# TECHNOLOGICAL INNOVATION AND PROVINCIAL CARBON ABATEMENT IN CHINA

YANRAN LIU

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School of Economics and Management

# Technological Innovation and Provincial Carbon Abatement in China

Yanran LIU

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Yanran LIU (Name of student)

# Abstract

Human production and living activities have an increasing demand for natural resources, causing a large amount of carbon dioxide-based ($CO_2$) greenhouse gas emissions and ultimately harming the earth's ecological environment. The increased atmospheric $CO_2$ concentration has led to a severe greenhouse effect, which has caused tremendous damage to global agriculture and animal husbandry, ecosystems, water resources, coastal zones, and social economy. In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) was established; in 1997, the Kyoto Protocol was signed; in 2016, the Paris Agreement entered into force, which has laid the political foundation and legal framework for countries around the world to work together and address climate change. The international community reached a consensus on carbon peaking and carbon neutrality. Many countries have emphasized the role of technological innovation in their core strategies to deal with climate change.

However, previous literature has found that technological innovation can increase and inhibit carbon emissions. The research on the relationship between technological innovation and carbon emission reduction is not systematic, and the view that technological innovation promotes is the core of carbon emission reduction lacks empirical research and testing. Limited research has explored the optimization and simulation of the carbon emission reduction path. At present, China is the largest carbon emitter. It is necessary to examine the spatial characteristics of carbon emissions in China's provinces in-depth and systematically and study technological innovation's effect and paths on carbon abatement to help achieve the "dual carbon" goal.

Based on spatial autocorrelation, system dynamics, game theory, innovation theory, sustainable development, and circular economy theory, this research used literature induction, statistical analysis, computer simulation, and scenario analysis to study the effect and path of technological innovation in promoting provincial carbon abatement in China.

The IPCC method was used to calculate the provincial carbon emissions, and the Moran's I, and the Moran scatts plots were used to explore the spatial characteristics and spatial agglomeration of the provincial carbon emissions. The spatial $\beta$ convergence model and spatial Durbin model (SDM) were established to investigate provincial carbon emission's conditional and absolute convergence trends.

The Moran's I and Moran scatter plots were used to identify the spatial autocorrelation of technological innovation. SDM and quantile regression were used to

explore the spatial effect of technological innovation on provincial carbon emissions. The moderation effect of environmental regulation was tested at the national and province levels. Hansen's threshold model was used to identify the threshold value and threshold effect of environmental regulation on the relationship between technological innovation and provincial carbon emissions.

A multiple mediation model was established using industrial structure upgrade and energy structure adjustment as the mediation variables to identify mechanisms through which technological innovation influences carbon emission reduction. The moderating effect of the environmental regulation on the mediating variable was tested using Bootstrap methods.

A system dynamics model was established to simulate the technological innovation-driven carbon abatement system. The Vensim PLS software was used to test the correctness and effectiveness of the basic system dynamics model. To acquire the quantitative feedback loop of the system dynamics model, the evolutional game model was integrated into the system. The optimal scenarios and carbon abatement strategy were identified for both inland and coastal regions based on sensitivity analysis of technology investment structure and intensity of environmental regulation. The system was simulated under different scenarios and the results of the static and dynamic simulations were compared to identify the optimal parameter configurations under different scenarios.

The major conclusion of this dissertation includes the following.

(1) This dissertation constructed a system dynamics model, obtained the optimal configuration of variables in the system through dynamic simulation, and established optimal paths for carbon emission reduction under different scenarios. This dissertation provides a new perspective and points out the strategic direction for the coordinated and unified development of society, economy, and ecological environment. The results can effectively help with the urgent challenges brought by global climate change.

(2) China's provincial carbon emissions show a significant spatial agglomeration effect and conditional and absolute $\beta$-convergence. From 2008 to 2019, provincial carbon emissions in China continued to increase. The increasing trend of carbon emissions in coastal provinces slowed down, and the carbon emissions in inland provinces showed a nonlinear trend. Regional carbon emissions showed spatial dependence. The spatial absolute $\beta$ convergence coefficient is $-0.161$ on the national level, and that in inland and coastal provinces are $-0.141$ and $-0.235$, respectively, indicating absolute spatial $\beta$ convergence, and the degree of convergence in coastal regions is more significant than that in the inland areas. The spatial conditional $\beta$ convergence coefficient is $-0.353$ on the national level, and that in inland and coastal provinces are $-0.372$ and $-0.473$, respectively, indicating conditional spatial $\beta$

convergence, and the degree of convergence in coastal regions is more significant than that in the inland areas. Technological innovation is one of the main factors that affect the amount of provincial carbon emission and increases the convergence speed.

(3) Technological innovation has a significant promoting effect on carbon emission reduction and shows spatial-temporal heterogeneity. For every 1% increase in technological innovation, provincial carbon emissions decrease by 0.086%. The promoting effect of technological innovation on carbon emission reduction in inland regions is greater than that of coastal areas (the coefficients are −0.145 and −0.114), and the inhibiting effect further strengthened after 2013 (coefficient is − 0.197 in 2013 and after, − 0.060 before 2013). Environmental regulation boosts the promoting impact of technological innovation on carbon emission reduction in the inland regions. When environmental regulation is above the threshold value of 11.964, the coefficient of technological innovation on provincial carbon emissions changes from −0.102 to −0.099, showing a decrease in the inhibiting effect.

(4) Industrial structure change and energy structure adjustment moderate the relationship between technological innovation and provincial carbon emissions. Three mediating paths are identified: path 1 is technological innovation → industrial structure upgrades → carbon emissions (effect value − 0.072), path 2 is technological innovation → energy structure adjustment → carbon emissions (effect value −0.059), and path 3 is technological innovation → industrial structure upgrades → energy structure adjustment→ carbon emission (effect value 0.024). Environmental regulation has a moderating effect on the mediating effects. In path 1, only when the environmental regulation is greater than −0.725, the negative impact of technological innovation on carbon emissions is significant. In Path 3, when the environmental regulation is within (− 1.33, − 0.12), technological innovation promotes provincial carbon emissions, and when environmental regulation is greater than 0.55, the promoting effect of technological innovation on provincial carbon emissions reduction is more substantial.

(5) The optimal path for inland provinces should address short-term dynamic adjustments, and the technological investment in clean energy is the key to carbon emission reduction; the optimal path for coastal provinces should address long-term static stability, and the technological investment in the upgrade of industrial structure is the key to carbon emission reduction. Based on the system dynamics model, this research used sensitivity analysis of the technology investment structure (i.e., the proportion of technology innovation investment in energy structure optimization, industrial structure upgrade, and green technology innovation) and intensity of environmental regulation to adjust the dynamic and static optimization path

of carbon control through technological innovation. The optimal path for inland provinces in the simulation model: the ratio of technology investment in clean energy structure optimization, industrial structure upgrade, and green technology innovation is 0.57:0.2:0.23, with the highest environmental regulation intensity, which has an estimated carbon peaking time of 2024 with the peak value 91.56 million tons. The optimization path in the inland regions is sensitive to the structure of science and technology investment, and the proportion of technology investment in clean energy structure optimization is the key to carbon emissions control. The optimal path for coastal provinces in the simulation model: the ratio of technology investment in clean energy structure optimization, industrial structure upgrade, and green technology innovation should stabilize at 0.02:0.18:0.8 in the long run, which has an estimated carbon peaking time of 2023 with a peak value of 152.96 million tons. The simulation of dynamic and static paths in the coastal regions shows similar results, emphasizing long-term technology investments in industrial structure upgrades and green technology innovation.

Keywords: technological innovation; carbon abatement; spatial econometrics; system dynamics simulation; empirical analysis

# Publications Arising from the Thesis

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# CHAPTER 1 INTRODUCTION

## 1.1 Research background and context

### 1.1.1 Global climate change and the urgent challenge facing humankind

Scientific research and observational data show that the global climate is changing with warming as the main feature since the Industrial Revolution. Human production and living activities have an increasing demand for natural resources, causing a large amount of carbon dioxide-based ($CO_2$) greenhouse gas emissions and ultimately harming the earth's ecological environment (Dar & Asif, 2018; Umar et al., 2020). Since the 1970s, the increase in atmospheric $CO_2$ concentration has led to a severe greenhouse effect, which has caused tremendous damage to global agriculture and animal husbandry, ecosystems, water resources, coastal zones, and social economy. Steel, cement, plastic, paper, and aluminum products dominate industrial $CO_2$ emissions, which also dominate energy used in material production; the demand for these products is likely to double by 2050, and by that time, the goal of global $CO_2$ emissions must be reduced by at least 50% (Sinha & Chaturvedi, 2019). At present, the impact of greenhouse gas emissions has exceeded the ecological environment field and spread out to politics, economy, society, natural resources, and other areas. According to the latest research report released by the World Meteorological Organization (WMO), in the past 50 years, more than 11,000 disasters have been caused by weather, climate, and water, causing 2 million deaths and 3.6 trillion US dollars in economic losses. Nearly 22 million people have become "climate refugees" (2021). Carbon emissions are becoming a major practical issue affecting human survival and development (Chu et al., 2021; Zhao et al., 2020). Social and economic development has simultaneously put much pressure on the natural environment. Copious amounts of carbon emissions expelled from industrial activities have caused significant global climate change and environmental challenges. The carbon neutrality targets have attracted worldwide attention from governments and academia (Ji et al., 2021; Tao et al., 2021).

### 1.1.2 The international consensus on carbon emission reduction and carbon neutrality

Since the last century, the international community in the United Nations has established the intergovernmental panel on climate change and has taken initiatives in international institutional arrangements on climate change. In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) was established; in 1997, the Kyoto Protocol was signed; in 2016, the Paris Agreement entered into force, which has laid the political foundation and legal framework for countries around the world to work together to address climate change.

It should be noted that with the economy's future growth, global $CO_2$ emissions will continue to grow for a certain period, coupled with population growth, resource demand, technological progress, and economic development. Therefore, addressing global climate change has become one of the most internationally concerned and far-reaching issues in the international political economy and the sustainable development of the energy industry, economy, international trading, finance, science, technology, etc. In order to effectively cope with the change in climate conditions, countries around the world have reached a consensus and gradually put forward strategies to pursue low-carbon economic development.

A rising number of countries are taking on carbon neutrality initiatives and other actions that deal with carbon emissions and climate change. The United States (U.S) has put forward several carbon emission reduction policies, including the Cap-and-Trade energy program (applied economy-wide), the U.S. Midcentury Decarbonization Strategy Projects (focusing on transportation, passengers, and trucks), and the Clean Energy Standard (targeting clean electricity) (Thompson et al., 2014). The Climate Change Act and the Government's Clean Growth Strategy of the United Kingdom (U.K.) target reducing emissions and promoting affordable clean energy. Countries such as Hungary, Sweden, New Zealand, and Denmark have targeted carbon neutrality in their laws. In contrast, countries such as Japan, China, South Africa, Ireland, Finland, and Austria have addressed carbon neutrality in their policies (Zhao et al., 2022).

The UNFCCC has proposed corresponding carbon peak and carbon neutrality targets. By December 2020, a total of 53 countries around the globe took the lead in achieving the carbon peak target, among which mainly are developed countries such as Germany, the U.K., and the U.S. China has established the goal of carbon peaking before 2030 and carbon-neutral before 2060 at the Central Economic Work Conference on December 16, 2020. By October 2021, 136 countries worldwide have set their carbon neutrality targets through legislation or declarations, covering 85% of the global population, 90% of GDP, and 88% of total carbon emissions.

### 1.1.3 China and the "Dual Carbon" goal

China plays a leading role in global green development as the largest developing economy (H. Zhang et al., 2020). As shown in Figure 1, China surpassed the United States in 2005 and has become the most significant carbon discharger ever since. In addition, China is also the largest energy consumer and has the world's most enormous energy intensity (i.e., energy consumption per unit of GDP) (H. Wu et al., 2020). In efforts to solve the significant problems of resource and environmental constraints, China has announced to reach a carbon peak by 2030 and achieve carbon neutrality by 2060 (referred to as the "Dual Carbon" Goal or the "30.60" Goal). At the 2020 Central Economic Work Conference, the CPC Central Committee and The State Council listed "carbon peaking and carbon-neutral work" as national critical annual economic tasks for the first time. In the 2021 Report on the work of the Government delivered by The State Council, Premier Li Keqiang pointed out that an action plan for peaking carbon emissions by 2030 would be formulated and incorporated into the 14th Five-Year Plan for economic and social development.

By the provisions of the Paris Agreement, the "Dual Carbon" Goal is a long-term carbon development strategy for the country in the mid-21st century, which expresses that from carbon peaking to carbon neutrality is the process from relative to absolute decoupling of economic growth and $CO_2$ emissions. However, there are many challenges facing the "Dual Carbon" Goal and the Chinese government. Scholars have pointed out that up to 85% of China's energy generation and consumption still rely on fossil fuels. China's low-carbon and zero-carbon technologies and economy are insufficient to support green and sustainable development (Zhao et al., 2022). China's climate and energy policy targets and intense carbon emission reduction goals (a reduction of 60-65% carbon intensity) are under economic uncertainty (e.g., labor productivity growth) and technological uncertainty (e.g., technology learning and costs) (Duan et al., 2018). In fact, the Chinese government has been addressing the critical role of technology investment and technology innovation in sustainable development and industrial structure change towards high-quality economic development. However, the relationship between technology innovation and carbon emission reduction is under-investigated. Furthermore, few studies have distinguished the impact of different types of technology innovation (e.g., general technology innovation, green and eco-innovation, carbon capture and utilization technology innovation, and digital innovation) on carbon emission reduction.

We can also see in Figure 1.1 that the annual national carbon emissions of developed countries such as the U.S., Japan, and Germany show a decreasing trend. In contrast, developing countries like China and India show an increasing trend. In fact, China is facing a much stricter carbon neutral goal and a much shorter time to deliver its commitments than any other country. In addition to the innovation and application of low-carbon technologies, many developed countries have transferred industries with high energy consumption and high emissions to developing countries, reducing their own carbon dioxide emissions. As the "world's factory", China's manufacturing industry consumes a lot of energy and natural resources, and it is also the largest carbon emitter due to technological constraints. Improving energy and production efficiency and adjusting the industrial structure (reducing the proportion of high-emission industries) are challenges and urgent tasks facing China.

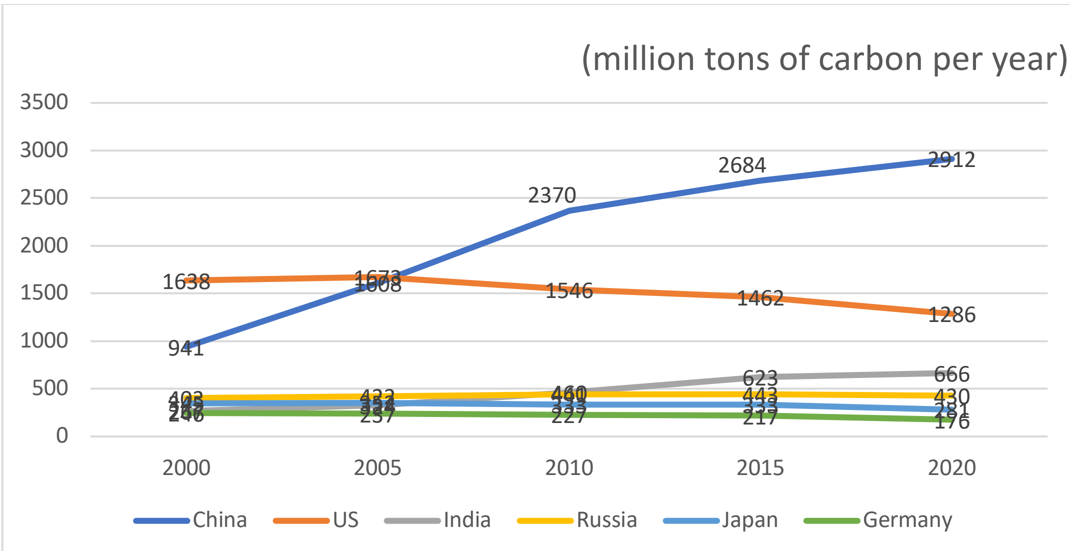



Figure 1.1 Annual national carbon emissions
Data source: the Global Carbon Budget (Friedlingstein et al., 2021)

However, the Chinese government faces many challenges in achieving absolute decoupling of economic growth from carbon dioxide emissions in such a short time. China's economic development has stimulated resource consumption and energy shortages. At the same time, China's traditional energy efficiency is low, and clean energy costs much more than traditional energy. Therefore, overcoming the energy shortage problem while ensuring steady economic growth is a common problem facing China and the world.

### 1.1.4 Technology innovation is the core of the low-carbon economy in China

Technology innovation is not only one of the critical drivers of the economic growth (Porter, 1981; Yigitcanlar et al., 2019) but also the core and key to the low-carbon economy (Dou, 2017) as well as the climate control (Afrifa et al., 2020). Many developed countries have elevated the research, development, and application of low-carbon technologies to the state level to ensure energy security, respond to climate change, and enhance national competitiveness and global influence. As the 'Factory of the World", China consumes an enormous amount of energy and natural resources; meanwhile, it is also the biggest carbon emitter due to technical limitations. It is challenging and urgent for China to increase energy and production efficiency and reduce carbon emissions through innovation in clean energy technology, renewable energy technology, emission control technology, etc. Through intensifying technology innovation, promoting the development and application of low-carbon technologies such as carbon capture and storage (CCS) technology, and adjusting and optimizing industrial structure, countries would be able to transform the steel industry, cement industry, and other high-energy-consuming and high-carbon-emission industries, and to eliminate and compress excess backward production capacity, ultimately reduce carbon emission intensity.

Investigating the role of technology innovation is the key to building a new development model for a low-carbon economy. China has a vast territory, with significant differences in regional resources, technology level, and economic status. Thus, analyzing the spatial differences in regional technology innovation and carbon emissions and the spillover effects on the low-carbon economy is essential. Energy depletion, environmental pollution, and global warming have attracted international attention. Energy-saving, emission reduction and a low-carbon economy have become the one urgent target shared by all nations. China is facing challenges in the massive use of fossil fuels and climate change, and it is also discovering opportunities in carbon emission reduction and a low-carbon economy. Compared with other means of carbon control, technology innovation is much easier to design and implement than directly regulating personal choices to reduce greenhouse gas emissions (Mikler & Harrison, 2012). Besides, technology innovation always contributes to economic growth; thus, the production and diffusion of technology innovation are much less challenging politically (Romer, 1986; Solow, 1957). Increasing investment in technology advances and increasing efficiency in innovation will help China achieve the "Dual Carbon" goal and sustainable development.

Therefore, this paper aims to clarify the spatial characteristics of regional technological innovation and carbon emissions and the spillover effects of technological innovation on carbon emissions in adjacent regions, to study different types of technological innovations (such as general technological innovation, green and ecological innovation, carbon capture, clean energy innovation, and digital technology innovation) on carbon emission reduction, to explore the mechanism and path of technological innovation in promoting carbon emission reduction. Furthermore, China's current environmental regulation is insufficient to support the sustainable use of natural resources due to low government enforcement and public participation. This paper will also explore the impact of government intervention (through environmental regulatory incentives and penalties) on the relationship between technological innovation and carbon emissions.

## 1.2 Research gap and objectives

### 1.2.1 Research gap

As global warming and GHG emissions become a legitimate development concern, more and more studies have tried to understand better the industry's technology strategies in the era of global warming. However, the previous research on GHG emissions reduction technology strategies is limited to the following aspects. First, some studies have proposed comprehensive methods and techniques to help decision-makers evaluate and select sustainable production technologies from different economic, environmental, political, and social aspects. Scholars have studied a model system that integrated technical and monetary policy to investigate, simulate, and analyze the effects of different policies on emissions to support the government decision-making (Jaccard et al., 2019; Liu et al., 2018; Taniguchi-Matsuoka et al., 2020). Scholars have explored carbon emission rights and environmental cooperation mechanisms and evaluated their effects on carbon emission reduction, including carbon pricing, carbon tax, carbon trading, and so forth (Herath & Jung, 2021; Kök et al., 2018; Lin & Jia, 2018; Tao et al., 2021). Scholars have studied the energy policy tools such as clean energy policy and their effects on greenhouse gas emissions (Duan et al., 2018; Kern et al., 2017; H. Wu et al., 2020). Scholars have explored the social-economic transformation by investigating the clean and renewable energy (Murshed et al., 2021), financial markets (Louche et al., 2019), investment (Owen et al., 2018), individual behavioral changes (Niamir et al., 2018), industrial value chains (R. P. Lee et al., 2018) that enable the transition towards a low-carbon economy.

Second, previous research focuses on how to apply new methods or technologies to industry from a scientific perspective. Scholars have investigated carbon emission reduction from the environmental technology perspective addressing mainly four types of environmental technology: carbon capture and carbon storage technology (CCS), low-carbon or zero-carbon technology, clean energy & technology, and other sustainable technologies. Scholars from the environment management field studied technologies that improve energy efficiency (Cantore et al., 2016) in agricultural cultivation (Apazhev et al., 2019), hydrocarbon fuels (Mohammed et al., 2019), residential building stock (Camarasa et al., 2019), manufacturing (Cantore et al., 2016) and so forth. Scholars from the applied energy field studied clean energy and technologies that support renewable applications and how they contribute to the environmental management (Lin & Li, 2021; Mikler & Harrison, 2012). Scholars from the bio-chemistry field studied carbon capture and storage technologies and their applications (Bui et al., 2018; Gabrielli et al., 2020).

There is no doubt that technological innovation plays a critical role in carbon-peaking and achieving carbon-neutrality (Raiser et al., 2017). However, few studies have studied the technological choices and implementation in response to global warming and GHG emissions from the perspective of technical strategies and environmental policies. The research on carbon emission reduction and technology innovation is associated with a broad and profound social-economic green transition concerning energy structure, industrial structure, transportation, agriculture, land use structure, and other economic sectors.

The literature and practice of technology innovation and carbon emissions are vast, involving many industries and fields such as economic society, industry, agriculture, urban, energy, and environment. There are specific differences in the results. Most literature has conducted in-depth research on a single sector or discipline. Few studies investigate industrial factors, energy structure, R&D input, environmental regulation, carbon emissions, and carbon emissions reduction in the same framework and explore the interrelationships among those various factors.

Research on the key influencing factors of technological innovation and carbon emissions lacks an assessment of the economic impact of carbon emissions control; research on the potential, efficiency, and strategy of innovation on carbon emissions abatement lacks empirical evidence due to the heterogeneity in regional resource endowments such as economic level, technological level, risk preference, innovation ability, and climate policies. There is currently no global legal agreement on the choice of carbon emission abatement paths; thus, carbon emission reduction depends not only on the macro-level carbon policies but also on the micro-level innovative activities of various industries and their responses to emission reduction policies. Therefore, systematic research on the internal mechanism and path optimization of technological innovation and provincial carbon emissions abatement is necessary and of theoretical and practical significance.

### 1.2.2 Research significance

This research extends technological innovation's sustainable development theory and circular economy theory. Through analyzing the spatial characteristics of provincial carbon emissions, the internal mechanism, and path optimization of technological innovation on provincial carbon emissions abatement, this research provides insight into the urgent environmental challenge and global climate change due to social and economic development. This dissertation also explores green and low-carbon technologies and the influences of technological innovation on industrial structure upgrades, energy structure, and regulation.

Chapter 3 applies Moran's I index, kernel density estimation, and spatial convergence analysis to investigate the spatial autocorrelation and heterogeneity of China's provincial carbon emissions and convergence trends.

Based on that, spatial econometric models are established to analyze technological innovation's direct effect on carbon emission abatement. A multi-mediation model is established to examine the indirect impact of technological innovation on carbon abatement. A panel threshold model is set to explore the threshold effect of environmental regulation. System dynamic models and scenario analysis are conducted to identify the optimal path of carbon abatement through technological innovation.

This dissertation also provides practical implications to policymakers. The findings suggest that national and local governments should set reasonable carbon emission governance policies according to economic development levels and local conditions. The results also provide guidance and decision support for regional carbon emission reduction target setting, low-carbon technology development, industrial and energy structure upgrading, etc.

## 1.3 Research methodology

This dissertation uses a combination of qualitative and quantitative research methods listed in the following paragraphs:

*Literature review approach*: this paper investigates classic and cutting-edge theoretical and empirical literature and obtains a comprehensive understanding of technological innovation, carbon emission reduction, and related research issues. Chapters 1 and 2 of this paper aim to understand the history and current academic research on technological innovation, energy technology, emission reduction technology, and carbon emission status and help determine the research topics. At the same time, this paper reviews the previous literature to identify the research gaps, thus, determining the research focus and direction and building a solid theoretical foundation for the following chapters.

*Empirical approach*: this paper studies the interconnectedness between factors through empirical methods. Chapter 3, Chapter 4, and Chapter 5 of this paper aim to explore the spatial characteristics of provincial carbon emissions and the internal mechanism of carbon abatement through technological innovation. Data sources include "China Statistical Yearbook," "China Foreign Economic and Trade Yearbook," "China Environmental Yearbook," "China Science and Technology Statistical Yearbook," "China High-tech Industry Statistical Yearbook," "China Science and Technology Investment Statistical Bulletin," and China Science and Technology Statistical Yearbook Statistics Network (www.sts.org.cn). Based on second-hand data, this paper empirically examines the relationship between carbon abatement, technological innovation, industrial structure upgrade, energy structure adjustment, energy consumption, environmental regulation, etc. Therefore, empirical approaches provide evidence for our theoretical models.

*Mathematical modeling* describes abstracting practical problems into mathematical models using mathematical symbols. Chapter 3, Chapter 4, Chapter 5, and Chapter 6 carry out corresponding research based on the idea of mathematical modeling.

*System dynamics approach*: System dynamics is a method to study the overall behavior of the entire system by analyzing the feedback relationship between the variables within the socio-economic system. The structure of the system determines the behavior of the system. With the help of the causal relationship between various elements and data, the calculation analysis and quantitative research are carried out. The system dynamics equations and causal relationship diagrams are combined with scenario analysis and conditional prediction. Chapter 6 mainly uses this method.

*Scenario analysis*: this paper uses the scenario analysis method to adjust the value of crucial influencing factors according to future trends and expected outcomes. Relying on computer simulation, this paper tests the likely scenarios and unlikely worst-case events on carbon abatement. Chapter 6 is based on scenario analysis and studies the carbon emissions abatement path through technological innovation.

## 1.4 Definition of key concepts

*Environmental degradation.* The unreasonable development and utilization of the ecological resources have caused changes in the structure of the environmental system, resulting in a decline in the environment's self-adjustment and functional decline. Poverty is a significant cause of environmental degradation, and the poor depend more on natural resources than the rich; developed countries relocate high-pollution industries to developing countries. The level of economic development is also one of the reasons for environmental degradation. A high level of economic activities and development of manufacturing industries lead to the consumption of resources that exceeds the regeneration of resources.

Moreover, environmental degradation and energy consumption are critical for economic development. As the economy develops towards prosperity, most energy demand is met by consuming fossil fuels. Fossil fuels are one of the main reasons for environmental pollution by discharging carbon into the environment, also known as collateral damage. Pollution is the unintentional result of activities for improving and developing the economy.

*Carbon emission.* Greenhouse gas (GHG) emissions are mainly from energy consumption, industrial production, transportation, and consumer consumption. The main components of GHG include $H_2O$, freon, carbon dioxide ($CO_2$), nitrous oxide ($N_2O$), methane (CH4), ozone ($O_3$), etc. GHG emissions are causing climate change and global warming. $CO_2$ contributes 60% to the greenhouse effect; thus, it is also the primary concern of academia and the industry. According to the daily carbon emission detection method of the global real-time carbon data (CarbonMonitor), the global carbon dioxide emissions mainly come from electricity (39%), industrial production (28%), land transportation (18%), aviation (3%), shipping (2%), and residential consumption (10%). Even if $CO_2$ emissions are controlled at the current levels, their concentration will double in the 22nd century. If no effective measures are taken to prevent $CO_2$ emissions, in the next 100 years, the global temperature is predicted to increase by 1.4 to 5.8 °C, and the sea level is expected to rise by 88 cm. Developed countries with high industrialization levels have peaked their $CO_2$ emissions, whereas developing countries with low industrialization levels and high energy consumption have been increasingly discharging carbon dioxide into the atmosphere.

*Carbon abatement.* Carbon abatement is the reduction of $CO_2$ emissions. As the global climate warms, emissions of greenhouse gases such as $CO_2$ must be reduced to alleviate the human climate crisis. There are two modes of carbon abatement: the first is mandatory emission reduction. The main obstacle is balancing the interests of all parties and high operating costs; the second is voluntary emission reduction, which depends on the utilization of the market's supply and demand relationship. In order to achieve the emission reduction target, it is necessary to develop renewable energy and clean energy and accelerate the development and application of low-carbon technologies, energy-saving, and emission-reduction technologies.

*Carbon peak and carbon neutral.* The broad understanding includes the peaking and neutralizing emissions of all greenhouse gases (such as methane, nitrous oxide, etc.). The narrow sense of carbon peaking and carbon neutrality refers to the peaking and neutralizing of $CO_2$ emissions.

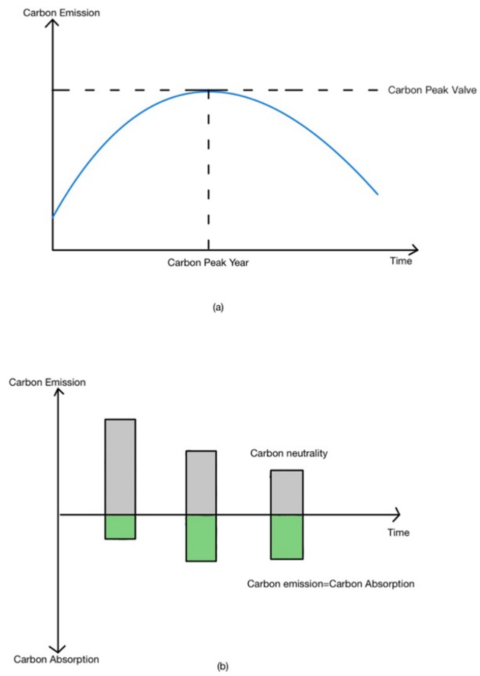



Figure 1.2 Carbon peak and carbon neutrality

*Carbon peak* refers to the process of carbon emissions from rising to falling. The highest point of carbon emissions is the carbon peak. The total carbon emissions reached the peak inflection point and gradually showed a downward trend after the peak year (Zhao et al., 2022). The essence of carbon peaking is the transformation of economic development mode; economic growth no longer depends on the input of fossil energy and other high-carbon natural resources, marking the decoupling of social-economic development and carbon emissions (Figure 2a).

*Carbon neutrality* means that the total amount of anthropogenic greenhouse gas emissions are offset by carbon sinks in the form of afforestation, energy conservation, emission reduction, carbon capture, utilization, and storage (CCUS), and the essence of carbon neutrality is to control global warming through natural system carbon sinks or engineered carbon removal technologies. Carbon neutrality indicates that the absolute value of carbon emissions caused by human economic and social activities is reduced to zero (Becker et al., 2020) (Figure 2b).

*Technology innovation.* Technology innovation or innovation is the activity and process of introducing a creative new combination of advanced technology, production elements, and production conditions into the production system to obtain potential profits through the market. Technology innovation is a series of significant breakthroughs in technology, theory, knowledge, etc., starting from novel ideas, resulting in discontinuous events of commercial availability or general practical significance (Mueser, 1985). Technology innovation is the process by which manufacturers produce new products or services and introduce them into the market to generate commercial profits through utilizing and re-searching technology progress or research findings.

