents the data, followed by methodology presented in Section 3. Section 4 briefly discusses the results and the last section concludes the paper.

3.2 Research Data

The multi-region input–output (MRIO) table of China and sectoral carbon emissions data are essential for constructing the embodied carbon emission network. For the MRIO tables, due to high data resolution requirement and complex composition methods, there is a significant time lag between each new release of input-output data tables. For examples, by the end of 2019, the latest MRIO tables of China have been the datasets for the year of 2012. In addition, China's National Bureau of Statistics has not published any official MRIO tables. Instead, the MRIO tables are compiled by several leading research team both within and outside China. For the sectoral carbon emissions calculation, IPCC and National Development and Reform Commission (NDRC) provide default emission factors for different energy types. However, the default emission factors are questioned to be higher than the real emissions factors (Liu et al, 2015).

This research used the data published in CEADs: China Emission Accounts and Datasets（http://www.ceads.net). It is stated in the website that ‘all datasets published by CEADs are the results of projects funded by Research Council UK, Newton Fund, the National Natural Science Foundation of China, Chinese Academy of Sciences’. The quality of the datasets are assured by the leading academic projects. In addition, these datasets are frequently used by leading scholars in the field, including publications in Nature and Nature Communication (Mi et al., 2017; Li et al 2015). Moreover, for the sectoral carbon emissions data, the datasets from CEADs are selected due to its comprehensiveness and accuracy. Both the carbon emissions from fossil fuel combustion and from industrial process are accounted in the emissions inventory. In addition, the default emission factor provided by IPCC and NDRC have been adjusted by the 602 coal samples results from the 100 largest coal-mining areas in China (Liu et al., 2015).

In order to reflect the latest embodied carbon emissions transmission in China, the multi-region input–output (MRIO) table of China in 2012 and the sectoral carbon emission data in 2012 were used to construct the embodied carbon emissions network. The MRIO table covers trade amongst 30 sectors and 30 provinces (excluding Tibet, Taiwan, Hong Kong and Macau due to lack of data) (Mi et al., 2017). The carbon emissions from 45 sectors for the year 2012 were calculated using the IPCC sectoral approach, based on energy consumption data and adjusted emissions factors from the Chinese statistics bureau (Shan et al., 2018b).

In order to keep sectors consistent between the China MRIO tables and the provincial-level CO_2 emission inventory (by IPCC Sectoral Approach), sectors were aggregated. Please see Table A1 in the Appendix A for details on sector matching between the two data bases. After the aggregation, there were 30 sectors and 30 provinces contained in the database.

3.3 Method

In order to track the embodied carbon emissions flows among sectors of different regions, the classic environmentally extended multi-region input-output(MRIO) model is adopted (Liu et al., 2015; Meng et al., 2011; Su and Ang, 2014; Zhang et al., 2015). The Leontief inverse matrix $\boldsymbol{L} = (\boldsymbol{I}-\boldsymbol{A})^{-1}$ reflects the direct and indirect input requirements of sector's outputs from other sectors. Complemented with the carbon intensity information of each sector, the embodied carbon emission flows among sectors of regions can be outlined. It provides the foundation for researching the transmission characteristics of the embodied carbon emissions.

However, common MRIO analysis techniques are not adopted in this research, mainly due to the consumption perspective they usually take to addresses the carbon emissions mitigation problems. For example, the multiplier effect analysis focuses on the systematic effect of sectors' final demand changes on the whole economy. The structural decomposition analysis (SDA) applys a disaggregated comparative statical approach to both final demand and technological structure (Cellura et al., 2012; Su and Ang, 2012; Su and Thomson, 2016; Yuan et al., 2015). Even if structural path analysis (SPA) and linkage analysis touches some transmission features of an economy, the research focus is still on some particular sectors, instead of the transmission structure of the whole economy (Feser and Bergman, 1998; Wood and Lenzen, 2003; Xu and Liang, 2019). For example, SPA examines supply chain paths contributing to particular sectors' carbon emissions (Liang et al. 2015). Linkage analysis studies the upstream and downstream impacts of particular sectors to the economy (Xu and Liang, 2019).

Recently there have been several attempts to fuse MRIO analysis with other methods to achieve different complementary purposes where input-output analysis on its own would not have provided the solution required. For example, it is possible to integrate EE-IO with life cycle assessment to enable a much more detailed account of total life-cycle carbon emissions, and makes it possible to adopt a cradle-to-grave philosophy for industries and regions (Bilec et al., 2010; Finnveden et al., 2009; Thiesen et al., 2008). In addition, MRIO analysis have been incorporated into computable general equilibrium (CGE) models to estimate how an economy may react to a change in policy, technology or other external factors. By providing simulation results based on different scenarios, the consequences of low-carbon policy choices are presented in a clear and easy to understand way. However, most of the attempts rely on the sectoral interrelationships outlined by the MRIO model directly to pursue their own research agenda on emissions inventory, impact analysis or predictions, instead of digging into the rich sectoral information contained in the MRIO model itself, and focusing on the transmission perspective.

To research the transmission feature of the embodied carbon emissions in an economy from a holistic perspective, network analysis is introduced to provide a framework and a suite of new metrics. While rich sectoral inter-relationship information is hidden in the technical coefficient matrix A and the Leontief inverse matrix $\boldsymbol{L} = (\boldsymbol{I}-\boldsymbol{A})^{-1}$ in input-output analysis, network analysis goes deep into the matrices, takes the economy structure as a whole, and carris out an in-depth study of sectoral dependency relationships. More specifically, the interdependent relationships between sectors can be modelled as a complex network. The transmission characteristics can be studied through the lens of network structure analysis from macro, meso and micro perspectives using a variety of network analysis metrics and algorithms.

3.3.1. Network Construction of 2012 Embodied Sectoral Carbon Emissions

The MRIO model tracks flows of products and services among sectors of different regions. The inter-industry production matrix is represented by $\boldsymbol{Z} = (z_{ij}^{rs})$ $(i, j = 1, \dots, M; r, s = 1, \dots, N)$ where element z_{ij}^{rs} represents the intermediate input from sector i (e.g., the metal sector) in region r (e.g., Hebei province) to sector j (e.g., the construction sector) in region s (e.g., Beijing). The final demand vector is represented by $\boldsymbol{f} = (\sum_{s=1}^{N} f_i^{rs})$, where element f_i^{rs} represents the amount of products from sector i in region r sold to final consumers in region s. The total output vector is represented by $\boldsymbol{x} = (x_i^r)$ where element x_i^r is the total output of sector i in region r. Total output is calculated as the sum of intermediate demand and final demand in the economy as shown by Equation (1).

$$\boldsymbol{x} = \boldsymbol{Zi} + \boldsymbol{f} \tag{1}$$

$A = (a_{ij}^{rs})$ is defined as technical coefficient matrix, where element $a_{ij}^{rs} = x_{ij}^{rs}/x_j^s$ is defined as geographical input coefficient. The element a_{ij}^{rs} is a constant and represents the direct requirement from sector i in region r per unit of output of sector j in region s. Formula (1) can be rewritten as

$$\boldsymbol{x} = \boldsymbol{Ax} + \boldsymbol{f} \tag{2}$$

$$\boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{f} = \boldsymbol{Lf} \tag{3}$$

where $\boldsymbol{I}$ is the identity matrix.

Equation (3) is the solution of the basic MRIO model. Given an exogenously specified demand, the equations can be used to calculate the total industrial output directly and indirectly generated by the demand. $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the Leontief inverse or total requirements matrix. Each element represents the total amount of products of sector i in region r that are needed to produce one unit of products of sector j in region s.

An MRIO-based Chinese economy can be regarded as a network where nodes represent economic sectors, and edges between nodes represent economic transactions between sectors. Carbon emission are transferred along the same economic pathways embodied in goods and services sold through the supply chain. In other words, the carbon emissions that are embodied in the production process of products, are embedded within traded goods or services from one sector to another. These virtual or embodied emissions are transferred from sector i to sector j are represented by the embodied carbon emission transfer network, $\boldsymbol{G}$ in Equation (4). From this notation nodes represent economic sectors and edges between nodes represent the flow of embodied carbon between them.

The embodied carbon emission transfer network of China can be constructed using the following equation.

$$\boldsymbol{G} = \widehat{\boldsymbol{k}}\boldsymbol{L}\widehat{\boldsymbol{f}} \tag{4}$$

where $\boldsymbol{k}$ is the carbon emission intensity vector, referring to each sector's direct production based carbon emission per monetary unit of its total output represented by the units (thousand tons CO_2/¥); $\boldsymbol{G}$ is a matrix with the element g_{ij}^{rs} representing the transfer of embodied carbon emissions from sector i in region r to sector j in region s to satisfy the multi-regional final demand f. Please note that the elements in the $\boldsymbol{G}$ matrix represent the total embodied emissions within each sector that are both directly and indirectly generated throughout the supply chain. The embodied carbon network is analyzed, and this research presents the final carbon emission transmission relationship among sectors and regions after all rounds of production.

The embodied carbon emission transfer network can be represented by $\boldsymbol{G}$ = ($\boldsymbol{V}$, $\boldsymbol{E}$). The set of nodes are defined by $\boldsymbol{V}$ = {(1,1), …, (M,1), (1,2), …, (M,2), …, (1,N), …, (M,N)}, i.e., (industry code, region code). $\boldsymbol{G} = \left(g_{ij}^{rs}\right)$ is the adjacent matrix of the network. The set of directed edges is $\boldsymbol{E} = \left\{(i,r)(j,s) \mid g_{ij}^{rs} > 0\right\}$and the carbon emission weights assigned to each edge of the matrix is given by $\left((i,r)(j,s)\right)\, g_{ij}^{rs}$.

3.3.2. Two-Step Reduction of the Carbon Network

It is difficult to draw information directly from the constructed embodied carbon emission network due to the very large number of non-zero edges contained in the network. Because of the nature of MRIO tables, almost all sector-region pairs are linked by some degree. The redundant intricacy and large number of edges presents challenges for network analysis and the functioning of some network metrics and algorithms. A common way to reduce the number of edges in a network is to set a threshold for edge weight and remove all the edges below the cut-off value.

However, setting the same threshold for all the regions and sectors will downplay the sectors with low carbon emission production, and has very limited noise reduction effect for reducing the statistically insignificant edges connected with the sectors with high carbon emission production. Nonetheless, the sectors with low carbon emission production may potentially be important for carbon emission transmission. In addition, while the edges of high carbon emission production sectors tend to be large in absolute values, some of them are not statistically significant compared with the source sectors' total emissions. Moreover, the embodied carbon emission network is a strongly disordered network with heavy-tailed statistical distribution of node strength and edge weight. It means that a high percentage of sectors have low carbon emission production and relatively week carbon emission transmission with other sectors. Therefore, it is difficult to set an appropriate threshold value large enough to reduce the number of edges to a manageable size for the network algorithm to function well, and small enough to keep the main structure for sectors with different scales of carbon emission production. For example, a threshold of one ton would reduce 9.5% percent of the total edges, and the noise for high carbon emission production sectors' edges would be left almost untouched.

In this research, we used Serrano et al.'s (Serrano et al., 2009) algorithm to extract the backbone of the embodied carbon emission network. By using this algorithm, each node was assigned a null model, which informed the random expectation for the distribution of weights associated to its edges, considering the node's total strength. Each edge was compared with the null model of the two nodes at the end of each edge. Only when an edge was statistically significantly deviant from the null model of at least one of the end nodes, the edge would be kept. The significance level was put at a = 0.05 for this research. By taking the procedure, the nodes with comparatively small strength were not ignored, and the total number of edges were reduced considering all scales in the network.

After the backbone algorithm reduction, we use the threshold of one ton to reduce the network further. If the carbon emission flows between two sectors was less than one ton, the transfer relationship was considered too weak to be included. Therefore, the edge between the two sectors was deleted to further reduce the noise. A total of 92.90% of edges were removed using the backbone algorithm and a further 0.04% of edges were removed using the threshold of 1 ton.

3.3.3. Community Detection in the Carbon Network

The multi-level modularity optimization algorithm from the R library igraph was adopted to reveal the communities in the embodied carbon emission network. It is a heuristic method based for modularity maximization (Blondel et al., 2008). This algorithm works well on a large network, especially in terms of computation time and quality measured by modularity. Modularity Q measures the extent to which a network can be grouped into communities with distinct boundaries. It is commonly used to detect unfolding communities in many large networks for a number of different contexts

(Bassett et al., 2011; Del Río-Chanona et al., 2017; Jia et al., 2018; Wagner et al., 2016). Additionally, in order to check the robustness of the community detection algorithm, fast greedy modularity optimization algorithm proposed by Clauset (2004) was also applied to the network. Both algorithms do not pre-define the number of communities in the network, and they are commonly used to detect community in large complex network. Some scholars made attempts to outline industrial clusters on the basis of input-output analysis. There are some differences between network analysis based community detection algorithms and input-output analysis based cluster detection algorithms. (Community and cluster have similar meaning, both refer to a group of sectors which have more intensive exchange within the group than outside. Community is more frequently used in network analysis, while cluster is used more frequently used in input-output analysis.) The basic difference lies in the perspective of how clusters/communities are approached. Take the cluster detection algorithm proposed by Kanemoto et al. (2018) and the multi-level modularity optimization algorithm (Blondel et al., 2008) used by the research for example. Kanemoto et. al (2018) stated that the "clusters" should be sub-groups alongside the pre-defined supply chain. In contrast, the community detection algorithm takes communities as condensed sub-groups detected in the whole network, without looking in detail at each supply chain. More specially, differences can be found in the objective function, optimization algorithms, assumption of community size, and the input treatment. Details are listed in table 3.1.

Table 3.1 Comparison between cluster detection method and community detection method

	Cluster detection algorithm by Kanemoto et al. (2017)	**Community detection algorithm by Blondel et al. (2008) and two-step reduced network**
Objective function	Minimize the normalized cut functions, aiming to detect the clusters who have the least inter-clusters connections along supply chains.	Maximize network modularity, aiming to find the communities who have the largest overall modularity from the whole network perspective
Optimization algorithms	Greedy, hierarchical and move based algorithms	Heuristic algorithm
Cluster/community assumption	Pre-define the size of cluster, which is seven sectors in each cluster	No assumption about the size and number of communities
Treatment of input	Whole dataset of input-output table	Two-step reduced network as input to reduce noise in the process of the community detection

Compared with Kanemoto et al. (2017)'s cluster detection method, our proposed method is more data-driven and more suitable in the context of the carbon emissions mitigation in China. Our method does not pre-define supply chains and the community size, and therefore the community detection result is more objective and data driven. In addition, the community is detected on the basis of the whole network and almost all the sectors of provinces are grouped into communities, instead of only focusing on the key small clusters of seven sectors. The result can provide more insight for a synergistic effect among all sectors of provinces in China. Last, our research proposes a two-step reduction method to treat the raw network, and it reduces noise in the process of the community detection and has much less computation demand.

3.3.4. Position Measurement of Sectors in the Carbon Network

In this paper, five classic network metrics at node level were adopted to analyze the embodied carbon emission network. Table 3.1 gives a brief introduction of the metrics. More detailed information about the metrics can be found in A.2. Network metrics in Appendix A.

Table 3.2 Network metrics in the context of carbon emissions transfer network

Network Metric		Measurement	Formula	Meaning in the Carbon Emission Network
Degree Centrality	In-degree	The number of inward edges a node directly has with other nodes	$D_i^{r\ in} = \sum_{(j,s)\in N_i} D_{ji}^{sr}$	A sector's number of import partners
	Out-degree	The number of outward edges a node directly has with other nodes	$D_i^{r\ out} = \sum_{(j,s)\in N_i} D_{ij}^{rs}$	A sector's number of export partners
Strength Centrality	In-strength	The total weights of inward-edges connected to a node	$W_i^{r\ in} = \sum_{(j,s)\in N_i} g_{ji}^{sr}$	The total volume of embodied carbon emissions imported to a sector
	Out-strength	The total weights of outward-edges connected to a node	$W_i^{r\ out} = \sum_{(j,s)\in N_i} g_{ij}^{rs}$	The total volume of embodied carbon emissions exported from a sector
Betweenness Centrality		The total volumn of flow going through a node	$b_i = fTJ_iTy$ * The formula is adjusted using Liang's 2016) algorithm.	The total volume of embodied carbon emissions going through a sector

3.4. Results and Discussions

3.4.1. Overview of the 2012 Embodied Carbon Emission Network of China

The 2012 embodied carbon emission network was constructed based on the 2012 MRIO table of China. The network had 900 nodes and 774,391 edges. For ease of clear expression, a sector of a province was denoted as a sub-sector, and a sector was denoted the sector at national scale for the following analysis. In the context of the national carbon emission network, there were 900 sub-sectors and therefore 900 nodes in the network. As discussed in Section 3.2, some network metrics cannot function well in a fully connected network. Take the degree centrality for example, 97.11% of all nodes had the same in-degree centrality 876 and out-degree centrality 882. The result was mainly due to the nature of input–output tables, where almost all sectors are connected after all rounds of production are considered. However, some connections are trivial in terms of total embodied emissions. Moreover, there was a large variance for the strength of edges. The maximum edge weight was 82.95 million tons, while the minimum was 0.003 g.

The final network used a backbone algorithm with a coefficient of a = 0.05 and an edge threshold of one ton. The final network therefore only consisted of edges that were statistically significant from the null model (higher than 95%) and with an edge weight that was above one ton. After the two-step network reduction, 886 nodes were retained in the final network. The deletion of 14 nodes were due to the fact that those sub-sector did not produce any carbon emissions and they did not have any significant in-flows and out-flows with other sectors. For example, Shanghai had no coal mining sector and this sector had no significant in-flows and out-flows, so the corresponding node was deleted from the raw network. After completing this process, the number of edges was reduced significantly retaining only 7.0% of all edges and eliminating 719,721 edges. At the same time, 93.0% of the total carbon missions were retained in the final network.

After all insignificant edges were removed, it was easier to extract the relevant information from the network. For an overview of the reduced network, both the degree and edge weight exhibited a long-tail characteristic. Take the degree including both in-degree and out-degree as an example. While the majority of nodes had a total degree of less than 200, there were still quite a few nodes having a much larger degree with a maximum of 921. In addition, the average degree including both in-degree and out-degree was 121. The overall network density was 0.071. (See detailed degree distribution in Figure A1 in the Appendix A.)

Figure 3.1 is a visualization of the 2012 embodied carbon emission transfer network after the two-step reduction process. The figure was drawn by Gephi using the OpenOrd algorithm. The algorithm (Martin et al., 2011) was good at visualizing a large graph and for revealing both a local and global structure. In the figure below, each node represents a sector within a province and all nodes belonging to the same province were made the same color. The edges among the nodes represent the transmission of embodied emissions between sectors. The color of edges was decided by the source node and all the edges below 100,000 thousand tons were removed to show the transmission pattern more clearly. The sectors with a close trading relationship are graphed by the algorithm to have a close proximity while those with a distant relationship are forced apart. It can be seen that the transmission of embodied carbon emissions is distributed unevenly among the network. In general sectors from the same province have a much closer relationship, because the nodes in the same color tend to be in close proximity. In addition, the provinces in the centre of the graph have their sectors highly connected. Especially for some sectors of Beijing, Inner Mongolia, and Jiangsu, which represent the heart of the network and show a close trading relationship with each other. On the other hand, there are some distinguished communities on the periphery of the network, especially for Qinghai and Hainan provinces.

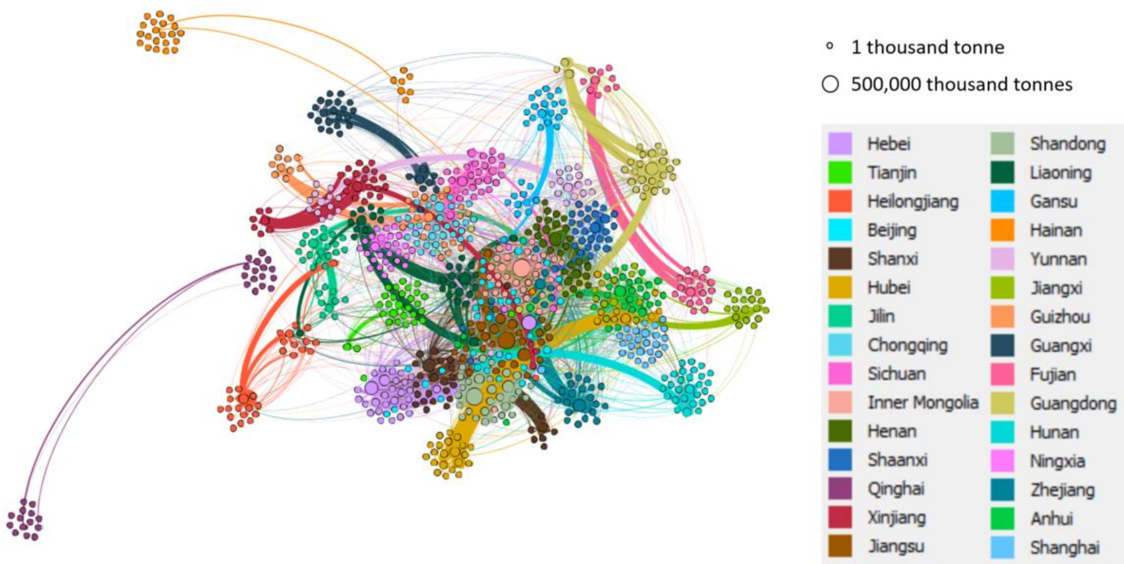


Figure 3.1 Visualization of the 2012 carbon emissions transfer network.

