

Assessing the Impact of High-Quality Economic Development on Carbon Productivity in China

by

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DECLARATION

I hereby declare that the work presented in this thesis was conducted in full compliance with the regulations of Universiti Malaysia Sarawak (UNIMAS). Except where proper acknowledgment is given, this work is solely the effort of the author. This thesis has not been accepted for the award of any other degree and is not being concurrently submitted for any other academic qualification.

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ABSTRACT

Under China's "dual carbon" strategy, enhancing carbon productivity has emerged as a crucial pathway for advancing green economic transformation and aligning high-quality development with carbon neutrality. As an indicator of economic output per unit of carbon emissions, carbon productivity is a measure of both ecological and economic value. While pursuing high-quality growth, China faces complex challenges, including growing resource and environmental constraints, industrial restructuring pressures, and significant regional disparities. With its commitment to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, China must operate within a narrow timeframe to fulfill its international responsibilities as a global economic power.

This study investigates carbon productivity in 30 provincial-level regions in China from 2008 to 2021 using an integrated analytical framework grounded in theories of sustainable development, low-carbon economy and decoupling theory, and spatial econometrics theories. It constructs a multidimensional index system to assess the influence of high-quality development on carbon productivity across static, dynamic, and spatial dimensions. Empirical analysis using static panel models, the system of Generalized Method of Moments, and the Spatial Durbin Model reveals that while carbon productivity in China has generally increased, regional disparities persist; most notably, there is a pattern of higher productivity in eastern regions as compared to western regions. High-quality economic development yields a significant positive impact on carbon productivity, particularly over the long term, indicating strong path dependence and structural reinforcement. Furthermore, spatial spillover effects are evident, whereby advancements in high-quality development within one region also improve the carbon productivity of neighboring areas. Additionally, factors such as energy intensity, urbanization, government environmental investment, and marketization exhibit diverse influences on carbon productivity across regions.

Drawing from these findings, the study proposes targeted policy recommendations, including deepening the high-quality development agenda, promoting green industrial

transformation, optimizing the energy structure, strengthening cross-regional coordination, and enhancing fiscal environment supports. It also underscores the strategic role of the state-owned sector in driving green transition, advocating for a “Chinese path” to low-carbon development—one that avoids the conventional Western trajectory of “pollute first, control later” and instead aligns with China’s developmental stage and governance framework.

Keywords: Carbon productivity; high-quality economic development; system GMM; spatial econometrics; spatial spillover; green transition; coordinated regional development.

Menilai Kesan Pembangunan Ekonomi Berkualiti Tinggi terhadap Produktiviti Karbon di China

ABSTRAK

Di bawah strategi “dwi karbon” China, peningkatan produktiviti karbon telah muncul sebagai laluan penting dalam memacu transformasi ekonomi hijau dan menyelaraskan pembangunan berkualiti tinggi dengan matlamat neutral karbon. Sebagai penunjuk kecekapan yang mengukur hasil ekonomi bagi setiap unit pelepasan karbon, produktiviti karbon mempunyai nilai ekonomi dan ekologi yang ketara. Dalam usahanya mencapai pembangunan berkualiti tinggi, China berdepan dengan pelbagai cabaran, termasuk tekanan terhadap sumber dan alam sekitar, keperluan penstrukturan semula industri, serta ketidakseimbangan pembangunan antara wilayah. Dengan komitmennya untuk memuncak pelepasan karbon menjelang 2030 dan mencapai neutral karbon menjelang 2060, China perlu mengimbangi tanggungjawab globalnya dalam jangka masa yang terhad.

Kajian ini meneliti 30 wilayah peringkat provinsi di China dari tahun 2008 hingga 2021 menggunakan rangka kerja analisis yang bersepadu berdasarkan teori pembangunan mampan, ekonomi rendah karbon, dan ekonometri spatial. Ia membina sistem indeks berbilang dimensi untuk menilai pengaruh pembangunan berkualiti tinggi terhadap produktiviti karbon dari perspektif statik, dinamik dan spatial. Analisis empirikal menggunakan model panel statik, dan Model Spatial Durbin mendapati bahawa produktiviti karbon di China telah meningkat secara keseluruhan, namun perbezaan wilayah masih ketara—dengan corak yang menunjukkan produktiviti tinggi di wilayah timur berbanding barat. Pembangunan ekonomi berkualiti tinggi memberikan kesan positif yang signifikan terhadap produktiviti karbon, terutamanya dalam jangka panjang, mencerminkan kebergantungan laluan dan kesan pengumpulan struktur. Selain itu, terdapat kesan limpahan spatial yang jelas, di mana peningkatan pembangunan berkualiti tinggi di sesuatu wilayah turut meningkatkan produktiviti karbon di wilayah berjiran. Faktor kawalan seperti keamatan tenaga, tahap urbanisasi, pelaburan kerajaan dalam perlindungan alam sekitar,

dan tahap pemeraksanaan pasaran pula menunjukkan kesan yang berbeza-beza merentas wilayah.