Technological innovation input is the funds required to carry out scientific and technological innovation activities, including research and development (R&D) activities, application of technical achievements, and technological service activities. R&D investment is the basis and key to technological innovation activities and the development of high-tech industries.

*Environmental technology (or green technology)* refers to the technology used to prevent or reduce emissions and conserve natural resources in production and consumption. Eco-innovation is also defined as innovation that leads to eco-efficient technologies. Eco-efficient technology refers to environmental technology that directly or indirectly improves the environment, including technologies that limit pollution, environmentally-friendly products and production processes, more effective resource allocation and management, and technological systems that reduce environmental impact. Kemp and Foxon (2007) defined ecological innovation as "the production, application or exploitation of a good, service, production process, organizational structure, or management or business method that is novel to the firm or user and which results, throughout its life cycle, in a reduction of environmental risk, pollution, and the negative impacts of resources use (including energy use) compared to relevant alternatives." Eco-innovation may reduce the cost of environmental improvement and bring better environmental benefits than the traditional economic model, which neglects the environmental factors ex-ante.

*Eco-innovation.* Ecological innovation (eco-innovation) is defined as innovations that attract green rents on the market. The concept of eco-innovation reflects innovative changes in the economic system, measuring how environmental issues are integrated into the financial process. As a specific concept in the field of innovation theory, eco-innovation is relatively recent.

*Industrial structure*. The interrelationships among various production factors within the economic sectors consist of the industrial structure, also known as the industrial system, which is expressed as the proportion of the primary, secondary and tertiary industries in the national economic structure. Industrial structure upgrade means the transfer of labor-intensive industries to knowledge- and capital-intensive industries, the transfer of primary and low-value-added products to high-level, high-value-added products, and the evolution from the primary industry to the secondary and tertiary industries.

*Energy structure*. The energy consumed by national economic activities includes petroleum, coal, electricity, natural gas, solar power, other petrochemical energy, and clean energy. In a certain period of time, the quantity of each energy consumed and its proportion to the total energy consumption is the energy consumption structure. Industrialization significantly affects the intensity of energy consumption. In the early and middle stages of industrialization, energy consumption increases slowly. In the later stage of industrialization, the economic growth model has undergone major changes, and energy consumption intensity has declined. Still, the total energy consumption has significantly increased due to rapid economic growth. Energy structure adjustment indicates an increase in the proportion of clean energy consumption in total consumption, thus reducing carbon emissions.

*Environmental regulation*. Environmental regulation is one of the social regulations. Because of the negative externality of environmental pollution, the government needs to formulate appropriate measures or policies to regulate economic activities and promote the coordination between economic development and the environment. There are many types of environmental regulation. Among them, market-incentive environmental regulation refers to the integration of environmental costs into products costs, and continuously stimulates enterprises to innovate in green technologies for energy conservation and emission reduction, so as to reduce the cost of environmental pollution control. The market-incentive environmental regulation not only improves resource productivity but also reduces the real economic cost of products and increases the added value of products. Command-and-control environmental regulation refers to policies and rules that not only regulate the amount but also the process by which a firm should commit to environmental protection. The government may require polluters to adopt green innovation and energy conservation or other emission reduction measures to ensure their production and business activities meet environmental requirements. By monitoring the process and analyzing the environmental outcome, the government may punish the entities that do not comply with the regulations or reward the entities that comply with the regulations or perform well environmentally. Environmental regulation also reflects the willingness of society to reduce and control environmental pollution.

### 1.5 Research objectives

Firstly, this research aims to study carbon emissions and technological innovation, energy structure, industrial structure, population, urbanization, and other economic factors in one comprehensive system, and explore the interrelationships among variables through system dynamic modeling and simulation.

Secondly, this dissertation aims to examine the impact of technological innovation on industrial factors and energy structure and the indirect effect of industrial structure and energy structure on the technological innovation - $CO_2$ nexus.

Thirdly, this dissertation aims to examine the effectiveness of government tools (such as technology investment or environmental regulation) on carbon abatement and explore the optimal path under different scenarios.

Lastly, this dissertation aims to examine technological innovation and carbon emissions nexus considering the heterogeneity in regional resource endowments such as economic, technology, and climate policies using spatial econometrics models.

### 1.6 Research scope and research questions

#### 1.6.1 Research scope

With the rapid development of industrialization and urbanization in China, the problems of environmental degradation and $CO_2$ emissions have become increasingly prominent. Since the research on carbon emission abatement involves several disciplines, this paper will focus on technological innovation and carbon abatement from the perspective of technology management and carbon abatement strategies. The leading carbon emission control technologies and policies studied in this dissertation are from the national or provincial level. The data comes from "China Statistical Yearbook," "China's Foreign Economic and Trade Yearbook," "China Environmental Yearbook," "China Science and Technology Statistical Yearbook," "China High-tech Industry Statistical Yearbook," "China Science and Technology Investment Statistical Bulletin," China Science and Technology Statistics

Network (www.sts.org.cn), etc. Due to unavailable data, this dissertation does not include data from Tibet, Hong Kong SAR, Macau SAR, and Taiwan Province.

### 1.6.2 Research questions

RQ of Study 1: What are the spatial characteristics and convergence trends of provincial carbon emissions in China? How do provincial carbon emissions change over time? (GAP4)

RQ of Study 2: How does technological innovation influence provincial carbon emissions? Are there direct spatial spillover effects of technological innovation on provincial carbon emissions? (GAP2)

RQ of Study 3: What is the internal mechanism of technological innovation-driven carbon emission abatement? How do industrial factors (i.e., industrial structure change), energy consumption dynamics (i.e., energy structure adjustment), and climate policy (i.e., environmental regulation) affect the technological innovation and carbon emissions nexus? (GAP1&3)

RQ of Study 4: What is the optimal carbon emissions abatement path under different levels of technological innovation, industrial structure, energy structure, and environmental regulation. (GAP1, 3, &4)

## 1.7 Structure of the dissertation

This research consists of seven chapters. Chapter 1 identifies the research background, research content, research gaps, research scope, research methods, research questions, and research objectives.

Chapter 2 presents the theoretical foundations of this research, including the definition, evolution, connotation, and impact of sustainable development theory and circular economy theory; this chapter also provides a detailed review of literature on technological innovation and carbon dioxide emission abatement, information and communication technology-enabled low-carbon technologies, carbon footprint and implied carbon, key impact factors of carbon emissions, and provides an overall synthesis and critical analysis on the literature.

Chapter 3 analyses the spatial characteristics and convergence trends of China's provincial carbon emissions. Using data from 30 provinces in China from 2008 to 2019, this chapter analyzes the status quo of provincial carbon emissions. The regional characteristics and spatial dependence of provincial carbon emissions were analyzed, and the absolute convergence and conditional convergence trends of provincial carbon emissions were explored. The findings of the chapter provide the theoretical foundation and evidence for Chapters 4 and 5.

Chapter 4 presents an empirical examination of the direct effect of technology innovation on China's provincial carbon emissions. By analyzing the internal mechanism, this chapter clarifies the impact of technological innovation on provincial carbon abatement in China and the spatial spillover effect of technological innovation. In addition, this chapter also provides an endogenous test, a robustness test, and a heterogeneity test. The findings of Chapter 4 illustrate relationships between technological innovation and provincial carbon emissions and provides quantitative relationships for Chapter 6.

Chapter 5 presents an empirical examination of the indirect effect of technology innovation on China's provincial carbon emissions. This chapter further analyzes the mechanism of technological innovation-driven carbon abatement, considering the mediating role of industrial structure, energy structure, and environmental the moderating effect of environmental regulation. The findings of 5 illustrate two indirect paths in the technological innovation and carbon emissions nexus and provides quantitative relationships for Chapter 6.

Chapter 6 presents simulation research on the system of technological innovation-driven carbon abatement using a system dynamic model integrated with an evolutionary game. This Chapter also performs sensitivity analysis on R&D investment structure and intensity of environmental regulation to simulate their effect on carbon emission and carbon peak time in the system. Applying the Vensim PLS software, the system is simulated in different scenarios and the optimal parameter configurations in different scenarios are obtained.

Chapter 7 concludes and discusses the research findings, theoretical and managerial implications, limitations, and future research.

# CHAPTER 2 LITERATURE REVIEW

## 2.1 Theoretical foundation

### 2.1.1 Technology innovation theory

#### 2.1.1.1 The Schumpeterian understanding of innovation

Technology is defined by J.K. Galbraith (Jaccard et al., 2019) as 'the systematic application of scientific or other organized knowledge to practical tasks.' The concept of technological innovation originated from the innovation theory in the early 20th century. The economist Joseph A. Schumpeter (1942, 2017) describes technology change as a gradual process of invention, innovation, and diffusion; he explains the meaning of innovation in his book The Economic Development Theory as the application of new technology, the creation of new methods and the new mode of production, and proposed that innovation is the decisive factor of economic development. Innovation is the process of establishing a new production function, introducing a new combination of production factors and conditions to obtain excess profits. Schumpeter summarizes the innovation portfolio he refers to in the following five forms: 1) introduce new products or provide products; 2) adopt new production methods and new technological processes; 3) open up new markets; 4) develop and utilize new sources of supply for raw materials or semi-finished products; 5) adopt new organizational methods. Schumpeter's innovation theory provides a new explanation for the internal mechanism of economic growth and economic cycle. The Schumpeterian understanding of innovation explains the reasons for the socialist economy cycle of "prosperity-recession-depression-recovery," which addresses that the degree of innovation leads to three economic cycles of varying lengths, thus confirming the decisive role of innovation in economic growth.

The five innovation combinations described by Schumpeter can be roughly classified into three categories: Firstly, technological innovation, including new products development, the transformation of old products, adoption of new production methods, acquisition of new sources of supply, and utilization of new raw materials; secondly, market innovation, including expanding the share of the original market and developing new markets; thirdly, organizational innovation, including changing the original operating forms of organization and establishing new operating organizations. Schumpeter's leading followers decompose the theory of innovation and develop two independent branches: the theory of technological innovation, which mainly examines technological innovation and market innovation, and the theory of organizational innovation, which primarily focuses on organizational change and organization formation. Therefore, this dissertation will focus on the theory of innovation that addresses technological innovation.

Freeman and Soete (1982) provide the definition of technical innovation or innovation as 'the introduction and spread of new and improved products and processes in the economy and the definition of technological innovation as 'advances in knowledge.' Technological innovation is always associated with production efficiency, cost, profitability, and growth (Abernathy & Townsend, 1975). According to Romer's economic growth model, technological changes are one of the principal driving forces of growth (Romer, 1990), industry competition, and industrial structure change (Porter, 1981).

Early theoretical perspectives regard the innovation process as a relatively simple one-way journey from basic research to applied research, technology diffusion, and technology development. This linear model indicates that technological advances in knowledge decide the rate and direction of innovation. The best way to promote technology innovation is to increase the investment in research and development (R&D), the so-called technology push or supply push. As an opposite of the linear model, the demand-pull perspective regards market demand for products and services as the critical factor that stimulates innovative activities and inventions. The supply- or demand- pushed views are considered vital to technology innovation, but they are challenged as over-simplistic Fields (Rothwell, 1992).

The meaning of innovation is more profound than invention because the former must consider its application in practice and realization of potential economic value. Innovation transforms perceptions and technologies into new products, processes and methods, and services that can create new market values, drive economic growth, and improve living standards.

#### 2.1.1.2 The evolutionary economics approach

The evolutionary economics approach is built on the Schumpeterian understanding of innovation and introduces the ideas of 'bounded rationality and 'uncertainty' into exploring innovation. The evolutionary perspective suggests that bounded rationality (i.e., decision-makers have a limited capability to collect and process information rather than being absolutely profit-maximizing. With bounded rationality, decision-makers tend to find the best routine (i.e., technical, procedural, strategic, or organizational technique) that fits the business activities instead of finding the optimal solution. An important implication of bounded rationality is that the companies' future expectations fundamentally influence their present decisions. Factors characterized by the uncertainty of the future market, technology potential, and regulatory environment will affect the direction of innovation and search.

Innovation activities are associated with inherent uncertainty, particularly innovation decisions related to emerging technologies (i.e., technologies in their early stages of development) (Meijer et al., 2007), which is a double-edged sword for decision-makers. On the one hand, a high level of uncertainty means that the new technologies may provide various opportunities. On the other hand, the uncertainty poses the threat of not knowing what will happen and not being able to determine the success or failure of the technology path in advance. In addition, the uncertainty comes not only from the technology per se but also from the social-institutional setting embedded in the technology. In the development and implementation of technologies, the delay could result from technological, competitive, political factors, suppliers, consumers, or other resource providers (Meijer et al., 2007). Bounded rationality and uncertainty will lead to decision-making favoring incremental innovations in current products or processes.

#### 2.1.1.3 Increasing returns to adoption

There are four main types of increasing returns to the adoption of new technology (i.e., the more users adopt new technology, the more likely it is to be further adopted), including economies of scale, learning effects, adaptive expectations, and network effect (Arthur & Arthur, 1994). Economies of scale arise from reducing per-unit costs because fixed costs are distributed over increasing output, which leads to increasing demand. As experience accumulated in the technology production and application process, the learning effects reflect the improvements in products or services and decreased costs. As increasingly more adoptions of the technology, users and manufacturers are less uncertain and more confident in the performance and quality of the technology, thus generating adaptive expectations of the technology. The network effect suggests that the more users there are, the more valuable the technology is, commonly seen in digital technologies such as mobile apps or digital platforms.

#### 2.1.1.4 The learning effects

The learning effect is not only the fundamental component of technology innovation but also of production and technology diffusion. There are three fundamental types of learning: learning-by-doing (Arrow, 2015; Rosenberg, 1976), learning-by-using (Mcwilliams & Zilbermanfr, 1996; Rosenberg, 1982), and learning-by-interacting (Lundvall, 1998; von Hippel, 2007). Learning-by-doing is the accumulating knowledge through the process of producing.

Learning-by-using is the gain of learning through using the products or technology. Learning-by-interacting occurs when users and producers interact and establish trust and behavior codes. Scholars believe that these three types of learning generally happen within a current technological system, thus often leading to incremental innovation field (Christensen, 1997; Sheng & Chien, 2016), whereas the fourth type of learning, learning-by-researching, often gives rise to radical innovation because learning-by-researching focuses on improvements of technological features (Elia et al., 2021; Kahouli-Brahmi, 2007).

Research and development (R&D) activities are one of the main drivers of technological progress and are present in all phases of the development and maturity of a technology. Nevertheless, R&D is not the only source of technical change because, during the process of production and utilization, knowledge and experiences are gained through learning. A learning curve is a mathematical approach to measuring technology change, which firstly defines unit cost reduction of a product as a one-factor power function of a learning source (Arrow, 1971) that estimates learning-by-doing. In 2000, the two-factor learning curve was introduced, which integrated R&D spending and measured the stock of knowledge from learning-by-researching as the second factor in the function (Kouvaritakis et al., 2000). The one-factor learning curve tends to leave out the primary influence of technology diffusion. Still, the two-factor learning curve is appropriate to analyze the evolving and emerging process of the technologies (Jamasb, 2007).

#### 2.1.1.5 Path dependence approach

History and past decisions are essential for technology development, especially for complex technology innovation in self-organizing networks (i.e., networks without centralized leadership or governance). Organizations generate, acquire, and exchange diverse knowledge through organizational links in networks, including joint ventures, supply chain relationships, and strategic alliances. In this co-evolving technology network where technology innovation is shaped by network and network is shaped by the technology, technologies and networks interactions move along a trajectory. With positive feedback on historical status, the co-evolution of technology and network may continue and rely on past experiences even though past circumstances are no longer relevant or superior routes are available. One historical event may at least influences sequences of technological improvements in one direction (Rosenberg, 1994). The more institutional rules or structural elements are established, the more stable the development path is, and thus the more technology development relies on the track. The process of innovation reinforces the dependency on a specific route.

### 2.1.2 Sustainable development theory

Sustainable development (SD) first appeared in the report "Our Common Future" of the World Commission on Environment and Development in 1987 and has been widely recognized by the international community. SD means development that meets the current generation's needs without compromising future generations' ability to meet their needs. Sustainability in the development literature refers to improving and sustaining a healthy social, environmental, and economic system for human development (Mensah, 2019; Mensah & Enu-Kwesi, 2019). Equity, continuity, and commonality are the three basic principles of SDT. The principle of equity refers to the equality of opportunity (i.e., intra-generational and inter-generational equity); the principle of sustainability is the ability of the ecosystem to maintain its productivity under the influence of resources and the environment; the principle of commonality is to achieve global sustainability.

Sustainable development includes the coordinated and unified development of the economy, ecology, and society, and it is a comprehensive strategy to guide social and economic development. SD emphasizes the importance of protecting the environment while maintaining economic growth. On the one hand, economic development is the core of development, so it is unacceptable to hinder economic growth in the name of protecting the environment. On the other hand, improving the quality of economic development could increase economic efficiency, save resources, and reduce waste. Economic and social development must coordinate with the environmental carrying capacity. Although different countries have different development stages and goals, it is necessary to create a stable and safe social environment to improve the quality of human life, protect human health, and achieve sustainable development.

The continuously growing world population increases consumption, resources deplete, and the environment deteriorates. Technological progress can promote production and economic growth only to a limited extent. The theory of sustainable utilization of resources believes that the sustainable development of human society and economy depends on whether the natural resources can be used sustainably.

### 2.1.3 Circular economy theory

Social and economic development has simultaneously put much pressure on the natural environment. Little attention was paid to the close relationship between economics and atmosphere until the American economist Boulding proposed the circular economy (CE) in 1966. The development of the economy requires the realization of resource circulation and reduction of waste because of resource scarcity and the environment's assimilative waste capacity. By the 3R principles, which are to reduce, reuse, and recycle materials, CE describes the large-scale natural and economic system, strategic, comprehensive, and preventive measures taken in material transformation. CE addresses the importance of reducing the excessive use of natural resources and the environment by economic activities and easing the negative impact of environmental degradation on humankind. CE aims to better integrate the human economic and social cycle with the natural cycle and realize the system optimization configuration of regional material, energy, and capital flow.

#### 2.1.3.1 The connotation of circular economy

A circular economy is an economical form of sustainable development, which refers to an economic development model characterized by resource conservation and recycling, and in harmony with the environment. Referred to as a cowboy economy (Boulding, 1966), a traditional one-way economy system convert natural resources into waste via production, which removes natural capital from the environment through mining or unsustainable harvesting and reduces the value of natural capital through air or water pollution by waste (Murray et al., 2017). CE emphasizes that economic activities are a cyclical closed-loop system of "resources-products-renewable resources" requiring low mining, high utilization, and low emissions. All materials and energy can be used reasonably and last in this continuous loop-closing process, and the economic activities should have no net impact on the environment.

Due to advances in science and technology development, productivity has dramatically improved, and consumption of the environment has increased enormously. However, natural resources are not finite, and the environmental capacity is limited. With the rapid global population increase, the traditional economic development model is unsustainable. Germany and Japan are the first developed countries to promote CE and propose that new management strategies should be developed to deal with the rapid growth of solid waste. On the one hand, the sorting, recovery, and recycling of waste could reduce the amount of garbage generation and landfill occupation; on the other hand, industrial activities consume a massive amount of natural resources, and CE help in resource conservation and the 3R.

#### 2.1.3.2 The development of circular economy in practice

The development of the circular economy has been promoted by the governments and has received positive responses from multinational companies. Eco-industrial parks are one of the necessary forms of the circular economy. Since the end of the 1980s, some companies have used the 3R principles to organize internal material recycling; for instance, the Kalundborg eco-industrial park has implemented the sharing and symbiosis of energy, water, steam, and environmental protection treatment among more than a dozen companies (Gertler, 1995). The practice in developed countries shows that the comprehensive utilization of waste can form an ecological industrial chain and gradually transform into an eco-industrial park (Ayres & Ayres, 2002).

In the 1990s, influenced by the enactment of recycling laws in Germany and Japan, China also switched to a circular economy. In 2005, a document on a circular economy policy issued by the State Council proposed that a circular economy is an essential response to economic and environmental risks caused by excessive resource consumption (Yuan et al., 2006). China's National Development and Reform Commission (NDRC) and the Ministry of Environmental Protection have also issued documents implementing circular economy policies to promote examples of industrial symbiosis mechanisms, such as the Rizhao Economic Development Zone. China has introduced a series of taxation, finance, price, and industry policies and allocated funds to support the transformation of industrial parks into eco-industrial clusters. The Chinese government encourages local companies to reuse resources through tax incentives; NDRC, together with the People's Bank of China, the Banking and Securities Regulatory Commission, and other financial regulatory agencies, provides financial support for innovative firms through preferential loans or direct capital financing.

Suzhou High-tech Zone (SND) is a typical example of China's circular economy development. In 2005, it was selected as one of the first 13 industrial parks in China's national circular economy pilot. In 2008, together with the nearby China-Singapore Eco-Industrial Park and Tianjin Economic and Technological Development Zone, it became one of the first three national-level eco-industrial demonstration parks.

The scale of the Suzhou High-tech Zone is much larger than that of Western national eco-industrial parks such as  Kalundborg. As of 2014, SND's industrial symbiosis is composed of more than 16,000 companies and nearly 4,000 manufacturing companies, many of which are engaged in the manufacturing of electronic products, biotechnology, and medical equipment; In 2015, the total industrial output value of SND (including manufacturing, mining and utility companies) reached 288 billion yuan (Mathews et al., 2018).

#### 2.1.3.3 Benefits of Circular Economy

Generating profits in recycling waste resources and utilization of resources is the internal driving force for developing a circular economy. Profit-driven has two meanings: reducing costs and creating value. Recycling waste or by-products can save costs on raw materials and reduce the cost of products; simultaneously, the process of using waste materials also generates economic benefits. The circular economy is an essential part of sustainable development. China is not a country with rich natural resources and environmental capacity; thus, it needs to develop with the minimum resource cost and protect the environment at the minimum economic price.

## 2.2 Literature review

### 2.2.1 Technology innovation and $CO_2$ reduction

#### 2.2.1.1 Environmental technology and eco-innovation

Eco-innovation consists of new or modified processes, techniques, systems, and products that avoid or reduce environmental harm, bringing either technical or organizational changes to a company (Kemp & Arundel, 1998). There are two main methods to classify technological and environmental innovations: motivations or reasons for the innovative activities or the purpose of the invention. The first type of eco-innovation is easy to identify because the impact on the environment can be seen directly, indicating that those innovations are developed in compliance with government regulations. The second type of eco-innovation is somehow more problematic because the environmental benefit can be a side-effect of other goals. The ecological component can be identified with different kinds of innovation.

In the eco-innovation framework proposed by Carrillo-Hermosilla et al. (2010), the authors point out that design, user, product, service, and governance are the four main dimensions to estimate the results of eco-innovation. The design dimension represents two rationales for innovation: redesigning production systems to reduce environmental impacts or innovative activities to minimize those impacts. Both causes are associated with either incremental or radical technological change. The user dimension of eco-innovation involves user acceptance and interaction. The user dimension is one of the critical aspects that concern the successfulness of eco-innovation because commercialization depends on user demands in the target market. Users not only apply and spread eco-innovation but also lead future innovation directions. The product-service dimension represents a sustainable business model which includes production, consumption, delivery, and disposal. Eco-innovation in this dimension is related to the whole value chain and relevant actors because the changes in product-service deliverables and processes must provide higher value or revenue for the innovation to be successful. The fourth dimension of eco-innovation is governance. Innovation is never an isolated island but needs the coordination of all relevant parties and stakeholders. Governance means that managers and relevant innovators need to renew their relationships or establish new relationships within the value network to overcome the barriers and boundaries that influence eco-innovation.

Many scholars also consider Eco-innovation as a critical factor that affects environmental quality and carbon abatement due to its role in improving industrial structure and sustainability. Scholars study the application of eco-friendly technologies in developing countries and find that eco-friendly technologies enable sustainable production patterns and consumption, thus abating carbon emissions (Ding et al., 2021; Işık et al., 2019; L. Wang et al., 2020; K. Zhang et al., 2017).

#### 2.2.1.2 The technology options for reducing GHG emissions framework

This theoretical analysis follows and extends the technology options for reducing GHG emissions framework presented by Lee (2013). In this framework, the author classifies two aspects of technology strategies: the radicalness of clean production technological innovation and the energy and material flow (Figure 3) and raises five types of technology options: energy-saving methods, process innovation, energy source substitution, material substitution, and GHG treatment.

The framework classifies technology innovation according to its radicalness. According to the intensity of innovation, technological innovation can be divided into incremental innovation and breakthrough innovation/radical Innovation. Radical technological innovation comes with new scientific discoveries and engineering knowledge, different from established technologies and experiences in the industry. Radical innovation alters the elements of an existing set or combination of components, whereas incremental innovation alters the performance of an existing set of components (Henderson & Clark, 1990). While radical innovation requires new knowledge and significant technological changes in systems, processes, and products, incremental innovation only requires minimal efforts in adjusting, renovating, modifying, or improving existing principles, which fully exploits the potential of existing technologies, and strengthens the advantages and organizational capabilities of existing companies. Incremental innovation has low requirements for technical ability and company scale. Although incremental innovation does not make effective use of new scientific principles, it gradually produces huge cumulative economic effects (e.g., improving customer satisfaction and increasing the efficacy of a product or service), and compared with the risks and difficulties of radical innovation, many companies tend to adopt an incremental innovation model. Even though most technology innovation trends are incremental, radical innovation is essential to achieving the environmental targets and improvements (Moors, 2006; Ölundh Sandström & Tingström, 2008).

This framework also identifies three stages of the energy and material flow, including the inbound stage, the in-process stage, and the outbound stage. The inbound stage represents the raw materials and the source of energy (e.g., fossil fuel or renewable energy) that consist of the input of the production process. Relevant technologies in the inbound stage include substituting raw materials (option 4) or energy sources (option 3); thus, technological innovation is related to clean and renewable energy and new materials. The in-process stage represents the manufacturing process of the final products. Technological innovation in the in-process stage means innovative activities involving energy-saving (option 1) and process (option 2) that improve energy efficiency, increase productivity, and reduce GHG emissions. The outbound stage represents GHG emissions as a byproduct of the output, which pollutes the environment if not carefully controlled and managed. Technology innovation in this stage represents the technology progress in CCS and other types of GHG management technologies (option 5). Despite the abovementioned technology innovation, which may exist primarily during one stage in the model, other technologies such as the end-of-pipe and cleaner production technologies last in multiple stages.

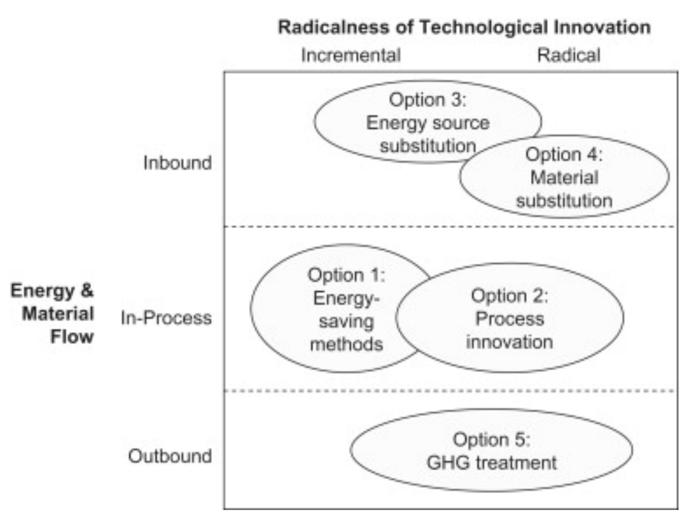



FIGURE 2.1 Technology options for reducing GHG emissions (Source: S.-Y. Lee, 2013)

#### 2.2.1.3 Technology options for $CO_2$ emission reduction

According to the two-dimensional matrices, the abovementioned framework identifies several sets of technology options. This subsection describes the technologies and approaches for $CO_2$ emissions reduction.

*Energy-saving approaches: improving energy efficiency*

Energy-saving approaches are the highest priority option because high energy consumption is the source of increased carbon emissions. Thus, this option involves saving energy in the whole production process, including technologies that improve production efficiency, optimize the energy system, and recover energy from waste heat or materials.

*Energy source substitution: clean and renewable energy*

Energy source substitution technologies involve the substitution of high carbon emission fuels for low-carbon or carbon-free fuels. This dissertation will focus on using renewable energy (e.g., wind energy, solar energy) and clean energy (e.g., biofuels and hydrogen energy) substitution rather than replacing fossil fuels with other traditional low-carbon fuels such as coal or diesel.

The literature on renewable energy mainly revolves around two perspectives, which sum up the discussion on both the demand and supply sides. More precisely, research from the supply-side perspective revolves around energy consumption in production and explores it in the labor and capital (Furlan & Mortarino, 2018; Salim et al., 2014). Meanwhile, from the demand-side perspective, research revolves around energy demand and usage and explores its costs and output (Gozgor et al., 2020; Omri & Nguyen, 2014). However, studies on the supply side report a positive linkage between renewable energy and economic growth (Apergis & Payne, 2014), whereas studies on the demand side report the direct long-term relationship between renewable energy and output, especially carbon emissions (Gielen et al., 2019; Moutinho et al., 2018; Saidi & Omri, 2020)

Precisely, Chen et al. (2019) studied renewable and non-renewable energy production with the gross domestic product (GDP), per capita $CO_2$ emissions, and foreign trade in China covering the period 1980 to 2014 by autoregressive distributed lag (ARDL) bounds testing approach and vector error correction model (VECM) Granger causality approach. The findings confirm a long-run relationship among those variables, a negative relationship between renewable energy production and $CO_2$ emissions, and a bidirectional causality from

$CO_2$ emissions to renewable energy production. Hu et al. (2018) analyze the relationships between renewable energy consumption, services trade, economic growth, and $CO_2$ emissions in 25 developing countries from 1996 to 2012 by the Granger causality test and long-run panel estimates (FMOLS and DOLS). They find that increasing the share of renewable energy consumption in total energy consumption contributes to carbon emission reduction, whereas increasing the size of renewable energy consumption without an equivalent decline in fossil fuel does not help reduce carbon emissions. Nguyen and Kakinaka (2019) further find that the long-term relationship between renewable energy consumption, output, and carbon emissions relates to the development stage by a panel cointegration analysis of 107 countries from 1990 to 2013 and find apparent differences between low- and high-income countries. More specifically, they find that renewable energy consumption in low-income countries is negatively associated with output and positively associated with carbon emissions. In contrast, renewable energy consumption in high-income countries is positively associated with production and negatively associated with carbon emissions.

*Energy innovation and carbon dioxide emissions abatement*

The environmental Kuznets curve (EKC) hypothesis (Kuznets, 1955) explains that there is an inverted U-shaped relationship between income per capita and pollution levels, indicating that pollution proliferates in the early stages of industrialization due to heavy material output and that pollution levels will drop in the long term with increasing interest in environmental quality. Scholars also find that energy technology advances are the key to improved environmental quality and carbon emissions. (Álvarez-Herránz et al., 2017; Lantz & Feng, 2006). However, scholars that incorporate energy technology variables in EKC for carbon emissions analysis get mixed findings. For example, Balsalobre-Lorente et al. (2019) examined the role of energy innovation and corruption in EKC for carbon emissions through a panel data model of 16 selected member countries of the Organization for Economic Co-operation and Development (OECD) during the period 1995-2016. The empirical results show that corruption limited the positive effect of energy innovation on carbon emission reduction. Wang and Zhu (2020) explore the relationship between energy technology innovations and carbon emissions in China utilizing a spatial econometric model. They find that fossil energy technology innovation is ineffective in carbon emission reduction. In contrast, renewable energy technology innovation is beneficial to $CO_2$ abatement. Bai et al. (2020) further investigate the non-linear relationships among carbon emissions, renewable energy innovation, and income inequality using a panel fixed effect regression model and a panel threshold model. They find a single-threshold effect regarding income equality; only when income inequality is above the threshold value the positive relationship between renewable energy innovation and per capita carbon emission reduction is significant. Cheng and Yao (2021) investigate the effect of renewable energy innovation on carbon intensity in 30 provinces of China using a panel estimation covering the period 2000 to 2015. Their investigation considers slope heterogeneity and cross-section dependence and shows that carbon intensity is reduced by 0.051% for every 1% increase in renewable energy technology innovation level.