3.4.2. Position of Sub-Sectors and Sectors in the 2012 Embodied Carbon Emission Network

3.4.2.1. Outward Flows

Out-degree and out-strength capture the characteristics of a sector's outward embodied carbon emission flows. The out-degree metric counts a sector's export partners, and the sectors with high out-degree centrality are more likely to transmit its emissions to a wide range of other sub-sectors. On the other hand, the out-strength counts the total volume of embodied carbon emissions exported from a sector. Based on the reduced 2012 embodied carbon emission network, out-degree and out-strength for each sub-sector and sector are calculated using the metrics definition in Table 3.1. See Table 3.2 below for the summary of the two metrics at sub-sector and sector level. (More details about sector level network metrics can be found in Table A2 in the Appendix A.) In addition, out-strength is closely associated with the amount of carbon emissions a sector directly produces. The Spearman correlation between the production-based accounting rank of the sub-sectors and the out-strength rank was 0.94. The high correlation suggested that although carbon intensive sectors produced a large amount of carbon emissions during the production procedure, these carbon-intensive products were mainly used to satisfy the final demand of other sectors.

Table 3.3 Summary of out-degree and out-strength metrics.

Network Metric		**Mean**	**Median**	**Standard Deviation**	**Maximum**	**Minimum**
Sector at provincial level	Out-degree	60.70	41.00	95.64	886.00	0
	Out-strength	9042.79	301.26	36,487.83	445,774.85	0
Sector at national level	Out-degree	59.76	40.90	76.97	454.43	23.80
	Out-strength	8902.12	540.55	27,701.59	146,000.77	17.00

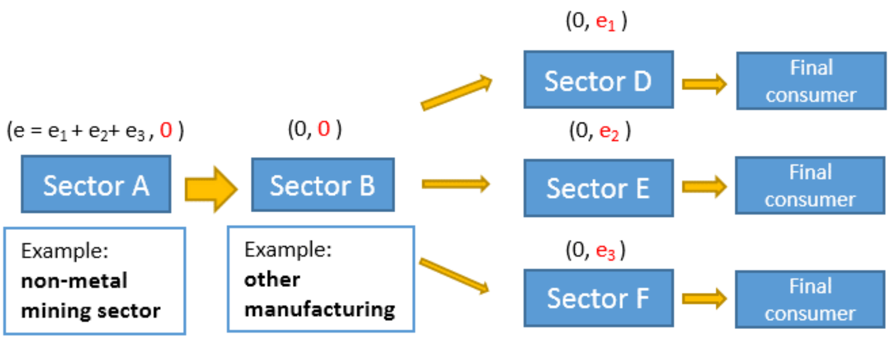
(Unit of out-strength: Thousand tons).

The electricity and hot water production and supply (EWPS) sector had the largest out-degree and out-strength values in every province and at national level. It was mainly due to the fact that the EWPS sector used a very large amount of fossil fuels energy to produce electricity, and electricity was used as inputs almost in all sectors for production. After all rounds of production, those partnerships were strengthened and EWPS sub-sectors ended up with a high out-degree and out-strength centrality.

However, there was a significant mismatch between out-degree rank and out-strength rank for the majority of other sectors. The Spearman correlation between out-degree rank of 900 sub-sectors and out-strength rank was 0.49. (More details about the comparison between out-degree and out-strength rank can be found in Tables A3 and A4 in Appendix A.) This means those sectors with a large export of embodied carbon emissions ar below average for transmitting emissions to a wide coverage of other sub-sectors. Take the non-metal product sub-sector as an example. It was listed 23 times in the top 100 high out-strength rank, but only 2 times in the top 100 high out-degree rank. This means that while the non-metal sub-sector is a carbon intensive sector, but the majority of its products are taken as intermediate inputs by a comparatively small number of other sub-sectors.

Figure 3.2 shows an example to demonstrate the importance of sectors with a high out-degree. The example in Figure 3.2 is not intended to draw out sectoral connections in the real economy, but to create a simple five-sector economy for demonstration. Suppose only sector A directly produces carbon emissions e during the whole supply chain. Only sector D, E, and F produce products that are used by final consumers, and they cause carbon emissions at the source by e_1, e_2, and e_3 respectively. From the whole system perspective, the carbon emissions produced at the source should be equal to the carbon emissions caused by final demand, so $e = e_1 + e_2 + e_3$. The values in brackets are the amount of carbon emissions calculated from a production perspective (left in black) and consumption perspective (right in red).

The carbon intensive sector A has a high out-strength, but it does not transmit the carbon emissions to a large coverage of other sectors, which results in low out-degree, such as the non-metal mining sector. It is sector B that spreads out carbon emissions and has a high out-degree, such as "other manufacturing" sector. Sector B is not deemed as important from neither a production or consumption perspectives, but it plays an important role in transmitting the carbon emission out to a wide coverage of other sectors. From a policy perspective, sector B is very important in tracking carbon emissions. By informing the downstream suppliers with carbon information. In time, with relevant policy guidance, it is more likely to bring out the collective efforts of all the downstream players on carbon emission mitigation together.



Metrics	Results for A	Results for B
Out-degree	1	3
Out-strength	$e_1 + e_2 + e_3$	$e_1 + e_2 + e_3$

Note: The values in brackets are the amount of carbon emissions produced and induced by each sector. The value on the left in black is the amount calculated from a production perspective, and the value on the right in red is the amount calculated from a consumption perspective.

Figure 3.2 A five-sector example illustrating the importance of high out-degree sector.

3.4.2.2. Inward Flows

In-degree and in-strength capture the characteristics of a sector's inward embodied carbon emission flows. The in-degree metric counts a sector's number of import partners, and the sectors with high in-degree centrality are more likely to receive embodied emissions from a wide range of other sub-sectors. On the other hand, the in-strength counts the total volume of embodied carbon emissions imported to a sector. Based on the reduced 2012 embodied carbon emission network, in-degree and in-strength for each sub-sector and sector are calculated using the metric definition in Table 3.1. See Table 3.3 below for the summary of the two metrics at sub-sector and sector level. In addition, the Spearman correlation between the in-strength rank of the sub-sectors and the consumption-based accounting rank was 0.96, a very high correlation between the ranks.

Table 3.4 Summary of in-degree and in-strength metrics

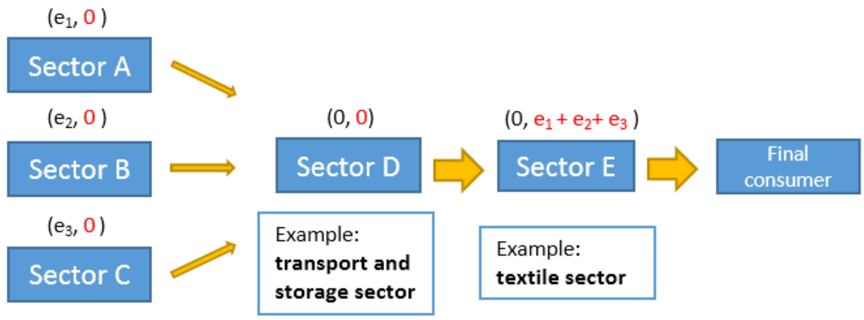
Network Metric		**Mean**	**Median**	**Standard Deviation**	**Maximum**	**Minimum**
Sector at provincial level	In-degree	60.71	41	78.11	791	0
	In-strength	9042.79	1889.56	23,105.88	262,254.91	0
Sector at national level	In-degree	59.76	41.17	60.42	347.27	17.57
	In-strength	8902.12	3089.64	18,297.25	98,819.55	61.32

(Unit of in-strength: Thousand tons)

The construction sector had the largest in-degree and in-strength values in every province and at national level. It was mainly because the construction sector uses a large amount of carbon intensive products during the production procedure. In addition, the products of the construction sector, i.e., construction buildings, were mainly used to satisfy final demand. Even though a small percentage of construction buildings were used as intermediate inputs by other sectors, because the sector only produces a small amount of carbon emissions directly and the construction of buildings can be only used locally, the out-strength and out-degree were very small. Therefore, the construction sector can be regarded to be at the end of the value chain.

A mismatch between in-degree rank and in-strength rank for the majority of other sectors can be observed. The Spearman correlation between in-degree rank of 900 sub-sectors and in-strength rank was 0.73. (More details about the comparison between in-degree and in-strength rank can be found in Tables A5 and A6 in the Appendix A.) It suggests that sectors inducing a large amount of carbon emission from consumption perspective were more likely to have high in-degree values. However, there were still some sectors inducing small amount of carbon emissions from consumption perspective had high in-degree values, such as the 'other manufacturing' sector of Shanghai with a difference of 335 in the two ranks.

Figure 3.3 shows an example to demonstrate the importance of sectors with a high in-degree value. Suppose only sector A, B, C produce carbon emissions during the production procedure, and only sector E produces products that are used by final consumers. The carbon intensive sector E has a high in-strength, but it does not receive the carbon emissions from a large range of other sectors, which results in low in-degree, such as the textile sector. It is the sector D that receive carbon emissions from a wide range of sectors and it has a high in-degree, such as transport and storage sector. Sector D is therefore not deemed as important from either a production or consumption perspective, but it plays an important role in transmitting the carbon emission from a wide coverage of sectors. From a policy perspective, sector D is also very important in tracking carbon emissions. By asking for carbon information, sector D is pushing the upstream suppliers to implement carbon tracking practice. In addition, it is good for sector D and the downstream suppliers to make informed decisions to reduce carbon intensive inputs.



Metrics	Results for D	Results for E
In-degree	3	1
In-strength	$e_1 + e_2 + e_3$	$e_1 + e_2 + e_3$

Note: The values in brackets are the amount of carbon emissions produced and induced by each sector. The value on the left in black is the amount calculated from a production perspective, and the value on the right in red is the amount calculated from a consumption perspective.

Figure 3.3 A five-sector example illustrating the importance of high in-degree sector.

3.4.3.3. Betweenness

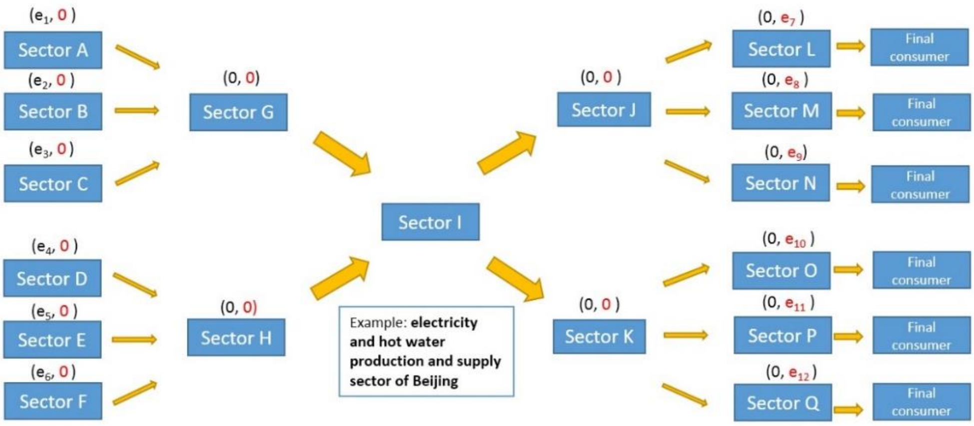
The betweenness of a sub-sector measures its influence as a transmission vehicle for embodied carbon. It examines the amount of embodied carbon emissions going through a sector to satisfy other sectors' final demand. Sectors with high betweenness are different from carbon emission senders (i.e., out-degree and out-strength) and carbon emission receivers (i.e., in-degree and in-strength). These sectors are in the middle of the supply chain and act purely in a transmission role. Based on the reduced 2012 embodied carbon emission network, betweenness for each sub-sector and sector are calculated using the metric definition in Table 3.1. See Table 3.4 below for the summary of this metric at sub-sector and sector level. In addition, metallurgy sector had the largest betweenness value in every province and national level. It suggests that metallurgy takes carbon-intensive inputs from other sub-sectors, and their products are largely used as intermediate inputs for the production of other sub-sectors. (More details about betweenness ranks of sectors and sub-sectors can be found in Tables A7 and A8 in the Appendix A.)

Table 3.5 Summary of betweenness metrics

Network Metric		Mean	Median	Standard Deviation	Maximum	Minimum
Betweenness	Sector at provincial level	19,381.32	6244.21	41,304.82	490,225.03	1.07
	Sector at national level	19,079.83	24,915.33	12,150.82	109,897.99	1541.98

(Unit: Thousand tons).

Figure 3.4 shows an example to demonstrate the importance of sectors with high betweenness value. Suppose only six sectors A-F produce carbon emissions during production, and only six sectors J-K produce products that are used by final consumers. In addition, the sum of e_1, e_2, e_3, e_4, e_5, and e_6 is equal to the sum of e_7, e_8, e_9, e_{10}, e_{11}, and e_{12}. In the theoretical situation where sectors G, H, I, J, and K do not produce any emissions and do not sell any products to final consumers, these sectors will be ignored from both a production and consumption perspective. However, these sectors have large betweenness values from a transmission perspective. The betweenness sector focuses on the total amount of carbon emissions going through a sector from a whole economy perspective. In this case, sector I has the largest betweenness value. From a policy perspective, the sectors with high betweenness values can act as a leverage point for collective carbon emission reductions by reducing inputs of carbon-intensive products through production technology improvement. In addition, by supervising and implementing the carbon tracking practice, the sectors with high betweenness and their downstream suppliers can make informed decisions on choosing inputs.



Metrics	Results for G	Results for H	Results for I	Results for J	Results for K
In-strength	$e_1 + e_2 + e_3$	$e_4 + e_5 + e_6$	$e_1 + e_2 + e_3 + e_4 + e_5 + e_6$	$e_7 + e_8 + e_9$	$e_{10} + e_{11} + e_{12}$
In-degree	3	3	2	1	1
Out-strength	$e_1 + e_2 + e_3$	$e_4 + e_5 + e_6$	$e_7 + e_8 + e_9 + e_{10} + e_{11} + e_{12}$	$e_7 + e_8 + e_9$	$e_7 + e_8 + e_9$
Out-degree	1	1	2	3	3
Betweenness	$e_1 + e_2 + e_3$	$e_4 + e_5 + e_6$	$e_1 + e_2 + e_3 + e_4 + e_5 + e_6$	$e_{10} + e_{11} + e_{12}$	$e_{10} + e_{11} + e_{12}$

Note: The values in brackets are the amount of carbon emissions produced and induced by each sector. The value on the left in black is the amount calculated from a production perspective, and the value on the right in red is the amount calculated from a consumption perspective.

Figure 3.4 A simple economy example illustrating the importance of high-betweenness sectors

The sectors with high betweenness can serve as new acting points for carbon emission mitigation. Take the EWPS (electricity and hot water production and supply) sector of Beijing as an example. From a production perspective, among the EWPS sectors of 30 provinces, Beijing was ranked 27th in terms of direct carbon emission production from high to low. In comparison to other sectors it produced a relatively small amount of carbon emissions and exhibited clean energy characteristics. The carbon emission intensity (carbon emission produced per unit of GDP) was the lowest among all the provinces. From a production perspective, it was not deemed as an urgent sector for carbon emission abatement due to the small amount of carbon emission production and low carbon emission intensity. From a consumption perspective, because it did not induce large amount of carbon emissions from other sectors to satisfy its own final demand, it was not deemed as important either.

However, the EWPS sector of Beijing was identified as having high-betweenness and acted as an intermediary sector within the economy. From a consumption perspective, Beijing-EWPS sector had a comparatively high inflow. The amount of carbon emission transferred from Shanxi-EWPS and Inner-Mongolia-EWPS to Beijing-EWPS was 2.6 times as large as the carbon emission produced by Beijing itself. However, the EWPS was not used to meet final demand of the sector itself. Instead, it was mainly used to meet the final demands of other sectors. The EWPS was used by many other sectors in Beijing, such as the metallurgy sector, and then transferred to many other sectors in other provinces, such as transport equipment in Shanghai. Therefore, there was a comparatively larger amount of embodied carbon emission flows going through Beijing' EWPS sector, rather than being directly produced or consumed by the sector directly.

3.4.3. Community of the 2012 Embodied Carbon Emission Network

Nineteen communities of sub-sectors were revealed by using the multi-level modularity optimization algorithm with a modularity score 0.688. In addition, almost the same community structure was found by using the fast greedy modularity optimization algorithm, which assured the robustness of the community detection result.The modularity score measures the extent to which a network can be grouped into communities with distinct boundaries (C. Chen et al., 2010; Martin, 2012). It ranges from 0 to 1. The higher the modularity score, the clearer the boundary is. The high modularity score here suggests a fairly distinct boundary among all the communities. Please see Table 3.5 for the community details. The communities were ranked according to the percentage of the total carbon emission the sectors of a community transmitted were retained within the community (WoT). The carbon flow links among sectors within the community was more intensive than with the sectors outside a community, in terms of both number and weight of edges. In addition, WoT percentage ranged from 49.67% to 96.63%. It suggests that each community exhibited different characteristics. While some communities kept carbon emission flows within its community boundary, other communities had extensive carbon flow connections outside the community.

Figure 3.5 is a visualization of the embodied carbon emission flows among communities using OpenOrd algorithm in Gephi (Martin et al., 2011). The nodes represented the communities, and the node size was decided by the within-community carbon emission flows. The edges represented the emission flows transmitted among communities. The color of edges was decided by the source node, the arrows pointed out transmission direction, and the width corresponded to the emission amount. It can be seen that some communities had more intensive interactions than others, which were put in the middle of the network, such as the Jiangsu-Anhui community. Some communities had less interaction, which were put on the periphery of the network, such as Qinghai community. In addition, some communities had significant outflows and inflows with other communities, which can be seen in the large arrows. The significant flows from the Hebei community to the Jiangsu-Anhui community was a good example.

Table 3.6 Communities of the 2012 embodied carbon emission network.

Com. ID	Community Name	Size (# of Sub-Sectors)	# of Pro.	# of Sector	Total Com. Flow [1] (within + Outside Flows)	Within Com. Flow [2]	Outside Com. Flow [3]	WoT [4] (within Out of Total Flows)	WoC [5] (within Out of Total Flows in China)	Note (Unit of Flow Amount: Thousand Tons)
1	Hubei community	30	1	3	373,377	360,812.09	12,565.31	96.63%	3.83%	30 sectors of Hubei province were put into one community.
2	Sichuan community	30	1	30	310,668.62	292,369.45	18,299.17	94.11%	3.10%	30 sectors of Sichuan were put into one community.
3	Shandong (-Beijing) community	33	2	30	845,017.86	783,194.57	61,823.29	92.68%	8.31%	30 sectors of Shandong along with 2 sectors of Beijing (metal mining sector and petroleum and gas sector), and Petroleum and gas sector of Inner Mongolia were put into one community.
4	Guangdong community	29	1	29	459,988.24	416,401.65	43,586.59	90.52%	4.42%	29 sectors of Guangdong were put into one community.
5	Fujian community	29	1	29	220,926.38	198,008.19	22,918.19	89.63%	2.10%	29 sectors of Fujian province were put into one community.
6	Qinghai community	30	1	30	41,777.11	36,225.06	5552.05	86.71%	0.38%	30 sectors of Qinghai province were put into one community.
7	Shanghai-Zhejiang community	56	2	29	559,836.97	473,196.51	86,640.46	84.52%	5.02%	27 sectors of Shanghai and 29 sectors of Zhejiang were put into one community.
8	Heilongjiang-Jilin-Liaoning (-Beijing) community	91	4	30	933,198.84	761,873.19	171,325.65	81.64%	8.08%	30 sectors of Liaoning, Heilongjiang and Jilin along with wood processing and furnishing sector of Beijing were put into one community.
9	Jiangsu-Anhui (-Ningxia-Beijing) community	61	4	30	1,034,650.90	826,455.20	208,195.70	79.88%	8.77%	30 sectors Jiangsu, 29 sectors of Anhui, along with coal mining sector of Ningxia, metallurgy sector of Beijing were put into one community.
10	Guangxi-Hainan community	58	2	29	226,869.56	180,969.56	45,900.00	79.77%	1.92%	29 sectors of Guangxi and 29 sectors of Hainan were put into one community.
11	Hunan community	29	1	29	272,280.80	212,976.54	59,304.26	78.22%	2.26%	29 sectors of Hunan province were put into one community.