### 2.2.2 ICTs and ICT-enabled low-carbon technologies

The annual carbon emissions of the information technology and communication technology industry account for 2-3% of the total emissions of all sectors, which is approximately equal to the emissions of the entire aviation industry. The ICT industry also has enormous potential to solve social and environmental issues (97-98% of which are still untapped). Governments and companies worldwide have launched a series of new policies and technology innovation projects to promote green ICT, such as the "Green IT Action Plan" of the German Ministry of Economic Affairs and Technology and the “Cooperation for Sustainable Smart Transmission Grids" of IBM.

Research findings show that ICT has great potential in improving productivity and energy efficiency and promoting economic growth. ICT is also expected to help reduce global carbon emissions by 15% by 2020. Regarding energy-saving and environmental protection, ICT allows consumers to "virtualize" and "dematerialize" various activities through online shopping, e-commerce, video, teleconferencing, etc., thereby reducing the demand for fuel and raw materials. A more critical aspect is that ICT can provide solutions to help monitor emissions in real-time and optimize systems and processes to increase efficiency. A 15% reduction in global emissions can be achieved thanks to efficiency improvements through ICT solutions spanning almost all economic sectors, including powertrain, logistics, transportation, buildings, and power grids. It can be seen that ICT is not only an effective tool to solve environmental problems but also a contributor to economic development.

#### 2.2.2.1 The direct impact of ICT on $CO_2$ emissions

The energy-saving and emission reduction of ICT directly influence the demand for energy, raw materials, and $CO_2$ emissions. ICT improves the efficiency of energy and physical raw materials and helps with the recycling of obsolete equipment. More specifically, ICT helps through centralized management of network client computers that save power and improve management efficiency, virtualization software that saves material and energy, “dematerialization" through highly integrated information communication equipment, design materials, and energy-saving solutions, remote monitoring and communication that reduce emissions on transportation, and so forth.

#### 2.2.2.2 The indirect impact of ICT on $CO_2$ emissions

Using ICT in the production and distribution of social and economic activities and consumption of products and services improves efficiency and transparency in each transaction. By using partial or complete virtual substitutes (e.g., virtual reality and augmented reality technologies) that provide consumers with experiences equivalent to or even better than real ones while promoting dematerialization in human interaction, ICT helps reduce the demand for energy and materials of physical products or stores. More specifically, utilizing innovative technology such as artificial intelligence for managing traffic flow and dynamic diversion can help with traffic congestion, thus reducing energy consumption and carbon emissions. The design and construction of advanced ICTs in smart buildings enable monitoring and managing energy supply and consumption to achieve energy conservation and emission reduction. Intelligent factories leverage ICTs to improve energy efficiency in industrial production while reducing energy consumption and monitoring and managing wastes generated in the production process. An intelligent logistics system enhances the efficiency of cargo transportation and reduces carbon emissions and energy consumption caused by unnecessary transportation routes. ICTs also support and promote distributed management of employees and an online working environment, thereby reducing carbon emissions caused by traveling.

In summary, the role of ICT in energy conservation and emission reduction is mainly manifested in two aspects. On the one hand, the development of the ICT industry itself is conducive to reducing unnecessary costs and consumption of energy and materials in social and economic activities, thereby reducing the corresponding energy consumption and emissions. On the other hand, ICT can monitor and manage resources in the production process and reasonably allocate them to improve resource utilization. Applying ICT technology in upgrading and transforming traditional industries brings more excellent energy-saving effects and enhances companies' competitiveness.

#### 2.2.2.3 An example of ICT-enabled low-carbon technologies: The smart grid

ICTs have been widely and deeply applied in the power grid and organically integrated with traditional power technology, which has dramatically improved the intelligence level of the power grid. The application of sensor and information technology in the power grid provides technical support for system state analysis and auxiliary decision-making, making self-healing of the power grid possible. The maturity and development of dispatching technology, automation technology, and flexible power transmission technology guarantee the utilization of renewable energy and distributed power. The improvement in the communication network and user information collection technology has promoted the two-way interaction between the power grid and the users. The smart grid is characterized by high informatization, automation, interaction, and low carbon emissions by integrating new energy sources, new materials, advanced sensing technology, information technology, control technology, energy storage technology, and other new technologies.

#### 2.2.2.4 ICT and upgrades of traditional industries toward a low-carbon economy

The iron and steel manufacturing industry consumes the most considerable amount of energy among all the global manufacturing sectors, accounting for 4-5% of the total anthropogenic $CO_2$ emissions (Quader et al., 2015). A critical application of ICT in the iron and steel industry is the intelligent manufacturing execution system (SMES). SMES is an essential part of the information systems in the iron and steel industry. Energy management is a primary function of the SMES system, which deals with intelligent energy scheduling and optimization, improving energy and material efficiency through resource allocation, operation scheduling, data collection, maintenance management, performance analysis, reducing pollution emissions, and improving environmental quality.

The construction industry is the second largest energy consumption in the world. The application of ICTs, including real-time collection and analysis of pollution data, information optimization and integration, resource regeneration and reuse, and so forth, conserves energy and reduces emissions through optimizing material supply, transportation, and utilization, thus reducing environmental pollution and emissions. At the same time, the application of sophisticated ICT to monitor the lighting, heating, ventilation, and disaster prevention systems can reduce the daily energy consumption and operation costs of the commercial buildings, thus reducing $CO_2$ emissions.

### 2.2.3 Carbon emissions and carbon abatement

#### 2.2.3.1 Impact factors of carbon emissions

Scholars used the LMDI decomposition approach and found that household income and population (Zang et al., 2017), energy intensity and per capita GDP (J. Chen et al., 2018), industrial structure and energy structure (Cansino et al., 2015; Yi & Li, 2013, p. 2) are the main drivers of carbon emissions. Alola (2019) used the Dynamic Autoregressive Distributed Lag (ARDL) method to analyze the impact of trade policy, immigration, and health care on carbon emissions in the U.S. from 1990 to 2018 and found that immigration is positively related to carbon emissions and that trade policy has a significant positive impact on short-term carbon emission. Sharif et al. (Sharif et al., 2019) used panel data from 74 countries from 1990 to 2015 to explore the relationship between renewable and non-renewable energy consumption and carbon emissions. The results show that non-renewable energy consumption positively impacts environmental degradation, renewable energy negatively impacts ecological degradation, and financial development has a significant negative impact on environmental degradation.

Several scholars studied the impact factors of carbon emissions in China. Peng et al. (2018) used structural path analysis to identify critical supply chain paths that affect carbon emissions in China's steel industry based on global multi-regional input-output table and energy-related data. The results show that both the direct demand for the output of the Chinese steel industry and the indirect demand for consumer products from other sectors (e.g., construction, electrical equipment, etc.) lead to large consumption of coke oven gas in the Chinese iron and steel industry, resulting in a large number of carbon emissions. Moreover, developed countries such as the United States, the European Union, South Korea, and Japan import a large amount of iron and steel goods from China, which helps developed countries reduce their carbon emissions while bringing considerable energy consumption and carbon emissions to China. Shuai et al. (2018) used the STIRPAT (stochastic impacts by regression on population, affluence, and technology) model. They found that China's carbon emissions have five key factors: real GDP per capita, urbanization rate, ratio of tertiary to secondary industry, ratio of renewable energy, and fixed asset investment, among which the most significant contributor to carbon emissions is real GDP per capita, and the most critical inhibitor of carbon emissions is urbanization rate. Wang et al. (2019) used a geographically weighted regression (GWR) model to study the spatial heterogeneity in the impact of different factors on carbon emissions. The results show that economic growth, private car ownership, and energy consumption positively impact $CO_2$ emissions.

In contrast, the remaining factors have a bidirectional effect on $CO_2$ emissions in different regions of China. Economic growth and private car ownership have the most significant positive impact on central and western China cities. Energy consumption has a significant positive effect on $CO_2$ emissions in the southernmost regions of China. Road density and urban expansion are the key drivers of $CO_2$ emissions in northeast China. The industrial structure of cities in the Beijing-Tianjin-Hebei area has a significant positive impact on $CO_2$ levels. Foreign direct investment in $CO_2$ emissions is not significant in most cities except Guangdong province, where a significant positive relationship appears.

2.2.3.2 Impact factors of carbon abatement

Hashmi and Alam (2019) studied the two primary drivers of carbon emission reduction through climate change policies: promoting green innovation and regulating emissions through carbon pricing, based on a "stochastic impacts by regression on population, affluence, regulation, and technology (STIRPART) model and GMM models, they found that for every 1% increase in environmental friendly patents, carbon emissions decrease by 0.017% in OECD countries and that for every 1% increase in per capita environmental tax, carbon emissions decrease by 0.03% in OECD countries. Kocak and Ulucak (2019) used the dynamic panel data method to empirically analyze the impact of energy R&D expenditures on carbon dioxide emissions in 19 high-income OECD countries from 2003 to 2015. They found that energy R&D expenditures on energy efficiency and fossil energy positively affect $CO_2$ emissions, whereas R&D expenditures on power and storage negatively affect $CO_2$ emissions. Dong et al. (2019) (2019) used the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model and panel data of 128 countries from 1990 to 2014 to examine the key influencing factors of global and regional $CO_2$ emissions. The results showed that renewable energy could lead to a decline in global $CO_2$ emissions. Gillingham and Stock (2018) studied climate change policies in the U.S., including automobile fuel economy standards, gasoline taxes, renewable energy utilization, restrictions on fossil fuel extraction, and so forth, and reductions in greenhouse gas emissions. They also review various technologies' marginal abatement cost on greenhouse gas emissions abatement. Abrell et al. (2019) used weather conditions to evaluate renewable energy subsidies in Germany and Spain to assess their short-term direct costs of reducing $CO_2$ emissions; the results showed substantial heterogeneity in production costs, temporal availability of natural resources, and market conditions affect the prices of various types of renewable energy promoted.

Scholars also examined the critical impact factors and paths of carbon abatement in China. Wu at el. (2020) analyzed the allocation efficiency of carbon emission rights in six high-energy-consuming industries in China and found the tremendous potential for carbon emission reduction in the power industry and the iron and steel industry. They also found the insufficient use of energy-saving and emission-reducing technologies in the high-emission sectors. Song et al. (2021) examined the potential dynamic trends of $CO_2$ emission in China and used a spatial-temporal logarithmic mean division index model to explore the provincial emission reduction path. They found that from 2012 to 2017, environmental policies and increasing energy efficiency are the critical emission inhibitors in the primary, secondary, and tertiary industries. Zhang et al. (2017) used a system generalized method of moments (SGMM) approach to estimate the effect of environmental innovation on carbon emissions in China. They found that energy efficiency and resources for innovation play critical roles in carbon abatement. Sarwar (2019) studied the role of urbanization and industrialization in suppressing carbon emissions in China. Using the panel data from 2005 to 2015, the author found that high urban income negatively affects the urbanization-driven carbon emissions, and the investment in industrial treatment plants and forests negatively affects industrialization-driven carbon emissions.

#### 2.2.3.3 Key insights

The left-hand side of Figure 2.2 shows that factors such as energy intensity, private car ownership, energy consumption, and so forth positively affect carbon emissions. On the right-hand side, we can see factors such as green innovation and environmental policies negatively affect carbon emissions. However, we can also see factors on both sides, indicating mixed findings on certain aspects.

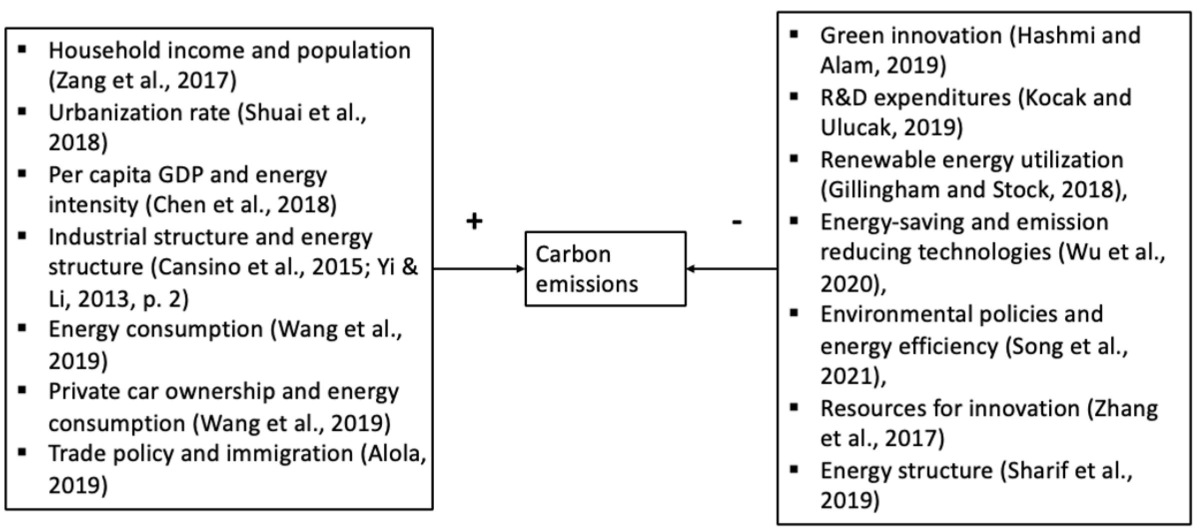



FIGURE 2.2 Impact factors of carbon emissions and carbon abatement

### 2.3 Summary of literature review

In section 2.2, related literature on carbon emissions and technological innovation is reviewed, and key impact factors are identified. Four research gaps are identified:

- GAP1: The research on carbon emissions is associated with a broad and profound social-economic green transition concerning energy structure, industrial structure, population, urbanization, and other economic factors. However, the results on carbon emissions are not consistent and need to be further explored.

- GAP2: Previous research on technological innovation and carbon emissions focuses on the direct impact and how to apply new methods or technologies to industry from a scientific perspective; moreover, previous research studies the direct effect of industrial factors and energy structure on carbon emissions. However, little research considers the impact of technological innovation on industrial factors and energy structure, and limited research considers the indirect effect of industrial structure and energy structure on the technological innovation - $CO_2$ nexus.
- GAP3: Some studies have proposed comprehensive methods and techniques to help decision-makers evaluate and select sustainable production technologies from different environmental, political, and social aspects. However, limited research examined the effectiveness of those tools on carbon abatement, and few studies explore the optimal path under different scenarios.
- GAP4: Research on the key factors influencing technological innovation and carbon emissions nexus lacks empirical evidence due to the heterogeneity in regional resource endowments such as economic, technology, and climate policies.

# CHAPTER 3 SPATIAL EVOLUTION CHARACTERISTICS AND CONVERGENCE ANALYSIS OF PROVINCIAL CARBON EMISSIONS IN CHINA

Greenhouse gas emissions and global warming are not only a concern to environmental degradation but also to human survival. As an accessory to economic development, $CO_2$ has become a significant challenge for the development of human society. As the world's largest carbon emitter, China's rapid economic growth is achieved at a considerable cost to the environment. Under the UNFCCC, the Chinese government put forward the "30.60" goal of reaching carbon neutrality in 2030 and a carbon peak in 2060. This chapter focus on the spatial evolution characteristics and convergence trend of provincial carbon emissions in China. Even though there is heterogeneity in provincial resource endowments and great differences in regional carbon emissions, there are significant spatial spillover effects and path-dependent characteristics in inter-provincial $CO_2$ emissions. Therefore, it is necessary to explore and reveal the complex spatial aspects of provincial carbon emissions in China.

## 3.1 Provincial carbon emissions and regional characteristics in China

### 3.1.1 Explained variable: carbon emissions (CE)

Total carbon dioxide emission ($CO_2$): Based on eight leading energy carbon emission coefficients provided by the Intergovernmental Panel on Climate Change (IPCC 2006), $CO_2$ denotes the total $CO_2$ emissions from fuel consumption of province $i$ in year $t$, which is calculated as:

$$CO_{2it} = \sum_{i=1}^{8} \delta_j * Q_{ijt} * \beta_j \tag{3.1}$$

where j denotes the type of energy source, $\delta_j$ denotes the converted coefficient of energy $j$ into $10^4$ tons of standard coal, $Q_{ijt}$ denotes the total energy consumption of energy $j$ in year $t$ of province $i$, $\beta_j$ denotes the energy carbon emission coefficient (Table 3.1).

The population and industrial structure of provinces are different; thus, comparing the total carbon emissions among regions may seem inappropriate. However, because the "Dual Carbon" goal aims to reduce the total amount of carbon emissions rather than carbon intensity, we considered the number of carbon emissions as our variable of interest instead of carbon intensity.

Table 3.1 standard coal and carbon emission coefficient of eight fossil energy sources

| Energy source | Coal | Coke | Crude oil | Gasoline |
|---|---|---|---|---|
| Standard coal | 0.7143 | 0.97 | 1.43 | 1.47 |
| carbon emission coefficient | 0.7476 | 0.1128 | 0.5854 | 0.5532 |
| Energy source | Kerosene | Diesel | Natural gas | Fuel oil |
| Standard coal | 1.4717 | 1.46 | 13.30 | 1.4286 |
| carbon emission coefficient | 0.3416 | 0.5913 | 0.4479 | 0.6176 |

Based on the IPCC method (Equation 3.1), eight primary energy sources are selected, and the provincial carbon emissions are calculated according to the standard coal and carbon emission coefficient. The results are shown in Figure 3.1 (provincial data gathered from the China Energy Statistical Yearbook, excluding Tibet, Taiwan, Hong Kong, and Macao).

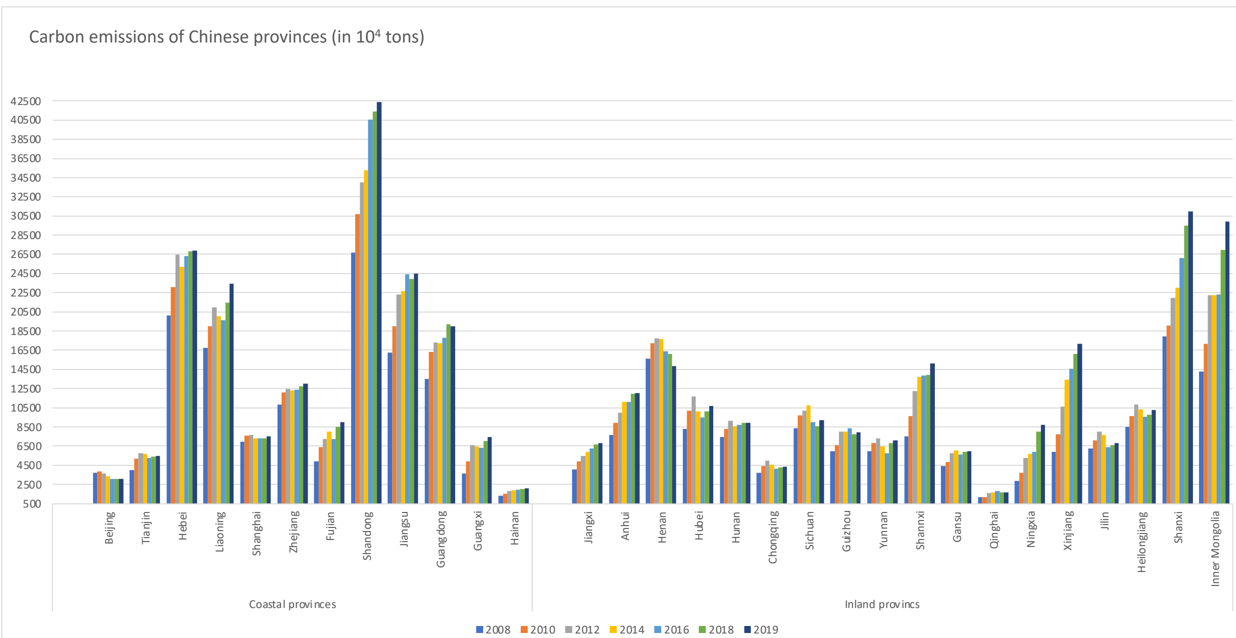



Figure 3.1 Total annual carbon emissions of Chinese provinces in 2008–2019.

### 3.1.2 Regional characteristics of provincial carbon emission in China

#### 3.1.2.1 National-level analysis

It can be seen from Figure 3.1 that the total volume of provincial carbon emissions is vast and growing. China is the world's largest energy consumer and carbon emitter, and its carbon emissions account for one-third of the global total. In the coming decades, China's emission reduction rate will be one of the most critical factors influencing climate control.

The carbon emissions of various regions in China show uneven spatial characteristics under the combined effect of economic level, geographical location, industrial structure, and other factors. In the context of inter-regional industrial transfer, the focal province consumes energy and generates direct carbon emissions in the process of economic development. Meanwhile, it indirectly creates carbon emissions due to energy consumption in corresponding regions. In the process of providing products and services, related areas further drive carbon emissions in focal provinces so that there is a complex relationship between regional carbon emissions.

Since the inland and coastal regions are at different economic levels and have disparities in natural endowment, technical capability, economic policies, and environmental regulation, this dissertation further analyzes the provinces of China on the regional level.

#### 3.1.2.2 Coastal provinces analysis

China has a vast territory. Due to different levels of economic development and resource endowments, there are significant differences in carbon emissions between coastal and inland provinces; Most of the coastal areas are in the eastern regions of China, which are economically developed in China. Most of the high emission and high energy consumption industries in the coastal areas benefit from the economic policies and have been transferred to inland provinces. The industrial structure had gradually upgraded and rationalized to achieve development quality in the coastal regions. The coastal provinces' economy mainly focuses on high-tech industries, digital economy, e-commerce, business services, and other tertiary industries.

Although the economic output is high, the carbon emissions in coastal provinces are still high, mainly due to the early stage's high-input and high-emission economic structure and energy structure. As we can see in Figure 3.1, except for Beijing, the carbon emissions in other provinces still show an increasing trend; the carbon emissions of some coastal areas (such as Hebei, Liaoning, etc.) exceed those of inland provinces.

Although the overall trend of carbon emissions in coastal provinces has been alleviated compared with inland provinces, the carbon emissions in coastal provinces are still considerable. It is necessary to adjust relevant policies and economic structures to promote carbon emission reduction further.

#### 3.1.2.3 Inland provinces analysis

The inland provinces (central and western regions) are the carrier of industrial transfer from the coastal areas. In the inland provinces in China, high-emission and high-energy-consumption industries are still the pillars of economic growth. As the primary energy source of the secondary industries, Fossil fuels are causing high carbon emissions in inland provinces. Although the industrial structure has shifted towards a more balanced supply-demand relationship under the promotion of national industrial policies, industrial structure upgrade is challenging with long-term overcapacity, the existence of zombie enterprises, low level of industrial innovation, and low production and energy efficiency, resulting in a band growth trend of carbon emissions in inland provinces.

According to Figure 3.1, the carbon emission of central provinces is higher than that of western regions, closely related to the economic and industrial structure. The micro-level data shows that Henan, Shanxi, and Inner Mongolia have significant carbon emissions, which belong to high emission agglomeration areas. They are the critical areas of national carbon emission control.

On the one hand, the local government of the inland provinces "races to the bottom," adopts an extensive industrial structure, and their carbon emission control policies are insufficient and incomplete. On the other hand, due to the low economic development level in the western province, the national monetary policy vigorously develops in the west region. However, due to the weak economic and technical development, economic growth in the western areas still depends on high-pollution and high-emission industries, which aggravates carbon emissions and surpasses carbon emissions in the central province.

## 3.2 Spatial evolution characteristics

### 3.2.1 Spatial autocorrelation analysis and Moran's I

Spatial autocorrelation determines whether the amount of carbon emissions in a particular province is dependent on the number of carbon emissions in its neighboring areas. By quantifying the spatial autocorrelation, it is possible to determine whether provincial carbon emissions are clustered and quantify how strongly it is pressed.

Before using econometric models to perform a regression, a spatial autocorrelation analysis tests whether spatial heterogeneity and spatial autocorrelation exist (Geniaux & Martinetti, 2018).

Global Moran's I disclose the spatial pattern of the provinces by calculating the degree of regional autocorrelation. The range of the Moran'I value is [-1, 1]. The attributed value of I greater than 0 implies a positive spatial autocorrelation. The closer the attributed value of I is to 1, the greater spatial agglomeration is present. When the attributed value of the I is closed to 0, it indicates a random spatial pattern. The attributed value of I less than 0 implies a negative spatial autocorrelation.

This dissertation uses global Moran's I to analyze the spatial autocorrelation of provincial carbon emissions, which is calculated as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i-\overline{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j\neq i} w_{ij}} \quad (3.2)$$

Equation (3.2) shows that $n$ is the total number of geographic units (i.e., the 30 provinces), $x_i$ and $x_j$ are the carbon emissions in the city $i$ and $j$; $\bar{x}$ and $S^2$ denote the mean and variance of the carbon emissions, respectively. $w_{ij}$ is the normalized spatial weight matrix corresponding to province pair $i$-$j$.

Based on the panel data model, the spatial weight matrix is integrated to clarify the positional relationship between individual provinces. The geographical weight matrix is used in this dissertation because with the continuous development of transportation and information technology, communication between non-adjacent regions becomes convenient, and the constraints of spatial adjacency are weakened. The geographic distance weight matrix is calculated as:

$$W_{ij} = \frac{1}{d_{ij}^2}, i \neq j \quad (3.3)$$

where $i$ and $j$ represent provinces $i$ and $j$, respectively, and $d$ is the distance between the capitals of the two provinces.

As shown in Figure 3.2, global Moran's I indexes are positive and statistically significant, indicating positive spatial correlation and that provinces with similar carbon emissions have a spatial agglomeration effect. The value of Global Moran's I shows a decreasing trend from 2008 to 2013, indicating decreasing agglomeration effect. The value of Global Moran's I increased with fluctuations from 2013 to 2019, marking a gradually strengthened agglomeration effect.

China has a vast geographical area, with regional resource differences in northern and southern regions and eastern and western regions. Resource endowments of neighboring provinces are similar; thus, under the economic environment of racing to the bottom, the same production factors will be invested to generate equal carbon emissions. Driven by the national technological innovation policy, technology progress among provinces inevitably generates a "ripple effect" that promotes the technology diffusion from one area to its surrounding regions, leading to the fluctuation in spatial agglomeration effect of provincial carbon emissions. However, the fluctuations do not affect the spatial autocorrelation of carbon emissions.

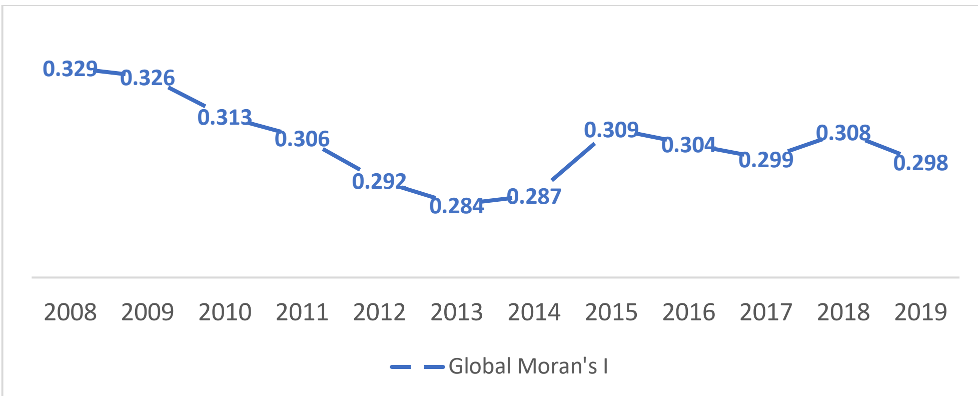



Figure 3.2 Global Moran's I of carbon emissions at the provincial level in China from 2008 to 2019

In order to visualize local spatial autocorrelation and spatial heterogeneity, the spatial distribution is divided into four categories: high-high, high-low, low-low, and low-high agglomeration. By combining LISA significant level test and Moran scatter diagram, this research shows the "Moran significant level figure" in the provinces scattered on the four-quadrant.

The Moran's I scatter diagram of carbon emissions based on the geographical weight matrix is provided using data in 2008 and 2019 as samples (Figure 3.3 & 3.4). It can be seen that the provincial carbon emissions are mainly concentrated in the first and third quadrants, showing a positive spatial autocorrelation. In 2008, six provinces showed a negative spatial autocorrelation, among which four provinces were in the second quadrant and two were in the fourth quadrant; In 2019, ten provinces showed a negative spatial autocorrelation, among which six provinces were in the second quadrant, and four are in the fourth quadrant.

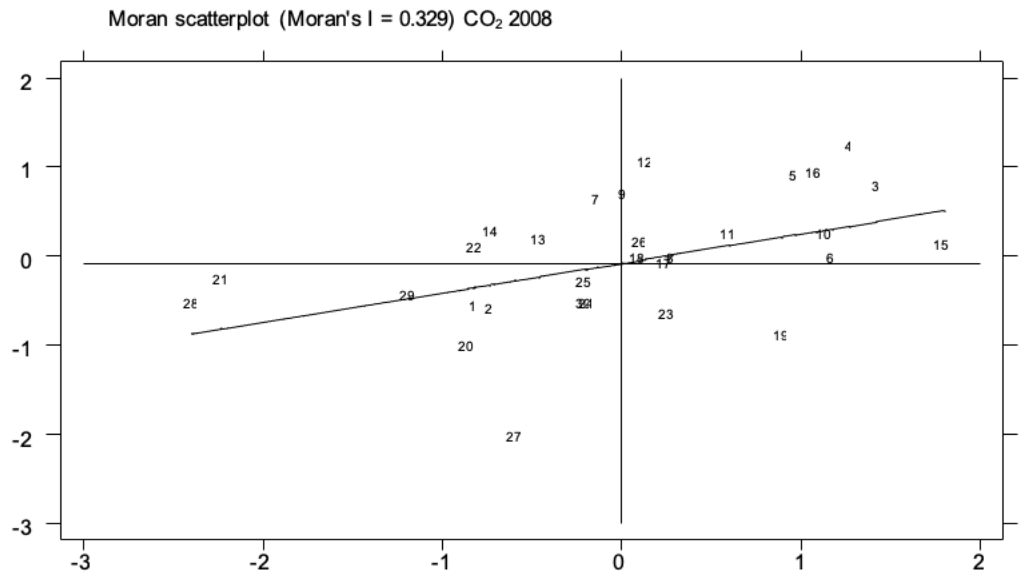



Figure 3.3 Moran's I scatter diagram of provincial $CO_2$ emissions in 2008

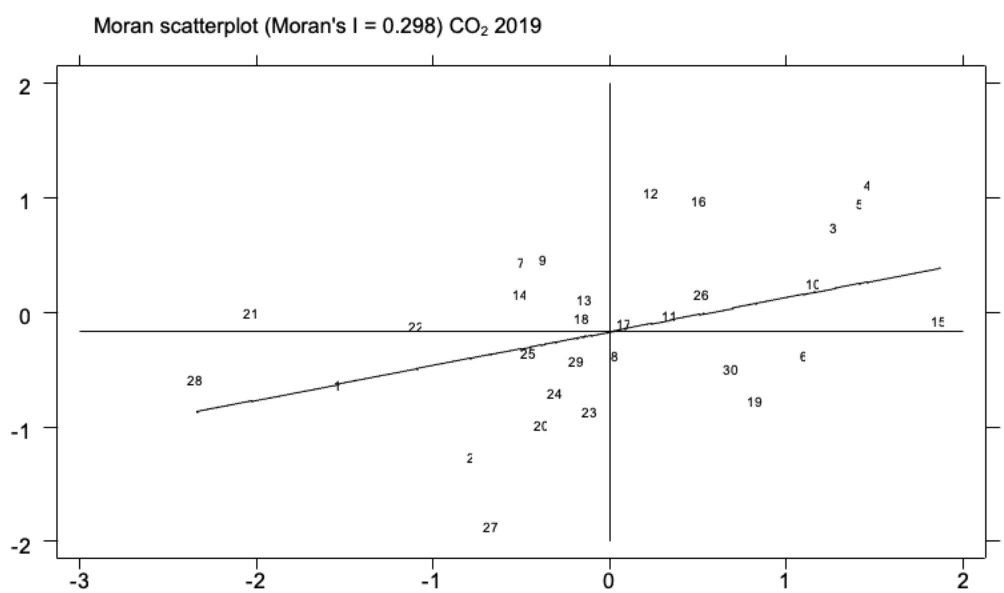



Figure 3.4 Moran's I scatter diagram of provincial $CO_2$ emissions in 2019

### 3.2.2 Local spatial autocorrelation and spatial heterogeneity

In order to reflect the spatial evolution of provincial carbon emissions more intuitively, this section uses ArcGIS to draw the spatial distribution map of provincial carbon emissions in 2008 and 2019. As shown in Figure 3.5 & 3.6, carbon emission values increase from 2008 to 2019.

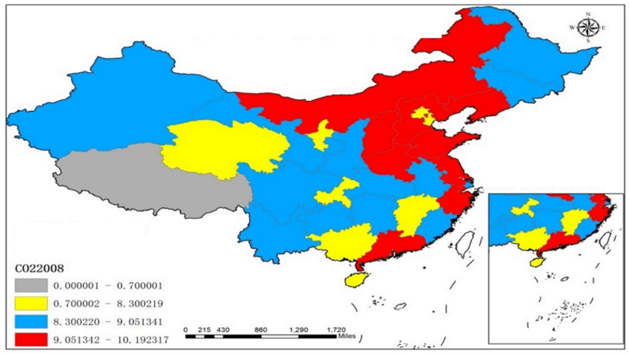



Figure 3.5 Spatial distribution map of provincial $CO_2$ emissions in 2008

As shown in Figure 3.5, the provincial carbon emission shows apparent spatial dependence, forming three-carbon pollution agglomeration areas (data exclude Hong Kong, Macao, Taiwan, and Tibet):

- High-carbon clusters: Hebei Province as the cluster center and Tianjin, Shanxi, Shandong, Henan, Inner Mongolia, Jiangsu, Zhejiang, Liaoning, and Guangdong as subsidiaries.
- Sub-high-carbon cluster: Hunan is the center, surrounded by central and southern provinces such as Hubei, Shaanxi, Anhui, and Jiangxi; Gansu and Xinjiang in the northwest and Jilin and Heilongjiang in the Northeast.
- Low carbon areas: mainly concentrated in Qinghai, Chongqing, Guangxi, Jiangxi, Ningxia, and other provinces. Beijing is independent of the high pollution cluster centered on Hebei. Due to Beijing's unique economic and political status, carbon emissions are significantly lower than Hebei and other surrounding regions.

Compared with the provincial carbon pollution spatial distribution map in 2008, the provincial carbon pollution in 2019 (Figure 3.6) presents noticeable changes and forms the following characteristics:

- Hebei is still the center of a high carbon pollution agglomeration area and shows an expansion trend. Shannxi and Xinjiang have become high-carbon-pollution provinces.
- Sub-high carbon pollution concentration area also changed significantly, forming a belt-shaped area from northeast to Southeast. Zhejiang's carbon pollution has been effectively controlled and successfully downgraded.

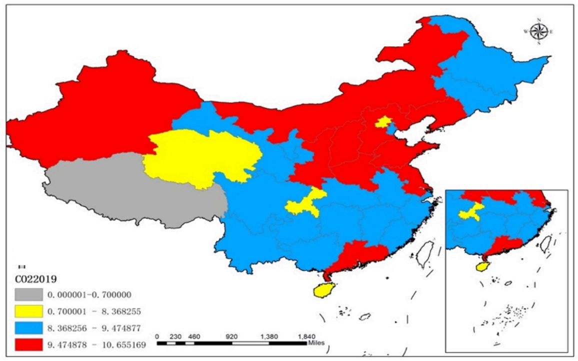



Figure 3.6 Spatial distribution map of provincial $CO_2$ emissions in 2019

### 3.2.3 Kernel density estimate of carbon emission areas

Kernel density estimation (KDE) is used to investigate the distribution of provincial carbon emissions. The estimation is a non-parameter estimation that starts from the data per se and avoids bias in the function setting of parameter estimation. As one of the most widely used methods to estimate the probability density of random variables, KDE has good adaptability to the unknown distribution and regional discrepancies in the geographical phenomenon (Kuang et al., 2020).

The kernel density estimate at any point $X_i$ calculated as:

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} k(\frac{\bar{x}-X_i}{h}) \tag{3.4}$$

where $n$ is the number of samples, ($X_1$, $X_2$, ..., $X_n$) represents the sample data, $h$ denotes bandwidth, $\bar{x}$ is the mean value, and $\sum_{i=1}^{n} k(\frac{\bar{x}-X_i}{h})$ is the kernel function. Since the type of kernel function (e.g. Epanechnikove, Gaussian, triangular, quartic) has little effect on the accuracy of the estimation results, this dissertation adopted the Epanechnikov kernel.

Provincial carbon emissions in the years 2008, 2010, 2012, 2014, 2016, and 2019 were selected as the original data. Applying the software STATA 15, the evolution characteristics of the dynamic distribution of carbon emissions in China from 2008 to 2019 are shown in the kernel density plot in Figure 3.7.

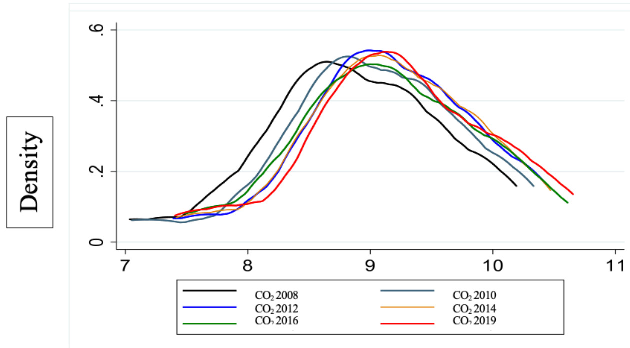



Figure 3.7 Kernel density plot of China's provincial $CO_2$ emissions from 2008 to 2019.

From 2008 to 2019, the kernel density curve of provincial carbon emissions is moving toward the right, showing that the carbon emissions are increasing in all regions. The main peak value increases from 2008 to 2019 and the single main peak pattern indicates that provincial carbon emissions present no polarization phenomenon. The horizontal axis has a narrowed data span, indicating decreased discrepancies in provincial carbon emissions in the selected period. In general, the KDE provides a foundation for spatial convergence analysis in section 3.3.

## 3.3 Spatial convergence analysis of provincial carbon emissions in China

### 3.3.1 Conditions of spatial convergence

With economic development, energy consumption in total is growing, and provincial carbon emissions are increasing as well. However, continuous industrial policy adjustment, industrial structure upgrading, and energy structure adjustment at the macro (systemic), meso (structural), and micro levels make the provincial carbon emission growth show a convergence trend.

In order to achieve the "dual carbon" goal, China has issued a series of policies and regulations to reduce carbon emissions. From the macro level, national and local government policies mainly influence carbon emissions convergence. Local governments have continuously improved the policy system for carbon emissions, environmental quality, energy conservation, and emission reduction. In addition, China continues to increase investment in environmental protection and regulation, attempting to reduce the interaction of carbon emissions among provinces and promote the convergence of provincial carbon emission reduction.

The structural impact on carbon emissions convergence mainly comes from industrial structure upgrades and energy structure adjustments. Technological innovation promotes the upgrading of industrial structures and the optimization of energy consumption structures. The structural impact indirectly curbs carbon emissions by reducing the proportion of high emission and high energy consumption industries in economic development. In addition, China has been vigorously developing new energy and renewable energy industries to gradually replace coal and other fossil fuels. For instance, as one of the largest automobile consumers globally, China's global market share of new energy vehicles reached 180,000 by the end of 2017, accounting for more than 50% of the total stake.

The micro-level impact on carbon emissions convergence is mainly from low-carbon technology innovation and consumer environmental preference. On the one hand, firms are encouraged to promote innovation and the application of low-carbon technologies. On the other hand, firms and consumers will have to pay more for environmental-friendly products under the increasingly strict environmental regulation.

### 3.3.2 The $\beta$-convergence of provincial carbon emissions

$\beta$-convergence comes from the neoclassical economic model where critical assumptions of a diminishing return to scale imply that long-term pollution should be bounded and approach a steady-state level even in the presence of positive growth in the per capita GDP (Runar et al., 2017). Suppose the growth rate of regions with higher initial carbon emission levels is less than that of regions with lower initial carbon emission levels (i.e., a lower level of initial emission level leads to a higher carbon emission growth rate) in the long run regardless of other factors, an unconditional convergence exists, which is called absolute $\beta$-convergence. Suppose certain other factors such as economic development level, environmental regulation and policy, industrial structure, urbanization, foreign direct investment, and other resource endowment conditions lead to different convergence paths; in that case, the convergence of carbon emissions will be conditioned on those factors, which is called conditional $\beta$-convergence.

In the convergence process of provincial carbon emissions, it is necessary to consider the spatial spillover effect of adjacent provinces. Equations (3.5) and (3.6) are the spatial $\beta$ convergence model and the spatial - convergence Durbin model.

$$In\frac{CO_{it+1}}{CO_{it}} = \alpha + \beta InCO_{it} + \sum_{k=1}^{n}\lambda_k X_{kit} + \varepsilon_{it} \tag{3.5}$$

$$In\frac{CO_{it+1}}{CO_{it}} = \alpha + \beta InCO_{it} + \sum_{k=1}^{n}\lambda_k Z_{kit} + \rho\sum_{j=1}^{n} w_{ij} In\frac{CO_{it+1}}{CO_{it}} + \sum_{j=1,k=1}^{n}\varphi_k w_{ij} X_{kit} + \varepsilon_{it} \tag{3.6}$$

where $CO_{it}$ represents the amount of carbon emission in year t in province i; α is a constant; $\beta$ is the convergence coefficient; $\rho$ is the spatial regression coefficient; $W$ is the spatial weighted matrix; $\lambda_k$ denotes the regression coefficients of control variables $X_{kit}$; $\varphi_k$ denotes the coefficient of interaction term of the spatial weight and control variables; $\varepsilon_{it}$ is the error term. When $\varphi_k = 0$, $\lambda_k = 0$, Equations (3.5) & (3.6) represent the absolute $\beta$ convergence model and the absolute spatial $\beta$ convergence Durbin model. When $\varphi_k \neq 0$, $\lambda_k \neq 0$, Equations (3.5) & (3.6) represent the conditional $\beta$ convergence model and the conditional spatial $\beta$ convergence Durbin model.

The spatial analysis can be divided into $\beta$-convergence of the spatial error model (SEM) and the spatial autoregressive (SAR) model (Lim, 2016). As shown in Table 3.2, the Hausman test indicates that the fixed effect is better than the random effect in this model. At the same time, according to LM and R-ML tests, the SAR is better than SEM. Therefore, the subsequent analysis focuses on the convergence of provincial carbon emissions based on the SAR model.

Table 3.2 Model selection

| Approach | Statistic | (p-value) | Approach | Statistic | (p-value) |
|---|---|---|---|---|---|
| LM-Spatial_Lag | 3.9124 | 0.048 | LM-Spatial_Error | 0.9756 | 0.323 |
| Robust-LM-Spatial_Lag | 5.1849 | 0.023 | Robust-LM-Spatial_Error | 2.2481 | 0.134 |
| Hausman | 27.8650 | 0.000 | | | |

### 3.3.3 Absolute convergence analysis of provincial carbon emissions

Absolute convergence indicates that the provincial carbon emission will grow to a similar level regardless of provincial resource endowment conditions. As shown in Table 3.3, the $\beta$ is significantly negative both in SEM and in SAR, indicating an absolute $\beta$-convergence in provincial carbon emissions in China.

Table 3.3 Absolute convergence analysis of provincial carbon emissions

| | SEM | | | | SLM | | | |
|---|---|---|---|---|---|---|---|---|
| | Coef. | Std.Err | Z | P>Z | Coef. | Std.Err | Z | P>Z |
| $\beta$ | -0.186 | 0.021 | -8.790 | 0.000 | -0.161 | 0.019 | -8.470 | 0.000 |
| $\lambda$ | 0.307 | 0.050 | 6.130 | 0.000 | | | | |
| $\rho$ | | | | | 0.287 | 0.047 | 6.110 | 0.000 |
| LOG-R | 528.772 | $R^2$ | 0.248 | | LOG-R | 528.997 | $R^2$ | 0.258 |

Table 3.4 Absolute convergence analysis of carbon emissions (inland vs. coastal)

| | Coastal | | | | Inland | | | |
|---|---|---|---|---|---|---|---|---|
| | Coef. | Std.Err | Z | P>Z | Coef. | Std.Err | Z | P>Z |
| $\beta$ | -0.235 | 0.032 | -7.430 | 0.000 | -0.141 | 0.024 | -5.880 | 0.000 |
| $\lambda$ | 0.167 | 0.071 | 2.350 | 0.019 | 0.287 | 0.059 | 4.880 | 0.000 |
| LOG-R | 323.156 | $R^2$ | 0.2161 | | LOG-R | 301.396 | $R^2$ | 0.2161 |

As shown in Table 3.4, $\beta$ is significantly negative both in coastal provinces and inland provinces, indicating absolute β-convergence in both regions. Meanwhile, the convergence coefficient of the coastal provinces is stronger than the inland provinces (−0.235 vs. −0.141) since coastal provinces are economically better developed, and the share of tertiary industry and high-tech industry is higher than the inland provinces. The spatial coefficients ρ and λ are also significantly greater than zero, indicating a significant positive spatial interaction in carbon emissions and that other factors may influence it. Therefore, it is necessary to investigate the conditional $\beta$-convergence based on the spatial models.

### 3.3.4 Conditional convergence analysis of provincial carbon emissions

To test the conditional convergence of provincial carbon emissions, we introduced the conditional variables (i.e., technological innovation (GI), foreign direct investment (FDI), industrial structure upgrading (ISU), energy consumption (EN), urbanization level (URB), industrialization level (ID) into the model.

Table 3.5 shows that the coefficient $\beta$ in both SAR and SEM is significantly negative, indicating that the provincial carbon emissions have significant conditional $\beta$-convergence.

In terms of the control variables, technological innovation has a significant negative effect on provincial carbon emissions overall; energy consumption, industrialization, and urbanization have a significant positive impact on provincial carbon emissions overall.

Table 3.5 Conditional convergence analysis of provincial carbon emissions

| | SEM | | | | SLM | | | |
|---|---|---|---|---|---|---|---|---|
| | Coef. | Std.Err | Z | P>Z | Coef. | Std.Err | Z | P>Z |
| $\beta$ | -0.375 | 0.033 | -11.390 | 0.000 | -0.353 | 0.032 | -11.120 | 0.000 |
| $\lambda$ | 0.259 | 0.055 | 4.700 | 0.000 | | | | |
| $\rho$ | | | | | 0.210 | 0.047 | 4.490 | 0.000 |
| GI | -0.081 | 0.019 | -4.350 | 0.000 | -0.076 | 0.018 | -4.280 | 0.000 |
| FDI | -0.006 | 0.006 | -0.920 | 0.360 | -0.001 | 0.006 | -0.130 | 0.896 |
| ISU | -0.048 | 0.125 | -0.390 | 0.698 | 0.030 | 0.123 | 0.250 | 0.804 |
| PGDP | -0.005 | 0.006 | -0.830 | 0.406 | -0.004 | 0.007 | -0.670 | 0.501 |
| EN | 0.447 | 0.050 | 8.890 | 0.000 | 0.422 | 0.048 | 8.780 | 0.000 |
| URB | 0.002 | 0.002 | 1.160 | 0.244 | 0.002 | 0.002 | 1.090 | 0.276 |
| ID | 0.000 | 0.001 | 0.030 | 0.978 | 0.001 | 0.001 | 0.460 | 0.648 |
| LOG-R | 566.550 | | | | LOG-R | 566.088 | | |
| $R^2$ | 0.423 | | | | $R^2$ | 0.434 | | |

Table 3.6 shows tGhat technological innovation has a negative effect on provincial carbon emissions in both coastal and inland regions; FDI has a significant negative impact on provincial carbon emissions, but its impact on inland provinces is not substantial; energy consumption has a significant positive impact on carbon emissions in both coastal and inland provinces; Urbanization has a significant positive effect on carbon emissions in coastal provinces, but its effect on inland provinces is not significant.

Table 3.6 Conditional convergence analysis of carbon emissions (inland vs. coastal)

| | Coastal provinces | | | | Inland provinces | | | |
|---|---|---|---|---|---|---|---|---|
| | Coef. | Std.Err. | Z | P>Z | Coef. | Std.Err. | Z | P>Z |
| $\beta$ | -0.473 | 0.057 | -8.310 | 0.000 | -0.372 | 0.042 | -8.920 | 0.000 |
| $\rho$ | 0.053 | 0.072 | 0.740 | 0.461 | 0.217 | 0.057 | 3.800 | 0.000 |
| GI | -0.072 | 0.030 | -2.430 | 0.015 | -0.068 | 0.033 | -2.090 | 0.037 |
| FDI | -0.026 | 0.011 | -2.290 | 0.022 | 0.013 | 0.008 | 1.540 | 0.123 |
| ISU | -0.141 | 0.292 | -0.480 | 0.630 | 0.048 | 0.140 | 0.350 | 0.729 |
| PGDP | -0.003 | 0.009 | -0.310 | 0.757 | -0.009 | 0.009 | -1.030 | 0.303 |
| EN | 0.475 | 0.088 | 5.380 | 0.000 | 0.488 | 0.064 | 7.630 | 0.000 |
| URB | 0.006 | 0.002 | 3.210 | 0.001 | -0.002 | 0.003 | -0.640 | 0.525 |
| ID | -0.000 | 0.003 | -0.070 | 0.944 | 0.001 | 0.001 | 0.440 | 0.657 |
| LOG-L | 249.216 | $R^2$ | 0.531 | | LOG-L | 328.610 | $R^2$ | 0.426 |

## 3.4 Implications

China's provincial carbon emissions show significant spatial characteristics and heterogeneity; thus, scholars and policymakers must consider spatial agglomeration and the spatial synergy effect of adjacent provinces. On the one hand, the carbon emissions of neighboring provinces affect each other. Local governments should strengthen the communication and cooperation between neighboring provinces, build a standardized carbon emission governance mechanism, and establish regular consultation and experience sharing across provinces. On the other hand, due to the differences in economic level, cultural, natural resources, and other endowments, there are significant differences in carbon emissions among provinces, and the governance models of carbon emission reduction between coastal and inland provinces are inconsistent. Therefore, local governments should formulate differentiated development strategies and policies for different regions to vigorously promote carbon emission reduction.

Technological innovation plays a critical role in carbon emission abatement in inland and coastal provinces. Thus, Local governments should promote investment in technological innovation, improve the scientific and technical innovation system, and improve the efficiency and management of resources.

Energy consumption is positively related to carbon emissions in inland and coastal provinces. The optimization of energy structure could help with carbon emission reduction. Meanwhile, for coastal provinces, upgrading the industrial structure promotes carbon emission reduction. The factors influencing carbon emission are different due to spatial heterogeneity. Thus local governments should make plans and policies accordingly.

## 3.5 Summary of the chapter

Chapter 3 mainly explores the spatial-temporal characteristics of provincial carbon emissions using panel data from 30 Chinese provinces from 2008 to 2019. IPCC approach is used to measure the total amount of carbon emission in each province. Moran's I is used to test the spatial autocorrelation. Kernel density estimation shows the dynamics and overall trend of provincial carbon emissions. Lastly, spatial econometric models with absolute and conditional $\beta$-convergence analysis are established to investigate the spatial convergence of provincial carbon emission. Findings in this chapter provide support to the research in the following chapters.

# CHAPTER 4 THE DIRECT EFFECT OF TECHNOLOGY INNOVATION ON $CO_2$ EMISSION: EVIDENCE FROM THE CHINESE PROVINCES

## 4.1 Introduction

The international community has gradually recognized that the greenhouse effect has become a significant challenge and threat. As a responsible country, China has announced the "30 · 60" carbon peak, carbon neutralization, and the target of the Paris Agreement, and has devoted itself to continue exploring the environmental-friendly development model to realize the green transformation of the economy. The Chinese government has always been committed to innovating carbon emission policies and has incorporated the "30 · 60" goals into the country's 14th five-year and the Vision 2035 Plan. However, compared to developed countries such as the United States, China's carbon emission reduction goal is much more challenging with tight and heavy tasks, especially with the uncertainties in the post-pandemic era.

Although scholars have explored carbon emission reduction paths, most of them focus on the influencing factors of carbon emissions. There is a lack of research on the factors that inhibit carbon emissions. Scholars believe that industrial structure upgrades and energy substitution are vital to carbon emission reduction. Meanwhile, scholars also argue the importance of technological innovation to carbon emission. Nevertheless, scholars have found mixed findings regarding the nexus of technological innovation and carbon emission due to diverse research perspectives. Regional economic and cultural differences cannot be neglected. Therefore, based on the interactive spatial characteristics of technological innovation and carbon emissions, this chapter used a space Durbin model to identify the effect of technology innovation on provincial carbon emissions.

## 4.2 Related literature

### 4.2.1 Technology innovation and its impact on $CO_2$ emission reduction

Previous literature explores the impact of technological innovation on carbon emissions, but the results are inconsistent. On the one hand, technological innovation promotes energy and resource efficiencies and clean energy and materials by replacing non-renewable energy and materials, energy-saving methods, carbon capture and storage technologies (CCS), and so forth, thus saving natural resources and reducing carbon emissions. On the other hand, technological progress increases economic activities and the demand for fuel and raw materials, thus increasing carbon emissions. Moreover, scholars pointed out the regional differences in technological innovation and the rebound effect of carbon emissions due to regional economic levels and environmental policies (Yang & Li, 2017).

Scholars have concluded that technological innovation is the core of regional carbon abatement and has led to the continuous improvement and development of the innovation system. However, from the results, the conversion rate of innovation is not ideal. Firstly, compared with traditional technological innovation, green elements need to be integrated into green innovation, and higher R&D capital needs to be invested in the early stage of technology development. Moreover, with an uncertain market environment, the risks are higher. Thus, small and medium-sized enterprises (SMEs) are limited by resources and will choose to avoid green R&D investment. Moreover, when radical technology innovation is introduced, the original production line and supporting facilities may be disrupted, and relevant employees and managers must be trained. The cost of labor and production transformation is also high, discouraging firms' innovative behavior.

Secondly, firms' social-environmental awareness is not sufficient. Under no government environmental regulation, firms are profit-driven and focus on short-term interests, ignoring the problem of high carbon emissions; the lack of a national green innovation system and professional talents also constrain firms to carry out technological innovation.

Thirdly, the patent protection system (e.g., intellectual property protection) has not yet been formed in China, and the government's support for technological innovation, especially green innovation, is insufficient. Carbon emissions are unique economic "accessory," and the governance and treatment of carbon emissions cannot rely solely on the power of the market due to its public goods attributes and negative externalities.

### 4.2.2 The threshold effect of environment regulation

Environmental regulation is an administrative measure taken by the state in response to the failure of market ecological governance, which can effectively avoid the negative externalities of carbon emissions with careful consideration of short-term and long-term interests. The environmental regulations restrict the number of carbon emissions.

Chapter 2 finds that technological innovation is not always good for local carbon abatement. Considering that when environmental regulation in a province is already stringent, it may have a lower carbon emission level, therefore, the effect of increasing input in technological innovation may not be not as good as rising that in regions with loose environmental regulations. Thus, we need to consider environmental regulation as the threshold variable.

Companies will neglect environmental degradation without government intervention while pursuing economic benefits without necessary ecological compensation. Environmental regulation is an administrative measure taken by the state in response to the failure of market ecological governance, which can effectively avoid the negative externalities of carbon emissions and balance short-term and long-term benefits.

When facing government environmental regulations, firms do not passively accept punishment but actively adjust their development strategies to activate their innovation potential, bringing additional benefits through green innovation and making up for the governance costs brought about by environmental regulations (Dechezleprêtre & Sato, 2017).

## 4.3 Research model and research design

### 4.3.1 Spatial regression model

Traditional linear regression models do not consider the spatial autocorrelation among the variables, which may lead to estimation error. The spatial economic models that take spatial interaction into account are appropriate in this study, including a spatial error model (SEM) and a spatial lag model (SAR). The spatial Durbin model (SDM) combines the advantages of SAR and SEM models, which can analyze the spatial correlation between technological innovation and carbon emissions and explore the spatial impact of random shocks. The spatial Durbin model is given by Equation 4.1:

$$CO_{it} = \beta_0 + \rho WCO_{it} + \beta_1 GI_{it} + \beta_2 X_{it} + \theta_1 WGI_{it} + \theta_2 WX_{it} + \omega_{it} \tag{4.1}$$

where $CO_{it}$ and $GI_{it}$ represent carbon emissions and technological innovation from province $i$ in year $t$; $\rho$ and $\theta$ represents a spatial coefficient; $X_{it}$denotes other control variables; $\omega_{it}$ is an error term. When the value of $\theta$ in equation (4.1) is equal to 0, the SDM model will degenerate into a SAR model, and when $\theta_i$=$-\beta_i$, the SDM model will degenerate into an SEM model.

In addition, a geographical distance matrix is used to reflect the spatial linkages between research units. The matrix element is defined by Equation (4.2), where $d_{ij}$ represents the geographical distance between the capitals of provinces $i$ and $j$.

$$W_{ij} = \frac{1}{d_{ij}^2}, i \neq j \tag{4.2}$$

### 4.3.2 Moran's I and Moran scatter diagram

Moran's I methods and calculations are the same as in section 3.2.1.

### 4.3.3 Hansen threshold model

This study introduced a panel threshold model to explore further the effect of technological innovation on carbon emission under different environmental regulations.

$$CO_2 = a_0 + a_1 GI\{ER \leq \varphi\} + a_2 GI\{ER \geq \varphi\} + \tau X_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{4.3}$$

where *ER* (environment regulation) is the threshold variable and $\varphi$ is the threshold level; $X_{it}$ denotes other control variables; $\varepsilon_{\mathrm{it}}$ is an error term.

### 4.3.4 Data description

In order to analyze the impact of technological innovation on provincial carbon emissions, we used data from 30 provinces (excluding Tibet, Taiwan, Hong Kong, and Macao due to data unavailability) gathered from the China Energy Statistical Yearbook, China Statistical Yearbook, China Environmental Statistical Yearbook, China Industrial Statistical Yearbook, and China Science and Technology Yearbook.

#### 4.3.4.1 Carbon emissions (CE)

The total provincial carbon emissions calculation is the same as in section 3.1.1.

#### 4.3.4.2 Technological innovation

This research mainly concerns the impact of increasing technological capital on carbon emissions. Following research that studies the influence and contribution of technology innovation, this research uses a perpetual inventory method to measure the technological innovation (Bin, 2008; C. Chen et al., 2022; K. Chen et al., 2018). Thus technological innovation is measured by technological investment. The R&D capital stock *K* is calculated by Equation (4.4):

$$K_t = (1-\delta)K_{t-1} + RDI_t \tag{4.4}$$

$$K_0 = RDI_1 / (g+\delta) \tag{4.5}$$

where $RDI_t$ denotes the R&D expenditure in year $t$; δ is the depreciation rate of R&D capital. The initial technology capital stock $K_0$ is calculated based on the annual growth rate of R&D expenditure and defined as Equation (4.5). $g$ is the annual growth rate of R&D expenditure.

#### 4.3.4.3 Other variables

Foreign direct investment (FDI): This paper used the logarithm of the total foreign investment to measure FDI.

Provincial GDP (PGDP): Economic development significantly impacts carbon emissions. Economic growth accelerates the circulation of resources and goods, thus leading to increased industrial activities and ultimately increasing carbon emissions. PGDP is calculated using the logarithm of provincial per capita GDP.

Energy consumption (EN): Most energy consumption is dominated by fossil fuels, which are sources of carbon emissions. In this study, EN is measured by the total energy consumption.

Industrialization level (ID): There is a complex relationship between industrialization and regional environmental quality. The traditional industrial system is the primary source of regional environmental pollution. However, the development of information technologies and production technologies alleviates regional environmental. The study used the ratio of the secondary industry to regional GDP to measure the industrialization level.

Urbanization (URB): Urban expansion, infrastructure construction, and housing construction consume many energy-intensive products such as steel and cement, resulting in significant carbon emissions. Therefore, urbanization is another cause of environmental degradation. In this study, urbanization is measured by the ratio of the end-of-year urban population to the total population.

Industrial structure upgrade (ISU): Industrial structure evolves from low-end to high-end industries. To characterize the degree of domestic industrial structure upgrading, we used a composite index to show this trend, given by Equation (4.6):

$$ISU = W_1 + 2W_2 + 3W_3 \tag{4.6}$$

where $W_1$, $W_2$, and $W_3$ denote the proportion of the primary, secondary, and tertiary industries, their weight is given as 1, 2, and 3, representatively. The higher the ISU index, the more significant the upgrade of provincial industrial structure.

#### 4.3.4.4 Threshold variable: environmental regulation

Environmental regulation (ER): ER is measured by calculating a comprehensive index that combines the utilization rate of industrial solid waste, the ratio of the operating cost of industrial waste gas treatment to the amount of industrial waste gas discharge, and the percentage of the operating cost of industrial wastewater treatment to the amount of industrial wastewater discharge, and we used an entropy method to determine the weights for the indicators.

## 4.4 Empirical analysis

The descriptive statistics of variables are shown in Table 4.1.

Table 4.1 Descriptive statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $CO_2$ | 360 | 9.086 | 0.744 | 7.036 | 10.655 |
| GI | 360 | 6.759 | 1.496 | 2.079 | 10.097 |
| PGDP | 360 | 10.651 | 0.524 | 9.196 | 12.009 |
| ISU | 360 | 2.348 | 0.131 | 2.102 | 2.832 |
| FDI | 360 | 12.719 | 1.649 | 7.310 | 15.086 |
| URB | 360 | 55.521 | 13.186 | 29.112 | 89.632 |
| EN | 360 | 9.377 | 0.672 | 7.034 | 10.625 |
| ID | 360 | 45.232 | 8.681 | 16.214 | 61.532 |

### 4.4.1 Spatial autocorrelation analysis

As shown in Figure 4.1, global Moran's I indexes are positive and statistically significant, indicating a positive spatial correlation between technological innovation and provincial carbon emissions and that provinces with similar technological innovation and carbon emissions have a spatial agglomeration effect. In terms of provincial carbon emissions, the value of Global Moran's I shows a decreasing trend from 2008 to 2013, indicating decreasing agglomeration effect. The value of Global Moran's I increased with fluctuations from 2013 to 2019, indicating a gradually strengthened agglomeration effect. In terms of technological innovation, the value of Global Moran's I shows an increasing trend from 2008 to 2019, indicating a more substantial spatial agglomeration during this period.