Com. ID	Community Name	Size (# of Sub-Sectors)	# of Pro.	# of Sector	Total Com. Flow [1] (within + Outside Flows)	Within Com. Flow [2]	Outside Com. Flow [3]	WoT [4] (within Out of Total Flows)	WoC [5] (within Out of Total Flows in China)	Note (Unit of Flow Amount: Thousand Tons)
12	Jiangxi community	29	1	29	158,945.48	120,314.06	38,631.42	75.70%	1.28%	29 sectors of Jiangxi province were put into one community.
13	Xinjiang community	30	1	3	250,476.59	185,677.48	64,799.11	74.13%	1.97%	30 sectors of Xinjiang province were linked together.
14	Chongqing-Guizhou-Yunnan community	88	3	30	585,524.86	432,993.81	152,531.05	73.95%	4.59%	30 sectors of Chongqing, 29 sectors of Guizhou and Yunnan were put into one community.
15	Henan community	30	1	30	511,065.76	321,072.97	189,992.79	62.82%	3.41%	30 sectors of Henan province were put into one community.
16	Gansu-Ningxia-Shaanxi community	88	3	30	537,411.05	332,506.59	204,904.46	61.87%	3.53%	30 sectors of Shaanxi and Gansu, along with 28 sectors of Ningxia were put into one community.
17	Hebei (-Beijing) community	37	2	30	758,969.89	465,106.72	293,863.17	61.28%	4.93%	30 sectors of Hebei province along with 7 sectors of Beijing were put into one community. The sectors in Beijing include textile, clothing, non-metal products, metal products, general and specialist machinery, electrical equipment and construction sectors.
18	Inner-Mongolia-Tianjin (-Beijing) community	77	3	30	864,690.16	482,815.92	381,874.24	55.84%	5.12%	18 sectors of Beijing, 30 sectors of Tianjin and 29 sectors of Inner Mongolia were put into one community.
19	Shanxi (-Beijing) community	31	2	30	483,149.24	239,981.49	243,167.75	49.67%	2.55%	30 sectors of Shanxi province and coal mining sector of Beijing were put into one community.

Note: (1) All the calculations were based on the backbone network of the embodied carbon emissions in 2012, not on the raw network. (2) Table heading explanation. [1] Total community flow: The total amount of carbon emissions the sectors of a community received and sent. [2] Within community flow: The amount of carbon emissions the sectors of a community sent out were received by the community sectors themselves, and vice versa. [3] Outside community flow: The amount of carbon emissions the sectors of a community sent outside the community and received from outside the community. [4] WoT percentage: The percentage of total community flows were the within-community flows. [5] WoC percentage: The percentage of total carbon emissions in China were the within-community flows.

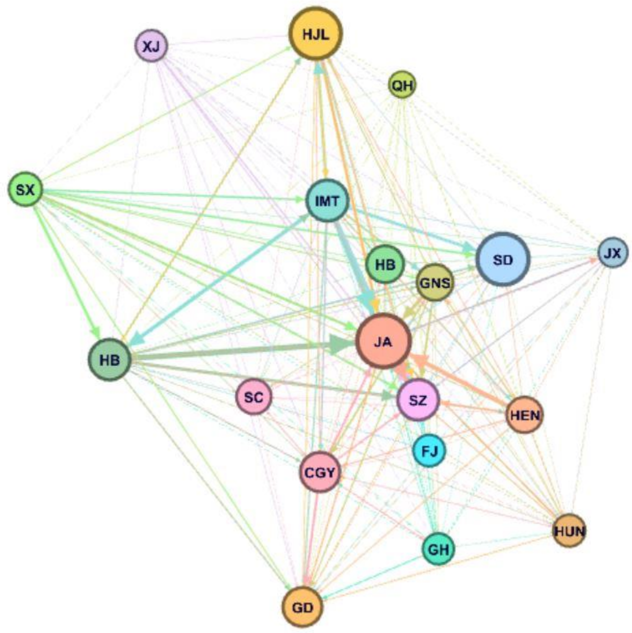


Figure 3.5 Visualization of the embodied carbon emission flows among communities in 2012

Note: The community names are abbreviated for visualization purpose in the figure. HB: Hubei community; SC: Sichuan community; SD: Shandong (-Beijing) community; GD: Guangdong community; FJ: Fujian community; QH: Qinghai community; SZ: Shanghai-Zhejiang community; HJL: Heilongjiang-Jilin-Liaoning(-Beijing) community; JA: Jiangsu-Anhui (-Ningxia-Beijing) community; GH: Guangxi-Hainan community; HUN: Hunan community; JX: Jiangxi community; XJ: Xinjiang community; CGY: Chongqing-Guizhou-Yunnan community; HEN: Henan community; GNS: Gansu-Ningxia-Shaanxi community; HB: Hebei(-Beijing) community; IMT: Inner-Mongolia-Tianjin (-Beijing) community; SX: Shanxi(-Beijing) community.

This research identified three community typologies. The first typology included community sectors only belong to one province, and all the sectors of the province were put into this community. Nine communities belonged to this typology, such as Fujian and Jiangxi provinces. In these typologies, the percentage of in-community flow compared to total-flows ranged from 62.8% in the Henan community to 96.6% to Hubei community. They kept the majority of carbon emission flows within their provincial boundary. The second and third typologies included community sub-sectors of more than one province and there were 10 communities belonging to this typology.

The second type of typology, such as the Shanghai-Zhejiang community, had all sectors of the relevant provinces put into one community. The provinces were equally important in terms of the number of sectors put within the community. For the third typology, there was at least one dominant province existing within the community, all of whose sectors were put into the community. The province(s) in a peripheral position had a small number of sectors grouped into the community. Take the Shanxi(-Beijing) community for example. Shanxi province was the dominant province consisting of all 30 sectors. Due to the intensive carbon emission flows between the coal mining sector of Beijing and other sectors of Shanxi, especially considering the large amount of coal mining products directly demanded from Shanxi to Beijing's coal mining sector, the coal mining sector of Beijing was put into the same community of Shanxi. For the latter two typologies, 8 out of 10 communities kept more than 61.3% of their carbon emissions within the community. However, the Inner Mongolia-Tianjin(-Beijing) community and the Shanxi(-Beijing) community still had extensive carbon emission links outside the communities, with in-community flows out of total flows representing 59.84% and 49.67% respectively.

It can be observed that some provinces which had close economic ties were not put into the same community in the embodied carbon emissions network. For example, from the economic network perspective, Shanghai was in the same community with Jiangsu due to close economic connections. However, when the community detection was based on the emissions transmission network, Shanghai was in the same community with Zhejiang, instead of Jiangsu. The main reason was that the sectoral carbon emissions with Jiangsu province was less carbon intensive than with Zhejiang, and when the insignificant edges of emissions were removed from the raw network, both the number and strength of edges between Shanghai and Jiangsu was much less in the carbon emissions network than the economic network. At the same time, the sectoral connections between Shanghai and Zhejiang was much more carbon intensive. In the carbon emissions network, Shanghai and Zhejiang were put into the same community. Thirty sectors of Beijing were separated into six different communities across eleven provinces. This suggests that Beijing is a highly interconnected province. In addition, the amount of imported emissions was much larger than exported emissions. The main reason for this is that Beijing, as the capital of China, is the most developed and populous city in the north, with substantial demand for goods and services from the rest of the economy. While the Beijing has comparatively low production emissions, with the third lowest carbon emissions across all thirty provinces, it consumes a large quantity of carbon intensive products from other areas.

In general, sectors within the same community have a geographically close proximity. This is consistent with the traditional wisdom of regional divisions of China, and at the same time revealed another level of insight. It is common to see six or seven regional division cited in in official sources of China, such as the National Bureau of Statistics of China. Please see Table 3.6 for details about regional divisions. Provinces in the same region are in close proximity and share similar culture and tend to have higher trading volumes. Duan(Duan et al., 2018), Zhao(Zhao et al., 2015), and Zhou (Zhou et al., 2017) all used similar regional divisions. This suggests a common assumption from researchers that provinces within regions have intensive carbon emissions exchange.

Our research finds that there is a consistent difference between regional boundaries and the geography of carbon communities. Carbon communities involving multiple provinces are usually formed within a regional boundary. The results showed that there are at least two communities within one region and there is only one community crossing a regional boundary (Inner-Mongolia-Tianjin community). This means that carbon emission flows were not distributed evenly within a region. For the central and north regions, the provinces were comparatively more independent, with each province forming its own community. For other regions, it was common to see two or more provinces put into one community demonstrating a close connection within these provinces. Take East China for example, there were Shanghai-Zhejiang community and Jiangsu-Anhui community. It meant that even though the four provinces were geographically close to each other, the carbon emissions exchange were much more intensive between Shanghai and Zhejiang, and between Jiangsu and Anhui. See more details about the comparison between regional division and community division in Table 3.6 and Figure 3.6.

Table 3.1 Comparison between region division and community

ID	Region	Province	# of Communities	Community Description
1	North	Beijing, Tianjin, Hebei, Shanxi	3	Tianjin, Hebei and Shanxi were independent from each other's communities. Beijing's sectors were put into each of the three communities with different sectors.
2	Northeast	Inner Mongolia, Liaoning, Jilin, Heilongjiang	2	Liaoning, Heilongjiang and Jilin were put into one community. Heilongjiang was relatively independent and was put into the Inner-Mongolia-Tianjin (-Beijing) community.
3	East	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong	4	Shanghai and Zhejiang were put into one community. Anhui and Jiangsu were put into one community. Fujian, Jiangxi and Shandong were independent communities.
4	Central	Henan, Hubei, Hunan	3	Henan, Hubei and Hunan were independent communities.
5	South [1]	Guangdong, Guangxi, Hainan	2	Guangdong was an independent community. Guangxi and Hainan were put into one community.
6	Southwest	Chongqing, Sichuan, Guizhou, Yunnan, Tibet	2	Chongqing, Guizhou and Yunnan were put into one community. Sichuan was an independent community; (due to lack of data in Tibet, Tibet was excluded in the network analysis.)
7	Northwest	Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	3	Gansu, Ningxia and Shaanxi were put into one community. Qinghai and Xinjiang were two independent communities

Note: The community division is based on 2012 embodied carbon emission network.

[1] South China and Central China are sometimes combined as South-Central China.

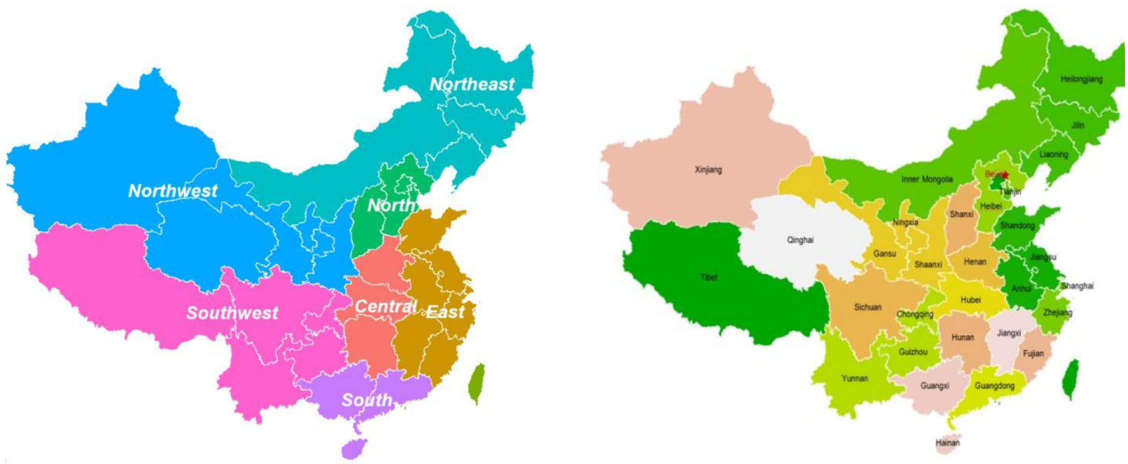


Figure 3.6 Comparison between region division and community division

Note: The community division was based on the 2012 embodied carbon emissions transfer network. In addition, Provinces in the same community was put into the same color.

3.4.4. Position of Sectors in Carbon Communities

Each community should adopt different priorities for reducing carbon emissions within its sectors, incorporating insights from the outflow, inflow and betweenness perspectives. Despite the fact that EWPS, construction and metallurgy sectors were taken as priority sectors in all communities using outflow, inflow and betweenness perspectives respectively, the majority of the sectors had different roles to play in different carbon communities. Take the outflows in the case of Shanxi community and Hubei community for example. While the coal mining sector, petroleum sector as well as transport and storage sector were sectors with large out-flows, this was not the case in the Hubei community. Instead, food processing and tobacco sector, metal sector, and transport equipment sectors were the large out-flow sectors in Hubei.

There was consistency between community features and sub-sector features. This suggests that localized policies for different communities may provide an alternative policy option. Even for the same metrics, the values vary substantially for each community and therefore require bespoke policies. Looking at out-degree there was significant differences between the top five high out-degree sectors between Shanxi and Hubei communities. In Shanxi community, the out-degree of EWPS sector was 855, and the 5th highest out-degree sector, i.e., the transport and storage sector, was 174. In Hubei community, the out-degree of EWPS sector was 147 and the 5th highest out-degree sector, i.e., transport equipment, was 39. This metric result can partly explain the fact that Shanxi community had a comparatively low percentage of in-community flow compared to total-flows, while Hubei community had a high one. In addition, Shanxi province should put more effort in tracking carbon emissions to find out the parties which should be in position to share the responsibility for carbon emission abatement.

3.5 Conclusions and Policy Implications

Betweenness, out-degree and in-degree provide new information on the transmission pathways within an economy and new opportunities for targeting carbon emission reductions. The EWPS sector in Beijing with a high betweenness metric is one example for targeting carbon mitigation policy. The importance of this sector is missed when using either a production or consumption perspective, but it can act as an important gatekeeper to reduce carbon-intensive inputs for overall carbon emissions reduction. In addition, the low correlation between degree and strength suggests that the sectors which produce or induce large amounts of carbon emissions are not always in a good position to spread or receive emissions from other sectors. Instead, the sectors with high out-degree or in-degree act as a bridge and therefore could serve as new acting point to reduce carbon emissions.

EWPS (electricity and hot water production and supply) sector, construction sector, and metallurgy sector have largest out-flows, in-flows and betweenness flows respectively at provincial, community and national levels. They are important both in the quantity of flows and the number of their sector links. In addition, the EWPS and metallurgy sectors should be given more close attention, because they have large out-flows and betweenness flows at the same time at both local and national levels. However, the majority of sub-sectors had different degree centrality, strength centrality, and betweenness in different communities. Therefore, localized policies should be formed for the same sector in different communities.

Moreover, this analysis highlights the importance of provincial governments in mitigating carbon emissions. Because there are more carbon emissions flows within a community, there may be a synergistic effect if efforts were directed on a carbon community rather than individual sectors. This analysis showed that many communities are formed within the geographical boundary of provinces. This implies that provincial governments have an important role to play in mitigating emissions within their jurisdiction.

Finally, the community detection results provide insights for collaboration among provincial governments tackling the carbon emission mitigation problem together. The discrepancy between the sectors which produce large amount of carbon emissions and the sectors which induce large amount of carbon emissions by consumption asks for collaboration among sectors for dealing with the problem together. The identification of key carbon communities explicitly provides the information about which sub-sectors should be partnered together for effective emissions reduction.

Based on the research results and conclusions, we propose the following policy suggestions. Firstly, the EWPS, metallurgy and construction sector should be prioritized as a focus for carbon emissions reduction from both national and local levels. The recently launched national Emission Trading Scheme (ETS) put the electricity sector as the first priority for carbon mitigation. This is consistent with results from this research which confirms EWPS sector as the top priority for carbon mitigation. The metallurgy sector and construction sector are also important sectors to focus on but have not been on the policy radar yet. In addition, for the majority of sectors, targeted policies should be formed specifically for each different carbon community and local government within a province.

Secondly, carbon emission mitigation policies should give close attention on the sectors with high out-degree, in-degree or betweenness. All three metrics are important for tracing embodied carbon emissions. While the sectors with high out-degree are critical to implementing carbon tracking practice, the sectors with high in-degree are critical for supervising other downstream sectors. The carbon tracking practice can help clarify a sectors' responsibilities and help governance bodies and companies to make informed decisions to reduce carbon emissions. In addition, for the sectors with high betweenness, which have a large amount of embodied carbon emissions going to these sectors, should focus on reducing the intake of carbon-intensive inputs, which in turn can reduce the carbon emissions at the whole system level. Take the EWPS sector of Beijing as an example, which has high betweenness and out-degree values. For upstream suppliers, the requirement of the carbon tracking information and the preference for low-carbon products, such as wind-generated electricity, can push the upstream sectors to reduce carbon emissions. For the sector itself, it is a key acting point to implement carbon tracking practice to make sure that the carbon emissions are traceable for a large number of downstream suppliers. In this way, the downstream players will be in a better position to collectively work towards carbon emission mitigation by making informed low-carbon purchase decisions.

Thirdly, the community detection results provide direction for provincial governments' external collaboration and the percentage of in-community flows compared to total-flows suggests the focus for internal improvement or external cooperation. For communities with one province and high percentage of in-community flows compared to total-flows, such as Hubei province, the efforts for carbon emission mitigation would benefit from more internal focus with proposed solutions being the responsibility of individual local governments. For communities consisting of more than one province with high percentage of in-community flows compared to total-flows, close collaboration between the provinces in the same community should be prioritized. Take Shanghai-Zhejiang community for example, the cooperation between the two local governments would yield a synergistic benefit policy benefit. In addition, for communities with comparatively low percentage of in-community flows compared to total-flows, such as Shanxi community, efforts should be made from two directions. While the collaboration within the community should be encouraged, because at least half of carbon emission were kept within the community, the outside links the community has should also be given close attention. In the case of Shanxi community, the strong interactions with Heilongjiang-Jilin-Liaoning community, Hebei community, and Inner-Mongolia-Tianjing also should be considered together for effective emission mitigation.

Finally, Beijing should play roles for the carbon emissions mitigation in China in terms of supervision and knowledge sharing. The fact that the thirty sectors of Beijing were separated into six carbon communities mainly in the north and with a large amount of net imported carbon emission flows requires a strong supervision role with its close trading partners. If Beijing could show clear preference of low-carbon products for both sectors and final demand intakes, it would push the low-carbon transition for the whole northern part of China. In addition, Beijing has the advantage of upgrading low-carbon technology due to an educated workforce. The knowledge sharing between Beijing and the relevant communities would further assist the transition to a low carbon economy.

Appendix A

Appendix A.1. Sector Matching between MRIO Tables and Sectoral Carbon Emission Inventory

Table A1. For sector matching between multi-region input–output (MRIO) tables and sectoral carbon emission inventory.

Carbon Emission Industries Inventory (Raw)	Carbon Emission Industries Inventory No. (Raw)	Industries No. (Matched)	MRIO No. (Raw)	MRIO (Raw)
Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy	1	1	1	Agriculture
Coal Mining and Dressing	2	2	2	Coal mining
Petroleum and Natural Gas Extraction	3	3	3	Petroleum and gas
Ferrous Metals Mining and Dressing	4	4	4	Metal mining
Nonferrous Metals Mining and Dressing	5			
Non-metal Minerals Mining and Dressing	6	5	5	Non-metal mining
Other Minerals Mining and Dressing	7			
Logging and Transport of Wood and Bamboo	8	6	6	Wood processing and furnishing
Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products	9			
Furniture Manufacturing	10			
Food Processing	11	7	7	Food processing and tobaccos
Food Production	12			
Beverage Production	13			
Tobacco Processing	14			
Textile Industry	15	8	8	Textile
Garments and Other Fiber Products	16	9	9	Clothing, leather, fur, etc.
Leather, Furs, Down and Related Products	17			
Papermaking and Paper Products	18	10	10	Paper making, printing, stationery, etc.
Printing and Record Medium Reproduction	19			
Cultural, Educational and Sports Articles	20			
Petroleum Processing and Coking	21	11	11	Petroleum refining, coking, etc.
Raw Chemical Materials and Chemical Products	22	12	12	Chemical industry
Medical and Pharmaceutical Products	23			
Chemical Fiber	24			
Rubber Products	25			
Plastic Products	26			

Non-metal Mineral Products	27	13	13	Non-metal Mineral Products
Smelting and Pressing of Ferrous Metals	28	14	14	Metallurgy
Smelting and Pressing of Nonferrous Metals	29			
Metal Products	30	15	15	Metal products
Ordinary Machinery	31	16	16	General and specialist machinery
Equipment for Special Purposes	32			
Transportation Equipment	33	17	17	Transport equipment
Electric Equipment and Machinery	34	18	18	Electrical equipment
Electronic and Telecommunications Equipment	35	19	19	Electronic equipment
Instruments, Meters, Cultural and Office Machinery	36	20	20	Instrument and meter
Other Manufacturing Industry	37	21	21	Other manufacturing
Scrap and waste	38			
Production and Supply of Electric Power, Steam and Hot Water	39	22	22	Electricity and hot water production and supply
Production and Supply of Gas	40	23	23	Gas and water production and supply
Production and Supply of Tap Water	41			
Construction	42	24	24	Construction
Transportation, Storage, Post and Telecommunication Services	43	25	25	Transport and storage
Wholesale, Retail Trade and Catering Services	44	26	26	Wholesale and retailing
		27	27	Hotel and restaurant
Others	45	28	28	Leasing and commercial services
		29	29	Scientific research
		30	30	Other services

Appendix A.2. Network Metrics

Appendix A.2.1. Degree Centrality

Degree centrality captures the connectedness of a node in the network. It measures the importance of a node on counting the number of links the node directly has with other nodes. In a directed network, degree centrality can be categorized into in-degree centrality (number of inbound links) and out-degree centrality (number of outbound links).

In the context of carbon emission network, in-degree centrality measures a sector's number of import partners, which transferred carbon emissions to this sector. Out-degree centrality measures a sector's number of export partners, which received carbon emissions from this sector. The sectors with high degree centrality are likely to be in a good position to quickly transfer its emissions to/from other sectors.

The equation for calculating in-degree centrality and out-degree centrality are as follows.

$$D_i^{r\ in} = \sum_{(j,s)\in N_i} D_{ji}^{sr}$$

$$D_i^{r\ out} = \sum_{(j,s)\in N_i} D_{ij}^{rs}$$

where N_i is the set of nodes connected to node (i, r). If there is an edge from (j, s) to (i, r), $D_{ji}^{sr} = 1$, otherwise $D_{ji}^{sr} = 0$. If there is an edge from (i, r) to (j, s), $D_{ij}^{rs} = 1$, otherwise $D_{ij}^{rs} = 0$.

Appendix A.2.2. Strength

Node strength measures the total weights of edges connected to a node. In a directed network, strength is categorized into in-strength and out-strength. In the carbon emission network, in-strength denotes the total volume of embodied carbon emissions imported to a sector. Out-strength denotes the total volume of embodied carbon emissions exported from a sector. The sectors with high strength centrality are likely to produce a large amount of carbon emissions.

The equation for calculating in-degree centrality and out-degree centrality are as follows.

$$W_i^{r\ in} = \sum_{(j,s)\in N_i} g_{ji}^{sr}$$

$$W_i^{r\ out} = \sum_{(j,s)\in N_i} g_{ij}^{rs}$$

where N_i is the set of nodes connected to node (i, r). $\boldsymbol{G} = \left(g_{ij}^{rs}\right)$ is the adjacent matrix of the network. The set of directed edges is $E = \{(i, r)\ (j, s) | g_{ij}^{rs} > 0\}$ and the carbon emissions weight assigned to the edge $((i, r)\ (j, s))$ is g_{ij}^{rs}.

Appendix A.2.3. Betweenness

The betweenness of one node is defined by the number of shortest paths going through it. Betweenness usually measures the media capability of nodes in the network. If one sector has high betweenness, it means that this sector has strong media capacity. However, this metric is usually based on unweighted and undirected network, and it assumes the connections between nodes happen along with the shortest path (Newman, 2010). The embodied carbon emission network is a directed and weighted network, and carbon emission flows do not always go along with the shortest path for geographical, economic or historical reason. Therefore, this classic metric algorithm does not function well in the context.

Liang [(2016)] adjusted the algorithm to better reflect a sector's media capacity. It considered the direction and weights of input–output network, as well as the weights of nodes' self-flows. The algorithm calculated the total amount of flows going through a node. Details of the adjusted algorithm can be seen from Liang [(2016)] paper on betweenness-based method. In the paper, the betweenness of a node $b_i = \boldsymbol{fTJ_iTy}$, where row vector $\boldsymbol{f}$ is the carbon intensity for each sector's output, $\boldsymbol{T} = \boldsymbol{LA}$ ($\boldsymbol{A}$ is technology coefficient matrix, and $\boldsymbol{L}$ is Leontief inverse matrix), $\boldsymbol{J_i}$ is a diagonal matrix with all the values on the diagonal equaling to 1, and column vector $\boldsymbol{y}$ is final demand of products from each sectors.

Appendix A.3. Degree Distribution

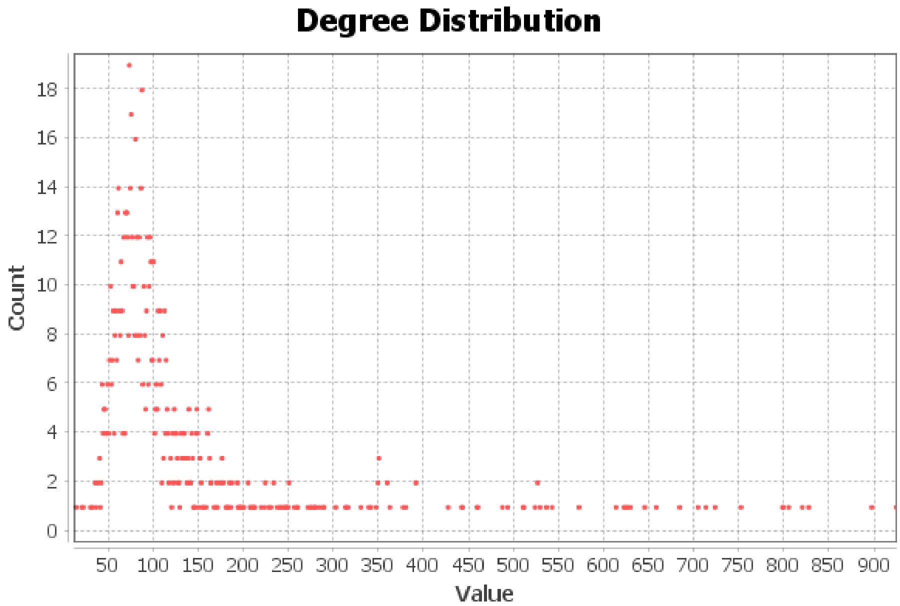


Figure A1. Degree distribution of the 2012 reduced embodied carbon emission network.

Appendix A.4. Network Metrics for Sectors at National Level

Table A2. For network metrics value of sectors at national level.

Sector	Average Out-Degree	Average Out-Strength	Average In-degree	Average In-strength	Average Betweenness	Average Self-Loop	Production Emissions	Consumption Emissions
Chemical industry	60.40	4756.92	49.07	8055.66	65,239.25	1566.38	206,390.50	317,275.88
Clothing, leather, fur, etc.	44.73	56.80	45.97	5872.28	4643.70	200.47	7124.48	203,643.81
Coal mining	80.97	9570.67	25.23	896.22	20,405.66	501.38	319,850.76	44,813.61
Construction	29.60	38.30	347.27	98,819.55	4331.37	2047.81	58,307.49	3,174,293.51
Electrical equipment	34.23	154.76	80.60	15,179.85	16,995.74	257.95	11,996.64	502,838.24
Electricity and hot water production and supply	450.43	146,000.77	39.70	2168.37	83,872.45	16,107.26	4,548,789.48	556,276.01
Electronic equipment	32.13	66.78	63.80	7236.20	10,923.22	163.84	6595.64	247,003.45
Food processing and tobaccos	57.13	621.81	64.03	11,482.08	16,893.54	1182.46	55,971.57	421,979.86
Gas and water production and supply	37.20	242.51	30.00	837.78	2592.76	152.77	12,781.76	33,066.07
General and specialist machinery	39.47	459.3	108.13	24,586.45	19,551.11	1305.95	50,371.35	836,847.89
Hotel and restaurant	36.70	818.74	39.57	2808.39	5239.45	655.32	44,953.13	115,884.32
Instrument and meter	32.50	17.00	38.40	1293.28	1728.40	23.71	1178.40	45,718.79
Leasing and commercial services	29.30	345.93	40.93	1194.57	6298.45	88.27	13,776.08	44,664.42
Metal mining	42.67	650.90	17.57	128.04	13,276.97	12.10	21,454.92	4315.03
Metal products	28.90	273.99	45.63	7000.87	17,859.51	194.17	13,869.27	241,269.06
Metallurgy	125.70	47,060.83	36.23	2887.12	109,897.99	2718.01	1,433,169.01	179,072.66
Non-metal mining	25.40	301.90	27.90	111.57	4699.81	10.81	9700.49	4116.60
Non-metal products	44.80	27,113.44	35.70	3232.70	40,310.77	4163.13	900,754.84	234,073.08
Other manufacturing	42.77	198.78	32.53	459.38	4262.79	38.68	8327.07	17,062.04
Other services	46.00	822.15	132.40	24,824.28	15,369.45	2867.98	107,908.38	912,925.01

Paper making and stationary	34.80	747.68	40.40	2946.57	10,931.34	417.63	35,801.06	113,367.06
Petroleum and gas	45.93	1389.57	20.43	61.32	4062.40	54.21	52,434.20	3734.86
Petroleum refining, coking, etc.	78.33	6721.61	39.47	1726.34	18,747.34	870.56	249,780.24	84,809.07
Scientific research	23.80	80.16	51.30	2444.44	1541.98	215.26	8294.02	92,331.57
Textile	41.40	450.10	34.73	3659.83	12,172.27	357.73	24,564.82	133,715.20
Transport and storage	91.00	13,872.84	57.23	4947.59	22,022.48	6207.92	616,950.13	354,506.71
Transport equipment	40.40	146.40	110.73	19,756.32	14,184.96	797.13	26,544.96	675,957.41
Wholesale and retailing	44.90	1780.72	45.77	4664.28	7409.99	1915.97	110,141.76	216,410.07
Wood processing and furnishing	30.97	119.11	41.40	2629.64	4800.41	145.59	7637.02	95,175.06

Appendix A.5. Tables for Comparison of Network Metrics

Table A3. The frequency of sub-sectors listed in the top 100 sub-sectors in terms of high out-degree and out-strength.

Sector	Out-Degree	Out-Strength
Electricity and hot water production and supply (EWPS)	29	29
Metallurgy	19	25
Transport and storage	17	11
Coal mining	10	7
Petroleum refining, coking, etc.	8	4
Chemical industry	6	1
Petroleum and gas	5	0
Clothing, leather, fur, etc.	2	0
Non-metal products	2	23
Agriculture	1	0
Food processing and tobaccos	1	0

Table A4. Out-degree rank and out-strength rank from national sector perspective.

Sector	Out-Degree Rank	Out-Strength Rank	Average Out-Degree	Average Out-Strength	Production Emissions	Consumption Emissions
Electricity and hot water production and supply	1	1	450.43	146,000.77	4,548,789.48 (50.01%)	556,276.01 (5.48%)
Metallurgy	2	2	125.70	47,060.83	1,433,169.01 (15.76%)	179,072.66 (1.77%)
Transport and storage	3	4	91.00	13,872.84	616,950.13 (6.78%)	354,506.71 (3.50%)
Coal mining	4	5	80.97	9570.67	319,850.76 (3.52%)	44,813.61 (0.44%)
Petroleum refining, coking, etc.	5	6	78.33	6721.61	249,780.24 (2.75%)	84,809.07 (0.84%)
Chemical industry	6	7	60.40	4756.92	206,390.50 (2.27%)	317,275.88 (3.13%)
Food processing and tobaccos	7	15	57.13	621.81	55,971.57 (0.62%)	421,979.86 (4.16%)
Other services	8	11	46.00	822.15	107,908.38 (1.19%)	912,925.01 (9.00%)
Petroleum and gas	9	10	45.93	1389.57	52,434.20 (0.58%)	3734.86 (0.04%)
Wholesale and retailing	10	9	44.90	1780.72	110,141.76 (1.21%)	216,410.07 (2.13%)
Non-metal products	11	3	44.80	27,113.44	900,754.84 (9.90%)	234,073.08 (2.31%)
Clothing, leather, fur, etc.	12	28	44.73	56.80	7124.48 (0.08%)	203,643.81 (2.01%)
Other manufacturing	13	22	42.77	198.78	8327.07 (0.09%)	17,062.04 (0.17%)
Metal mining	14	14	42.67	650.90	21,454.92 (0.24%)	4315.03 (0.04%)
Textile	15	17	41.40	450.10	24,564.82 (0.27%)	133,715.20 (1.32%)
Transport equipment	16	24	40.40	146.40	26,544.96 (0.29%)	675,957.41 (6.66%)
Agriculture	17	8	40.23	2183.21	130,496.03 (1.43%)	235,704.85 (2.32%)
General and specialist machinery	18	16	39.47	459.30	50,371.35 (0.55%)	836,847.89 (8.25%)
Gas and water production and supply	19	21	37.20	242.51	12,781.76 (0.14%)	33,066.07 (0.33%)
Hotel and restaurant	20	12	36.70	818.74	44,953.13 (0.49%)	115,884.32 (1.14%)
Paper making, printing, stationery, etc.	21	13	34.80	747.68	35,801.06 (0.39%)	113,367.06 (1.12%)
Electrical equipment	22	23	34.23	154.76	11,996.64 (0.13%)	502,838.24 (4.96%)
Instrument and meter	23	30	32.50	17.00	1178.40 (0.01%)	45,718.79 (0.45%)
Electronic equipment	24	27	32.13	66.78	6595.64 (0.07%)	247,003.45 (2.44%)
Wood processing and furnishing	25	25	30.97	119.11	7637.02 (0.08%)	95,175.06 (0.94%)
Construction	26	29	29.60	38.30	58,307.49 (0.64%)	3,174,293.51(31.30%)
Leasing and commercial services	27	18	29.30	345.93	13,776.08 (0.15%)	44,664.42 (0.44%)
Metal products	28	20	28.90	273.99	13,869.27 (0.15%)	241,269.06 (2.38%)
Non-metal mining	29	19	25.40	301.90	9700.49 (0.11%)	4116.60 (0.04%)
Scientific research	30	26	23.80	80.16	8294.02 (0.09%)	92,331.57 (0.91%)

Table A5. The frequency of sectors listed in the top 100 sectors in in terms of high in-degree and in-strength.

Row Labels	In-Degree	In-Strength
Chemical industry	2	3
Clothing, leather, fur, etc.	3	4
Construction	29	29
Electrical equipment	4	7
Electronic equipment	4	2
Food processing and tobaccos	4	5
General and specialist machinery	11	10
Instrument and meter	0	1
Metal products	3	5
Other services	21	19
Paper making, printing & stationery	1	1
Scientific research	1	0
Textile	1	1
Transport and storage	2	0
Transport equipment	13	12
Wholesale and retailing	1	1

Table A6. In-degree rank and In-strength rank from national sector perspective.

Row Labels	In-Degree Rank	In-Strength Rank	In-Degree	In-Strength	Production Emissions	Consumption Emissions
Construction	1	1	347.27	98,819.55	58,307.49 (0.64%)	3,174,293.51 (31.30%)
Other services	2	2	132.40	24,824.28	107,908.38 (1.19%)	912,925.01 (9.00%)
Transport equipment	3	4	110.73	19,756.32	26,544.96 (0.29%)	675,957.41 (6.66%)
General and specialist machinery	4	3	108.13	24,586.45	50,371.35 (0.55%)	836,847.89 (8.25%)
Electrical equipment	5	5	80.60	15,179.85	11,996.64 (0.13%)	502,838.24 (4.96%)
Food processing and tobaccos	6	6	64.03	11,482.08	55,971.57 (0.62%)	421,979.86 (4.16%)
Electronic equipment	7	8	63.80	7236.20	6595.64 (0.07%)	247,003.45 (2.44%)
Transport and storage	8	12	57.23	4947.59	616,950.13 (6.78%)	354,506.71 (3.50%)
Scientific research	9	20	51.30	2444.44	8294.02 (0.09%)	92,331.57 (0.91%)
Agriculture	10	11	50.67	5152.72	130,496.03 (1.43%)	235,704.85 (2.32%)
Chemical industry	11	7	49.07	8055.66	206,390.50 (2.27%)	317,275.88 (3.13%)
Clothing, leather, fur, etc.	12	10	45.97	5872.28	7124.48 (0.08%)	203,643.81 (2.01%)
Wholesale and retailing	13	13	45.77	4664.28	110,141.76 (1.21%)	216,410.07 (2.13%)
Metal products	14	9	45.63	7000.87	13,869.27 (0.15%)	241,269.06 (2.38%)
Wood processing and furnishing	15	19	41.40	2629.64	7637.02 (0.08%)	95,175.06 (0.94%)
Leasing and commercial services	16	24	40.93	1194.57	13,776.08 (0.15%)	44,664.42 (0.44%)
Paper making, printing, stationery, etc.	17	16	40.40	2946.57	35,801.06 (0.39%)	113,367.06 (1.12%)
Electricity and hot water production and supply	18	21	39.70	2168.37	4,548,789.48 (50.01%)	556,276.01 (5.48%)
Hotel and restaurant	19	18	39.57	2808.39	44,953.13 (0.49%)	115,884.32 (1.14%)
Petroleum refining, coking, etc.	20	22	39.47	1726.34	249,780.24 (2.75%)	84,809.07 (0.84%)
Instrument and meter	21	23	38.40	1293.28	1178.40 (0.01%)	45,718.79 (0.45%)
Metallurgy	22	17	36.23	2887.12	1,433,169.01 (15.76%)	179,072.66 (1.77%)
Non-metal products	23	15	35.70	3232.70	900,754.84 (9.90%)	234,073.08 (2.31%)
Textile	24	14	34.73	3659.83	24,564.82 (0.27%)	133,715.20 (1.32%)
Other manufacturing	25	27	32.53	459.38	8327.07 (0.09%)	17,062.04 (0.17%)
Gas and water production and supply	26	26	30.00	837.78	12,781.76 (0.14%)	33,066.07 (0.33%)
Non-metal mining	27	29	27.90	111.57	9700.49 (0.11%)	4116.60 (0.04%)
Coal mining	28	25	25.23	896.22	319,850.76 (3.52%)	44,813.61 (0.44%)
Petroleum and gas	29	30	20.43	61.32	52,434.20 (0.58%)	3734.86 (0.04%)
Metal mining	30	28	17.57	128.04	21,454.92 (0.24%)	4315.03 (0.04%)

Table A7. The frequency of sectors listed in the top 100 high betweenness sub-sectors.

Sector	Sum of Times	Sum of Betweenness
Metallurgy	24	3,195,886.66
Electricity and hot water production and supply (EWPS)	21	2,290,397.60
Chemical industry	13	1,558,228.00
Non-metal products	11	850,299.90
General and specialist machinery	4	350,934.32
Coal mining	3	281,548.00
Electrical equipment	3	260,655.33
Metal products	3	255,348.45
Textile	3	210,511.45
Petroleum refining, coking, etc.	3	196,670.97
Transport and storage	3	161,884.80
Electronic equipment	2	157,179.64
Transport equipment	2	142,936.07
Metal mining	1	120,801.21
Food processing and tobaccos	2	119,357.02
Paper making, printing & stationery	2	105,142.12

Table A8. Betweenness rank from national sector perspective.

Sector	Rank	Betweenness	Production Emissions	Consumption Emissions
Metallurgy	1	3,296,939.67	1,433,169.01 (15.76%)	179,072.66 (1.77%)
Electricity and hot water production and supply	2	2,516,173.47	4,548,789.48 (50.01%)	556,276.01 (5.48%)
Chemical industry	3	1,957,177.38	206,390.50 (2.27%)	317,275.88 (3.13%)
Non-metal products	4	1,209,323.13	900,754.84 (9.90%)	234,073.08 (2.31%)
Transport and storage	5	660,674.48	616,950.13 (6.78%)	354,506.71 (3.50%)
Coal mining	6	612,169.69	319,850.76 (3.52%)	44,813.61 (0.44%)
General and specialist machinery	7	586,533.17	50,371.35 (0.55%)	836,847.89 (8.25%)
Petroleum refining, coking, etc.	8	562,420.31	249,780.24 (2.75%)	84,809.07 (0.84%)
Metal products	9	535,785.36	13,869.27 (0.15%)	241,269.06 (2.38%)
Electrical equipment	10	509,872.17	11,996.64 (0.13%)	502,838.24 (4.96%)
Food processing and tobaccos	11	506,806.21	55,971.57 (0.62%)	421,979.86 (4.16%)
Other services	12	461,083.42	107,908.38 (1.19%)	912,925.01 (9.00%)
Transport equipment	13	425,548.66	26,544.96 (0.29%)	675,957.41 (6.66%)
Metal mining	14	398,309.01	21,454.92 (0.24%)	4315.03 (0.04%)
Textile	15	365,168.00	24,564.82 (0.27%)	133,715.20 (1.32%)
Agriculture	16	363,881.14	130,496.03 (1.43%)	235,704.85 (2.32%)
Paper making, printing, stationery, etc.	17	327,940.31	35,801.06 (0.39%)	113,367.06 (1.12%)
Electronic equipment	18	327,696.49	6595.64 (0.07%)	247,003.45 (2.44%)
Wholesale and retailing	19	222,299.72	110,141.76 (1.21%)	216,410.07 (2.13%)
Leasing and commercial services	20	188,953.55	13,776.08 (0.15%)	44,664.42 (0.44%)
Hotel and restaurant	21	157,183.42	44,953.13 (0.49%)	115,884.32 (1.14%)
Wood processing and furnishing	22	144,012.39	7637.02 (0.08%)	95,175.06 (0.94%)
Non-metal mining	23	140,994.22	9700.49 (0.11%)	4116.60 (0.04%)
Clothing, leather, fur, etc.	24	139,310.85	7124.48 (0.08%)	203,643.81 (2.01%)
Construction	25	129,941.03	58,307.49 (0.64%)	3,174,293.51 (31.30%)
Other manufacturing	26	127,883.62	8327.07 (0.09%)	17,062.04 (0.17%)
Petroleum and gas	27	121,871.87	52,434.20 (0.58%)	3734.86 (0.04%)
Gas and water production and supply	28	77,782.68	12,781.76 (0.14%)	33,066.07 (0.33%)
Instrument and meter	29	51,851.99	1178.40 (0.01%)	45,718.79 (0.45%)
Scientific research	30	46,259.43	8294.02 (0.09%)	92,331.57 (0.91%)

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Chapter 4 THE CONTRIBUTION OF CARBON TRANSFER NETWORK STRUCTURE TO SECTORS' CARBON EMISSIONS

Preface

This chapter studies the role played by the sector of province node level structure and the community level structure on sectors' direct carbon emissions using a hierarchical linear model. Chapter 3 has identified the hotspots and carbon communities in the 2012 embodied carbon emissions network of China using network analysis metrics and algorithms. On this basis, Chapter 4 goes further to quantitatively examine the effect of network structure on sectors' carbon emissions. When analysing the factors affecting sectoral carbon emissions, the majority of existing research does not take account of the emissions network structure. Even if it is counted, only the structure variables at the sector node level, such as in-degree and out-degree, is considered, and they are usually assumed to have a fixed effect on sectors' carbon emissions. This chapter introduces a hierarchical linear model to measure the effect of network structure variables at both the sector of province node level and community level, based on the embodied carbon emissions networks of China from 2007 to 2012. In addition, the interactive effects of the two levels is considered in the model. The research results confirm that a sector's direct carbon emissions are affected by both its node level structure and also the community structure where the sector belongs to. Moreover, the effect of the node level structure is influenced by the community structure, and they interact with each other and affect the sectors' direct carbon emissions together. Policy suggestions, including 'one community – one policy', are proposed on the basis of the research results for carbon emissions mitigation.