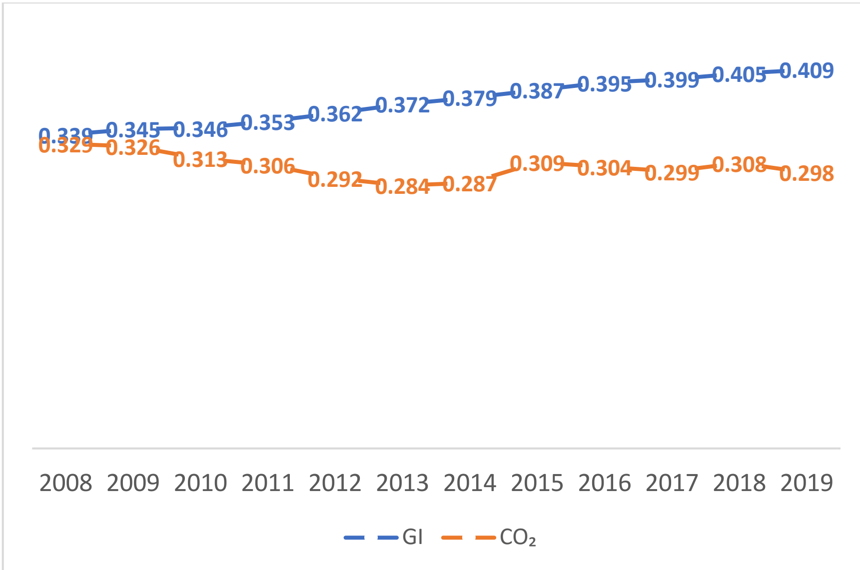



Figure 4.1 Spatial autocorrelation of Technological innovation and provincial carbon emissions

In order to visualize local spatial autocorrelation and spatial heterogeneity, the spatial distribution is divided into four categories:high-high, high-low, low-low, and low-high agglomeration. The Moran's I scatter diagram of technological innovation based on the geographical weight matrix is provided using data in 2008 and 2019 as samples (Figure 4.2).

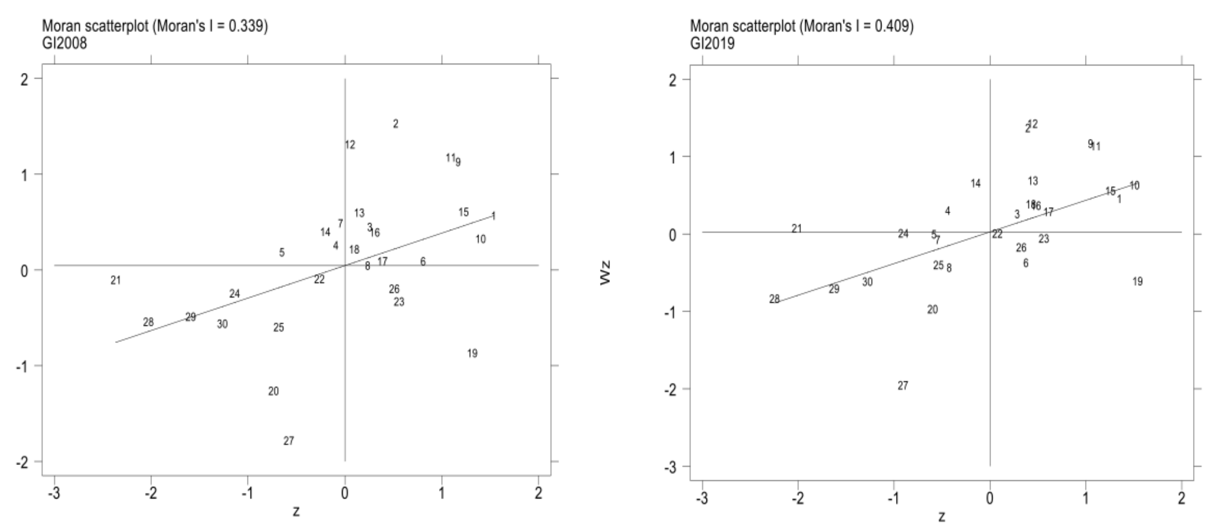



Figure 4.2 Moran scatter diagram of technological innovation in 2008 and 2019

The results show that technological innovation is mainly concentrated in the first and third quadrants, showing a positive spatial autocorrelation. In 2008, seven provinces showed a negative spatial autocorrelation, among which four provinces were in the second quadrant and three were in the fourth quadrant; In 2019, seven provinces showed a negative spatial autocorrelation, among which three provinces were in the second quadrant, and four are in the fourth quadrant.

### 4.4.2 Spatial econometrics model

In order to demonstrate the relationship between variables, spatial econometric models are introduced for empirical analysis. The Hausman test verifies that the fixed-effects model is more suitable than the random-effects model. At the same time, with the help of LM and R-LM tests, the SAR model is better than the SEM model, and it can also be seen from the Wald and LR tests that the SDM model cannot be degraded to SAR, SEM, see Table 4.2.

Table 4.2 Model selection

| Methods | Stat. | Prob. | Methods | Stat. | Prob. |
|---|---|---|---|---|---|
| LM-Spatial_Lag | 3.912 | 0.048 | Wald-Spatial_Lag | 42.410 | 0.000 |
| Robust-LM-Spatial_Lag | 5.185 | 0.023 | LR-Spatial_Lag | 40.563 | 0.000 |
| LM-Spatial_Erro | 0.976 | 0.323 | Wald-Spatial_Erro | 30.145 | 0.000 |
| Robust-LM-Spatial_Erro | 2.248 | 0.134 | LR-Spatial_Erro | 28.290 | 0.000 |

Table 4.3 shows the parameter estimation of the SDM model and the estimated results of direct, indirect, and total effects of explanatory variables. The parameter estimate of GI is 0.086, which passes the test at the 10% significance level. It can be seen that there is a significant effect of technological innovation in abating provincial carbon emissions; that is, for every percentage increase in technological innovation, carbon emissions are reduced by 0.086%.

The parameter estimates of *GI*, *PGDP*, *ISU*, *FDI*, *EN*, *URB,* and *ID* in Table 4.3 are consistent with the direct effect results, indicating that these factors influence a province's carbon emissions. The coefficients of the *EN* and *URB* are positive and significant at the 1% confidence level, indicating that these variables will increase carbon emissions. Therefore, energy consumption and urbanization will increase carbon emissions.

The spatial lagged variables of explanatory variables indicate the impact of a province's carbon emission reduction drivers on the carbon emissions of neighboring provinces. Among them, the coefficients of *W*PGDP*, *W*ISU*, and *W*FDI* are all positive and significant, indicating that a province's own economic growth, industrial structure upgrade, and foreign investment positively drive carbon emissions of neighboring provinces. The estimation of *W*GI* is negative but not significant, indicating that at this stage, the effect of technological innovation in one province can not lead to carbon emission reduction in its neighboring provinces. The indirect effect indicates the cumulative effect value of the spatial spillover of adjacent regions. According to the results, only *PGDP*, *ISU*, and *FDI* have significant cumulative spatial spillover effects. The total impact reflects the accumulation of its driving factors and the spatial spillovers from various factors. The results show that technological innovation's direct, indirect, and total effect on carbon emissions are negative, and the main contribution comes from the direct inhibitory effect. The overall effects of industrial structure upgrading, foreign investment, and energy consumption are positive and significant. *ISU* and *FDI* are dominated by spatial effects, and *EN* is dominated by direct effects.

Table 4.3 Spatial Durbin Estimation

| $CO_2$ | SDM | | Direct effect | | Indirect effect | | Total effect | |
|---|---|---|---|---|---|---|---|---|
| | Coef. | p | Coef. | p | Coef. | p | Coef. | p |
| GI | $-0.086^{*}$ | 0.053 | $-0.090^{*}$ | 0.053 | -0.108 | 0.117 | $-0.198^{***}$ | 0.010 |
| PGDP | 0.001 | 0.951 | 0.003 | 0.791 | $0.041^{*}$ | 0.052 | 0.044 | 0.118 |
| ISU | -0.164 | 0.346 | -0.079 | 0.644 | $1.133^{***}$ | 0.000 | $1.054^{***}$ | 0.004 |
| FDI | -0.007 | 0.440 | -0.004 | 0.672 | $0.054^{***}$ | 0.002 | $0.050^{**}$ | 0.021 |
| EN | $1.159^{***}$ | 0.000 | $1.165^{***}$ | 0.000 | 0.099 | 0.447 | $1.264^{***}$ | 0.000 |
| URB | $0.007^{***}$ | 0.001 | $0.007^{***}$ | 0.001 | -0.002 | 0.571 | 0.005 | 0.243 |
| ID | -0.002 | 0.353 | -0.002 | 0.406 | 0.001 | 0.712 | -0.001 | 0.894 |
| W*GI | -0.078 | 0.249 | | | | | | |
| W*PGDP | $0.035^{*}$ | 0.058 | | | | | | |
| W*ISU | $1.005^{***}$ | 0.000 | | | | | | |
| W*FDI | $0.049^{**}$ | 0.002 | | | | | | |
| W*EN | -0.114 | 0.400 | | | | | | |
| W*URB | -0.003 | 0.444 | | | | | | |
| W*ID | 0.001 | 0.690 | | | | | | |

Note: $^{***}$, $^{**}$, and $^{*}$ represent confidence level at 1%,5%, and 10%, representitively.

### 4.4.3 Quantile regression analysis

The panel quantile regression can effectively reflect the differential impact of technological innovation in abating regional carbon emissions. To this end, panel quantile regression was introduced, and three quantile points of 0.25-0.5-0.75 were selected for quantile regression. The regression results are shown in Table 4.4.

Compared with Table 4.3, there are differences in the role of technological innovation under different quantiles of carbon emissions. Overall, the direction of the coefficients of the panel quantile regression is consistent with Table 4.4.

Table 4.4 Quantile regression analysis

| | 25th quantile | | | 50th quantile | | | 75th quantile | | |
|---|---|---|---|---|---|---|---|---|---|
| $CO_2$ | Coef. | SE | Z | Coef. | SE | Z | Coef. | SE | Z |
| GI | -0.023*** | 0.040 | -5.56 | -0.176*** | 0.046 | -3.82 | -0.245*** | 0.058 | -4.21 |
| PGDP | -0.085** | 0.032 | -2.68 | -0.044 | 0.028 | -1.58 | -0.061** | 0.034 | -1.78 |
| ISU | -1.068** | 0.491 | -2.18 | -0.343 | 0.31 | -1.1 | 0.168 | 0.407 | 0.41 |
| FDI | 0.022 | 0.041 | 0.52 | 0.012 | 0.028 | 0.42 | 0.037** | 0.021 | 1.72 |
| EN | 1.329*** | 0.056 | 23.94 | 1.196*** | 0.049 | 23.94 | 1.257*** | 0.085 | 14.77 |
| URB | 0.016*** | 0.003 | 5.17 | 0.006** | 0.002 | 2.69 | 0.001 | 0.003 | 0.21 |
| ID | -0.009* | 0.005 | -1.66 | 0.001 | 0.003 | 0.29 | 0.001 | 0.004 | 0.23 |
| Cons | 2.574 | 1.136 | 2.27 | 1.381 | 0.711 | 1.94 | 0.979 | 0.864 | 1.13 |
| Mean dependent var | 9.086 | | | | SD dependent var | | 0.744 | | |

Note:***,** ,and * represent confidence level at 1%,5%, and 10%, representitively.

Under different quantiles, the strength of technological innovation in abating carbon emissions shows an overall upward trend with the increase of quantiles. In the 75th quantile, with an increase of 1 percentage of technological innovation, carbon emissions will be reduced by 0.245%. In the 50th quantile, with an increase of 1 percentage of technological innovation, carbon emissions will be reduced by 0.176%. In the 25th quantile, with an increase of 1 percentage of technological innovation, carbon emissions will be reduced by 0.023%. It can be seen that the effect of technological innovation on provincial carbon emissions is positively correlated with the intensity of local carbon emissions; that is, the more considerable amount of carbon emissions in a province, the more significant the effect of technological innovation on carbon abatement.

### 4.4.4 Endogeneity test

Table 4.5 SYS-GMM results

| $CO_2$ | Coef. | St.Err. | p-value | CI | |
|---|---|---|---|---|---|
| $L.CO_2$ | 0.711*** | 0.038 | 0.000 | 0.637 | 0.785 |
| GI | -0.192*** | 0.018 | 0.000 | -0.227 | -0.157 |
| PGDP | -0.007* | 0.004 | 0.079 | -0.016 | 0.001 |
| FDI | 0.013*** | 0.005 | 0.004 | 0.004 | 0.023 |
| CZ | 0.011*** | 0.003 | 0.001 | 0.004 | 0.017 |
| ISU | 0.233 | 0.216 | 0.277 | -0.19 | 0.655 |
| URB | 0.457*** | 0.051 | 0.000 | 0.357 | 0.557 |
| ID | 0.003* | 0.002 | 0.074 | 0 | 0.007 |
| Constant | 0.002 | 0.752 | 0.998 | -1.468 | 1.472 |
| Number of obs | 330 | AR(1) p-value | | 0.000 | |
| Sargan p-value | 0.987 | AR(2) p-value | | 0.556 | |

Note:***,** ,and * represent confidence level at 1%,5%, and 10%, representitively.

Endogenous is a significant problem in spatial econometric models. We used a system-GMM estimator to deal with endogeneity concerns, and the results are shown in Table 4.5. The results from SYS-GMM are consistent with the results from the spatial Durbin model.

### 4.4.5 Heterogeneity test

The contribution of technological innovation to carbon emission reduction may depend on the specific social and economic environment. In 2013, China promulgated the "Ten Air Regulations" to enforce gas governance. Innovation-driven economic development becomes the core of green economic development. We focused on the relationship between technological innovation and carbon emissions for six years before and after 2013. In addition, inland and coastal provinces also have significant differences in technology development, social and economic level, and resource endowments. In order to identify the heterogeneity, we grouped the 30 provinces into inland and coastal and compared the differences in the results.

As shown in Table 4.6, from 2008 to 2013, *ISU* and *FDI* have a significant negative impact on provincial carbon emissions, and *URB* positively impacts provincial carbon emissions. From 2014 to 2019, *GI*, *FDI*, and *ID* have a significant negative impact on provincial carbon emissions. From 2008 to 2019, *EN* always has a significant positive impact on provincial carbon emissions. Moreover, from 2014 to 2019, the coefficient of *W*GI* is negative and significant, indicating that technological innovation in one province has an inhibiting effect on surrounding provinces' carbon emissions; the coefficients of *W*FDI*, *W*URB*, and *W*ID* are positive and significant, indicating that foreign direct investment, urbanization, and industrialization in one province raise carbon emissions in surrounding regions.

Compared with the coastal provinces, technological innovation in the inland provinces significantly reduces carbon emissions. FDI reduces carbon emissions in the coastal areas while increasing carbon emissions in the inland provinces. Energy consumption in both inland and coastal provinces raised carbon emissions. Technological innovation in one coastal province grew carbon emissions in its surrounding regions, but it has a neglectable spatial spillover effect in the inland provinces.

Table 4.6. Heterogeneity analysis

| | 2008-2013 | 2014-2019 | Coastal | Inland |
|---|---|---|---|---|
| $CO_2$ | Coef. | Coef. | Coef. | Coef. |
| GI | -0.060 | -0.197** | -0.114 | -0.145** |
| PGDP | 0.009 | 0.006 | -0.006 | -0.012 |
| ISU | -0.502** | 0.133 | -0.262 | -0.322 |
| FDI | -0.053*** | -0.036*** | -0.051*** | 0.047*** |
| EN | 1.167*** | 1.374*** | 0.658*** | 1.217*** |
| URB | 0.007* | 0.002 | 0.014*** | -0.006 |
| ID | -0.002 | 0.005** | -0.003 | -0.003 |
| W*GI | 0.138 | -0.245** | 0.484*** | -0.083 |
| W*GDP | -0.005 | 0.006 | -0.005 | -0.008 |
| W*ISU | -0.072 | 0.381 | 0.394 | 0.658* |
| W*FDI | 0.030 | 0.043*** | 0.035 | 0.026 |
| W*EN | -0.132 | -0.370 | -0.626** | 0.101 |
| W*URB | 0.000 | 0.012** | 0.021*** | 0.009 |
| W*ID | -0.002 | 0.008** | -0.003 | -0.004 |

Note:***,** ,and * represent confidence level at 1%,5%, and 10%, representitively.

## 4.4.6 Other robustness checks

To probe the robustness of the findings, we performed two additional tests. Firstly, we replaced the measurement of our independent variable with the output of technological innovation (i.e., patent number) and reran the model.

Table 4.7. Robustness checks

| Economic distance weight | | | | Alternative measurement | | | |
|---|---|---|---|---|---|---|---|
| $CO_2$ | Coef. | SE | Z | $CO_2$ | Coef. | SE | Z |
| GI | -0.140*** | 0.041 | -3.410 | GI | -0.044*** | 0.018 | -2.460 |
| PGDP | -0.006 | 0.010 | -0.570 | PGDP | 0.004 | 0.010 | 0.370 |
| ISU | -0.071 | 0.185 | -0.380 | ISU | -0.249 | 0.165 | -1.500 |
| FDI | -0.007 | 0.009 | -0.780 | FDI | -0.010 | 0.009 | -1.170 |
| EN | 1.092*** | 0.063 | 17.450 | EN | 1.171*** | 0.054 | 21.680 |
| URB | 0.007*** | 0.002 | 3.040 | CZ | 0.006*** | 0.002 | 2.880 |
| ID | 0.001 | 0.002 | 0.340 | IN | -0.004** | 0.002 | -1.970 |
| | | | | | | | |
| W*GI | -0.104 | 0.114 | -0.920 | GI | 0.013 | 0.027 | 0.460 |
| W*PGDP | -0.052* | 0.029 | -1.800 | PGDP | 0.045*** | 0.018 | 2.490 |
| W*ISU | -0.073 | 0.567 | -0.130 | ISU | 0.951*** | 0.262 | 3.630 |
| W*FDI | -0.055** | 0.024 | -2.250 | FDI | 0.036** | 0.015 | 2.450 |
| W*EN | 0.287* | 0.169 | 1.700 | EN | -0.229* | 0.120 | -1.910 |
| W*URB | -0.003 | 0.006 | -0.540 | CZ | -0.004 | 0.004 | -1.090 |
| W*ID | 0.006 | 0.005 | 1.220 | IN | -0.001 | 0.003 | -0.500 |
| $\rho$ | -0.396*** | 0.109 | -3.640 | rho | 0.186*** | 0.060 | 3.110 |

Note:***,** ,and * represent confidence level at 1%,5%, and 10%, representitively.

Secondly, we used the economic distance as our weight matrix in the spatial Durbin model instead of geographical distance. The results of the two robustness checks are shown in Table 4.7. The results confirmed that technological innovation negatively affects provincial carbon emissions, but the spatial spillover effect is insignificant.

### 4.4.7 Threshold analysis

We also used the Hansen threshold analysis considering environmental regulation as the threshold variable and investigated the role of technological innovation in abating provincial carbon emissions. The threshold test is shown in Table 4.8.

Table 4.8. Threshold effect test

| Variable | Environmental regulation as the threshold variable |
|---|---|
| 95% confidence interval of single threshold estimation | 11.964 [11.759, 12.019] |
| F- statistics | 22.15 |
| MSE | 0.005 |
| 1% critical value | 32.497 |
| 5% critical value | 23.794 |
| 10% critical value | 19.416 |

Table 4.9. Regression estimation results of the panel threshold model

| $CO_2$ | Coef. | SE | T | P>t | CI | |
|---|---|---|---|---|---|---|
| ID | 0.001 | 0.002 | 0.900 | 0.368 | -0.002 | 0.005 |
| EN | 1.131 | 0.051 | 22.140 | 0.000 | 1.031 | 1.232 |
| ISU | -0.374 | 0.180 | -2.080 | 0.038 | -0.729 | -0.020 |
| FDI | 0.002 | 0.009 | 0.230 | 0.816 | -0.016 | 0.021 |
| URB | 0.005 | 0.002 | 2.180 | 0.030 | 0.000 | 0.009 |
| PGDP | -0.011 | 0.010 | -1.120 | 0.265 | -0.030 | 0.008 |
| GI \| ER<11.964 | -0.102 | 0.025 | -4.100 | 0.000 | -0.151 | -0.053 |
| GI \| ER>11.964 | -0.099 | 0.025 | -3.990 | 0.000 | -0.149 | -0.050 |
| trim(0.01 0.01) grid(300) bs(500 500) | | | | | | |

We carried out the regression analysis using environmental regulation as the threshold variable based on the threshold test. The results of the threshold effect test are shown in Table 4.9. It can be seen that when the environmental regulation exceeds the threshold value of 11.964, the coefficient of GI increases changed from -0.102 to -0.099, indicating that when environmental regulation is above the threshold level, the effect of technological innovation on abating carbon emissions is slightly weakened. When environmental regulation is relatively strict, firms that try to meet the environmental requirements face high costs when dealing with pollution; firms may be under a situation where the provision of regulation exceeds the firm's technical capability. Thus, the effect of technological innovation on provincial carbon abatement is weaker when environmental regulation is above the threshold.

## 4.5 Conclusions

This chapter tested the effect of technological innovation on carbon emission using panel data of 30 provinces in China between 2008 and 2019 using the Global Moran's I, Moran scatter diagram, spatial Durbin model, and panel threshold model. The main findings are:

- Technological innovation and provincial carbon emissions show positive spatial agglomeration effect and spatial autocorrelation.
- Technological innovation negatively affects provincial carbon emissions, and technological innovation has a more substantial carbon abating effect in provinces with higher emissions.
- The effect of technological innovation on carbon emission shows significant temporal-spatial heterogeneity.
- There is a single threshold effect of environmental regulation on the impact of technological innovation on provincial carbon emissions. When environmental regulation is above the threshold, the effect of technological innovation on abating carbon emission slightly decreases.

# CHAPTER 5 THE EFFECT OF TECHNOLOGICAL INNOVATION ON $CO_2$ EMISSION: THE MEDIATING ROLE OF INDUSTRIAL STRUCTURE UPGRADE AND ENERGY STRUCTURE ADJUSTMENT

## 5.1 Introduction

Since its Open-up in 1978, China has achieved significant social and economic development and environmental degradation due to industrial activities and resource structure. Technological innovation has become the core of China's transformation toward a high-quality and sustainable economy. Technology has changed to economic development mode from extensive growth to innovative growth (Huang et al., 2021). Meanwhile, technological innovation is one of the main drivers of industrial structure change. It brings new products and new industries and eliminates backward technology and industries with low production efficiency. Technological innovation promotes the upgrade of industrial structure towards capital-intensive and technology-intensive industries and optimizes the scale and structure of demand. Industries with high energy consumption and increased carbon emissions will be gradually eliminated with the development of advanced technologies.

Energy consumption is the main source of carbon emissions. China's energy carbon emissions account for more than 90%, and industrial carbon emissions account for more than 70% of energy consumption carbon emissions. In the State Council's 2030 Carbon Peak Action Plan, the upgrading of the industrial structure and the optimization of the energy consumption structure are clearly identified as important tasks in achieving the dual carbon goal.

Technological innovation promotes upgrading industrial and energy structure adjustment, thus indirectly reducing carbon emissions. Moreover, technological innovation can improve or replace high carbon emission energy sources such as fossil fuels, reduce the input and consumption of traditional fossil energy with clean and renewable energy, and improve energy efficiency and structure. Therefore, this chapter focuses on the mediating effect of industrial structure upgrade and energy structure adjustment of technology-driven carbon abatement.

## 5.2 Literature review and hypothesis development

### 5.2.1 Technological innovation and industrial structure upgrade

The upgrading of industrial structure in China refers to increasing the proportion of tertiary industry (service industry and the circulation industry such as transportation, financial, technical service industries, and so forth) in the national economy (Chen & Zhao, 2019). China's tertiary sector accounted for 53.9% of the total industries in 2019 (Lin & Zhou, 2021), which is much lower than the developed countries. As the source of industrial activities, natural resources are the basis of economic activities and, to a certain extent, determine the path and mode of economic development. Resource-based industries are both leading, and pillar industries in many provinces of China, and they are also closely related to other industries. With the further development of China's economy, the demand for natural resources will maintain a growth trend, and it is impossible to alleviate the resource pressure by comprehensively reducing production. The country cannot entirely abandon the resource-based industries in the short term without hurting the smooth transition of the economy and industrial structure.

Technological innovation is critical considering the natural resource constraints on industrial change because it provides renewable substitutes for natural resources (e.g., clean energies) and materials and increases their utilization efficiency. Technology progress and innovation can improve the efficiency of natural resource utilization and optimize the allocation of resources and market demand. Technological innovation transfers production factors from primary and secondary to tertiary industries, forming emerging industries and promoting industrial upgrading. Secondly, technological innovation influences the direction and speed of industrial development (Su et al., 2021). The increasing level of technological innovation could raise the efficiency of resource allocation and bring capital investments and labor to industries with higher production efficiency, thus improving the rationalization of industrial structure. Technological innovation has a "selection" effect on industrial structure such that resources and material inputs flow into new industries that have improved efficiencies and demanding products (Peneder, 2003). Thirdly, technological innovation can promote product R&D, and improve output efficiency and product added value in both the production and sales processes. Therefore, we propose that:

Hypothesis 1: Technological innovation is positively associated with provincial industrial structure upgrades.

### 5.2.2 Industrial structure upgrade and carbon emissions

Carbon intensity varies from industry to sector. Provinces with different industrial structures may significantly influence regional carbon emissions. The industrial structure determines the allocation of production elements (e.g., labor, technology, energy, labor, and so forth) so that it determines the emission and pollution associated with industrial activities. Currently, China's industrial sectors are dominated by energy-intensive industries. Industrial structure upgrades shift production from low-value-added, high-emission industries to high-value-added, low-carbon industries, thus reducing the proportion of pollution-intensive industry output value in the national economy and improving carbon emission efficiency.

Scholars found that improving the rational industrial structure could mitigate carbon emissions and increase resource utilization efficiency (Z. Li et al., 2017; Shao et al., 2016). Previous empirical evidence showed that industrial structure upgrades negatively affect carbon emissions. For example, Shen et al. (2018) found that industrial structure adjustments significantly contribute to carbon emission reduction in Beijing between 1995 and 2004. Zheng et al. (2019) explored regional development patterns in China and found that industrial structure reduced carbon emissions by 1% from 2013 to 2016. Therefore, industrial structure upgrades will promote carbon emission reduction. Taken together with H1, we proposed that:

Hypothesis 2: The negative effect of technological innovation on regional carbon emissions is mediated by industrial structure upgrades.

### 5.2.3 Technological innovation and energy structure adjustment

With the rapid development of clean energy technology, its production and utilization costs are also reduced. The energy consumption structure is optimized through substituting fossil fuels with clean energies, thus increasing the proportion of clean energy consumption and decreasing the proportion of fossil energy consumption, thereby reducing carbon emissions.

On the one hand, technological innovation can improve the efficiency of fossil energy, thus decreasing the consumption of high-emission fuels. Tandon & Ahmed (2016) applied structural decomposition analysis and found that technological change in economic production significantly contributes to energy saving and lowers the demands for additional energy in India. Wang & Wang (2020) applied the Malmquist-Luenberger index and a panel dataset of 284 Chinese cities to estimate total factor energy efficiency (TFEE) and found that technological innovation increases TFEE. Pan et al. (2019) used structure vector autoregression and a panel dataset of 30 provinces in China and found that market incentive environmental regulation drives energy efficiency through technological innovation.

On the other hand, it can promote the development of clean energy and promote the continuous optimization of the energy structure. Affordability is the major challenge facing the clean and renewable energy consumption (Singh & Ru, 2022). In order to ensure affordable energy and better living quality, heavy investment in technology is required (Nathwani & Kammen, 2019).

With innovation in energy technologies, clean and renewable energy becomes more affordable, and traditional energy becomes more efficient, thus optimizing the energy structure through increasing the proportion of clean energy consumption and reducing the proportion of fossil fuel consumption in total energy consumption. Therefore, we propose that:

Hypothesis 3: Technological innovation is negatively associated with the proportion of fossil fuel consumption in total energy consumption.

### 5.2.4 Energy structure adjustment and carbon emissions

Energy structure refers to the composition of energy consumption. China's energy consumption currently heavily relies on fossil fuels, especially coal. Energy structure adjustment promotes the substitution of fossil fuels with low-carbon and renewable energy to reduce the proportion of non-renewable energy. Li et al. (2021) used an expanded STIRPAT model and found that energy structure (i.e., the proportion of coal consumption) is highly related to carbon emissions but the intensity of its impact varies significantly with the economic development levels. Ge et al. (2022) found a positive correlation between coal consumption and carbon emissions, and they also found a negative correlation between non-fossil energy consumption and carbon emissions. Therefore, adjustment toward a cleaner energy structure will promote carbon emission reduction. Taken together with H3, we propose that:

Hypothesis 4: The negative effect of technological innovation on carbon emission is mediated by energy structure (i.e., the proportion of coal consumption in total energy consumption).

### 5.2.5 Technological innovation and environmental regulations

Porter & Linde (1995) suggested that firms will perform more innovation activities to offset the environmental costs under appropriate environmental regulation. When the government implements a strict environmental pollution regulation, pollution abatement expenditures rise. Firms are facing significant regulatory pressure on emission control. In that regard, innovative technologies might reduce the cost of carbon emission control and environmental production. Environmental regulation strengthens the effect of technological innovation on carbon emissions. Environmental regulation will lead to the reallocation of resources among different sectors and push capital investment, talents, and other resources towards environmentally friendly industries, thereby promoting carbon emission reduction driven by technological innovation. Therefore, we proposed that:

Hypothesis 5: The indirect effect of technological innovation on carbon emission via industrial structure upgrades is moderated by environmental regulation, such that the indirect effect will be stronger when environmental regulation is stricter compared to looser.

Hypothesis 6: The indirect effect of technological innovation on carbon emission via energy structure adjustment is moderated by environmental regulation, such that the indirect effect will be stronger when environmental regulation is stricter compared to looser.

## 5.3 Empirical analysis

### 5.3.1 Data and measures

#### 5.3.1.1 Explained variable: carbon emissions (CE)

The measurement of carbon emission is the same as in section 3.1.1.

### 5.3.2 Explanatory variable: technological innovation (GI)

The measurement of carbon emission is the same as in section 4.3.4.2.

### 5.3.3 Mediating variables

The measurement of industrial structure upgrade is the same as in section 4.3.4.3.

Energy structure adjustment is measured by the proportion of fossil fuel consumption in total energy consumption.

### 5.3.4 Moderating variable: environmental regulation

The measurement of industrial structure upgrade and energy structure adjustment is the same as in section 4.3.4.4.

### 5.3.5 Empirical results

The moderated mediation effect (H1 to H6) is tested using the PROCESS macro in SPSS (Hayes, 2017), which is an observed variable OLS and logistic regression path analysis modeling tool that estimate direct and indirect effects. The Sobel test requires a large sample size; thus, this research applied the Bootstrap method.

#### 5.3.5.1 Testing mediation effects

According to the empirical results in Table 5.1, technological innovation is negatively related to carbon emissions ($\beta = -0.34$, p<0.001); technological innovation is positively related to industrial structure upgrade ($\beta = 0.569$, p<0.001) and negatively related to energy structure adjustment ($\beta = -0.466$, p<0.001); industrial structure upgrade is negatively related to carbon emissions ($\beta = -0.126$, p<0.05); energy structure adjustment is positively related to carbon emissions ($\beta = 0.126$, p<0.001). Therefore, technological innovation indirectly influences carbon emissions via industrial structure upgrade and energy structure adjustment, and H1, H2, H3, and H4 are supported (Figure 5.1 shows the path coefficient in the research model).