4.1 Introduction

Based on the two-step reduced embodied carbon emission network model and the metrics used to analyse network structure, this chapter analyses the influence of the embodied carbon emissions network structure on sectors' direct carbon emissions.According to complex network theory, network structure determines network performance. Network structure also affects a sector's carbon emissions. By constructing four regression models, the contribution of network structure to carbon emissions is analysed at the sector of province node level and the communities of sectors level.

4.2 Research Data

As in Chapter 3, energy consumption datasets and carbon emissions datasets, as well as the multi-region input–output (MRIO) table datasets, from China Emission Accounts and Datasets (CEADs) (http://www.ceads.net) are used for the research, due to its authority, comprehensiveness and accuracy. The datasets for sectoral carbon emissions from CEADs are selected due to its comprehensiveness and accuracy. Both the carbon emissions from fossil fuel combustion and from industrial process are accounted in the emissions inventory. In addition, the default emission factor provided by IPCC and NDRC have been adjusted by the 602 coal samples results from the 100 largest coal-mining areas in China (Liu et al., 2015). In order to keep sectors consistent between provincial-level CO_2 emission inventory and the China MRIO tables, sectors needed to be aggregated. Compared with MRIO tables composed by other leading research teams which may cover more sectors (Wang, 2017), the division of sectors used in the MRIO tables published in CEADs is more consistent with the selected carbon emissions datasets, which avoids less assumption in the sectors aggregation process.

The multi-region input–output (MRIO) table for China and sectoral carbon emissions data for the years 2007, 2010 and 2012 are used to construct three embodied emissions networks. For the MRIO tables, due to high data resolution requirement and complex composition methods, there is a significant time lag between each new release of input-output data tables, and the latest MRIO table availabe is for the year 2012. However, the information about the flows of inputs and outputs among both sectors and provinces are important for designing effective emissions mitigation policies, as provincial governments are mainly responsible for carrying out emissions mitigation tasks. We follow the same procedures as described in Chapter 3 to aggregate sectors for data consistency. In addition, the proposed two-step reduction method is applied to reduce the network edges significantly, while maintaining the multi-level network structures. The carbon flows between the 30 sectors within 30 provinces of China in 2007, 2010 and 2012 are represented in the three embodied carbon emissions networks.

Each network is represented by $\mathbb{G}(N, L)$. The set of nodes is defined by vector $\mathcal{V}(N) = \{1,2,\cdots,N\}$, N= 900, and the set of directed edges is defined by the matrix $L = \{e_{ij} | i \rightarrow j, i, j \in \mathcal{V}(N), q_{ij} > 0\}$. The term q_{ij} denotes the carbon emission weights assigned to each edge of the matrix, and q_{ij} is equal to the quantity of embodied carbon emissions transferred from sector i to sector j.

4.3 Research method

Input-output analysis, network analysis and statistical analysis are selected to research how sectors' transmission-related characteristics can influence emissions. As in Chapter 3, environmentally extended input-output model is used to track embodied carbon emission flows among sectors of region. The Leontief inverse matrix $\boldsymbol{L} = (\boldsymbol{I}-\boldsymbol{A})^{-1}$ reflects the direct and indirect input requirements of sector's outputs from other sectors.

Complemented with the carbon intensity information of each sector, the embodied carbon emission flows among sectors of regions can be outlined. On this basis, network analysis metrics are used to examine the transmission pattern systematically, including the metrics at sector of province node level and community level. Moreover, in network theory, the changes in the topological structures of the underlying network have critical influence on how the whole network will function or perform. In the context of this research, the structure of the embodied carbon emissions network may have an effect on sub-sectors carbon emissions.

Statistical analysis is adopted to measure the effect of transmission-related characteristics on sectors' carbon emissions. SDA (structural decomposition analysis) is frequently used to analyse the overall change of Leontief inverse matrix on carbon emissions. Though Leontief inverse matrix reflects economic structure information at macro perspective, a more systematic perspective is required to make use of the rich information provided by the matrix. By using statistical analysis, we can examine the influence of economic structure in more detail, including both micro sub-sector perspective and meso community perspective. For example, the effect of a sub-sector's outflow amount on carbon emissions, or the effect of its community size, can all be examined, which cannot be revealed by SDA analysis.

4.3.1 Statistical model

Embodied carbon emission networks have multi-level structures. In these nested structures, the quantity of carbon emissions produced by a sector is influenced, not only by the network structure at the individual sector level, but also by the structure of the community the sector belongs to, as shown in Figure 4.1. The influence mechanisms at the node and community levels interact with each other and affect a sector's carbon emissions. For example, two sectors with the same values for characteristics such as their out-degrees may have different influences on emissions depending on their roles in the communities they belong to. At the same time, sectors that belong to the same community have the same community structure metric values, such as the community size. However, the current research focuses mainly on the influence of sector-level structure (Jiang et al., 2019; Song et al., 2019), while the community-level structure and its interactive effects are are not considered as part of this research.

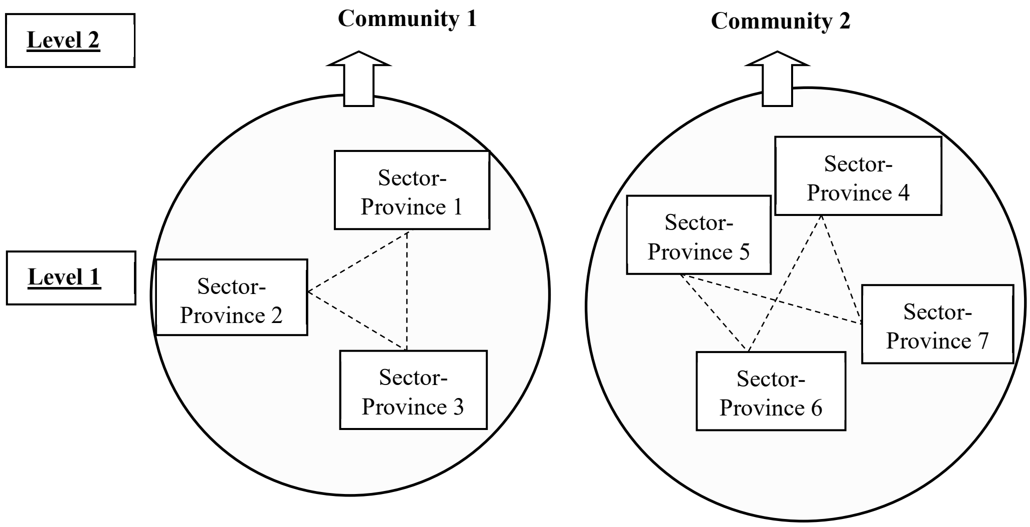

Figure 4.1 Multi-level data structure

Traditional statistical models can be inadequate for processing multi-level nested structure data. This is for two reasons. Firstly, the independence and homoscedastic assumptions regarding observations cannot be assured because sectors in the same community jointly determine the features of that community, such as community size and density. This joint determination violates the independence assumptions of traditional statistical models and causes deviations in estimates of the coefficients and their standard errors (Heck and Thomas, 2015). Secondly, traditional statistical models ignore the interactions between sector-level network structures and community-level structures.

This may cause misunderstandings about the ways in which network structures influence sectors' carbon emissions (Hofmann, 2002).

This study uses a hierarchical linear model to measure the effect of sector-level and community-level network structures on sectors' carbon emissions, as well as their interactions. The hierarchical linear model is widely used in management, education, and medical research (Bowers & Urick, 2011; Gentry & Martineau, 2010; Otaniet al., 2012; Zhanget al., 2018). It allows the individual-level variables to act on the outcome variable differently in each group by adding a random effect. During the estimation procedure, both the fixed effects which occur at multiple levels and the heterogeneity of individual-level variables' influence are considered. Specifically, the heterogeneity is achieved by adding a random effect on the basis of fixed effect for the sector level network structure variables in the model.

4.3.2 Independent variables

1) Level 1: sector-level network structure variables

Degree. In complex network theory, the 'degree'measures the connectedness of a node by counting the number of direct links the node has with other nodes. In a directed network, degrees are further divided into in-degrees and out-degrees. In the context of embodied carbon emission transfer networks, the in-degree for a sector is the number of other sectors transferring carbon emissions to that sector, while out-degree for a sector is the number of other sectors receiving carbon emissions from that sector. Sectors with high in-degree or out-degree values can accelerate the transfer of carbon emissions. The in-degree and out-degree of sector *i* are given by the formulas (4.1) and (4.2) respectively.

$$Degree_i^{in} = \sum_{i \neq j, i,j \in \mathcal{V}(N)} I[q_{ji} > 0] \qquad (4.1)$$

$$Degree_i^{out} = \sum_{i \neq j, i,j \in \mathcal{V}(N)} I[q_{ij} > 0] \qquad (4.2)$$

In these formulas, I is an indicator function, and its value equals 1 when the quantity of carbon emissions transferred between two sectors is larger than 0.

Strength. In a weighted network, the strength of a node is the sum of the weights of all edges directly connected to it. In a directed network, strength are further divided into 'in-strength' and 'out-strength'. In the context of a carbon emission network, in-strength measures the total quantity of carbon emissions transferred to the sector, while out-strength measures the total quantity of carbon emissions transferred out of the sector to other sectors. The sectors with high in-strength or high out-strength transfer a large quantity of carbon emissions. The in-strength and out-strength of sector i are given by the formulas (4.3) and (4.4):

$$Strength_i^{in} = \sum_{i \neq j, i, j \in V(N)} q_{ji} \qquad (4.3)$$

$$Strength_i^{out} = \sum_{i \neq j, i, j \in V(N)} q_{ij} \qquad (4.4)$$

Clustering Coefficient. In social networks, one phenomenon is very common: Two people who are both friends of a third person are likely to know each other. This characteristic is called clustering and is usually measured by a clustering coefficient. Clustering can also be explained as the interconnectedness within a group of nodes.

In a carbon emissions network, the clustering coefficient measures the completeness of a sector's local network. The larger the clustering coefficient of a node is, the more likely that its transfer paths form a local, small-scale, closely interconnected sub-network. The clustering coefficient ($CC_{\mathbb{G}(i)}$) of sector i is:

$$CC_{\mathbb{G}(i)} = \frac{\#\{jk|k \neq j, j \in N_{\mathbb{G}(i)}, k \in N_{\mathbb{G}(i)}\}}{d_{\mathbb{G}(i)}(d_{\mathbb{G}(i)} - 1)/2} \qquad (4.5)$$

In this formula, N is the number of nodes in the network and $d_{\mathbb{G}(i)}$ represents the sum of the in-degrees and out-degrees of sector i in the network.

Betweenness. The betweenness of a node is the number of shortest paths going through it. Betweenness is usually used to measure the media capability of a node in the network, that is, its ability to be connected to other nodes in the network. As explained in Chapter 3, this research adopts Liang's (2016) adjusted betweenness algorithm. Combined with industry input-output analysis methods, this adjusted betweenness metric calculates the quantity of total carbon emissions going through a sector and better reflects the mediate capacity of a sector in a carbon emissions network. The betweenness of sector i is

$$Betweenness_i = fTJ_iTy \qquad (4.6)$$

In this formula, the row vector f is the carbon emission intensity of each sector, $T = LA$ (where $\boldsymbol{L}$ is the *Leontief* inverse matrix, and $\boldsymbol{A}$ is the direct technical coefficient matrix), J_i is a diagonal matrix with all values on the diagonal being 1, and the column vector y is the final demand for each sector's products.

Closeness. The closeness of a node measures its distance to other nodes based on the shortest path. In a carbon emission network, in reference to Liang's (2016) adjusted betweeness algorithm, this research defines two forms of closeness: closeness-up and closeness-down. Closeness-up measures the total weights of the carbon emission transfer paths ending in a sector, and closeness-down measures the total weights of the carbon emission transfer paths starting in a sector. In other words, the two metrics measure the relative positions of a specific sector along a carbon emissions transfer path. Closeness-up measures the importance of a particular sector as a consumer of carbon emissions, while closeness-down measures its importance as a producer. The closeness-up and closeness-down of sector *i* are defined in formulas (4.7) and (4.8), respectively:

$$ClosenessUp_i = f \cdot (\textstyle\sum_l^\infty A^l) \cdot J_i \cdot \mathbb{Y} = fTJ_i\mathbb{Y} \qquad (7.7)$$

$$ClosenessDown_i = f \cdot J_i \cdot (\textstyle\sum_l^\infty A^l) \cdot \mathbb{Y} = fJ_iT\mathbb{Y} \qquad (7.8)$$

Because the values of betweenness, closeness-up and closeness-down are skewed, and they are measured in kilotons, this research conducts a logarithmic transformation on the three variables to increase the reliability of the model.

2) Level 2: community-level network structure variables

Identification of communities in carbon emission networks. This research adopts multi-level modularity optimisation algorithm to identify the communities in a carbon emission network, as described in Chapter 3. This is an exploratory method based on modularity optimisation (Blondel et al., 2008). The modularity Q value measures the degree to which a network can be divided into groups with distinct boundaries (Chenet al., 2010; Martin, 2012). Modularity Q values range from 0 to 1. The higher the modularity Q value, the closer the nodes within the community are, and the sparser the nodes between communities are. For communities in a carbon emission network, carbon emissions flows are much more intensive within a community than outside, in terms of both number and weight of edges. Additionally, in order to check the robustness of the community detection algorithm, fast greedy modularity optimization algorithm proposed by Clauset (2004) was also applied to the network.

Community size. The size of a community is defined as the number of sectors contained within it.

Community density. The density of a community refers to the ratio of the existing edges to the number of all possible edges. The greater the community density, the higher the ratio of actual edges to possible edges. For community *j* with *n* nodes in the carbon network, the community density is defined as:

$$Density_j = \frac{l}{[n*(n-1)]/2} \qquad (4.9),$$

where l is the number of carbon emission transfer links actually observed in the community.

The community average path length. The community average path length (APL) measures the closeness of nodes in a community. The shorter the APL is, the closer the nodes in the community are. For any two nodes *m* and *n* in the network, the path length $d(v_m, v_n)$ between the two is defined as the number of edges on the shortest path from node m to n. Therefore, for community j, the average path length (APL_j) is equal to the expected value of the distance between any two nodes in the community, that is:

$$APL_j = \frac{1}{n\cdot(n-1)} \cdot \sum_{i\neq j} d(v_m, v_n) \qquad (4.10)$$

In this formula, n is the number of nodes in the community j. $d(v_m, v_n)$ refers to the shortest path length between nodes m and n. If there is no connection between nodes m and n, then $d(v_m, v_n) = 0$.

Assortativity. According to the definition of assortativity (Newman, 2003), if nodes with high degrees tend to be connected with other nodes with high degrees, then the network is regarded as homogeneous (i.e. they possess assortativity); otherwise, the network is regarded heterogeneous (i.e. they do not possess assortativity). By studying the assortativity of communities in the network, the emission transfer mode among sectors can be better understood. The assortativity coefficient of community j is defined as:

$$r_j = \frac{\frac{1}{|D_j|}\cdot\sum k_m k_n - \left[\frac{1}{|D_j|}\cdot\sum\frac{1}{2}\cdot(k_m+k_n)\right]^2}{\frac{1}{|D_j|}\cdot\sum\frac{1}{2}\cdot({k_m}^2+{k_n}^2) - \left[\frac{1}{|D_j|}\cdot\sum\frac{1}{2}\cdot(k_m+k_n)\right]^2} \qquad (4.11)$$

In this formula, $|D_j|$ is the total number of edges in community j, and k_m, k_n are the degrees of sectors m and n in the community respectively. If the assortativity coefficient $r > 0$, the community is a homogeneous sub-network; if $r < 0$, the community is a heterogeneous sub-network.

4.3.3 Dependent variable

The dependent variables of the model are the quantities of carbon emissions directly produced by each sector in 2007, 2010 and 2012 (in thousands of tons). Figure 4.2 shows that the carbon emissions of various sectors each year have a highly skewed distribution.

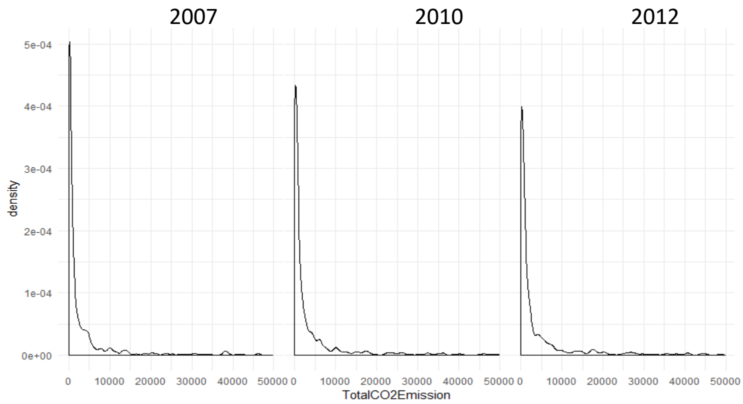

Figure 4.3 Probability density distribution of total carbon emissions in 2007, 2010 and 2012

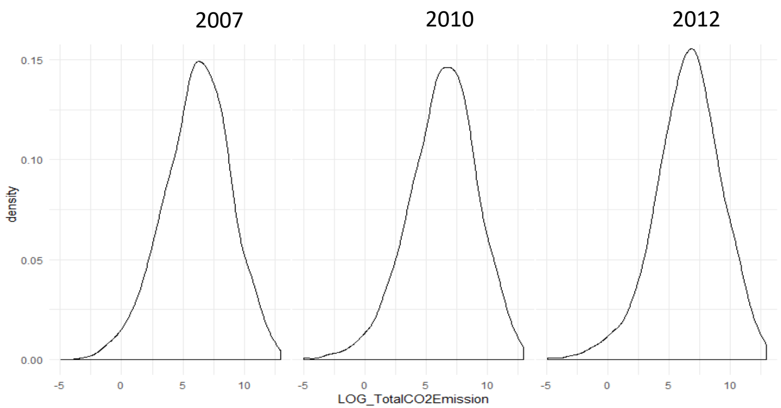

Figure 4.2 Probability density distribution of total carbon emissions in 2007, 2010 and 2012 (logarithmic transformation)

Therefore, this study intends to perform a logarithmic transformation of the dependent variables (see Figure 4.3), thereby adjusting the data so it is more in line with the statistical model assumptions.

4.3.4 Other control variables

The data used in this study covers the three years of 2007, 2010 and 2012. For the analysis, it is necessary to consider the effect of time on the relationships between structure variables on carbon emissions. Therefore, this study introduces two time-effect dummy variables:

$$Year\_2010 = \begin{cases} 1, & \text{if from year 2010 data;} \\ 0, & \text{if not from 2010 data;} \end{cases}$$

$$Year\_2012 = \begin{cases} 1, & \text{if from year 2012 data;} \\ 0, & \text{if not from 2012 data;} \end{cases}$$

Because the characteristics of the sector itself may impact its carbon emissions, they are also taken as control variables in this study. Two dummy variables are introduced that characterise the nature of the sector, whether it belongs to primary sector, manufacturing sector or service sector:

$$Sector\_Indus = \begin{cases} 1, & \text{if it is a manufacturing sector;} \\ 0, & \text{if else;} \end{cases}$$

$$Sector\_Serv = \begin{cases} 1, & \text{if it is a service sector;} \\ 0, & \text{if else;} \end{cases}$$

In addition, variables reflecting differences in economic characteristics, industrial production processes and energy use are also introduced. To reflect a sector's economic characteristics, measures of its GDP, compensation of employees, net taxes on production, depreciation of fixed capital and operating surplus are added to the model after logarithmic transformation. Carbon emissions per unit of added value, and the ratio of intermediate input to final output, are added to the model as proxies for variations in production processes. In addition, to reflect a sector's preference in energy use, as coal is the primary energy type in China, the ratio of coal to all fossil fuel is used as a proxy for the sector's energy use structure.

4.4 Model preparation, results and discussion

To construct a hierarchical linear model, the multi-level structure should be determined beforehand. While the network structure at the sector node level is regarded as level 1, the community level is regarded as level 2. Moreover, for level 2, a time effect is added to communities. The data modeled in this study cover the years 2007, 2010 and 2012 and each sector belongs to a year-community. For example, the agriculture sector for Beijing in 2012 belongs to 2012-community 3, and the textile sector of Shanghai in 2010 belongs to 2010-community 4. In this way, 2653 sectors are divided into 53 mutually exclusive year-communities. In addition, to assure the robustness of the community detection result, the fast greedy modularity optimization algorithm was also applied to the emissions network of 2007, 2010 and 2012. Almost the same community structure was revealed by using the multi-level modularity optimisation algorithm and the fast greedy modularity optimization algorithm. More details about robustness check can be found in Chapter 5.2 research conclusion. To avoid multicollinearity and to increase the interpretability of the model, variable centralising is a commonly used method of variable transformation (Aguinis et al., 2013). Therefore, all the network structure variables are centralised. In addition, due to large differences in the measurement units, the variables are further standardised for ease of interpretation.

4.4.1 Model setting

In accordance with the common practice adopted in hierarchy linear models (Luke, 2004), four models were set up in the study.

Model (1). This is a random intercept model that contains only individual sector-level network structure variables as fixed effects. Because this study standardises all the dependent and interpreted variables, there is no intercept term in the estimation equation.

Models (2), (3) and (4) are treated in the same way. In addition, y_{ij} is the independent variable, referring to the carbon emissions (logarithm) produced by sector i of year-community j.

Level 1:

$$y_{ij} = \sum_{\mathscr{k}=1}^{K} \beta_{\mathscr{k}} \cdot Sector\_Level\_Features_{ij\mathscr{k}} + \xi_{0j} + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma^2)$$

$$(i = 1, \ldots, 2653, \ j = 1, \ldots, 53) \qquad (4.12)$$

Level 2:

$$\xi_{0j} = u_{0j}, \quad u_{0j} \sim N(0, \tau_{00}^2) \qquad (4.13)$$

In these formulas, $Sector\_Level\_Features_{ij\mathscr{k}}$ is the $\mathscr{k}$-th sector-level network structure variable of sector i of year-community j. ξ_{0j} is a random variance differences between communities. ε_{ij} is the random error term of the model at the sector level, satisfying the homoscedastic assumption of statistical models. Model (1) does not include any independent variables at the year-community level, and all the information relevant to communities is attributed to the random term ξ_{0j}.

Model (2): This is a random intercept model that includes sector- and community-level network structure variables as fixed effects. On the basis of Model (1), Model (2) adds network structure variables at the community level as fixed effects $\gamma_{\ell}(l = 1, \ldots, 4)$.

Level 1:

$$y_{ij} = \sum_{\mathscr{k}=1}^{K} \beta_{\mathscr{k}} \cdot Sector\_Level\_Features_{ij\mathscr{k}} + \sum_{\ell=1}^{L} \gamma_{\ell} \cdot Community\_Level\_Features_{\ell} + \xi_{0j} + \varepsilon_{ij},$$

$$\varepsilon_{ij} \sim N(0, \sigma^2), \quad i = 1, \ldots, 2653, \quad j = 1, \ldots, 53 \qquad (4.14)$$

Level 2:

$$\xi_{0j} = u_{0j}, \quad u_{0j} \sim N(0, \tau_{00}^2) \qquad (4.15)$$

The coefficients $\beta_{\mathscr{k}}(\mathscr{k} = 1, \ldots, 8)$ of sector-level network structure variables in both Model (1) and Model (2) do not change with the year-communities. In other words, the individual sector-level network structure influences a sector's carbon emissions in the same way in all year-communities.

Model (3): This is a random coefficient model that includes sector- and community-level network structure variables. On the basis of Model (2), for the influence mechanism of sector-level structure on carbon emissions, a random term that varies with year-communities is added, so that sector-level network structure influences a sector's carbon emissions differently in each year-community.

Level 1:

$$y_{ij} = \sum_{\mathscr{k}=1}^{K} \beta_{\mathscr{k}j} \cdot Sector\_Level\_Features_{ij\mathscr{k}} + \sum_{\ell=1}^{L} \gamma_{\ell} \cdot Community\_Level\_Features_{\ell} \quad + \xi_{0j} + \varepsilon_{ij},$$

$$\varepsilon_{ij} \sim N(0, \sigma^2), \; i = 1, \ldots., 2653, \; j = 1, \ldots, 53 \qquad (4.16)$$

Level 2:

$$\beta_{\mathscr{k}j} = \delta_{\mathscr{k}j} + \epsilon_{j\mathscr{k}}, \; \epsilon_{j\mathscr{k}} \sim N(0, \tau_{\mathscr{k}j}^2)$$

$$\xi_{0j} = u_{0j}, \; u_{0j} \sim N(0, \tau_{00}^2) \qquad (4.17)$$

In these formulas, the effect of the $\mathscr{k}$-th sector level structure variable on carbon emissions is composed of a fixed part ($\delta_{\mathscr{k}j}$) and a random term ($\epsilon_{j\mathscr{k}}$). The former can be interpreted as the average effect of sector-level structure on carbon emissions, and the latter as a random effect which will be different for each year-community. This random term is introduced to take account of the heterogeneity of the effect of sector-level structure variables on carbon emissions, reflecting the multi-level structure of the data.

Model (4): On the basis of Model (3), Model (4) adds control variables to the model, reflecting the differences in sectors' economic characteristics, industrial production processes and energy use.

When developing multi-level linear models, maximum likelihood estimation or restricted maximum likelihood estimation are generally used. There is not a large difference in the values of the estimated coefficients between the two. The main difference is reflected in the estimation of the variance part of the fixed effect and the random effect in the multi-level linear model. This study uses restricted maximum likelihood estimation, as it is more common in the literature (Leeuw et al., 2008).

4.4.2 Descriptive statistics and exploratory analysis of main variables

Figure 4.4 shows the probability density distribution of sectors' carbon emissions in logarithmic form for each year-community. The panels are sorted by the order of community number and by year. Significant differences can be observed for the distribution of each year-community. Take distribution of community 1 in 2007 (panel 2007_1), 2010 (panel 2010_1), and 2012 (panel 2012_1) as an example. Though they generally follow a normal distribution, there were two peaks in 2007, one relatively high peak in 2010, and no significant peak but wide value range of total carbon emissions in 2012. By adopting a multi-level linear model, the differences in each year-community are considered, thereby reducing estimation bias.

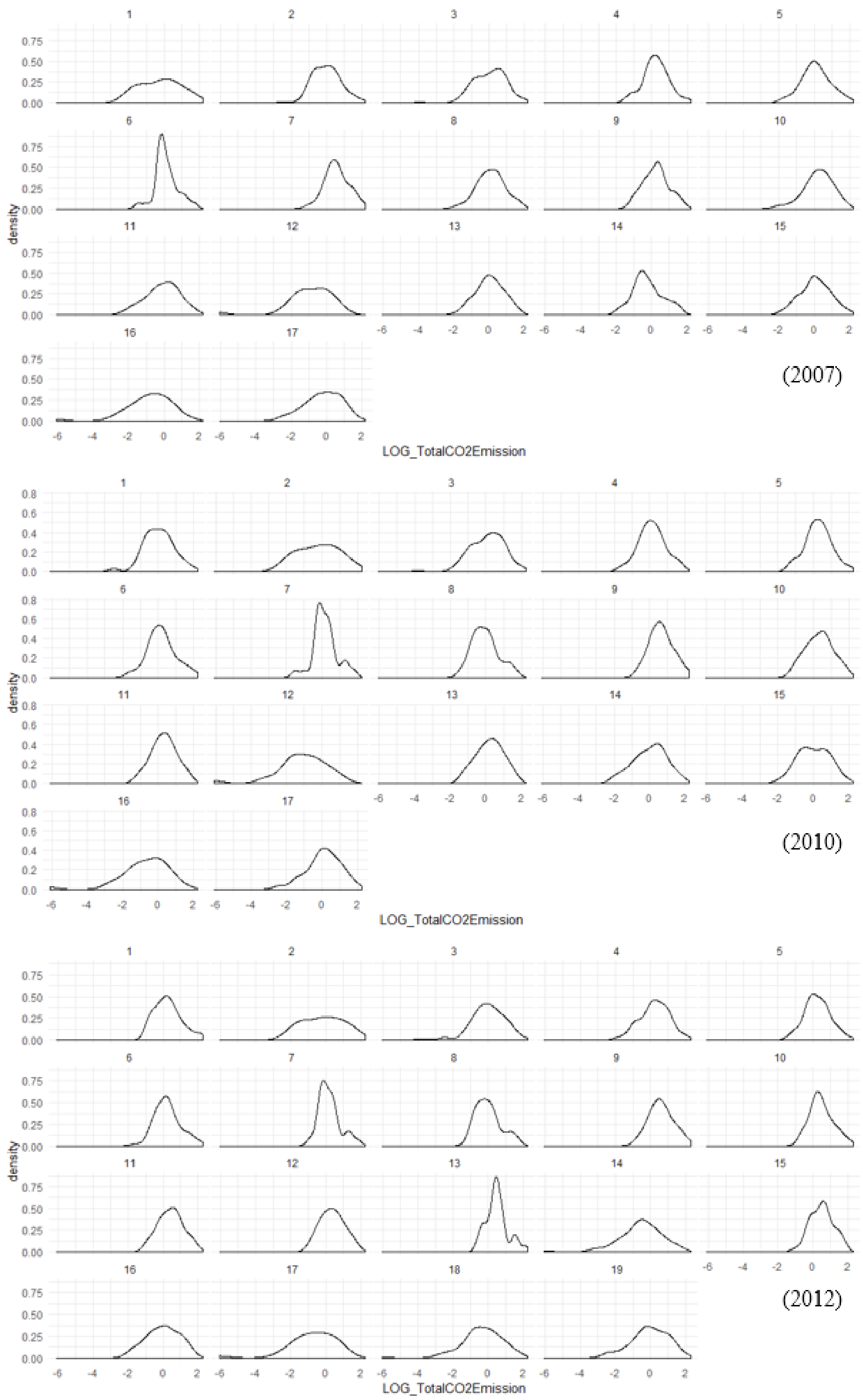

Figure 4.4 Probability density of sector carbon emissions for each year-community in 2007, 2010 and 2012

Table 4.1 gives descriptive statistics for network structure variables at the sector and community levels. Due to the use of different measurement units, the differences in the ranges of variables is large. In addition, there are significant imbalances in the distributions of variables, which can be observed in the values of skewness and kurtosis. The skewness and kurtosis of a normal distribution are 0 and 3 respectively. The further the skewness value is from zero, the greater the right or left skewness of the distribution. The further the kurtosis value is from 3, the thicker or slenderer the tails of the distribution are. Therefore, in order to improve the reliability of the empirical analysis, this study standardises all explanatory variables.

Table 4.1 Descriptive statistics of the network structure variables of China's carbon emissions transfer network (original values)

	Minimum	mean	maximum	S.D	Skewness	Kurtosis
Individual level characteristics						
In-degree	0	59.66	797	73.253	4.894	33.097
Out-degree	0	59.63	877	93.946	5.833	40.745
In-strength	0	8603.6	263668.1	19094.51	5.065	39.45
Out-strength	0	8401.9	477974.0	32633.23	7.607	74.773
Clustering coefficient	0.2334	0.7957	1.1923	0.133	-1.146	4.615
Upward closeness	-11.513	6.519	12.343	3.839	-2.974	14.423
Downward closeness	-11.513	5.508	12.836	3.111	-0.774	6.143
Betweenness	-11.513	7.510	12.819	2.553	-2.225	14.164
Group level characteristics						
Size	27	66.58	120	32.985	0.249	1.677
Density	0.207	0.446	0.854	0.207	0.563	1.733
Average path length	0.011	0.477	3.343	0.586	3.329	14.614
Assortativity	-0.097	-0.048	0.030	0.030	0.326	2.307

Table 4.2 gives the partial correlation coefficients of each network structure variable to determine whether the model has an obvious multi-collinearity problem. The correlation between structure variables at the community level is relatively high because sectors belonging to the same community have the same community network structure variable values. This collinearity problem can be solved by using the hierarchical linear model, which consider the objects in the same group have similar variable effect. Except for the partial correlation coefficients between degree and strength, the absolute values of the other network structure variables at the sector and community levels are all less than 0.5, indicating weak correlations. The partial correlation coefficients between out-degree and out-weight, in-degree and in-weight are higher than 0.8, indicating strong correlations. In addition, by including out-strength as an independent variable, it may cause endogeneity concern due to the fact that both the dependent variable i.e. a sector's direct carbon emissions, and out-strength, i.e. the amount of embodied carbon emissions that a sector transmits outward, are measured by the carbon emissions amount. Both of them are determined or partly determined by a sector's economic output and carbon emissions intensity.

Table 4.2 Partial correlation coefficient matrix of structural characteristics of China's carbon emissions transfer network (original variables)

	Out-degree	**In-degree**	**Out-strength**	**In-strength**	**Clustering coefficient**	**Closeness-Up**
Out-degree	-					
In-degree	-0.048***	-				
Out-strength	0.893***	-0.035*	-			
In-strength	0.123***	0.823***	0.153***	-		
Clustering	-0.576***	-0.407***	-0.484***	-0.450***	-	
Closeness-up	0.100***	0.410***	0.121***	0.405***	-0.113***	-
Closeness-	0.449***	0.027	0.447***	0.132***	-0.377***	0.275***
Betweenness	0.312***	0.224***	0.313***	0.282***	-0.237***	0.369***
Size	0.023	-0.005	-0.028	-0.069***	-0.007	-0.132***
Density	-0.026	0.018	0.042**	0.101***	0.017	0.170***
APL	0.014	0.037*	0.069***	0.145***	-0.036**	0.081***
Assortativity	-0.009	0.123***	0.058***	0.158***	-0.032*	0.195***

	Closeness-down	Betweenness	Size	Density	APL	Assortativity
Closeness-	-					
Betweenness	0.270***	-				
Size	-0.072***	-0.140***	-			
Density	0.142***	0.213***	-0.888***	-		
APL	0.162***	0.180***	-0.343***	0.356***	-	
Assortativity	0.173***	0.265***	-0.711***	0.720***	0.393***	-

Note: ***, **, and * indicate that results are at 1%, 5% and 10% significance levels respectively; closeness-up, closeness-downward and betweenness are logarithmically transformed values.

In order to deal with the high correlation between degree and strength and the potential endogeneity problem, this study uses the out-degree to in-degree ratio and out-strength to in-strength ratio as independent sector-level network structure variables, rather than absolute values. Specifically, for sector i, the out-degree to in-degree ratio (out-in degree ratio) and out-strength to in-strength ratio (out-in strength ratio) are defined as

$$Ratio\_OutInDegree = {Degree_i^{out}}\Big/{Degree_i^{in}}$$

$$Ratio\_OutInStrength = {Strength_i^{out}}\Big/{Strength_i^{in}}$$

Table 4.3 shows the partial correlation coefficients between variables after introducing the ratio variables. The partial correlation coefficients between sector-level variables and cross-level variables have decreased significantly and are less than 0.5, indicating weak correlation.

The endogeneity brought by including out-strength is also solved by using the out-strength to in-strength ratio. While this constructed variable maintains an embodied emissions transmission feature, it is not determined by a sector's economic output and carbon emissions intensity. Instead, it is determined by a sector's production function, including the input requirement from other sectors, technical advancement and the sector's local resource endowment. Moreover, the insignificant correlation observed between the out-strength and ratio of out-/in-strength can further relieve the endogeneity concern. If those two variables are highly correlated, the inclusion of the ratio of out-/in-strength will cause severe endogeneity, and otherwise not. The empirical result showed that no statistically significant correlation is found between the out-strength and ratio of out-/in-strength (ρ=0.0281, p-value = 0.1485). Therefore, there is no endogeniety involved in introducing the ratio of out-/in-strength variable.

Table 4.3 Partial correlation coefficient matrix of topological characteristics of China's carbon emissions transfer network

	Ratio_Out InDegree	Ratio_Out InStrength	Clustering coefficient	Closeness-Up	Closeness-down	Betweenness
Ratio_OutInDegree	-					
Ratio_OutInStrength	0.081^{***}	-				
Clustering coefficient	-0.200^{***}	-0.076^{***}	-			
Closeness-Up	-0.477^{***}	-0.291^{***}	-0.113^{***}	-		
Closeness-down	0.100^{***}	0.079^{***}	-0.377^{***}	0.275^{***}	-	
Betweenness	-0.130^{***}	-0.014	-0.237^{***}	0.369^{***}	0.270^{***}	-
Size	0.072^{***}	0.023	-0.007	-0.132^{***}	-0.072^{***}	-0.140^{***}
Density	-0.067^{***}	-0.021	0.017	0.170^{***}	0.142^{***}	0.213^{***}
APL	0.009	-0.003	-0.036^{**}	0.081^{***}	0.162^{***}	0.180^{***}
Assortativity	-0.053^{***}	-0.021	-0.032^{*}	0.195^{***}	0.173^{***}	0.265^{***}
	Size	**Density**	**APL**	**Assortativity**		
Size	-					
Density	-0.888^{***}	-				
APL	-0.343^{***}	0.356^{***}	-			
Assortativity	-0.711^{***}	0.720^{***}	0.393^{***}	-		

Note: ***, **, and * refer to significance levels of 1%, 5%, and 10% respectively; closeness-up, closeness-downward and betweenness are logarithmically transformed values.

4.4.3 Necessity analysis of the use of a hierarchical linear model

The multi-level nested data structure should be verified before moving on to applying the hierarchical linear model. Three indexes, as presented in Table 4.4, are commonly used to determine whether data is in a multi-level structure and whether it is necessary to use a hierarchical linear model. ICC(1) measures the extent to which the effect variance of sector-level structure variables can be explained by community membership (Raudenbush and Bryk, 2002). ICC(2) measures the reliability of the mean values of each community (Bliese et al., 2002), and it is affected by ICC(1) and the community size. The $r_{wg(j)}$ agreement index measure the interchangeability of individual sector's response among communities. The higher the $r_{wg(j)}$ value is, the lower the interchangeability is, indicating greater difference in one community member's response to another community member's response (Klein and Kozlowski, 2000). The three indexes range from 0 to 1. The larger the coefficient, the greater the need to use a hierarchical linear model. For the sector-level network structure variables, as presented in Table 4.4, ICC (1), ICC (2), and $r_{wg(j)}$ values are all significantly non-zero, and in particular ICC(2) and $r_{wg(j)}$ have large values. Therefore, it is justified and reliable to adopt the hierarchical linear model in this study.

Table 4.4 ICC (1), ICC (2) and $r_{wg(j)}$ estimates of sector-level carbon emissions transfer network structure variables

	ICC(1)	ICC(2)	$r_{wg(j)}$
Ratio_OutInDegree	0.0146	0.4265	0.8783
Ratio_OutInStrength	0.0018	0.0813	0.8958
Clustering Coefficient	0.2228	0.5386	0.4878
Upward closeness	0.1972	0.8435	0.6526
Downward closeness	0.1044	0.8537	0.5727
Betweenness	0.2140	0.9316	0.6629

Note: closeness-up, closeness-downward and betweenness are logarithmic transformed values.

4.4.4 Results and discussion

Table 4.5 presents the estimates of the influence of China's carbon emission transfer network structure variables on sectors' carbon emissions (in logarithmic form) in each of the four models. Overall, the empirical results confirm that the network structure variables at both the sector and community levels all have a significant influence on sectors' carbon emissions.

From Model (1) to Model (4), the nested multi-level data for sector-level and community-level network structure variables have been verified, and the fitting effect of the models has been significantly improved. The model fitting index ICC measures the extent to which the variance in the responses of sectors' carbon emissions to sector-level structure variables' influences can be explained by the nested multi-level data structure. Because Model (1) and Model (2) only include the network structure variables as fixed effects, and do not reflect the multi-level data structure, the value of ICC is 0.000 for these two models. In addition, while Model (1) only considers the sector-level structure, by adding the community structure variables, the fitting effect of Model (2) has been increased ($\mathcal{X}^2 = 9.1108$, $Pr(> Chisq) = 0.0584$). By taking account of random effects, Model (3) allows the sector-level structure's effect on emissions to differ in each year-community, and the fitting effect has been improved significantly ($\mathcal{X}^2 = 932.27$, $Pr(> Chisq) < 0.0000$). In addition, the ICC of Model (3) has increased significantly to 0.973, meaning that 97.3% of the variance in the responses of sectors' carbon emissions to sector-level structure variables' influences can be explained by the multi-level data structure. At the same time, moving from Model (1) to (4), both AIC and BIC, which are goodness of fit indexes, decrease significantly, and this also indicates that the model fitting effect has been improved.