Table 5.1 Multi-mediation regression analysis (standardized)

| | DV=$CO_2$ | | DV=ISU | | DV=ENU | | DV=$CO_2$ | |
|---|---|---|---|---|---|---|---|---|
| | $\beta$ | t | $\beta$ | t | $\beta$ | t | $\beta$ | t |
| FDI | 0.075* | 2.39 | -0.387*** | -11.46 | 0.153* | 2.30 | 0.024 | 0.65 |
| PGDP | -0.037 | -1.91 | -0.003 | -0.16 | -0.16*** | -4.54 | -0.017 | -0.89 |
| URB | 0.052 | 1.78 | 0.598*** | 19.15 | -0.682*** | -9.08 | 0.187*** | 4.18 |
| ID | -0.002 | -0.11 | -0.291*** | -12.52 | 0.353*** | 7.52 | -0.071** | -2.61 |
| EN | 1.117*** | 31.10 | -0.061 | -1.59 | 0.351*** | 5.38 | 1.068*** | 29.28 |
| GI | -0.34*** | -6.97 | 0.569*** | 10.85 | -0.466*** | -4.57 | -0.234*** | -4.15 |
| ISU | | | | | 0.337*** | 3.77 | -0.126* | -2.56 |
| ENU | | | | | | | 0.126*** | 4.39 |
| $R^2$ | | 0.886 | | 0.868 | | 0.627 | | 0.886 |
| F | | 455.417 | | 386.553 | | 84.441 | | 455.417 |

Note: *p<0.05, **p<0.01, ***p<0.001

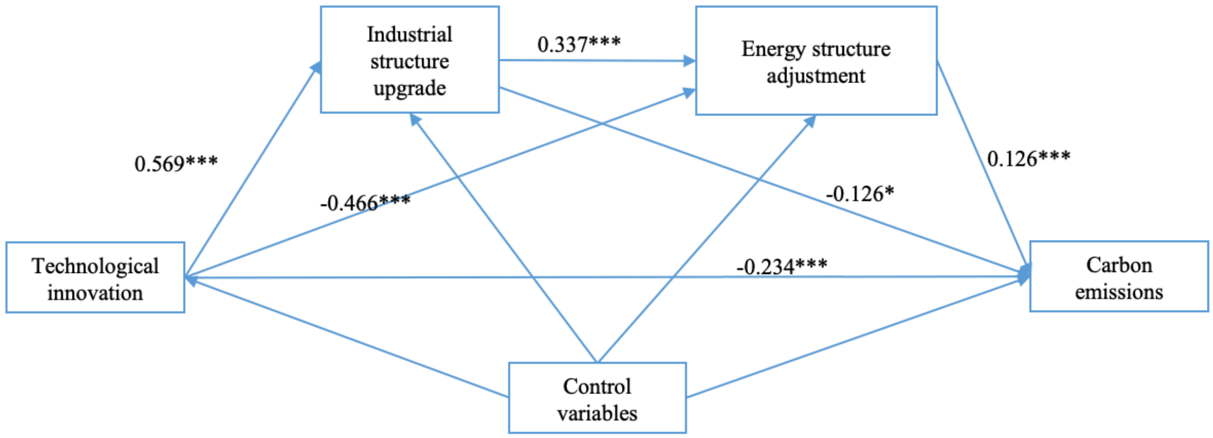



Figure 5.1 The path coefficient of the mediation model

To further identify the mediating effects, the nonparametric percentile bootstrapping procedure was performed (5000 replications). In Table 5.2, the results show that the mediating effect of industrial structure upgrade is −0.072 and the 95% bias-corrected confidence interval by bootstrapping 5000 samples excludes zero. Thus, the indirect effect of industrial structure upgrade accounts for 19.64% of the total mediation effect. The mediating effect of energy structure adjustment is -0.059 and the 95% bias-corrected confidence interval also excludes zero. The indirect effect of energy structure adjustment accounts for 16.09% of the total mediation effect. One thing that is worth noticing is that the path from industrial structure upgrade to energy structure adjustment shows a significant positive effect on carbon emissions. That is to say, technological innovation promotes industrial structure upgrade and increase fossil energy consumption, thus increasing carbon emissions. This mediation effect accounts for 6.65% of the total effects.

Table 5.2 Bootstrap test on the mediation effects (standardized)

| | Effect | Boot SE | LL 95% CI | UL 95% CI | Mediation effect % |
|---|---|---|---|---|---|
| Total | -0.106 | 0.03 | -0.165 | -0.047 | 42.38% |
| ISU | -0.072 | 0.029 | -0.129 | -0.015 | 19.64% |
| ENU | -0.059 | 0.02 | -0.102 | -0.026 | 16.09% |
| ISU=>ENU | 0.024 | 0.009 | 0.009 | 0.042 | 6.65% |

*Note.* Bootstrap sample size=5000; LL=lower limit; UL=upper limit; CI=confidence interval.

5.3.5.2 Testing the moderated mediating effects

The moderating effect of environmental regulation on the mediating model of industrial structure upgrade and energy structure adjustment was tested to explain the relationship between technological innovation and carbon emissions. The results are shown in Table 5.3.

The coefficient of the interaction term of technological innovation and environmental regulation on carbon emissions is −0.0589 ($p<0.001$); the coefficient of the interaction term of technological innovation and environmental regulation on industrial structure upgrade is 0.1879 ($p<0.001$); the coefficient of the interaction term of technological innovation and environmental regulation on energy structure adjustment is −0.1204 ($p<0.01$); the coefficient of the interaction term of industrial structure upgrade and environmental regulation on carbon emission is −0.1297 ($p<0.001$); the coefficient of the interaction term of energy structure adjustment and environmental regulation on carbon emission is −0.1882 ($p<0.001$).

Table 5.3 The moderated mediation model

| | DV=$CO_2$ | | DV=ISU | | DV=ENU | | DV=$CO_2$ | |
|---|---|---|---|---|---|---|---|---|
| | $\beta$ | t | $\beta$ | t | $\beta$ | t | $\beta$ | t |
| FDI | 0.0623* | 1.71 | -0.2006*** | -5.60 | 0.2031*** | 2.96 | -0.0044 | -0.12 |
| PGDP | -0.0323* | -1.73 | -0.0087 | -0.47 | -0.1375*** | -4.09 | -0.0338* | -1.86 |
| URB | 0.0532* | 1.75 | 0.4939*** | 16.52 | -0.7455*** | -10.41 | 0.1493*** | 3.46 |
| ID | -0.0245 | -1.09 | -0.3355*** | -15.19 | 0.3183*** | 5.91 | -0.0719** | -2.42 |
| EN | 1.0326*** | 22.1 | -0.2233*** | -4.86 | 0.0927 | 1.06 | 0.9098*** | 18.93 |
| GI | -0.193*** | -2.99 | 0.7432*** | 11.69 | -0.0668 | -0.49 | 0.0518 | 0.67 |
| ISU | | | | | 0.3856*** | 4.02 | -0.1916*** | -3.52 |
| ENU | | | | | | | 0.0295 | 1.01 |
| ER | -0.1028** | -2.32 | -0.2556*** | -5.87 | -0.3827*** | -4.67 | -0.178*** | -3.82 |
| GI*ER | -0.0589*** | -3.13 | 0.1879*** | 10.15 | -0.1204** | -2.32 | -0.0127 | -0.46 |
| ISU*ER | | | | | 0.0619* | 1.95 | -0.1297*** | -5.59 |
| ENU*ER | | | | | | | -0.1882*** | -7.15 |
| $R^2$ | | 0.89 | | 0.9 | 0.67 | | | 0.91 |
| F | | 372.44 | | 386.55 | 72.2 | | | 294.49 |

To further examine the moderating effect on the mediation model, the conditional indirect effect of each conditional path at low (−1 SD) and high (+1 SD) levels of environmental regulation were tested using bootstrapping (5000 replications) and 95% bias-corrected confidence intervals. The results are shown in Table 5.4. Hypothesis 5 and 6 posited that the negative effect of technological innovation on carbon emissions mediated by industrial structure upgrade and energy structure adjustment would be stronger at higher environment regulation levels. First, the mediation effects of industrial structure upgrade were significant at the higher levels of environmental regulation (conditional indirect effect = −0.2995, 95% CI [−0.4287, −0.1865]), and the confidence interval of the difference between the lower and higher levels of environmental regulation excluded zero. Thus, hypothesis 5 was supported and the moderation effects were shown in Figure 5.2 (a).

However, the mediation effects of energy structure adjustment at higher and lower levels of environmental regulation did not show a significant difference. Therefore, Hypothesis 6 was not supported. The mediation effect through industrial structure upgrade to energy structure adjustment was significant positive at lower level of environmental regulation (conditional indirect effect = 0.0392, 95% CI [0.0125, 0.0693]), and was significant negative at higher level of environmental regulation (conditional indirect effect = −0.0662, 95% CI [−0.1151, −0.0258]). The difference between these indirect effects was also significant (95% CI [−0.1718, −0.0448]). As such, higher environmental regulation could negatively moderate the indirect effect of technological innovation on energy structure adjustment through industrial structure upgrade. The moderating effect is shown in Figure 5.2 (b).

Table 5.4 Conditional indirect effects

| | Moderation variable | effect | BootSE | LL 95% CI | UL 95% CI |
|---|---|---|---|---|---|
| ISU | M-1SD | -0.0343 | 0.0298 | -0.0958 | 0.0199 |
| | M+1SD | -0.2995 | 0.0621 | -0.4287 | -0.1865 |
| | Diff. | -0.2652 | 0.0435 | -0.3569 | -0.1872 |
| ENU | M-1SD | 0.0117 | 0.0253 | -0.0408 | 0.0583 |
| | M+1SD | 0.0298 | 0.0262 | -0.0182 | 0.0857 |
| | Diff. | 0.0181 | 0.0470 | -0.0701 | 0.1146 |
| ISU=>ENU | M-1SD | 0.0392 | 0.0145 | 0.0125 | 0.0693 |
| | M+1SD | -0.0662 | 0.0231 | -0.1151 | -0.0258 |
| | Diff. | -0.1054 | 0.0325 | -0.1718 | -0.0448 |

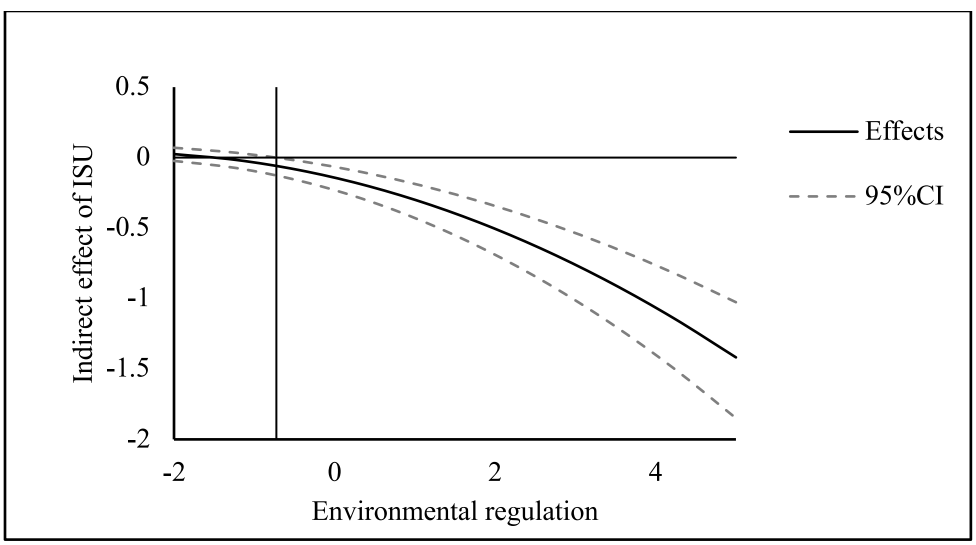



Figure 5.2 (a) Moderation effect of environmental regulation on the mediation effect of industrial structure upgrade

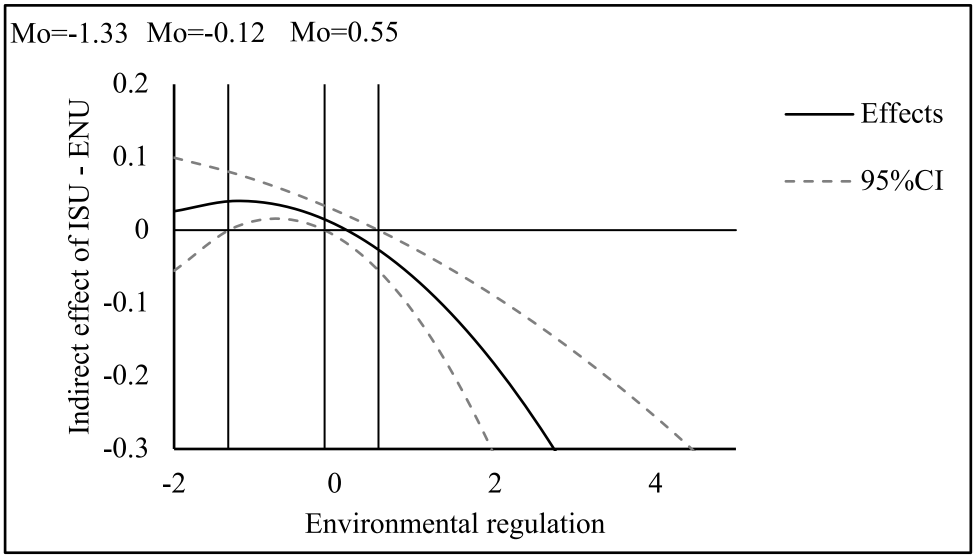



Figure 5.2 (b) Moderation effect of environmental regulation on the mediation effect of industrial structure upgrade and energy structure adjustment

## 5.4 Conclusion and implication

### 5.4.1 Summary of findings

This chapter applied a multi-mediation regression and a moderated mediation analysis to investigate the indirect effect of technological innovation on carbon emissions and the mechanisms. The results showed that industrial structure upgrade and energy structure adjustment mediated the negative relationship between technological innovation and carbon emissions. The mediation effect of industrial structure upgrade and energy structure adjustment showed effect values of −0.072 ($p<0.001$) and −0.059 ($p<0.001$), representatively. Meanwhile, the mediation path through industrial structure upgrade to energy structure adjustment was significantly positive with a path coefficient of 0.024 ($p<0.001$). Moreover, environmental regulation had a moderating effect on the mediation effects such that when environmental regulation is strict, the indirect inhibiting effect of technological innovation on carbon emissions through industrial structure upgrade was stronger. The moderating effect of environmental regulation on the indirect path through energy structure adjustment is insignificant.

### 5.4.2 Implication

China's economy currently relies on high pollution and high emission sectors. Through industrial structure upgrades and energy structure adjustment, technological innovation could indirectly promote carbon emission reduction. Technological innovation could encourage firms to adopt cleaner production methods and invest in low-carbon industries; meanwhile, it can also promote the adoption of clean and renewable energy and improve energy efficiency.

The implementation of environmental regulations will increase pollution-related expenditures, and strict environmental regulations will strengthen the role of technological innovation activities in promoting carbon emission reduction through the advanced industrial structure. However, environmental regulation without sufficient financial subsidy will not promote clean energy consumption due to high substitution costs. Moreover, considering the positive effect of the industrial structure upgrade on fossil energy consumption, a higher level of environmental regulation could depress the chained mediation effect on carbon emissions.

Therefore, technological innovation could not only promote carbon abatement directly but also indirectly through industrial structure upgrade and energy consumption structure adjustment. The local government should strengthen the supply of low-carbon technology and the top-level design of the government's technological innovation system to promote the technological innovation-driven carbon abatement strategy. Also, technology policies should strengthen the role of technological innovation activities in promoting industrial structure upgrading and traditional energy efficiency improvements. Meanwhile, the high costs of renewable and clean energy are one of the most urgent challenges causing the slow transition to a low-carbon economy in China. Thus, reasonable and appropriate pollution regulations and compensation policies could formulate synergistic functions of environmental regulation tools, and force firms to innovate and maximize the efficiency of carbon emission control.

# CHAPTER 6 THE EVOLUTIONARY GAME ANALYSIS AND SIMULATION WITH SYSTEM DYNAMIC MODELING FOR TECHNOLOGY-DRIVEN PROVINCIAL CARBON ABATEMENT

The previous chapters have empirically examined the direct and indirect effects of technological innovation on carbon abatement. According to previous chapters, three paths to were identified: technological innovation (green technology innovation) → carbon emission reduction (direct effect), technological innovation → industrial structure upgrade → carbon emission reduction emission (mediating effect); technological innovation → energy consumption structure adjustment → carbon emission reduction (mediating effect). This chapter will apply the evolutionary game and system dynamics modeling to simulate the carbon abatement path through technological innovation in the context of the dual carbon target in China.

## 6.1 The evolutionary game: government and research institution behavior under the dual carbon target

Innovative activities are mainly conducted by research entities (including enterprises, research institutions, universities, etc., which create relevant technologies, standards, and management methods through scientific research activities, and contribute to carbon emission reduction). Technological innovation-driven carbon emission reduction requires multiple dynamic cooperation requirements between the government and research entities. The government's incentive and punishment policies will prompt research entities to increase their investment in R&D. The reduction of carbon emissions brought about by the active R&D activities of research entities may cause a decrease in the willingness of the government to regulate and participate.

Therefore, this study considers the government and research entities as the two main subjects in the system of technological innovation-driven carbon abatement. I analyzed the behavior and strategy of both parties based on evolutionary game theory and built the game model to provide the quantitative relationship for the system dynamics model.

### 6.1.1 Model assumptions

Before constructing the model, the limiting condition of the evolutionary game was given:

(1) The government and the research entities were the two main players in the innovation-driven carbon abatement system. Let x represent the willingness of government regulation. The government may conduct a strong intervention on research entities with a probability of x, that is, actively introduces policies to encourage research entities to conduct innovative activities; the government may also conduct a weak intervention with a probability of 1−x, that is, it is completely left to the market to adjust the innovation willingness of research entities. The research entities may invest in R&D activities with a probability of y, and may not invest in R&D with a probability of 1−y, according to the input and output of innovation activities, where y represents the willingness of research entities to invest in R&D.

(2) When the government conducts a strong intervention with a probability of x, it needs to invest intervention cost $C_2$ (e.g., to regulate human capital and provide resources, or to introduce incentive and punishment policies to stimulate the willingness of research entities to invest in R&D. If the research entities do not invest in R&D, they will be punished by $P_t$ (e.g., taxation, funding adjustment). If the research entities invest in R&D, the government will reap the benefit $R_3$ (e.g., environmental protection and benefits due to governance). When the government conducts a weak intervention with a probability of 1−x, if the research entities invest in R&D, the government will still reap the benefit $R_3$, but if the research entities do not invest in R&D, it will incur a reputation loss $B$ of the government due to poor governance.

(3) When the research entities invest in R&D with a probability of y, it will incur a research and development cost $C_1$, and at the same time, they will receive benefits $R_1$ due to the innovation activities and outputs. Meanwhile, if the government intervenes strongly, the research entities will receive a government subsidy $R_2$; When the research entities do not invest in R&D with the probability of 1 − y, if the government intervenes strongly, they will be punished by $P_t$ by the government.

(4) In the system of technological innovation-driven carbon abatement, to ensure the authenticity and effectiveness of the system dynamics simulation, supplementary assumptions were made. Considering current carbon emission as $e_0$ and the government's expected target carbon emission as $e$, then the carbon emission

reduction target is $\Delta e = e_0 - e$. The factors that may influence the decision-making of the two main players are related to not only carbon emission reduction targets but also regional characteristics. Thus, all variables were calculated using a fixed and a floating variable. The fixed variable is related to the attributes of the region, including local GDP, R&D investment, and so forth, while the floating variable is a unified variable based on the national carbon emission reduction target.

Table 6.1 Parameters description in the evolutionary game model

| Variable | Descriptions |
|---|---|
| $x$ | The probability that the government implement strong environmental regulations |
| $y$ | The probability that the research entities invest in R&D |
| $e_0$ | Current carbon emission/GDP |
| $e$ | Predicted carbon emission/GDP |
| $\Delta e$ | Target carbon intensity $\Delta e = e_0 - e$ |
| $C_1$ | Research entities' R&D input $C_1 = \alpha + \delta(\Delta e)^2$ |
| $\alpha$ | Constant $\alpha$ in the R&D input according to local economic level |
| $\delta$ | Coefficient of R&D input according to target carbon intensity |
| $R_1$ | Research entities' R&D benefit $R_1 = \lambda + \mu\sqrt{\Delta e}$ |
| $\lambda$ | Constant in general benefit $R_1$ related to regional development levels |
| $\mu$ | Coefficient in the general benefit $R_1$ |
| $R_2$ | When government strongly intervenes and research entities invest in R&D, research entities will receive subsidy (the government will pay) $R_2 = \mathrm{f}(\mathrm{GDP}, \Delta \mathrm{e}) = \xi GDP + \theta\Delta e$ |
| $\xi$ | Coefficient of economic subsidy in $R_2$ |
| $\theta$ | Coefficient of carbon emission subsidy in $R_2$ |
| $P_t$ | When government strongly intervenes and research entities do not invest in R&D, the research entities will pay (the government will receive) the penalty of $P_t = \mathrm{g}(\mathrm{GDP}, \Delta \mathrm{e}) = \omega GDP + \tau\Delta e$ |
| $\omega$ | Coefficient of economic penalty in $P_{\mathrm{t}}$ |
| $\tau$ | Coefficient of carbon emission penalty in $P_t$ |
| $C_2$ | Government regulation cost (time, resource, human capital) |
| $R_3$ | When research entities invest in R&D, the government will receive general benefits of $R_3 = \pi + \gamma\Delta e$ |
| $\pi$ | Constant in general benefit $R_3$ related to regional development levels |
| $\gamma$ | Coefficient in the general benefit $R_3$ |
| $B$ | Under weak government intervention and the research entities do not invest in R&D, the reputation loss incurs to the government $B = \sigma + \rho e_0$ |
| $\sigma$ | Constant in reputation loss $B$ related to regional development levels |
| $\epsilon$ | Coefficient in the reputation loss $B$ |

The summary of parameters is shown in Table 6.1. Based on the above assumptions, the payoff matrix is shown in Table 6.2.

Table 6.2 Payoff matrix between the government and the research entities

| | | Research entities | |
|---|---|---|---|
| | | Invest in R&D ($y$) | Not invest in R&D ($1$-$y$) |
| **Government** | Regulate ($x$) | $R_3 - C_2 - R_2$, $R_1 - C_1 + R_2$ | $P_t - C_2$, $-P_t$ |
| | Not regulate ($1$-$x$) | $R_3$, $R_1 - C_1$ | $B$, 0 |

### 6.1.2 The basic model of the evolutionary game

According to the payoff matrix and the relationship between the government and research entities, the expected benefits of the government and research entities can be calculated, and a replication dynamic equation can be constructed. On this basis, the strategic stability of both parties can be analyzed.

#### 6.1.2.1 The evolutionary game strategy model of the government

Let $E_x$ and $E_{1-x}$ represent the expected earning of the government "Regulate" and "Not regulate", representatively. The payoffs of the government are as follows:

$$E_x = y(R_3 - C_3 - R_2) + (1 - y)(P_t - C_2) \tag{6.1}$$

$$E_{1-x} = yR_3 + (1 - y)(-B) \tag{6.2}$$

The replicator dynamic functions (Friedman, 1991) of the government and the first-order derivation are as follows:

$$F(x) = \frac{dx}{dt} = x(1 - x)[P_t + B - C_2 - y(R_2 + B + P)] \tag{6.3}$$

$$F'(x) = (1 - 2x)[P_t + B - C_2 - y(R_2 + B + P)] \tag{6.4}$$

Assuming that the government is in a stable state using an intervention strategy, it must satisfy: $F(x) = 0$ and $F'(x) < 0$.

**Proposition 1**

When $y > y_0$, the government's stabilization strategy is to choose "not regulate" (weak intervention); when $y < y_0$, the government's stabilization strategy is to choose "regulate" (strong intervention); when $y = y_0$, the stabilization strategy cannot be identified, where $y_0 = P_t + B - C_2/P_t + B + R_2$.

**Proof 1**

Let $(y) = P_t + B - C_2 - y(R_2 + B + P)$, $\partial N(y)/\partial y < 0$. When $y > y_0$, then $N(y) < 0$, $F(0) = 0$, $F'(0) < 0$, and the government reaches the stable state of $x = 0$; when $y < y_0$, then $N(y) > 0$, $F(1) = 0$, $F'(1) < 0$, and the government reaches the stable state of $x = 1$; when $y = y_0$, then $N(y) = 0$, $F(x) = 0$, $F'(x) = 0$, and $x\epsilon[0,1]$, the stabilization strategy cannot be identified. When $P_t + B - C_2 < 0$, $y_0 < 0$, then $y > y_0$, and the government will stably choose the weak intervention strategy.

Proposition 1 illustrated that in the system of technological innovation-driven carbon abatement, the research entities can spontaneously invest in scientific and technological research and development at a high level under an effective market mechanism, and the government will gradually withdraw from the intervention for cost reduction; once R&D investment of the research entities is too low, and carbon emissions cannot be effectively controlled, the government will adopt a strong intervention strategy.

6.1.2.2 The evolutionary game strategy model of the research entities

Let $E_y$ and $E_{1-y}$ represent the expected earning of the research entities "Invest" and "Not invest", representatively. The payoffs of the research entities are as follows:

$$E_y = x(R_1 + R_2 - C_1) + (1 - x)(R_1 - C_1) \tag{6.5}$$

$$E_{1-y} = x(-P) \tag{6.6}$$

The replicator dynamic functions of the research entities and the first-order derivation are as follows:

$$F(y) = \frac{dy}{dt} = y(1 - y)[R_1 - C_1 + x(R_2 + P)] \tag{6.7}$$

$$F'(y) = (1 - 2y)[R_1 - C_1 + x(R_2 + P)] \tag{6.8}$$

Assuming that the research entities are in a stable state using an investment strategy, it must satisfy: $F(y) = 0$ and $F'(y) < 0$.

**Proposition 2**

When $x > x_0$, the research entities' stable strategy is to invest in R&D; when $x < x_0$, the research entities' stable strategy is to not invest in R&D; when $x = x_0$, the stabilization strategy cannot be identified, where $x_0 = C_1 - R_1/P_t + R_2$.

**Proof 2**

Let $K(x) = R_1 - C_1 + x(R_2 + P)$, $\partial K(x)/\partial x > 0$. When $x > x_0$, then $K(x) > 0$, $F(1) = 0$, $F'(1) < 0$, and the research entities reach a stable state at $y = 1$; when $x < x_0$, then $K(x) < 0$, $F(0) = 0$, $F'(0) < 0$, and the research entities reach a stable state at $y = 0$; when x= $x_0$, then $K(x) = 0$, $F(y) = 0$, $F'(y) = 0$, and $y \epsilon [0,1]$, the stabilization strategy cannot be identified. When $C_1 - R_1 > P_t + R_2$, then $x_0 > 1$ and $x < x_0$, thus, the research entities will choose not to invest in R&D.

Proposition 2 illustrated that when the input and output of R&D activities are considerable, the research entities will spontaneously and actively invest in technological innovation, and the government does not need to intervene at this time. Therefore, in addition to considering environmental regulations and policies to regulate the behavior of scientific research subjects, the government also needs to pay attention to the continuous improvement of the market environment. When the investment of research entities is too low ($C_1 - R_1 > P_t + R_2$), there will be government failures.

Therefore, two supplementary assumptions are made based on propositions 1 & 2. First, this game model assumes that $P_t + B - C_2 < 0$ in order to avoid the situation where the government chooses not to intervene due to high regulation costs. Second, this game model assumes that $C_1 - R_1 < P_t + R_2$ in order avoid the situation where government failure occurs when the research entities choose not to invest due to higher costs than benefits of technological innovation.

6.1.2.3 The stability analysis of the evolutionary game

In the dynamic game process between the government and research entities, the two players' participating probability x and y when choosing the game strategy are related to the time t, which are denoted as $x(t)$, $y(t) \epsilon [0,1]$. Let the replicator dynamic system be Eq.(6.3) = 0 and

Eq. (6.7) = 0, we can get the four equilibrium points (0,0), (0,1), (1,0), and (1,1). The Jacobian matrix (Eq. 6.9) is applied to further analyze the equilibrium points.

$$J = \begin{pmatrix} \partial F(x)/\partial x & \partial F(x)/\partial y \\ \partial F(y)/\partial x & \partial F(y)/\partial y \end{pmatrix} \tag{6.9}$$

According to the determinant (Det) and the trace (Tr) of J, the analysis is shown in Table 6.3. By analyzing the conditions of different stable points, a stable combination of strategies can be obtained. In the early stage of carbon emission reduction regulation, due to a lag in the government's awareness of environmental protection, the government's willingness to regulate environmental pollution is low. At this time, the research entities have not yet formed an effective accumulation of carbon emission control and reduction technologies. The cost of government regulation is relatively high. Thus, the equilibrium point will be stable at (0,0), that is, the government will "not regulate" and research entities will "not invest". With growing environmental degradation and reputation loss, the government will take initiatives to intervene by issuing environmental protection; but due to undeveloped markets and immature government regulations, the research entities will still not invest in technological innovation due to high initial costs. Thus, the equilibrium point will move to (1,0), that is, the government will "regulate" but the research entities will "not invest". With accumulated capabilities and knowledge of the research entities and gradually matured low-carbon market, the research entities will establish internal incentive mechanisms that drive innovative activities and maintain technological investments without government intervention. Thus, the equilibrium will be stable at (0,1), that is, the government will "not regulate" and the research entities will "invest".

Table 6.3 Equilibrium points of the replicator dynamic function

| Equilibriums | $\lambda_1, \lambda_2$ | *Det J, Tr J* | Stability |
|---|---|---|---|
| (0,0) | $P_t + B - C_2, R_1 - C_1$ | $U, U$ | Stable when meet condition 1 & 2 |
| (0,1) | $-C_2 - R_2, C_1 - R_1$ | $-, U$ | Stable when meet condition 3 |
| (1,0) | $-(P_t + B - C_2), R_1 + R_2 + P_t - C_1$ | $-, U$ | Stable when meet condition 4 |
| (1,1) | $C_2 + R_2, -(R_1 + R_2 + P_t - C_1)$ | $+, U$ | Not stable |

Note: Condition 1. $P_t + B - C_2 < 0$; 2. $R_1 - C_1 < 0$; 3. $C_1 - R_1 < 0$; 4. $R_1 + R_2 + P_t - C_1 < 0$.

## 6.2 The system dynamic model and simulation for technological innovation-driven carbon abatement

### 6.2.1 The system dynamic model

Based on the variables and analysis in Chapters 4 and 5, the system dynamic (SD) model causal loop diagram (Figure 6.1) shows the causal relationships among the related variables. The SD model can be divided into four subsystems: the technology subsystem, the energy subsystem, the carbon emissions subsystem, and the environmental regulation subsystem.

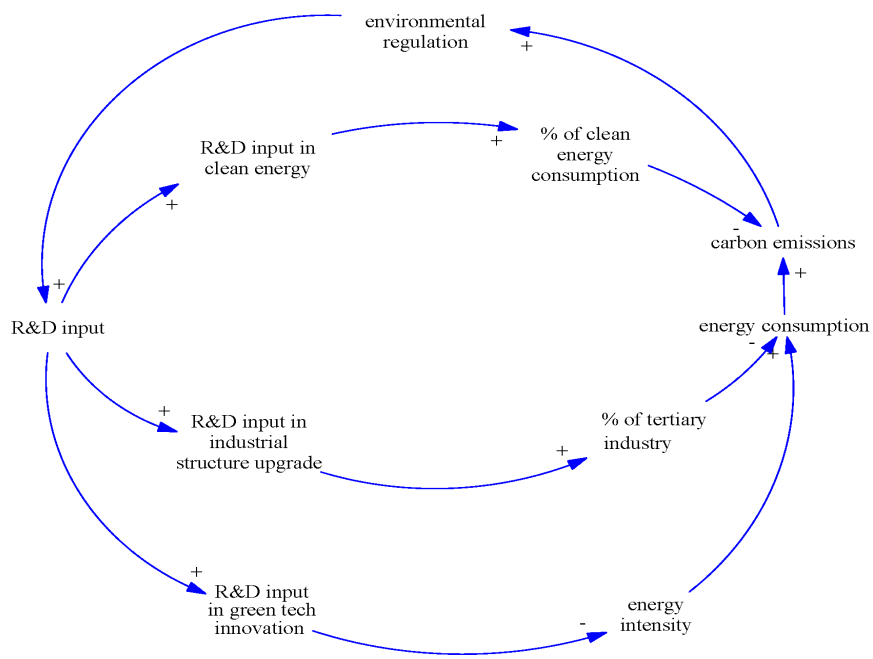



Figure 6.1 Causal loop diagram of SD model

The flowchart (Figure 6.2) integrated the four subsystems and describes the quantitate relationships between variables in the SD model. The SD model has three assumptions. First, it is assumed that energy carbon emissions are from coal, coke, natural gas, fuel oil, gasoline, kerosene, diesel, crude oil, and electricity consumption. Second, it is assumed that the R&D input is divided into industrial structure upgrade investment, clean energy investment, and other green technology investments. Third, it is assumed that regional industrial structure upgrade can be measured by the change in the proportion of the tertiary industry in total GDP. The SD benchmark model contains five level variables, six rate variables, and 19 auxiliary variables.

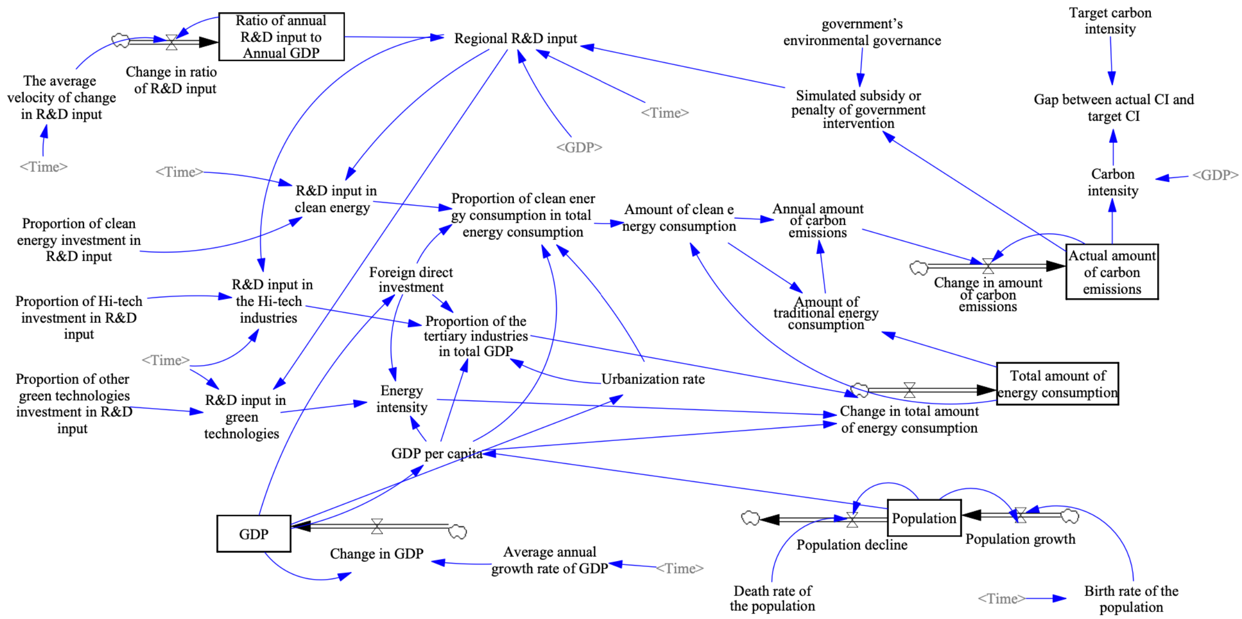



Figure 6.2 Stock-flow diagram of SD model

The SD model of the evolutionary game was further explored to reveal the effect of environmental regulation on technological innovation-driven carbon abatement. Figure 6.3 shows the complete model. The parameters' descriptions are shown in Table 6.4.

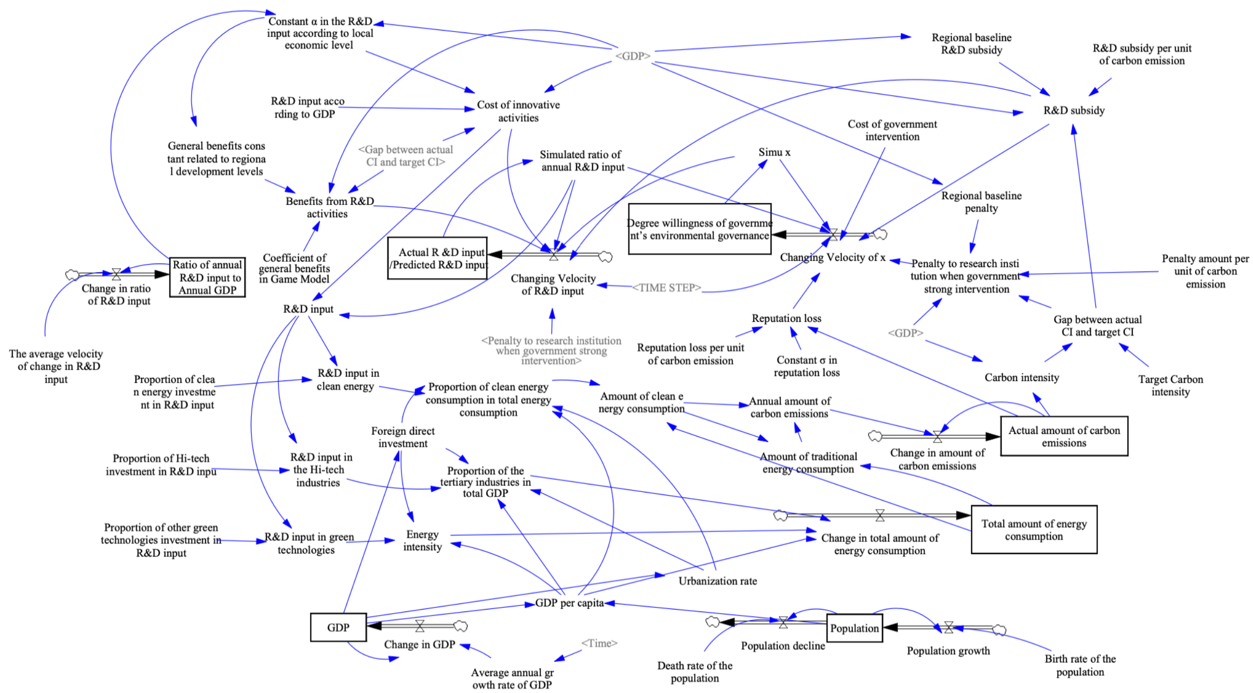



Figure 6.3 The SD model of the evolutionary game

Table 6.4 Parameters and description

| Abbreviation | Description |
|---|---|
| Rat_rd | Ratio of annual R&D input to Annual GDP |
| Cha_rd | Change in ratio of R&D input |
| Vel_rd | The average velocity of change in R&D input % |
| Reg_rd_input | Regional R&D input |
| $\boldsymbol{\alpha}$ | Constant $\alpha$ in the R&D input according to local economic level |
| $\boldsymbol{\delta}$ | R&D input according to GDP |
| $\boldsymbol{\lambda}$ | General benefits constant related to regional development levels |
| $\boldsymbol{\mu}$ | Coefficient of general benefits in Game Model |
| $\boldsymbol{R_1}$ | Benefits from R&D activities ($R_1 = \lambda + \mu\sqrt{\Delta e}$) |
| $\boldsymbol{C_1}$ | Cost of innovative activities ($C_1 = \alpha + \delta(\Delta e)^2$) |
| **y** | Actual R&D input / Predicted R&D input |
| Simu_rat_rd | Simulated ratio of annual R&D input [0,1] |
| $\boldsymbol{dy/dt}$ | Changing Velocity of R&D input |
| **x** | Degree willingness of government's environmental governance |
| $\boldsymbol{dx/dt}$ | Changing Velocity of x |
| $\boldsymbol{C_2}$ | Cost of government intervention |
| $\boldsymbol{B}$ | Reputation loss ($B = \sigma + \epsilon e_0$) |
| $\boldsymbol{\sigma}$ | Constant $\sigma$ in reputation loss |
| $\boldsymbol{\epsilon}$ | Reputation loss per unit of carbon emission |
| $\boldsymbol{P}$ | Penalty to research institution when government strong intervention ($P = \omega + \tau\Delta e$) |
| $\boldsymbol{\tau}$ | Penalty amount per unit of carbon emission |
| $\boldsymbol{\omega}$ | Regional baseline penalty |
| $\boldsymbol{R_2}$ | R&D subsidy ($R2 = \xi + \theta\Delta e$) |
| $\boldsymbol{\theta}$ | R&D subsidy per unit of carbon emission |
| $\boldsymbol{\xi}$ | Regional baseline R&D subsidy |
| clea_rd | R&D input in clean energy |
| indu_rd | R&D input in the Hi-tech industries |
| gree_rd | R&D input in green technologies |
| % clea_rd | Proportion of clean energy investment in R&D input |
| % indu_rd | Proportion of hi-tech investment in R&D input |
| % gree_rd | Proportion of other green technologies investment in R&D input |
| % clea_cons | Proportion of clean energy consumption in total energy consumption |
| Clea_cons | Amount of clean energy consumption |
| Annu_CE | Annual amount of carbon emissions |
| Chan_CE | Change in amount of carbon emissions |
| CE | Actual amount of carbon emissions |
| CI | Carbon intensity (carbon emissions/GDP) |
| Gap_CI | Gap between actual CI and target CI |
| ER | Simulated subsidy or penalty of government intervention |
| Chan_EN | Change in total amount of energy consumption |
| EN | Total amount of energy consumption |
| % ter_ind | Proportion of the tertiary industries in total GDP |
| UR | Urbanization rate, urban population/total population |
| EI | Energy intensity (total energy consumption/ GDP) |
| FDI | Foreign direct investment |
| GDP_per_capita | Gross domestic product per capita |
| GDP | Gross domestic product |

The technology subsystem mainly contains the innovative activities of research entities, and the variables include green technology R&D investment, industrial structure upgrade R&D investment, clean energy R&D investment, GDP, GDP growth rate, etc. The energy subsystem mainly contains the energy consumption of traditional fuels and clean energy, and the variables include consumption of fossil fuels and non-fossil fuels, annual growth in energy consumption, the intensity of fossil and non-fossil energy and etc. The carbon emission subsystem mainly contains the carbon emissions from production and energy consumption, and the variables include annual total carbon emissions, annual carbon emissions from traditional fuels, annual carbon emission from clean energy consumption, carbon intensity, and target carbon intensity (net-zero by 2060), and etc. The environmental regulation subsystem mainly contains the pollution governance and environmental protection policies that may encourage technological investment and carbon emission reduction, and the variables include environmental subsidies or penalties.

### 6.2.2 The benchmark analysis

Considering regional heterogeneity in the technological innovation-driven carbon abatement system, system dynamic benchmark models were established for the coastal area and inland area. The birth rate, economic growth rate, natural increase rate of R&D input, the proportion of input in clean energy, industrial structure upgrading, and green technology innovation were generated at different year according to the actual data. The historical data from 2008 to 2019 and the correlations obtained from Chapters 4 and 5 were used to establish the relationship among factors for the SD model. See Appendix B for detailed equations and related parameters used in calculations. The simulation models for 2020 to 2070 were developed using data derived from previous literature and statistics analysis.

### 6.2.3 Historical simulation and model verification

This research applied the Vensim PLS software to build the system dynamics model integrated with the evolutionary game. After setting the variable function relationship and parameters, I used Vensim to simulate and debug the system dynamics model, compare the simulation results with historical data, and further adjust the system parameters and variable relationships according to the comparison results, so that the system model can accurately simulate the actual system of technology-driven carbon abatement system.

According to the research results of Chapters 4 and 5, the model test shows reasonable causal relationships, clear process structure, reliable data, and accurate measurements. After running the Vensim software, the tracking inspection and compilation error detection all passed, and no error was reported during the system operation, which verifies that the model dimensions are consistent, and the structure is reasonable.

By simulating several key variables and comparing the simulated results with historical data for the period 2008 to 2019. The simulation error $\mu$ was calculated as:

$$\mu = \left|\frac{Y-X}{Y}\right| (\%) \tag{6.10}$$

where $X$ is the simulated value and $Y$ is the historical value.

Overall, the results (Table 6.5) showed that the simulation effectively approximated the actual value with most variables' relative error controlled within 10%.

Table 6.5 Relative error between the actual value and simulation value

| | Year | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|
| R&D input in the coastal area (10000 RMB) | Simulated value | 2800410 | 3415300 | 4213440 | 5197250 | 6197150 | 7046360 |
| | Actual value | 2800414 | 3416184 | 4208112 | 5219702 | 6157285 | 7065212 |
| | Relative error （%） | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 |
| Energy consumption in the coastal area (10000 tons) | Simulated value | 17131 | 18147 | 19106 | 20001 | 20831 | 21607 |
| | Actual value | 17131 | 18107 | 16423 | 21923 | 22467 | 22443 |
| | Relative error （%） | 0.00 | 0.00 | 0.16 | 0.09 | 0.07 | 0.04 |
| Carbon emissions in the coastal area (10000 tons) | Simulated value | 10310 | 10942 | 11484 | 11975 | 12460 | 12901 |
| | Actual value | 10715 | 11294 | 12463 | 13592 | 13850 | 13697 |
| | Relative error （%） | 0.04 | 0.03 | 0.08 | 0.12 | 0.10 | 0.06 |
| R&D input in the inland area (10000 RMB) | Simulated value | 696644 | 944525 | 1117100 | 1344010 | 1618330 | 1870720 |
| | Actual value | 696833 | 945103 | 1117437 | 1345676 | 1615491 | 1870023 |
| | Relative error （%） | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Energy consumption in the inland area (10000 tons) | Simulated value | 9000 | 9691 | 10356 | 11024 | 11642 | 12168 |
| | Actual value | 11378 | 12085 | 12224 | 14941 | 15547 | 15731 |
| | Relative error （%） | 0.21 | 0.20 | 0.15 | 0.26 | 0.25 | 0.23 |
| Carbon emissions in the inland area (10000 tons) | Simulated value | 5647 | 6118 | 6573 | 6995 | 7349 | 7699 |
| | Actual value | 7545 | 8001 | 8730 | 9812 | 10166 | 10195 |
| | Relative error （%） | 0.25 | 0.24 | 0.25 | 0.29 | 0.28 | 0.24 |

Table 6.5 Relative error between the actual value and simulation value (cont'd)

| | Year | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|
| R&D input in the coastal area (10000 RMB) | Simulated value | 7741100 | 8440280 | 9314860 | 10386100 | 11504900 | 12751600 |
| | Actual value | 7748123 | 8415161 | 9316541 | 10380756 | 11495715 | 12741339 |
| | Relative error (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Energy consumption in the coastal area (10000 tons) | Simulated value | 22344 | 23048 | 23722 | 24362 | 24971 | 25547 |
| | Actual value | 22762 | 23242 | 23933 | 24462 | 25527 | 26341 |
| | Relative error (%) | 0.02 | 0.01 | 0.01 | 0.00 | 0.02 | 0.03 |
| Carbon emissions in the coastal area (10000 tons) | Simulated value | 13268 | 13614 | 13954 | 14337 | 14668 | 14981 |
| | Actual value | 13787 | 14135 | 14356 | 14639 | 14904 | 15317 |
| | Relative error (%) | 0.04 | 0.04 | 0.03 | 0.02 | 0.02 | 0.02 |
| R&D input in the inland area (10000 RMB) | Simulated value | 2067870 | 2254050 | 2505820 | 2855500 | 3264740 | 3799130 |
| | Actual value | 2064184 | 2260315 | 2497045 | 2859087 | 3266314 | 3805354 |
| | Relative error (%) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Energy consumption in the inland area (10000 tons) | Simulated value | 12690 | 13181 | 13729 | 14229 | 14804 | 15367 |
| | Actual value | 16106 | 16048 | 16045 | 16955 | 17609 | 18412 |
| | Relative error (%) | 0.21 | 0.18 | 0.14 | 0.16 | 0.16 | 0.17 |
| Carbon emissions in the inland area (10000 tons) | Simulated value | 8021 | 8390 | 8711 | 9107 | 9475 | 9838 |
| | Actual value | 10380 | 10227 | 10284 | 10609 | 11077 | 11570 |
| | Relative error (%) | 0.23 | 0.18 | 0.15 | 0.14 | 0.14 | 0.15 |

## 6.3 Equilibrium stability simulation analysis of the evolutionary game

To test the stability and sensitivity of the strategic choices of the government and research entities regarding environmental regulation and technological investment, nine sets of initial values of government's willingness to regulate ($x$) and research entities' willingness ($y$) to invest were selected to simulate the evolutionary game based on assumptions and equations between the variables (Table 6.6).

Table 6.6 Scenarios setting based on initial strategies

| $y$ initial / $x$ initial | 0.1 | 0.5 | 0.9 |
|---|---|---|---|
| 0.1 | Low-Low (LL) | Low-Mid (LM) | Low-High (LH) |
| 0.5 | Mid-Low (ML) | Mid-Mid (MM) | Mid-High (MH) |
| 0.9 | High-Low (HL) | High-Mid (HM) | High-High (HH) |

The simulation analysis of equilibrium stability was performed for both the coastal and inland areas considering the geographical heterogeneities.

### 6.3.1 Asymptotic stability analysis for the inland regions

Figure 6.4 (a) and (b) reflect the evolving dynamics of the government's willingness to regulate and the research entities' investment proportion over time under 9 simulation scenarios in inland regions. The system stability of the evolutionary game of technological innovation-driven carbon abatement in inland regions is greatly affected by the initial value of the government's willingness to regulate and the research entities' actual R&D investment ratio. The realization of the stable point (0,1) depends on the high initial willingness of either party to participate. Specifically, in scenarios HH, MH, LH, HM, and HL, the system finally reached the (0,1) stable point, which is consistent with the previous analysis. In scenario MM, the system failed to achieve stability before 2070. In scenarios ML, LL, and LM, the system simulation was terminated because the value of % R&D input dropped to zero.

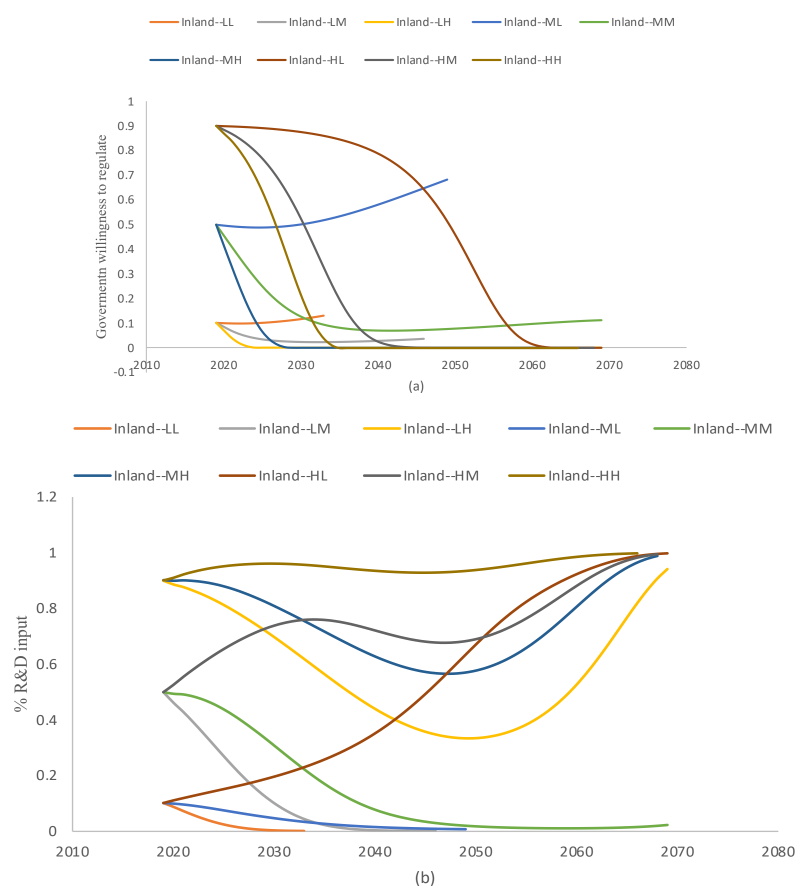



Figure 6.4 Simulation results of the asymptotic stability for the inland regions

Consistent with the analysis in 6.1.1, the system will reach the stable point (0,1) when the research entities' R&D investment benefits could fully cover its costs ($C_1 - R_1 < 0$). The government's strong intervention through environmental regulation may encourage the research entities to continuously invest in R&D until they can generate net benefits from R&D investment.

### 6.3.2 Asymptotic stability analysis for the coastal regions

Figure 6.5 (a) and (b) reflect the evolving dynamics of the government's willingness to regulate and the research entities' investment proportion over time under 9 simulation scenarios in coastal regions.

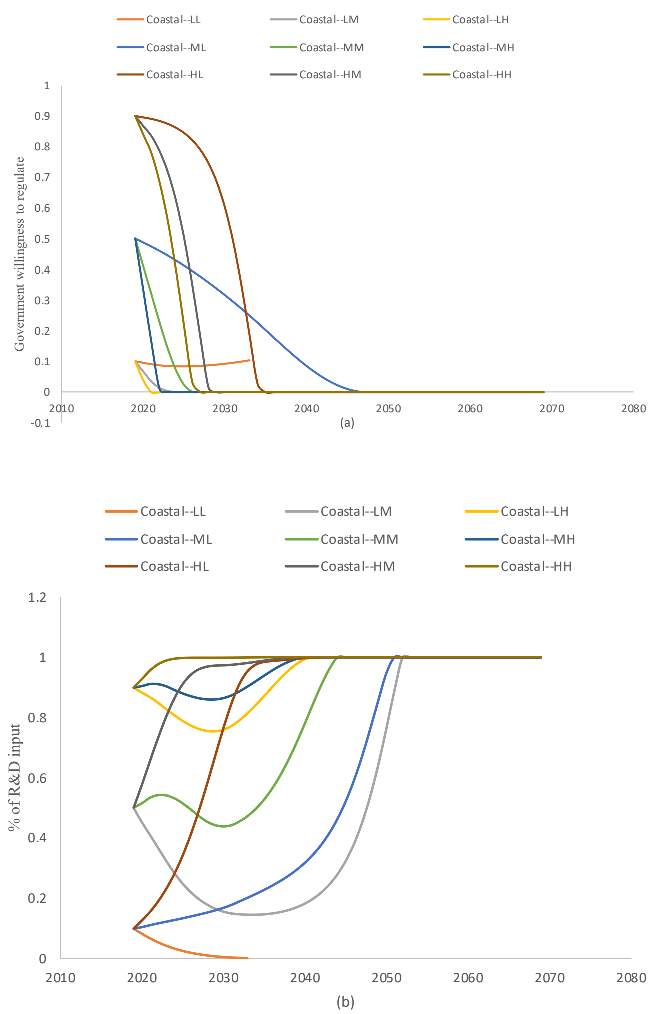



Figure 6.5 Simulation results of the asymptotic stability for the coastal regions

The system stability of the evolutionary game of technological innovation-driven carbon abatement in coastal regions is less affected by the initial value of the government's willingness to regulate and the research entities' actual R&D investment ratio. In the coastal regions, except for the scenario of LL, the remaining eight conditions eventually reached the stability point (0,1).

The economic conditions and technology capabilities of the coastal areas are generally better than that of the inland, thus, the time required for reaching the condition $C_1 - R_1 < 0$ in coastal areas is less than that of the inland areas. Consistent with the previous analysis, with a high initial willingness of either the government to regulate or the research entities to invest, the system will reach the (0,1) equilibrium point. With a low initial willingness of either the government to regulate or the research entities to invest, the system tends to develop towards the (0,0) equilibrium point. Overall, the system dynamics model of the evolutionary game effectively reflects the game process and enhances the credibility of the simulation. Therefore, the system dynamics model of the evolutionary game provides a reliable foundation for the technological innovation-driven carbon abatement system.

## 6.4 Scenario analysis and sensitivity analysis

According to the previous conclusion, environmental regulation and the R&D input structures (i.e., the proportion of R&D input in green technology, clean energy, and industrial structure upgrade) are effective tools to promote technological innovation-driven carbon abatement. Therefore, scenarios and sensitivity analysis were performed by adjusting R&D input structures and the strength of environmental regulations (i.e., amount of innovation subsidies or carbon emission punishments)

### 6.4.1 Scenarios and parameter setting

The initial government willingness to regulate was set to 0.9 and research entities' willingness to invest was set to 0.1 based on previous analysis. Four scenarios were assumed based on the relative proportion of the driving factor in the R&D investment structure, including (1) S0: current; (2) S1: energy; (3) S2: industry; (4) S3: green-tech. The four scenarios were further explored in both the coastal and inland regions (Table 6.7). First, the current scenario presents all parameters and variables in their actual values, which reflects the natural development and the current R&D investment structure (investment in clean energy, industrial structure upgrades, and green technology: 0.29:0.59:0.12 in the inland regions and 0.08: 0.73: 0.19 in the coastal regions). Environmental regulation under S0 is set to 1000 subsidy per ton of carbon emission reduction. Second, to investigate the role of clean energy technology investment, the clean energy input in the energy scenario was simulated by adjusting the ratio of clean energy R&D input from 0 to 1 while keeping industrial structure upgrade and green technology input at a fixed ratio of 0.59:0.12 (inland) and 0.73: 0.19 (coastal). Third, to investigate the role of industrial structure upgrade investment, the industrial structure upgrade input in the industry scenario was simulated by adjusting the ratio of the industrial structure upgrade R&D input from 0 to 1 while keeping clean energy input and green technology input at a fixed ratio of 0.29:0.12 (inland) and 0.08: 0.19 (coastal). Finally, to investigate the role of other green technology investment, the industrial structure upgrade input in the green-tech scenario was simulated by adjusting the ratio of green technology R&D input from 0 to 1 while keeping clean energy input and industrial structure upgrade input at a fixed ratio of 0.29:0.59 (inland) and 0.08:0.73 (coastal). In So models, the environmental regulation.

Table 6.7 Scenario and key parameters setting

| | Inland region | Coastal region |
|---|---|---|
| | **Inland-S0**<br>0.29:0.59:0.12 | **Coastal-S0**<br>0.08:0.73:0.19 |
| S1 energy: adjusting the ratio of clean energy input | **Inland-S1**<br>Industrial structure upgrade: green technology = 0.59:0.12 | **Coastal-S1**<br>Industrial structure upgrade: green technology = 0.73:0.19 |
| S2 industry: adjusting the ratio of industrial structure upgrade | **Inland-S2**<br>Clean energy input: green technology = 0.29:0.12 | **Coastal-S2**<br>Clean energy input: green technology input = 0.08:0.19 |
| S3 green-tech: adjusting the ratio of green technology input | **Inland-S3**<br>Clean energy input: industrial structure upgrade = 0.29:0.59 | **Coastal-S3**<br>Clean energy input: industrial structure upgrade = 0.08:0.73 |

### 6.4.2 Sensitivity analysis on R&D investment structure for inland regions

(1) Inland Scenario 1

The simulated results of carbon emissions under Inland-S1 are shown in Figure 6.6. By adjusting the proportion of clean energy investment to 0, 0.2, 0.4, 0.6, 0.8, and 1, the carbon peaking time and peak value vary. As the increase in the proportion of clean energy input, the time to reach carbon peaking decreases and the peak value decreases. The optimal case in this simulation illustrates a carbon peaking time around 2029 and a peak value of 97.08 million tons. When the proportion of clean energy investment is equal to 1, the carbon peaking time will be greatly delayed. Compared with the current scenario (Inland-S0), the increase in clean energy investment greatly contributes to carbon emission reduction and the dual carbon goal, which also indicates that the current investment ratio in clean energy is insufficient compared to the simulated optimal structure.

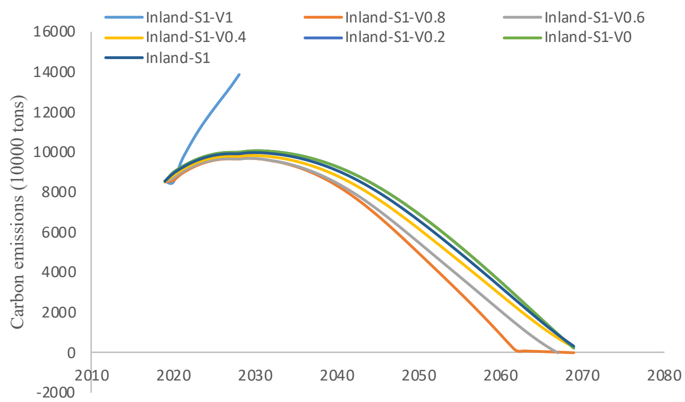



Figure 6.6 Simulated results of carbon emissions under Inland-S1

(2) Inland Scenario 2

The simulated results of carbon emissions under Inland-S2 are shown in Figure 6.7. By adjusting the proportion of industrial structure upgrade investment, the carbon peaking time and peak value vary. The proportion of clean energy input rises to 0.2 is the optimal case in this simulation which illustrates a carbon peaking time around 2025 and a peak value of 93.05 million tons. Compared with the current scenario (Inland-S0), the optimal case indicates that decreasing the proportion of industrial structure upgrade investment from 0.59 to 0.2 while increasing the proportion of clean energy investment and green technology could help achieve carbon peaking sooner at a lower peak value.

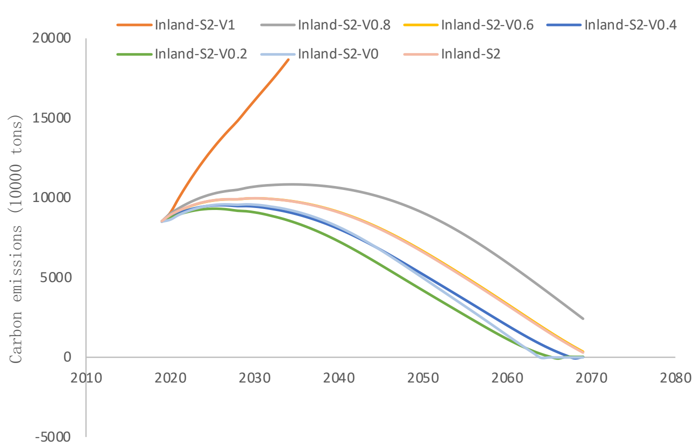



Figure 6.7 Simulated results of carbon emissions under Inland-S2

(3) Inland Scenario 3

The simulated results of carbon emissions under Inland-S3 are shown in Figure 6.8. By adjusting the proportion of green technology investment from 0 to 1, the carbon peaking time and peak value first decrease and increase after. The proportion of green technology input rises to 0.6 is the optimal case in this simulation which illustrates a carbon peaking time around 2025 and a peak value of 94.87 million tons. Compared with the current scenario (Inland-S0), the optimal case indicates that increasing the proportion of green technology investment from 0.12 to 0.6 while decreasing the proportion of clean energy investment and industrial structure upgrade investment could help achieve carbon peaking sooner at a lower peak value.