Table 4.5 The relationship between the network structure variables of China's carbon emissions transfer network and the carbon emissions

	Dependent variable: total carbon emissions (logarithmic)			
	(1)	**(2)**	**(3)**	**(4)**
Fixed effect				
Individual characteristics				
Ratio_OutInDegree	0.0128*	0.0117	-0.0173	0.0524**
	(0.0073)	(0.0073)	(0.0366)	(0.0199)
Ratio_OutinStrength	0.0277***	0.0288***	0.8082***	0.5082***
	(0.0065)	(0.0065)	(0.1385)	(0.1307)
Clustering Coefficient	-0.0795***	-0.0796***	-0.0744***	-0.0600***
	(0.0042)	(0.0042)	(0.0046)	(0.0041)
Upward closeness	0.2028***	0.2033***	0.3502***	0.2766***
	(0.0064)	(0.0064)	(0.0192)	(0.0175)
Downward closeness	0.9993***	0.9992***	1.0076***	1.0114***
	(0.0069)	(0.0069)	(0.0093)	(0.0102)
Betweenness	-0.1545***	-0.1564***	-0.2345***	-0.2888***
	(0.0089)	(0.0089)	(0.0189)	(0.0206)
Industry group level characteristics				
Size		0.0252**	-0.0145*	-0.0218**
		(0.0122)	(0.0088)	(0.0085)
Density		0.0134	-0.0193**	-0.0205**
		(0.0116)	(0.0090)	(0.0088)
Average path length		0.0094*	0.0001	-0.0031
		(0.0049)	(0.0045)	(0.0042)
Assortativity		0.0059	-0.0075	-0.0214***
		(0.0073)	(0.0062)	(0.0061)
Sector economic characteristics				
Compensation of employees				0.1066***
				(0.0112)
Net taxes on production				0.0080**
				(0.0035)
Depreciation of fixed capital				-0.0525***
				(0.0083)
Operating surplus				0.0121***
				(0.0034)
Intermediate input/ final output ratio				0.0129***
				(0.0040)
Coal/total fossil fuel ratio				-0.0043
				(0.0028)
GDP				0.0463***
				(0.0133)

	Dependent variable: total carbon emissions (logarithmic)			
	(1)	**(2)**	**(3)**	**(4)**
Time				
Year 2010	-0.0264**	-0.0267**	0.0096	-0.0178**
	(0.0124)	(0.0121)	(0.0099)	(0.0100)
Year 2012	-0.0352***	-0.0316**	-0.0072	-0.0254***
	(0.0121)	(0.0119)	(0.0096)	(0.0097)
Sector				
Manufacturing sector	0.0139	0.0143	0.0375***	0.0593***
	(0.0087)	(0.0086)	(0.0059)	(0.0060)
Service sector	0.0391***	0.0392***	0.0389***	0.0200**
	(0.0116)	(0.0115)	(0.0085)	(0.0091)
Random effects (variance)				
Ratio_OutInDegree			0.0419***	0.0071***
			(77.669)	(58.400)
Ratio_OutInStrength			0.6407***	0.5616***
			(97.344)	(28.075)
Clustering Coefficient			0.0003***	0.0002*
			(17.747)	(12.101)
Upward closeness			0.0151***	0.0114***
			(300.524)	(210.552)
Downward closeness			0.0024***	0.0032***
			(56.817)	(86.649)
Betweenness			0.0134***	0.0162***
			(280.117)	(369.673)
Model fitting information				
intra-class correlation (ICC)	0.000	0.000	0.973	0.966
AIC	-1438.911	-1406.679	-2309.238	-2565.888
BIC	-1368.309	-1312.544	-2097.434	-2312.9
Observed sample size	2,653	2,653	2,653	2,653

Note: ***, **, and * indicate that the data are significant at the of 1%, 5%, and 10% levels respectively, and the standard errors of the estimated coefficients are in parentheses.
For random effect (variance), the values in brackets are the likelihood ratio test statistics results.
Upward closeness, downward closeness, betweenness, compensation of employees, net taxes on production, depreciation of fixed capital, operating surplus and GDP are logarithmically transformed.

The network structure variables at the sector level have significant fixed effects on sectors' carbon emissions, in the same direction in all four models. As an example, take Model (4), which has the best fitting effect. Both the out-in degree ratio (relative out-degree) and the out-in strength ratio (relative out-strength) have a significant positive relationship with sectors' direct carbon emissions. For increases of one standard deviation in the out-in degree ratio and out-in strength ratio, carbon emissions increase by 0.054 ($exp(0.0524) - 1$) and 0.662 ($exp(0.5082) - 1$) standard deviations respectively. The higher the relative out-degree and relative out-strength are, the more carbon emissions the sector produces. In addition, compared with relative out-degree, relative out-strength has a more significant effect on the increase in carbon emissions. This may be due to the mismatch between the out-degree and out-strength in the network. Take the 2012 carbon emission transfer network as an example. The Spearman correlation coefficient between out-degree and out-strength is only 0.49. The industries generating large amounts of carbon emissions are not always in a good position to spread the carbon emissions to a wide range of other sectors in a number of provinces.

There is a significant negative relationship between the clustering coefficient and total carbon emissions. For one standard deviation increase to the clustering coefficient, the sector's carbon emissions will decrease by 0.062 standard deviations. For industries with high clustering coefficients, the local carbon emission transfer network has a tightly interconnected structure. This means that industrial carbon emissions flow continuously within a local range in a network, and the transfer path repeated many times, reducing the growth of carbon emissions.

Closeness-up and closeness-down measure the industry's position along the carbon emissions transfer path. The former measures the importance of specific sectors as carbon consumers, while the latter measures their importance as carbon producers. For one standard deviation increase of closeness-up and closeness-down, the sector's carbon emissions increase by 0.319 and 1.749 standard deviations respectively. The impact of closeness-down is 5.49 times stronger than closeness-up. This means that the closer the industry is to the upstream section of the carbon transfer chain, the higher the sector's carbon emissions will be. From the empirical data, for industries with a high closeness-down, such as the electricity and hot water production and supply sector, their products are often used as intermediate inputs in the production processes of other sectors. The driving force coming from the downstream industries keeps these sectors' production of carbon emissions at a high level.

There is a significant negative correlation between betweenness and a sector's carbon emissions. For one standard deviation increase of betweenness, a sector's emissions will decrease by 0.335 standard deviations. Betweenness measures the mediating role played by an industry in the carbon emission transfer network. An industry with a high betweenness serves as a bridge to conduct and promote the transfer of carbon emissions. During the process, the sectors with high betweenness do not 'produce' high carbon emissions by themselves. Instead, due to their wide transfer relationship, they directly and indirectly import a large amount of emissions through taking inputs from other sectors, and it reduces carbon emissions during their own production procedure. Take the electricity sector of Beijing for example, which reduces its own carbon emissions production through using the electricity from other provinces such as Shanxi and Inner-Mongolia. Therefore, sectors with high 'betweenness' are negatively correlated with emissions

On the basis of fixed effects, Models (3) and (4) allow the effect of node-level structure variables on sectors' carbon emissions to differ in each community, reflecting the multi-level data structure. The empirical results confirm that the sector-level structure variables have significant random effects, indicating that year-communities have significant regulating effects on the influence of sector-level structure variables on sectors' carbon emissions.

The community-level structure variables are also a focus in this study. In Model (2), which does not consider the random effects of node-level structure variables, the community-level structure variables have no statistically significant effect, except on the size of the community. However, when the random effects reflecting the multi-level structure are considered in Models (3) and (4), the fixed-effect regression coefficients of community size, community density, and assortativity are all significantly negative. In other words, most of the community-level network variables have significant restraining effects on sectors' carbon emissions. This proves the importance of community structure in China's carbon emission transfer network. For each sector, when its community size, density and assortativity increase by one standard deviation, its carbon emissions decrease by 0.022, 0.021 and 0.022 standard deviation respectively. When the scale of the community expands and the transfers between industries are more active, the carbon emissions produced by the sectors within the community will decrease.

The empirical results of Models (1) to (4) show that compared to 2007, sectors' carbon emissions in 2010 and 2012 slowed down significantly. This decline in carbon emissions was caused by many factors but there were two main reasons. First, China is accelerating the development of its low-carbon development strategy in response to climate change. In the performance evaluation of local governments, indicators such as carbon emissions intensity reduction have been added to further push the transition to a low-carbon economy. Secondly, the upgrading of industrial infrastructure and the increasing proportion of the economy occupied by service sectors is also contributing to the decline in carbon emissions.

The sectors' own production processes and economic characteristics also have an effect on carbon emissions. Compared with primary industry, secondary and tertiary industries produce more carbon emissions. In addition, the compensation of employees, net taxes on production and operating surpluses all have significant positive impacts on sectors' carbon emissions, while the depreciation of fixed capital has a significant inhibitory effect. Moreover, industries with higher intermediate input/ final output ratios produce more carbon emissions. For one standard deviation increase to the input/ final output ratio, a sector's carbon emissions will increase by 0.013 standard deviations. In addition, the proportion of carbon emissions which comes from coal use does not have a significant impact on carbon emissions. This is probably due to the fact that the emission reduction effect brought by non-fossil energy is not reflected in the percentage. Additionally, the emission factor among all the 17 fossil energy types is similar, ranging from 0.06 Mt CO_2/PJ to 0.08 Mt CO_2/PJ, except for coke and natural gas, which is 0.10 Mt CO_2/PJ and 0.05 Mt CO_2/PJ. Moreover, the GDP of a sector has a significantly positive correlation with its carbon emissions. When GDP increases by one standard deviation, the sector's emissions increase by 0.047 standard deviations.

4.5 Conclusions

This chapter adopts a hierarchical linear model to study the impact of China's carbon emissions transfer network structure on sectors' carbon emissions. The research results demonstrate that the embodied carbon emission network has a multi-level structure. Sectors' emissions are affected, not only by the node-level structure of the sector, but also by the community-level structure of the community that the sector belongs to. In addition, the effect of sector-level structure is influenced by the community structure, and they interact with each other and affect sectors' carbon emissions together. Therefore, to reduce the carbon emissions of a sector, the sector and its community should be considered together.

There are two types of network structure variables adopted in the models. The first type is the node-level network variables. They include degree, strength, clustering coefficients, betweenness, and closeness. The second type is the community-level variables. They include community size, community density, average path length and assortativity. In addition, to better measure the effect of network structure, a time effect variable, and variables reflecting sectors' own industrial production processes and economic characteristics, are also introduced as control variables.

Four estimation models were set up to analyse how the network structure affect sectors' carbon emissions. The empirical results confirm that both sector-level and community-level network structure variables play a significant role in determining sectors' carbon emissions. Both the out-in degree ratio and the out-in strength ratio have a positive correlation with sectors' carbon emissions. In sectors with high clustering coefficients, due to their tightly interconnected local network structures, carbon emissions are inhibited. Moreover, sectors with high betweenness play an important role in conducting and promoting carbon transfer, which also has a significant inhibitory effect on the growth of emissions. Additionally, the closer a sector is to the upstream section of the carbon transmission path, the more carbon emissions a sector produces. Last but not least, increases in the size and density of a community will inhibit the growth of carbon emissions.

For effective sectoral carbon emissions abatement, connections between sectors should be encouraged. By increasing the links between various sectors, the size and density of communities will be boosted and this will have an inhibitory effect on emissions. This is probably due to the self-purification effect brought by industrial agglomeration, which refers to a U-curved tendency between industrial agglomeration and environmental efficiency (Chen et al., 2018; Wang and Wang, 2019). Specifically, carbon emissions abatement efficiency improves as local industrial agglomeration proceeds, once agglomeration is beyond an inflection point. In addition, for industries with high direct carbon emissions, the growth of emissions can be slowed down through scale efficiencies and technology upgrades. For sectors at the consumer end, it is necessary to expand the sources of intermediate products, reduce the out-in degree and out-in strength ratios, and prioritise low-carbon inputs to promote low-carbon development along the entire supply chains.

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Chapter 5 FINAL DISCUSSION AND CONCLUSION

5.1 Introduction

The overarching aim of this thesis is to systematically examine the embodied carbon emissions transmissions between sectors of regions in China for effective emissions mitigation. Before moving on to specific research, a systematic literature review of the research on sectoral carbon emissions research in China was conducted to lay the foundations for the research topic and choice of methodology. The review chapter fills an important research gap by systematically reviewing all the major research methods in the field. To investigate emissions transmission, input-output analysis and network analysis methods were combined to develop a network model to trace the embodied sectoral carbon emissions between sectors of regions. Drawing on empirical data, the carbon emission transmission process which occurs across 30 sectors and 30 provinces in China were examined from macro, meso and micro perspectives, using network analysis metrics and algorithms. In addition, a hierarchical linear model was used to quantitatively examine the sectors' network structural role in carbon emissions. This final chapter builds on this research, along with the literature identified in Chapter 2 and the empirical findings from Chapters 3 and 4. It begins with a summary of the findings, conclusion and policy suggestions which emerged while addressing the research questions. Then this chapter discusses the contributions of the thesis to theory and practice. The thesis concludes with a discussion of the limitations of the research and future research recommendations.

5.2 Findings, conclusion and policy suggestions

This section is organised to validate the th research results and address each of the research questions.

5.2.1 Uncertainty and robustness analysis

The uncertainty of the research results mainly comes from the raw China's carbon emissions transfer network reduction procedure as well as the carbon community detection procedure, and robustenss check needs to be conducted for the statistical model used to examine the impact of emissions network structure variables on sectors' carbon emissions. It is necessary to present how the uncertainties are minimized during the research process and conduct robustness checks to validate the research results.

During the network reduction procedure, the main uncertainty lies in whether the structure features of the embodied carbon emission network are maintained, especially considering that the focus of the thesis is to examine the effect of transmission network structure on sectors' carbon emissions. Due to the nature of the MRIO model, its derived raw emission network is almost fully connected and has a large number of non-zero edges. The redundant intricacy and large number of edges present challenges for effective network analysis.

The two-step reduction algorithm was proposed and applied to maitain the multi-level structure of the raw network and minimize the uncertainty during the network reduction process. By using this algorithm, each node was assigned a null model, which informed the random expectation for the distribution of weights associated to its edges, considering the node's total strength. Each edge was compared with the null model of the two nodes at the end of each edge. Only when an edge was statistically significantly deviant from the null model of at least one of the end nodes, the edge would be kept. The significance level was put at a = 0.05 for this research. By taking the procedure, the nodes with comparatively small strength were not ignored, the network strcuture at all scales are were maintained, and the total number of edges were reduced considerably.

The robustness of the two-step algorithm is checked by its application to the network data for the three years, 2007, 2010 and 2012, as shown in Table 5.1. On one hand, the number of edges is dramatically reduced, with only about 7% of the raw network edges retained. On the other hand, more than 92% of the amount of embodied carbon emissions and multi-scale structural features are kept, such as the degree distribution and edge weight distribution of nodes. The network reduction work lays a good foundation for subsequent in-depth network structure analysis.

Table 5.1 Raw network and reduced network comparison

Year		2007	2010	2012
Raw Network	Number of nodes	900	900	900
	Number of edges	719,084	776,161	774,391
	Total edges weights (Unit: thousand tonnes)	6,501,038.594	7,928,532.445	10,143,742.76
Reduced network	Number of nodes	883	884	886
	Percentage of retained nodes	98.11%	98.22%	98.44%
	Number of edges	51,928	51,003	54,670
	Percentage of retained edges	7.22%	6.57%	7.06%
	Total edges weights (Unit: thousand tonnes)	6,019,726	7,376,856	9,428,826
	Percentage of retained edges weights	92.60%	93.04%	92.95%

Another uncertainty rises during the community detection procedure, whether the communities of sectors are outlined differently due to different algorithms applied to the networks. In chapter 3, a detailed comparision was conducted between network analysis based community detection algorithms and input-output analysis based cluster detection algorithms. The multi-level modularity optimization algorithm, which is network analysis based community detection algorithms, prevails in this research context mainly due to its advantage in no assumption of pre-defined supply chians and no pre-defined number of sectors for each community. The community detection result can provide more insight for a synergistic effect among all sectors of provinces in China.

The fast greedy modularity optimization algorithm (Clauset, 2004) - another frequently used community detection algorithm in large networks - is applied to check the sensitivity of community detection results to algorithms. Both multi-level modularity optimization algorithm and fast greedy modularity optimization algorithm are based on modularity optimization, aiming to find the communities with the most distinct boundaries, with no assumption of the number and size of communities. However, while multi-level modularity optimization algorithm is a heuristic method, fast greedy modularity optimization algorithm is a hierarchical agglomeration algorithm. The variation of information (VI) (Meila, 2003) and adjusted rand index (Hubert and Arabie, 1985) are introduced to evaluate the difference in community detection results. The more similarity two community structures share, the less the VI is and the higher the adjusted rand index is. Table 5.1 suggests that the community structure detected by the two algorithms have a high degree of similarity for the embodied carbon emissions network in years 2007, 2010 and 2012. In other words, the change of community detection algorithms does not affect the community significantly, and the community detection result is robust.

Table 5.1 Community detection result comparison

Year	variation of information (VI)	adjusted rand index
2007	0.011 (6.7833)	0.998
2010	0.059 (6.7844)	0.981
2012	0.035 (6.786)	0.991

Note: the number in the bracket under VI measurement is the theoretical upper limit of the VI obtained from the underlying network.

To ensure the validity of the empirical results obtained by hierarchy linear model in chapter 4, two robustness checks are conducted. This first one is to test the temporal significance of the hierarchy linear model. It is tested by lagging one period of the sectors' carbon emissions. The impact of the changes in the network structure on sectors' carbon emissions may be subject to a time lag effect. Therefore, this study explores the lag effect on carbon emissions of changes to a network's structure. In addition, due to data availability, this study keeps the same independent variables, and explores their influences on sectors' carbon emissions (in logarithmic form) in 2008, 2011 and 2013.

Table 5.2 shows estimates of the impact of structure variables for China's carbon emissions transfer network on carbon emissions in the following year in the four models. The results are consistent with Table 4.5, which indicates that the regression model is robust. In addition, it demonstrates that the structure of China's carbon emission transfer network has a long-lasting and consistent impact on carbon emissions.

Regression in a yearly manner is conducted to check the stability of the embodied carbon emissions network structure's effect on sectors' carbon emission. The results in each year are also consistent in terms of the direction and scale of estimated coefficients with Table 4.5, when all the data were pooled together with two time-effect dummy variables. This indicates that the empirical results based on the hierarchical linear model are robust.

Table 5.2 The relationship between the network structure variables of China's carbon emissions transfer network and the carbon emissions (one year lag behind)

	Dependent variable: total carbon emissions (logarithmic)			
	(1)	**(2)**	**(3)**	**(4)**
Fixed effect				
Individual characteristics				
Ratio_OutInDegree	0.0133	0.0124	0.0130	0.0795***
	(0.0084)	(0.0084)	(0.0345)	(0.0184)
Ratio_OutinStrength	0.0257***	0.0264***	0.9927***	0.4229**
	(0.0074)	(0.0075)	(0.1934)	(0.0757)
Clustering Coefficient	-0.0844***	-0.0846***	-0.0784***	-0.0632***
	(0.0048)	(0.0048)	(0.0054)	(0.0053)
Upward closeness	0.1950***	0.1953***	0.3448***	0.2653***
	(0.0074)	(0.0074)	(0.0224)	(0.0207)
Downward closeness	0.9806***	0.9808***	0.9870***	0.9757***
	(0.0080)	(0.0080)	(0.0140)	(0.0151)
Betweenness	-0.1369***	-0.1385***	-0.2156***	-0.2506***
	(0.0103)	(0.0103)	(0.0228)	(0.0237)
Industry group level characteristics				
Size		0.0228	-0.0331***	-0.0226*
		(0.0187)	(0.0114)	(0.0132)
Density		0.0077	-0.0288**	-0.0201
		(0.0176)	(0.0118)	(0.0134)
Average path length		0.0035	-0.0116**	-0.0173***
		(0.0070)	(0.0056)	(0.0059)
Assortativity		0.0093	-0.0092	-0.0149*
		(0.0107)	(0.0081)	(0.0089)
Sector economic characteristics				
Compensation of employees				0.0958***
				(0.0138)
Net taxes on production				0.0061
				(0.0045)
Depreciation of fixed capital				-0.0442***
				(0.0103)
Operating surplus				0.0103
				(0.0043)
Intermediate input/ final output ratio				0.0062
				(0.0050)
Coal/total fossil fuel ratio				-0.0096
				(0.0035)
GDP				0.0510***
				(0.0163)

	Dependent variable: total carbon emissions (logarithmic)			
	(1)	**(2)**	**(3)**	**(4)**
<u>Time</u>				
Year 2010	-0.0213	-0.0214	0.0162	-0.0317**
	(0.0170)	(0.0176)	(0.0133)	(0.0142)
Year 2012	-0.0664***	-0.0636***	-0.0397***	-0.0878***
	(0.0166)	(0.0172)	(0.0125)	(0.0148)
<u>Sector</u>				
Manufacturing sector	0.0137	0.0152	0.0507***	0.0817***
	(0.0117)	(0.0121)	(0.0073)	(0.0143)
Service sector	0.0822***	0.0835***	0.0943***	0.0763***
	(0.0146)	(0.0149)	(0.0104)	(0.0162)
<u>Random effects (variance)</u>				
Ratio_OutInDegree			0.0324***	0.0058**
			(34.017)	(18.436)
Ratio_OutInStrength			1.3309***	0.1065***
			(95.249)	(19.825)
Clustering Coefficient			0.0004*	0.0004**
			(12.243)	(16.385)
Upward closeness			0.0204***	0.0161***
			(241.101)	(158.868)
Downward closeness			0.0069***	0.0093***
			(88.535)	(128.270)
Betweenness			0.0198***	0.0230***
			(244.695)	(323.079)
<u>Model fitting information</u>				
intra-class correlation (ICC)	0.000	0.000	0.974	0.963
AIC	-685.218	-650.361	-1287.174	-1455.303
BIC	-614.617	-556.226	-1075.37	-1161.13
Observed sample size	2,653	2,653	2,653	2,653

Note: ***, **, and * indicate that the data are significant at the of 1%, 5%, and 10% levels respectively, and the standard errors of the estimated coefficients are in parentheses.
For random effect (variance), the values in brackets are the likelihood ratio test statistics results.
Upward closeness, downward closeness, betweenness, compensation of employees, net taxes on production, depreciation of fixed capital, operating surplus and GDP are logarithmically transformed.

Table 5.3 The relationship between the network structure variables of China's carbon emissions transfer network and the carbon emissions (2007, 2010,2012)

	Dependent variable: total carbon emissions (logarithmic)		
	2007	**2010**	**2012**
Fixed effect			
Individual characteristics			
Ratio_OutInDegree	0.0367***	0.0867*	0.0542
	(0.0091)	(0.0480)	(0.0392)
Ratio_OutinStrength	0.1549**	3.1801***	1.8883***
	(0.0480)	(0.6234)	(0.4008)
Clustering Coefficient	-0.0561***	-0.0566***	-0.0652***
	(0.0087)	(0.0060)	(0.0069)
Upward closeness	0.2639***	0.3753***	0.2779***
	(0.0445)	(0.0173)	(0.0203)
Downward closeness	0.9945***	1.0437***	1.0242***
	(0.0208)	(0.0097)	(0.0221)
Betweenness	-0.2597***	-0.2358***	-0.3212***
	(0.0432)	(0.0254)	(0.0358)
Industry group-level characteristics			
Size	-0.0293**	-0.0236*	-0.0247***
	(0.0142)	(0.0122)	(0.0055)
Density	-0.0344**	-0.0152	-0.0306***
	(0.0146)	(0.0126)	(0.0028)
Average path length	0.0007	0.0170*	-0.0043
	(0.0059)	(0.0102)	(0.0089)
Assortativity	-0.0307**	-0.0153	-0.0021
	(0.0112)	(0.0116)	(0.0111)
Sector economic characteristics			
Compensation of employees	0.1583***	0.0705***	0.0930***
	(0.0241)	(0.0152)	(0.0160)
Net taxes on production	0.0131*	-0.0080	0.0026
	(0.0070)	(0.0065)	(0.0058)
Depreciation of fixed capital	-0.0609***	-0.0570***	-0.0681***
	(0.0163)	(0.0116)	(0.0133)
Operating surplus	0.0171**	-0.0033	0.0112**
	(0.0081)	(0.0053)	(0.0046)

	Dependent variable: total carbon emissions (logarithmic)		
	2007	2010	2012
Intermediate input/ final output ratio	0.0203**	-0.0132**	0.0141**
	(0.0083)	(0.0059)	(0.0063)
Coal/total fossil fuel ratio	0.0022	-0.0049	-0.0013
	(0.0060)	(0.0038)	(0.0042)
GDP	0.0153	-0.0014	0.0847***
	(0.0265)	(0.0198)	(0.0209)
Sector			
Manufacturing sector	0.0506***	0.1756***	0.1071***
	(0.0076)	(0.0390)	(0.0213)
Service sector	0.0223	0.1278***	0.0638***
	(0.0163)	(0.0378)	(0.0234)
Random effects (variance)			
Ratio_OutInDegree	0.0071	0.0080	0.0087
	(0.253)	(7.276)	(2.172)
Ratio_OutInStrength	0.0297***	0.4245***	1.7115***
	(27.579)	(31.020)	(55.078)
Clustering Coefficient	0.0003	0.0001	0.0002
	(3.034)	(3.866)	(4.025)
Upward closeness	0.0281***	0.0051***	0.0042***
	(90.629)	(34.625)	(17.538)
Downward closeness	0.0041***	0.0064***	0.0069***
	(21.805)	(7.043)	(70.852)
Betweenness	0.0243***	0.0099***	0.0179***
	(113.780)	(102.462)	(138.904)
Model fitting information			
intra-class correlation (ICC)	0.704	0.884	0.908
AIC	-374.12	-1217.38	-1006.97
BIC	-178.01	-987.73	-810.71
Observed sample size	883	884	886

Note: ***, **, and * indicate that the data are significant at the of 1%, 5%, and 10% levels respectively, and the standard errors of the estimated coefficients are in parentheses.

For random effect (variance), the values in brackets are the likelihood ratio test statistics results.

Upward closeness, downward closeness, betweenness, compensation of employees, net taxes on production, depreciation of fixed capital, operating surplus, and GDP are logarithmically transformed.

5.2.2 Research Findings and conclusions

Ten research clusters and five representative families of empirical modelling methods were identified in the literature from 1997 to 2017 in the active research field of sectoral carbon emissions mitigation in China. This review found an increasing trend to use hybrid methods for complementary purposes to better address the chosen research question. On the basis of the 807 journal papers indexed in the Web of Science database, Chapter 2 identified, summarised and critiqued the five common families of empirical modelling methods in the research field through a manual review and a bibliometric analysis. These five representative families of methods are: 1) environmentally extended input-output analysis (EE-IOA), 2) index decomposition analysis (IDA), 3) econometrics, 4) carbon emission control efficiency evaluation and 5) simulation. In addition, driven by the large amount of co-citation data and knowledge mapping techniques, Chapter 2 categorised this research into ten research clusters and discussed the application and developing trends of the modelling methods in each research cluster. In addition, the important policy-relevant areas that have significant knowledge gaps are also identified in the research.

The research results in Chapter 2 have the potential to help scholars quickly identify and compare different methods for addressing research questions related to tackling emissions mitigations. Although sectoral emission mitigation research has been conducted from distinct perspectives ranging from the residential sector to international trade, there are three topics common to all of the research clusters: the emissions inventory, impact analysis, and predictions for carbon emission trends. The research methods were adopted (sometimes in hybrid form) for researching these topics with different advantages and disadvantages. A direct comparison of all methods also provides a quick method selection tool for scholars.To address my thesis research aim, I chose to focus on the ‘sector carbon emissions’ research cluster and the ‘carbon emission at regional level’ cluster, centering on the emissions inventory and impact analysis topics. A hybrid method of input-output analysis and network analysis, as well as an econometrics method, were selected to address the research questions.

Input-output analysis and network analysis was adopted to address Research Question 1, ‘How can the embodied carbon emissions transmission between sectors of regions in China be systematically examined?’ The classic environmentally extended input-output model was selected as the first step to track the carbon emission flows among sectors of different regions, which are embodied in the trade of the products and services of each sector. Based on the Chinese multi-region input-output table data and sectoral carbon emissions data, the embodied carbon emissions flows between 30 sectors of 30 province in China are outlined.

Network analysis is then introduced to analyse the carbon flow transfer relationships systematically. The emissions transfer relationships can be regarded as a network where nodes represent economic sectors, and edges between nodes represent the flows of embodied carbon between them. On the basis of the network, in-degree centrality, out-degree centrality, in-strength centrality, out-strength centrality and betweenness centrality are used to analyse carbon emissions flows at the micro sector of province node level. In addition, a multi-level modularity optimisation algorithm was used to identify emission communities, and indicators were developed to analyse the emissions transfer at the meso (local) level. Moreover, visualisation techniques were also used to demonstrate the network structure to aid with the visual communication of the results.The empirical analysis of the 2012 embodied carbon emission transfer network in chapter 2 aims to address Research Question 2: ‘Are there any patterns of transmission that can be found through this examination, and are there any leverage points for effective carbon emissions abatement?' The research results suggest that the carbon emission flows are not evenly distributed in the sector-province network. There are carbon hotspots and communities in the network which can be used as leverage points for effective emissions abatement. Centrality metrics can be used to identify hotspots for sectoral emissions abatement. In particular, betweenness, out-degree and in-degree centrality metrics can identify new opportunities for leveraging emissions mitigation effort. Take the EWPS (electricity and hot water production and supply) sector of Beijing, which has high betweenness, as an example. The importance of this sector is missed when using either a production or consumption perspective alone, but this sector-province can act as an important gatekeeper for reducing carbon-intensive inputs in order to achieve overall carbon emissions reduction through the whole supply chain. In addition, the sectors which produce or induce large amounts of carbon emissions are not always in a good position to spread or receive emissions from other sectors. Instead, the sectors with high out-degrees or high in-degrees act as a bridge and therefore can serve as new focal point for carbon emission reduction.

The EWPS sector, the construction sector, and the metallurgy sector have the largest out-flows, in-flows and betweenness flows respectively at the provincial, community and national levels. They are important both in the size of the transferred emissions flows and the number of connections they have with other sectors. In addition, the EWPS and metallurgy sectors should be given more attention because they have large out-flows and betweenness flows at the same time at the local and national levels. However, the majority of sub-sectors have different levels of degree centrality, strength centrality, and betweenness in different communities. Therefore, localised policies should be formed for the same sector in different communities.

The carbon communities identified in this research can provide new information to provincial governments' and through the identification of carbon communities in their regions, provincial governments can uncover areas of potential collaboration with external organisations. The multi-level modularity optimisation algorithm can be used to group the sectors of emissions networks into communities with distinct boundaries. The carbon flow links between sectors and within communities were found to be more intensive than their links with the sectors outside a community, in terms of both the number and the weights of the edges. For these communities, there is merit to focus effort on reducing internal flows within the community. In total there were nineteen communities in the 2012 embodied emissions network. These communities are different from administrative divisions, and they have significant self-organisation characteristics. The community structure is determined by the number and strength of carbon exchange flows within the sectors. A community can be formed within one individual province, or across provinces, which can be geographically adjacent or not adjacent to each other. For example, the 30 sectors of Hubei province formed a community, the sectors of the two provinces of Inner Mongolia and Tianjin formed a community, and the 30 sectors of Beijing are divided into six different communities.

Chapter 4 addresses Research Question 3: 'How can the metrics used to examine the transmission process influence sectors' direct emissions?' The research results confirm that sectors' emissions are affected, not only by the structure of the sector at the node level, but also by the structure of the community that the sector belongs to. In addition, the effect of the sector-level structure is influenced by the community structure, and they interact with each other and affect the sectors' carbon emissions together. Therefore, to reduce the carbon emissions from this sector, both the sector and its community should be considered together to achieve a more significant impact.

5.2.3 Policy suggestion

Carbon emission mitigation policies should give close attention to the sectors with high out-degrees, in-degrees or betweennesses for leverage effects. All three of these metrics are important for tracing embodied carbon emissions. While the sectors with high out-degrees are critical to implementing carbon tracking practice, the sectors with high in-degrees are critical for supervising other downstream sectors. Carbon tracking can help clarify a sector's responsibilities and help governance bodies and companies to make informed decisions to reduce carbon emissions. In addition, sectors with high betweenness are advised to set the requirement that their upstream suppliers must provide carbon tracking information and give preferences to low-carbon products, which can push upstream sectors to reduce carbon emissions. The sectors themselves are key acting points to implement carbon tracking practices to make sure that carbon emissions are traceable for a large number of downstream suppliers. In this way, downstream players will be in a better position to collectively work towards carbon emission mitigation by making informed low-carbon purchase decisions.

Each community exhibits different characteristics and they require a different focus for emissions mitigation efforts. For communities that are completely within one province and have a high percentage of in-community flows compared to total-flows, such as Hubei province, efforts at carbon emission mitigation would benefit from a more internal focus. For communities consisting of more than one province that have a high percentage of in-community flows compared to total-flows, close collaboration between the provinces in the same community should be prioritised. For communities with comparatively low percentages of in-community flows compared to total-flows, such as Shanxi community, efforts should be made to reduce external flows. While collaboration within the community should be encouraged, because at least half of the carbons emissions are kept within the community, the outside links the community has should also be given close attention.

'One community – one policy' is proposed for effective emissions mitigation. This is an approach which considers the network structure characteristics of both individual sectors and their associated communities. A hierarchical linear model was adopted to analyse the ways in which the network structure affects carbon emissions. The sector-level network structure acts on sectors' emissions differently in each community. Interestingly the out-in degree ratio, out-in strength ratio and closeness all have positive correlations with sectoral carbon emissions, but the clustering coefficient and betweenness are negatively correlated with sectoral carbon emissions. In addition, probably due to the self-purification effect brought about by industrial agglomeration (Chen et al., 2018; Wang and Wang, 2019), the size of the community, and the density of the community are also negatively correlated with sectoral carbon emissions. To mitigate carbon emissions, sectors should be encouraged to prioritise low-carbon inputs to promote the use of low-carbon sources along the entire supply chain. For communities, industrial agglomeration should be promoted to increase links between various sectors and to strengthen sectors' bridging roles. The size and density of communities should also be explored to create an inhibitory effect.

In addition, for industries with high direct carbon emissions, the growth of emissions can be slowed down through scale efficiencies and technology upgrades. For sectors at the consumer end, it is necessary to expand the sources of intermediate products, reduce the out-in degree and out-in strength ratios, and prioritise low-carbon inputs to promote low-carbon development along the entire supply chains.

5.3 Contributions to the body of knowledge

This research constructed a theoretical network model to track the embodied carbon emissions of sectors and provinces across China. It used network metrics to systematically examine transfer patterns. On the basis of empirical research, this study has identified hotspots and communities in the carbon network and it provides policy suggestions for effective carbon emissions mitigation. In addition, the effect of network metrics on sectoral carbon emissions is also quantitatively examined. As a result, this research makes three main contributions to the existing literature in terms of research perspective, theory development, and introducing new methods.

Unlike the traditional research approach which operates on the production responsibility principle and the consumption responsibility principle, this research focuses on the intermediate processes of embodied sectoral carbon emission transfer. It gives a better chance of a more robust solution. Current research mainly on the two ends of the entire industrial chain. They target the sectors that directly generate carbon emissions and the sectors whose final demand indirectly causes carbon emissions. This means that the roles played by the large number of sectors between these two ends are overlooked. Research on the transmission process can provide a theoretical basis and data support for identifying the key industries and industry clusters to target for effective emissions mitigation, harnessing the collective efforts of the entire industry chain, and achieving coordinated low-carbon economy development.

Input-output analysis and network analysis are combined to further understand the sectoral dependency relationships in an economy. On the basis of equilibrium analysis in neoclassical economics, Wassily Leontief, Nobel Laureate in Economics, put forward the theory of input-output analysis to explain the interdependence of industries in an economic system (Miller and Blair, 2009). The core of the input-output analysis approach is to construct input-output models. In these models, the relationships between sectors in an economy are represented by technical coefficient matrix $\boldsymbol{A}$, reflecting the direct input requirements of sectors' outputs from other sectors. Consequently, the Leontief inverse matrix $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$ reflects the direct and indirect input requirements of sector's outputs from other sectors. Input-output analysis theory and methods have been commonly used in the study of China's sectoral carbon emissions to track embodied carbon emissions and examine the effect of sectors' final demand on carbon emissions from a consumption perspective.

However, a more systematic perspective is required to make use of the rich information in technical coefficient matrix $\boldsymbol{A}$ and Leontief inverse matrix $\boldsymbol{L}$. Specific to sectoral carbon emissions research in China, it is very challenging to understand, by just looking at the matrix, how sectors interact with each other to transfer embodied carbon emissions, and how the structure at the sector level determines the carbon emissions of the entire economy. In addition, the cluster features of sectors in transferring carbon emissions are also missed in traditional input-output analysis. Moreover, the traditional analysis cannot be used to study the structure of the economy as a complete and integrated system. It does not provide indexes or metrics to summarise features of one economic system from a holistic perspective.

On the basis of input-output analysis, network analysis can be introduced to provide a framework and a suite of new metrics to study the structural features of an economic system. The interdependent relationships between sectors can be modelled as a complex network. This research carried out an in-depth study of sectoral dependency relationships through the lens of network structure analysis from macro, meso and micro perspectives. Specific to our research, degree-centrality, strength-centrality and betweenness-centrality are used to analyse a sector's interdependent relationships through the number of its transfer partners, the quantity of transferred emissions, and their mediating role in emissions from a system perspective. Network analysis algorithms were used to identify carbon communities in the network and analyse emission transfer features at the local level, where intensive embodied emissions exchanges take place between the sectors of a community. The research results can be used to provide policy suggestions for how to maximise the effectiveness of efforts to mitigate sectoral carbon emissions.

Lastly, fresh attempts are made in the construction of the emissions network and in quantifying the effects of network structure variables. A two-step reduction algorithm is applied to effectively transform the raw emissions network into a form suitable for use in network analysis metrics and algorithms. Community detection algorithm from network analysis, rather than cluster detection algorithm from input-output analysis, is applied to identify the group of sectors which have intensive embodied carbon emissions exchange. Compared with cluster detection algorithm, such as the algorithm proposed by Kanemoto et al. (2018), our proposed method is more data-driven and more suitable in the context of the carbon emissions mitigation in China. Our method does not pre-define supply chains and the community size, and therefore the community detection result is more objective and data driven. In addition, the community is detected on the basis of the whole network and almost all the sectors of provinces are grouped into communities, instead of only focusing on the key small clusters of seven sectors. The result can provide more insight for a synergistic effect among all sectors of provinces in China.

The community network structure variables are freshly introduced into the influencing factor analysis of sectoral carbon emissions. In previous research, when analysing the factors affecting sectoral carbon emissions, the emissions network structure variables have rarely been considered. Even in the small number of studies which touch on network structure, only the structure variables at the sector level are considered, such as in-degree and out-degree, and their effects are assumed to be consistent and fixed. Through introducing a hierarchical linear model, this research not only measures the effect of network structure variables at both the sector and community levels, but also verifies that the effects of structure variables at the sector level are different in different communities. The research results strengthen understanding of the network structure's effect on sectoral carbon emissions.

5.4 Limitations and suggestions for future research

In the past 20 years, sectoral carbon emissions research in China has made significant advances in both theoretical developments and empirical studies. However, there are still substantial gaps which need to be filled. Our research was limited by data availability, especially due to the slow updating of MRIO tables. Therefore, the analysis could not be based on the latest sectoral emissions transmission data or long time series data in China. Nevertheless, the framework, models, metrics and algorithms are ready to be used in a more effective manner once the data is made available. In the future, it will be possible to use this research as a basis to construct dynamic network models based on real-time emissions data.

The quality of emissions data for China for conducting emissions mitigation research needs to be considerably improved. GPS, GIS and remote-sensing data technology, as well as onsite surveys, could be employed to collect real-time, accurate and high-resolution data. In addition, differentiation should be encouraged in data management platforms targeting different regions and sectors, to better meet the needs of real-time monitoring, management and decisions. In addition, ETS data could be integrated into data management platforms.

To complement the new data, new approaches need to be developed for modifying models to better address research needs. One urgent need is to construct MRIO tables at higher resolution and with higher update frequencies. Due to improvements in computation ability and the progress of new methods such as machine learning and deep learning methods, various models have been continuously improved and optimised. Recent developments aim to improve carbon emissions efficiency measurement and low-carbon policy design through analysing large-scale complex relationships between the different factors driving carbon emissions.

The focus of sectoral carbon emissions research in China has gradually shifted from technology development to innovation in social governance systems. For example, new research trends are increasingly incorporating the establishment of environmental policies, analysing adjustments to industrial structures and constructing efficient low-carbon energy systems. The research variables have been expanded to include population, scientific and technological progress, national environmental awareness, urban-rural integration, and income distribution. In addition, while carbon emissions research used to be approached from national and provincial perspectives, it has now expanded into regional economic zones which cross several administrative divisions. From a regional perspective, the focus of carbon emissions research is on carbon emissions transfers caused by urbanisation, trade and internal immigration, and on the influence of these emissions transfers on efforts to optimise industrial structures and fulfil their carbon abatement responsibilities.

Due to the increasing integration of China's economy to the rest of the world, the sectoral carbon emissions mitigation in China can be also discussed from a global perspective. Because of the scope, time and resource limitations, we chose to focus on the internal efforts of China for the current research. More future efforts can be made from a global perspective to leverage the global efforts to tackle global climate change together.

The sectoral linkage and supply chain in the embodied carbon emissions network can be approached more closely for future work. There is already a great deal of research in China using sectoral linkage analysis to analyse the carbon emissions transmission in China (Liu et al., 2015; Meng et al., 2011; Zhang et al., 2015). In the current research, we fill a new gap in introducing network analysis. Instead of focusing on the sectoral linkage, the analysis is approached from macro, meso and micro perspectives. More specifically, for each sector of province, instead of focusing on the sector linkage along each supply chain, the research is more interested in examining its transmission role in the whole network through degree, strength and transmission perspectives. Due to scope constraints, this research does not undertake sectoral based linkages using supply chain analysis. However, more work can be accomplished in this aspect.

Cost information can be added to the embodied carbon emission system to further inform decisions on priority sectors for emissions mitigation. The research results of this thesis are helpful in identifying the sectors where mitigation has the largest leveraging potential. However, a good leveraging point with great mitigation potential could also be a sector or region that has large mitigation cost. For more informed policy making, emissions mitigation potentials and costs should both be examined. Carbon tax and emission trading system are the two established carbon pricing insturments for carbon emissions mitigation. More future research will be carried out to include the cost-effective perspective in prioritising sectors for emissions mitigation.

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