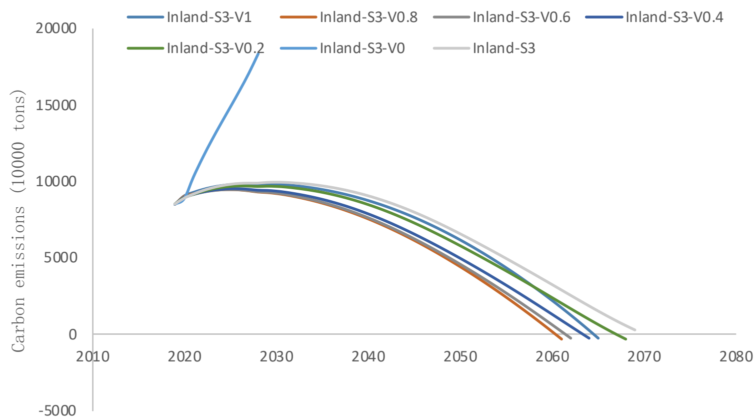



Figure 6.8 Simulated results of carbon emissions under Inland-S3

(4) Comparison among the Inland scenarios

The results of the comparative analysis of the R&D investment structure under different scenarios are shown in Table 6.8. The simulated optimal R&D investment structure in S1, S2, and S3 lead to shorter carbon peaking time and lower peak value among which Inland-S2 provides the shortest peaking time and lowest peak value.

Table 6.8 Simulated statical optimal R&D input structure the Inland scenarios

| | R&D investment structure | | | Carbon peak year | Peak value (million tons) |
|---|---|---|---|---|---|
| | Clean energy | Industrial strucutre upgrade | Green technology | | |
| S0 | 0.29 | 0.59 | 0.12 | 2030 | 99.5138 |
| S1 | **0.80** | 0.17 | 0.03 | 2029 | 97.0781 |
| S2 | 0.57 | **0.20** | 0.23 | **2025** | **93.0464** |
| S3 | 0.13 | 0.27 | **0.60** | 2025 | 94.8718 |

The results illustrate that given a fixed amount of R&D input, the inland regions should increase the proportion of clean energy input and green technology input and reduce the investment in industrial structure to an appropriate level.

### 6.4.3 Sensitivity analysis on R&D investment structure for coastal regions

(1) Coastal Scenario 1

The simulated results of carbon emissions under Coastal-S1 are shown in Figure 6.9. By increasing the proportion of clean energy investment from 0 to 1, carbon emissions increase and cannot reach the peak value during the simulated period. Therefore, in Coastal S1, there is no optimal R&D investment structure.

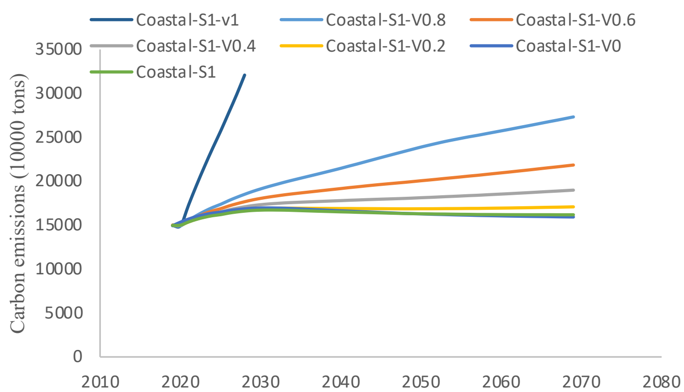



Figure 6.9 Simulated results of carbon emissions under Coastal-S1

(2) Coastal Scenario 2

The simulated results of carbon emissions under Coastal-S2 are shown in Figure 6.10. By increasing the proportion of industrial structure upgrade investment from 0 to 1, the time required for carbon peaking first decreases until the ratio reached 0.2, then increases. In the optimal case in Coastal-S2, carbon emissions will reach the peak in 2026 with a peak value of 154.82 million tons. Compared with Coastal-S0, where the ratio of industrial structure upgrade is 0.79, the simulated optimal R&D investment structure shows a significant decrease.

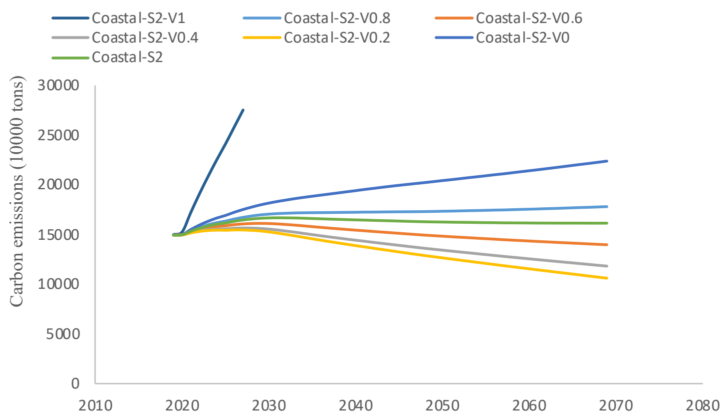



Figure 6.10 Simulated results of carbon emissions under Coastal-S2

(3) Coastal Scenario 3

The simulated results of carbon emissions under Coastal-S3 are shown in Figure 6.11. The optimal ratio of green technology investment in the simulated results is 0.8, and carbon emissions will reach the peak in 2023 with a peak value of 153.28 million tons.

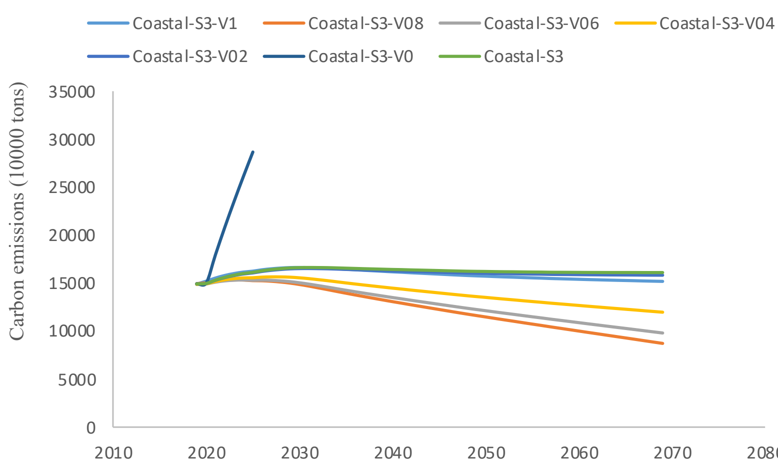



Figure 6.11 Simulated results of carbon emissions under Coastal-S3

(4) Comparison among the Coastal scenarios

The results of the comparative analysis of the R&D investment structure under different scenarios are shown in Table 6.9. The simulated optimal R&D investment structure in S2, and S3 lead to shorter carbon peaking time and lower peak value among which Inland-S3 provides the shortest peaking time and lowest peak value. The results illustrate that given a fixed amount of R&D input, the coastal regions should increase the proportion of green technology input and reduce the investment in industrial structure to an appropriate level.

Table 6.9 Simulated statical optimal R&D input structure of the Coastal scenarios

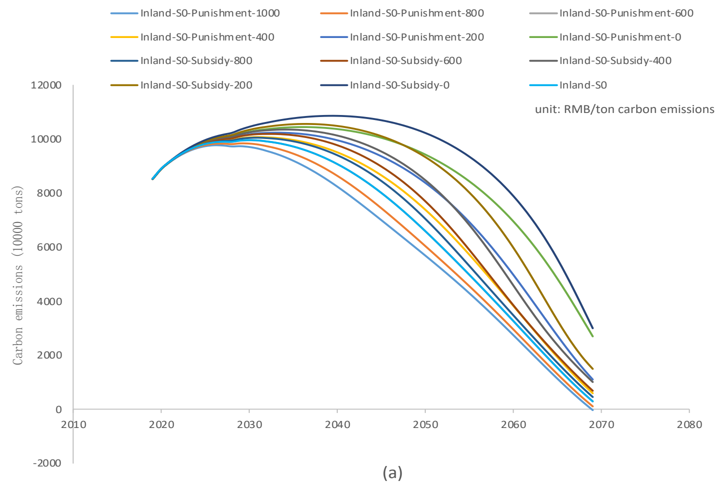
| | R&D investment structure | | | Carbon peak year | Peak value (million tons) |
|---|---|---|---|---|---|
| | Clean energy | Industrial strucutre Upgrade | Green technology | | |
| S0 | 0.08 | 0.73 | 0.19 | 2031 | 166.74 |
| S1 | **0.08** | 0.73 | 0.19 | 2031 | 166.74 |
| S2 | 0.23 | **0.20** | 0.57 | 2026 | 154.82 |
| S3 | 0.02 | 0.18 | **0.80** | **2023** | **153.28** |

### 6.4.4 Sensitivity analysis of environmental regulation

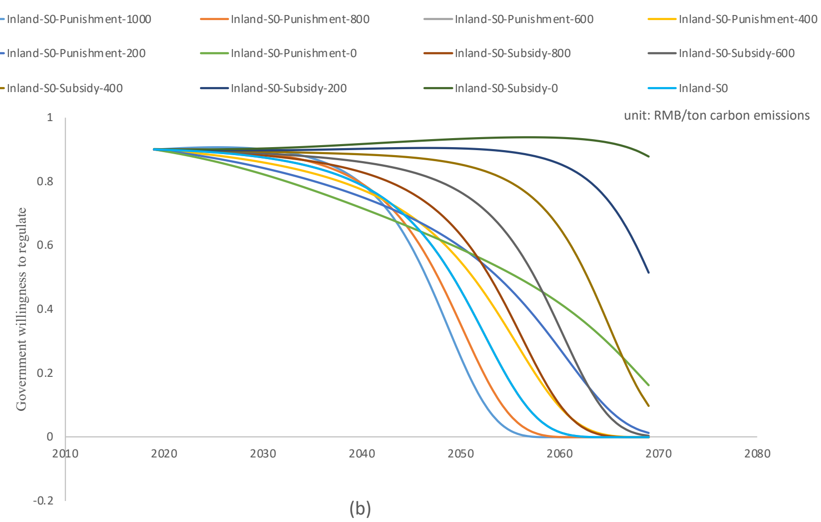
Environmental regulation is another key tool through which the government could promote technological innovation and carbon abatement. The subsidies could encourage research entities to perform more innovative activities, and the punishments could also push carbon abatement through green innovation. In this sensitivity analysis, the SD simulation was performed under different levels of environmental subsidies or penalties (ranging from 0 to 1000 RMB/ton carbon emission).

(1) Environmental regulation sensitivity analysis for inland regions

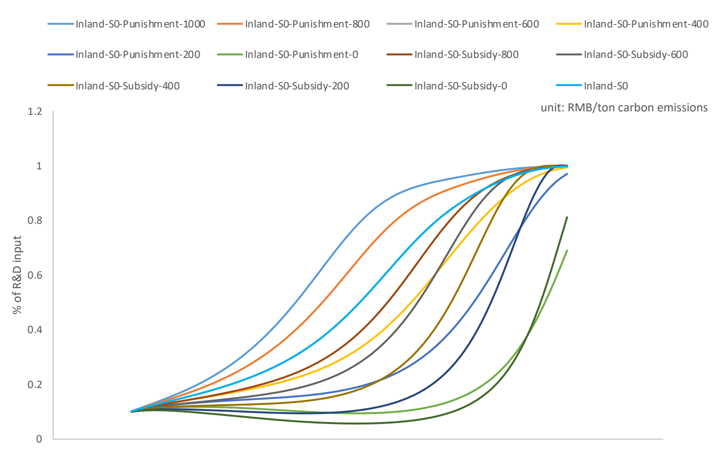
As shown in Figure 6.12 (a), when the environmental regulation punishment is at 1000/ton carbon emissions, the simulated result is optimal with a carbon peak time of 2026 and a peaking value of 97.83 million tons. Meanwhile, increasing punishment or subsidy policies could help shorten the time required to reach the carbon peak and lower the peak value. The results also indicate that the effect of punishment policies on carbon abatement is always better than incentive policies at the same rate. Moreover, with an increase in the strength of environmental regulation, the game between the government and the research entities could reach a stable status faster (Figure 6.12 b&c).




(a)




(b)

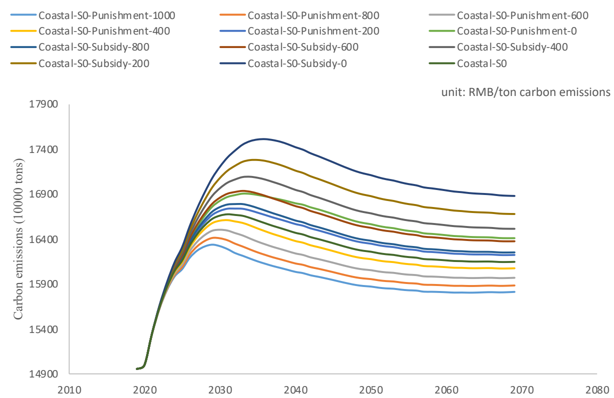



(c)

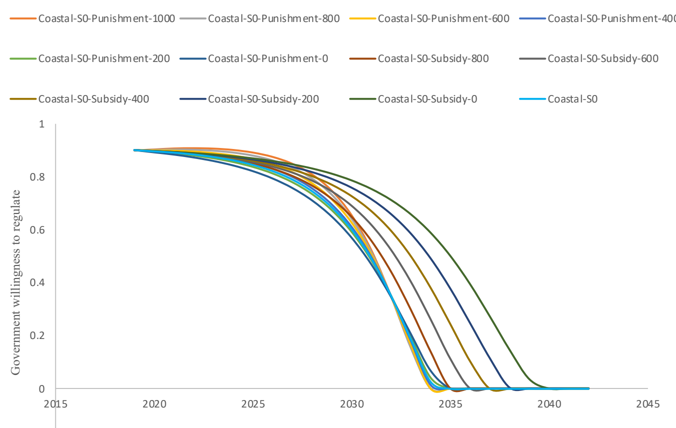
Figure 6.12 Sensitivity analysis of environmental regulation under Inland-S0

(2) Environmental regulation sensitivity analysis for coastal regions

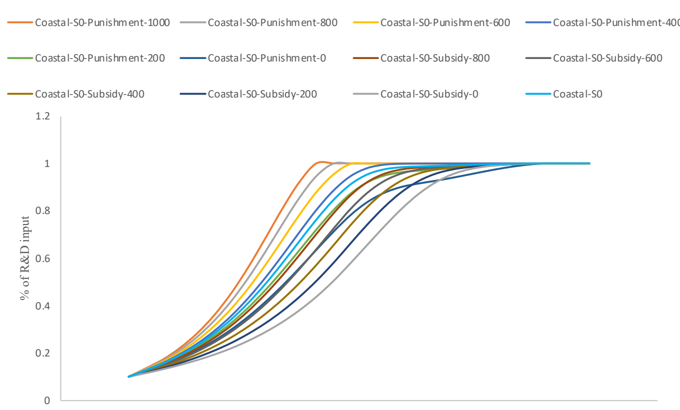
In general, the sensitivity analysis results of environmental regulation in the coastal regions exhibit the same pattern as the inland regions.




(a)




(b)




(c)

Figure 6.13 Sensitivity analysis of environmental regulation under Coastal-S0

As shown in Figure 6.13 (a), when the ecological regulation punishment is at 1000/ton carbon emissions, the simulated result is optimal with a carbon peak time of 2029 and a peaking value of 163.41 million tons. Meanwhile, increasing the level of punishment or subsidy policies could help shorten the time required to reach the carbon peak and lower the peak value. The results also indicate that the effect of punishment policies on carbon abatement is always better than incentive policies at the same rate. Moreover, with an increase in the strength of environmental regulation, the game between the government and the research entities could reach a stable status faster (Figure 6.13 b&c).

## 6.5 Dynamic system simulation

A dynamic simulation was performed to explore further the effect of R&D investment structure and environmental regulation on the technological innovation-driven carbon abatement system.

### 6.5.1 Dynamic scenario and parameters setting

Based on the optimal R&D investment structure in each scenario, the relationship between the target gap of carbon emission intensity and the R&D investment structure was established to adjust the parameters and dynamically simulate the scenarios (calculation see Table 6.10).

In addition, relationship between the gap of target and predicted carbon emission and the intensity of the environmental regulation was also established, to achieve dynamic adjustment of environmental regulation simulation by unit punishment amount = WITHLOOKUP (10000*GAP, ([(0,0)- ([(0,0) -(10000,2000)], (0,0), (0.1,100), (0.5,200), (1.5,300), (2,500), (2.5,800), (3,1000), (10000,1500))) and unit subsidy amount = WITHLOOKUP (10000*GAP, ([(0,0)- ([(0,0) -(10000,2000)], (0,0), (0.1,100), (0.5,200), (1.5,300), (2,500), (2.5,800), (3,1000), (10000,1500) )).

In the dynamic adjustment, the larger the gap, the closer the R&D investment ratio of each driving factor is to the optimal (statical optimal R&D input structure see Table 6.8 & 6.9); the smaller the gap, the R&D investment structure tends to remain current status. The dynamic simulation scenario design is shown in Table 6.10. For each scenario, as the gap between target and predicted carbon emission gradually decreases, the unit penalty and subsidy amount decrease in steps of 1000, 800, 500, 300, and 0, to ensure the optimal effect of environmental regulation in scenarios with the highest carbon emissions.

Table 6.10 Scenarios and parameters setting in dynamic simulation

| | Inland region | Coastal region |
|---|---|---|
| S1 energy: adjusting the ratio of clean energy input according to the gap between target and predicted carbon emission | **Inland-S1D** The larger the gap, the closer the investment ratio of clean energy is to the optimal ratio of 0.8; the smaller the gap, the investment ratio tends to remain current status. =WITHLOOKUP(100000*GAP, ([(0,0)-(10,10)],(0,0.3),(0.1,0.291686),(0.5,0.2917),(1,0.8),(3,0.8),(5,0.8) )) | **Coastal-S1D** Maintain current structure: 0.08:0.73:0.19 |
| S2 industry: adjusting the ratio of industrial structure upgrade according to the gap between target and predicted carbon emission | **Inland-S2D** The larger the gap, the closer the investment ratio of industrial structure upgrade is to the optimal ratio of 0.2; the smaller the gap, the investment ratio tends to remain current status. =WITHLOOKUP(100000*GAP, ([(0,0)-(10,10)], (0,0.5923), (0.1,0.5923), (0.5,0.592268), (1,0.2), (3,0.2), (5,0.2) )) | **Coastal-S2D** The larger the gap, the closer the investment ratio of industrial structure upgrade is to the optimal ratio of 0.2; the smaller the gap, the investment ratio tends to remain current status. =WITHLOOKUP(GAP, ([(0,0)-(10000,2000)],(0,0.731658),(0.1,0.7317),(0.5,0.7317), (1.5,0.7317), (2,0.2), (2.5,0.2), (3,0.2), (10000,0.2) ) |
| S3 green-tech: adjusting the ratio of green technology inputaccording to the gap between target and predicted carbon emission | **Inland-S3D** The larger the gap, the closer the investment ratio of green technology is to the optimal ratio of 0.6; the smaller the gap, the investment ratio tends to remain current status. =WITHLOOKUP(100000*GAP, ([(0,0)-(10,10)], ([(-10000,0)-(10000,10)],(-10000,0.116),(0,0.116046), (0.1,0.116), (0.5, 0.116), (1,0.6), (3,0.6), (5,0.6), (10000,0.6) )) | **Coastal-S3D** The larger the gap, the closer the investment ratio of green technology is to the optimal ratio of 0.8; the smaller the gap, the investment ratio tends to remain current status. =WITHLOOKUP(GAP, ([(0,0)-(10000,2000)],(0,0.1913),(0.1,0.1913),(0.5,0.191324), (1.5,0.191324), (2,0.8), (2.5,0.8), (3,0.8), (10000,0.8) )) |

### 6.5.2 Dynamic simulation results

Figure 6.14 shows the dynamic and static simulation results of carbon emission under the combined influence of environmental regulation and R&D investment structure. In the inland scenarios (Figure 6.14. a), Inland-S2D and Inland-S3D simulate a better effect of carbon emission reduction, and the carbon peak time is shorter compared to the current scenario (Inland-S0). Compared with the statical methods, Inland-S2D is the optimal case with a carbon peak time in 2024 and a peak value of 91.56 million tons. In addition, the static and dynamic simulation results of carbon emissions in Inland-S1 and S1D show different patterns, indicating that clean energy investment is very sensitive to the change in the R&D input structure.

In the coastal scenarios (Figure 6.14. b), Coastal-S2D and Coastal-S3D simulate a better effect of carbon emission reduction, and the carbon peak time is shorter compared to the current scenario (Coastal-S0). However, the effect of static stimulation is better than the dynamic simulation in the coastal scenarios, and Coastal-S3 still exhibits the shortest peaking time and lowest peak value.

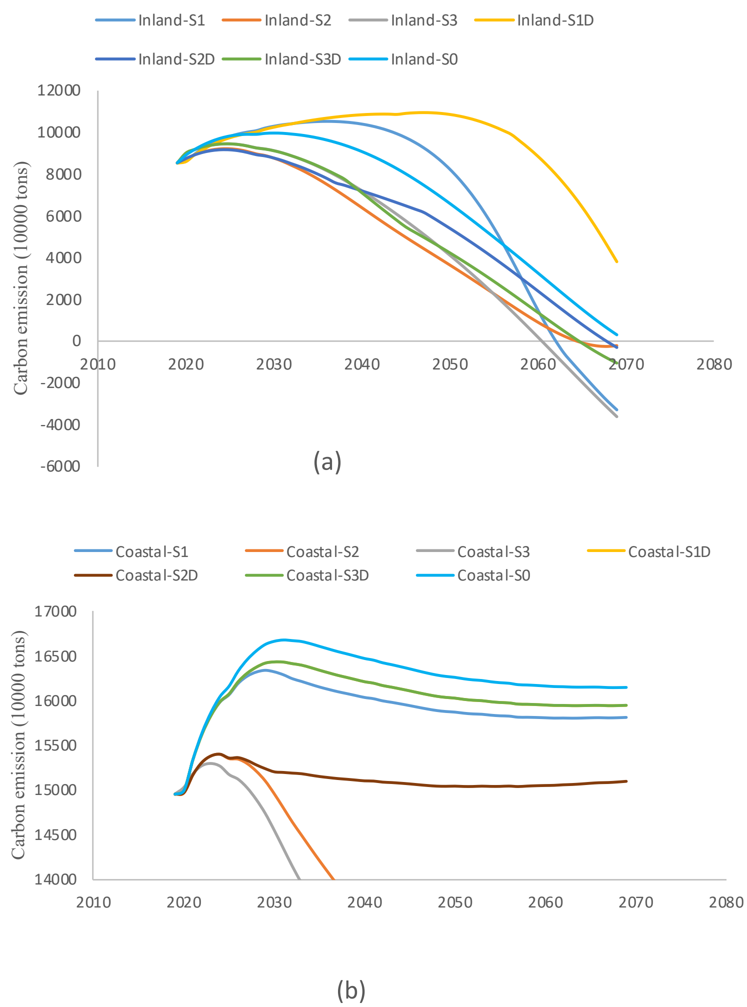



Figure 6.14 Comparison of statical and dynamic simulation results

The optimal R&D investment structure predicted carbon peak year and peak value in coastal and inland regions are shown in Table 6.11. In inland areas, dynamically adjusting the environmental regulation and the R&D investment structure shows a better promoting effect on carbon abatement. More specifically, reducing the investment proportion in industrial structure upgrade and gradually increasing technological input in clean energy and green technology is a more suitable carbon abatement strategy. The dynamic simulation also indicates that adjustments in the R&D investment structure may lead to an immediate carbon emission reduction effect.

In coastal areas, due to huge economic size, it is difficult to adjust the R&D investment structure and environmental regulation in a short period of time without hurting the economic growth. To achieve a better effect of technological innovation-driven carbon emission reduction and the "dual carbon" goal, the coastal regions should focus on long-term green technology investment and innovation.

Table 6.11 Optimal simulated R&D investment structure

| | R&D investment structure | | | Carbon peak year | Peak value (million tons) |
|---|---|---|---|---|---|
| | Clean energy | Industrial strucutre Upgrade | Green technology | | |
| Inland-S2D | 0.57 | 0.20 | 0.23 | 2024 | 91.56 |
| Coastal-S3 | 0.02 | 0.18 | 0.80 | 2023 | 152.96 |

Note: environmental regulation penalty and subsidy = 1000RMB/ton carbon emission

## 6.6 Conclusion and implication

### 6.6.1 Summary

In this chapter, the system of technological innovation-driven carbon abatement was established based on the system dynamic models integrated with the evolutionary game. The system consists of four subsystems: technology, energy, carbon emission, and environmental regulation. Applying the Vensim PLS software, this chapter explored the static and dynamic simulation of carbon emissions (the amount, carbon peak year, and carbon peak value) under different R&D investment structure and different intensities of environmental regulation in inland and coastal regions. Through the comparative analysis of the current scenario and the designed simulated scenarios, the simulated optimal structure of R&D investment is identified for both the inland and the coastal regions. The optimal results indicate that adjustments in the R&D investment structure may lead to an immediate carbon emission reduction effect in the inland regions, and the coastal regions should focus on long-term green technology investment and innovation to achieve a better effect of technological innovation-driven carbon emission reduction and to achieve the "dual carbon" goal. Further, increasing the intensity of punishment or subsidy regulation could help shorten the time required to reach the carbon peak and lower the peak value in the simulated system. The simulated results also indicate that the effect of punishment policies on carbon abatement is better than incentive policies at the same rate.

### 6.6.2 Implications

(1) The implementation of environmental regulations will promote technological innovation-driven carbon emission reduction and increasing environmental subsidies and penalties could push the research entities to increase investment in technological innovation or perform innovative activities in order to deal with environmental pollution. However, it should be noted that with the enormous economic volume and manufacturing scale of the coastal provinces, it is difficult to obtain a better effect of carbon abatement by adjusting the R&D investment structure and reinforcing the environmental regulation in the short term.

(2) The government can adjust the R&D investment structure to ensure the flow of capital input into the suitable technology for carbon emission reduction. With the change in the investment structure, the carbon peak time and peak value in inland and coastal areas also change accordingly. As the energy supply end, inland areas should gradually adjust the investment proportion in clean energy, industrial structure, and green energy innovation to an appropriate level.

(3) In comparing static and dynamic adjustment strategies, the government should choose the best intervention method according to local conditions. The willingness of research entities to invest in technological innovation in different regions is affected by the carbon abatement targets and the economic environment. Compared with coastal areas, inland areas are less economically developed and generate relatively fewer carbon emissions. The government intervention in the inland regions may have an immediate effect on the research entities and encourage them to invest more in technology to control carbon emissions. In coastal areas, due to the large economic size and relatively high carbon emissions, short-term government intervention may not effectively increase the willingness of research entities to invest. Coastal regions may integrate the long-term high-intensity environmental regulation and structural adjustment of technological investment.

(4) The policy maker should clarify the relationship between technological investment structure, environmental regulation, and the carbon control targets. Based on findings in this chapter, clean energy investment, industrial structure upgrade investment, and green technology investment have different effects on carbon emissions. Therefore, the government should be aware of the sensitivity of the R&D investment structure and the intensity of environmental regulation in different regions to provide better guidance on carbon abatement strategies.

# CHAPTER 7 CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This dissertation mainly explored the effect of technological innovation on carbon abatement by considering its direct and indirect mechanisms. Chapter 2 reviewed previous literature and identified the mechanisms and paths through which technological innovation affects carbon emissions and carbon emission reduction.

Chapter 3 mainly explored the spatial-temporal characteristics of provincial carbon emissions using panel data from 30 Chinese provinces from 2008 to 2019. IPCC approach was used to measure the total amount of carbon emission in each province. Moran's I was used to test the spatial autocorrelation. Kernel density estimation showed the dynamics and overall trend of provincial carbon emissions. Lastly, spatial econometric models with absolute and conditional $\beta$-convergence analysis were established to investigate the spatial convergence of provincial carbon emission.

Chapter 4 tested the effect of technological innovation on carbon emission using panel data of 30 provinces in China between 2008 and 2019 using the Global Moran's I, Moran scatter diagram, spatial Durbin model, and panel threshold model. According to the findings, technological innovation and provincial carbon emissions show positive spatial agglomeration effects and spatial autocorrelation. Technological innovation negatively affects provincial carbon emissions and has a more substantial carbon abating effect in provinces with higher emissions. The impact of technological innovation on carbon emission shows significant temporal-spatial heterogeneity. There is a single threshold effect of environmental regulation on the impact of technological innovation on provincial carbon emissions. When environmental regulation is above the threshold, the effect of technological innovation on abating carbon emission slightly decreases.

Chapter 5 applied a multi-mediation regression and a moderated mediation analysis to investigate the indirect effect of technological innovation on carbon emissions and the mechanisms. The results showed that industrial structure upgrade and energy structure adjustment mediated the negative relationship between technological innovation and carbon emissions. Moreover, environmental regulation had a moderating effect on the mediation effects such that when environmental regulation is strict, the indirect inhibiting effect of technological innovation on carbon emissions through industrial structure upgrade was stronger. The moderating effect of environmental regulation on the indirect path through energy structure adjustment is insignificant.

Chapter 6 applied the system dynamic models integrated with the evolutionary game and built the system of technological innovation-driven carbon. Applying the Vensim PLS software, this chapter explored the static and dynamic simulation of carbon emissions (the amount, carbon peak year, and carbon peak value) under different R&D investment structure and different intensities of environmental regulation in inland and coastal regions. Through the comparative analysis of the current scenario and the designed, simulated scenarios, the simulated optimal structure of R&D investment is identified for both the inland and the coastal regions. The optimal results indicate that adjustments in the R&D investment structure may lead to an immediate carbon emission reduction effect in the inland regions, and the coastal regions should focus on long-term green technology investment and innovation to achieve a better impact of technological innovation-driven carbon emission reduction and to achieve the "dual carbon" goal. Further, increasing the intensity of punishment or subsidy regulation could help shorten the time required to reach the carbon peak and lower the peak value in the simulated system. The simulated results also indicate that the effect of punishment policies on carbon abatement is better than incentive policies at the same rate.

Although the research of this paper has achieved some preliminary results, there are still several limitations in this dissertation that require further investigation. First, this dissertation applied R&D input data to measure technological innovation, which can only demonstrate the overall technology investment activities and the partial effect on carbon emissions. Future research could explore technological innovation by patent data to explore the impact of technology outcomes on carbon emission reduction. Moreover, future research could examine the carbon abating effect of different types of technology.

Second, this dissertation used panel data of China's provinces due to data availability, which can only reveal the provincial heterogeneities. In chapter 4, the hypothesis of the spatial spillover effect of technological innovation on adjacent provinces' carbon emission reduction was not supported. One possible reason is that the collaboration innovation mechanisms between provinces have not yet been established; thus, province-level data cannot reveal the spatial spillover.  Future research could collect city-level data and further explore the spillover effect among adjacent cities in the same province.

Third, the scenarios and parameters in the system of technological innovation-driven carbon abatement system need to be expanded. This dissertation only considered four subsystems and 36 variables in this complex system. Future research could expand the system by integrating additional parameters and quantitative relationships into the system dynamic model.

Fourth, although the methodologies used can be applied in counties beyond China, this dissertation only considered environmental regulation and technology investment in the Chinese context. Future research could collect data from other countries and study the relationships and variables in other contexts.

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