Berdasarkan penemuan ini, kajian mencadangkan beberapa cadangan dasar yang menyasarkan peningkatan produktiviti karbon, termasuk pengukuhan strategi pembangunan berkualiti tinggi, pemacuan transformasi industri hijau, pengoptimuman struktur tenaga, peningkatan kerjasama antara wilayah, dan pengukuhan mekanisme pasaran karbon. Kajian ini turut menekankan peranan strategik ekonomi milik negara dalam mendokong peralihan hijau, serta mengusulkan satu “laluhan China” ke arah pembangunan rendah karbon yang berbeza daripada model tradisional Barat “cemar dahulu, kawal kemudian,” selaras dengan tahap pembangunan dan struktur tadbir urus China.

Kata Kunci: Produktiviti karbon; pembangunan ekonomi berkualiti tinggi; GMM sistem; ekonometri spatial; limpahan spatial; transisi hijau; pembangunan serantau terkoordinasi.

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LIST OF ABBREVIATIONS

BP-LM	Breusch-Pagan Lagrange Multiplier Test
CBDR	Common But Differentiated Responsibilities
CEADs	China Emission Accounts and Datasets
CGSS	China General Social Survey
CIS	Commonwealth of Independent States
CO ₂	Carbon Dioxide
COP28	28th Conference of the Parties to the UNFCCC
CP	Carbon Productivity
CPC	The Communist Party of China
DEA	Data Envelopment Analysis
DID	Difference-in-Differences
EKC	Environmental Kuznets Curve
FDI	Foreign Direct Investment
FE	Fixed Effects Model
GMM	Generalized Method of Moments
GNS	General Nesting Spatial Model
GTFP	Green Total Factor Productivity
HQED	High-Quality Economic Development
IDA	Index Decomposition Analysis
IMF	The International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
LISA	Local Indicators of Spatial Association
LM	Lagrange Multiplier
LMDI	Logarithmic Mean Divisia Index
LR	Likelihood Ratio
MDGs	Millennium Development Goals
NOAA	The National Oceanic and Atmospheric Administration
ODE	Ordinary Differential Equation
OLS	Pooled Ordinary Least Squares
RE	Random Effects Model
SAC	Spatial Autoregressive Combined Model
SAR	Spatial Autoregressive Model
SBM	Slack-Based Measure Model
SDA	Structural Decomposition Analysis

SDGs	Sustainable Development Goals
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SFA	Stochastic Frontier Analysis
SOEs	State-Owned Enterprises
SPDA	Spatial Production Decomposition Analysis
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
SUR	Seemingly Unrelated Regression
TFCP	Total-Factor Carbon Productivity
TFP	Total Factor Productivity
TS-PDA	Temporal-Spatial Production-Theoretical Decomposition Model
VIF	Variance Inflation Factor
WCED	World Commission on Environment and Development

CHAPTER 1: INTRODUCTION

1.1 Introduction

Carbon productivity (CP), defined as the economic output generated per unit of carbon emissions, has emerged as a pivotal metric for evaluating the efficiency and sustainability of economic systems in the context of global environmental challenges. As the urgency of ecological and low-carbon transformation grows, CP is increasingly recognized not only as an environmental performance indicator but also as a key benchmark for gauging progress toward green and sustainable development (Zheng et al., 2012). Consequently, it has attracted substantial academic and policy attention, particularly in efforts to reconcile economic growth with carbon mitigation goals.

This research is situated within the broader discourse on sustainable development, with a specific focus on examining the dynamic relationship between high-quality economic development (HQED) and CP. While HQED emphasizes innovation, structural optimization, inclusivity, and environmental responsibility, its influence on CP remains an underexplored area in the existing literature. This study endeavors to fill this research gap by undertaking a rigorous theoretical exploration and empirical assessment of the mechanisms through which HQED affects CP across different regional and developmental contexts.

This chapter introduces the research background and formulates the central research problem, articulating both the academic motivation and the practical relevance of the study. It further specifies the research objectives, highlights the significance of the investigation, and introduces the conceptual framework that guides the subsequent analytical process. By establishing a clear trajectory for inquiry, this chapter provides a solid foundation for the theoretical development and empirical validation presented in the following chapters of the thesis.

1.2 Background of Study

Global climate change has emerged as one of the most pressing and complex challenges to sustainable development across the globe (Besada et al., 2013). As the world's leading carbon emitter, China is increasingly confronted with the intensifying contradiction between sustained economic expansion through its carbon-intensive industrial structure and its ambitious climate commitments. In recent years, the continued dominance of fossil fuels in China's energy portfolio, combined with the high energy intensity and heavy-emission characteristics of its industrialization model, have significantly impeded efforts to reconcile economic growth with environmental sustainability.

To address these developmental dilemmas, China has adopted a new growth paradigm known as HQED, which was formally proposed in the report of the 19th National Congress of the Communist Party of China in 2017. This development model aims to achieve a strategic synergy between economic expansion and ecological protection by prioritizing innovation-driven growth, industrial upgrading, and the advancement of green technologies (Jing & Iván, 2023). In 2020, China further elevated its environmental ambitions by announcing the “dual carbon” targets to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, signaling a move that reflects the country's proactive commitment to global climate governance and its low-carbon transition.

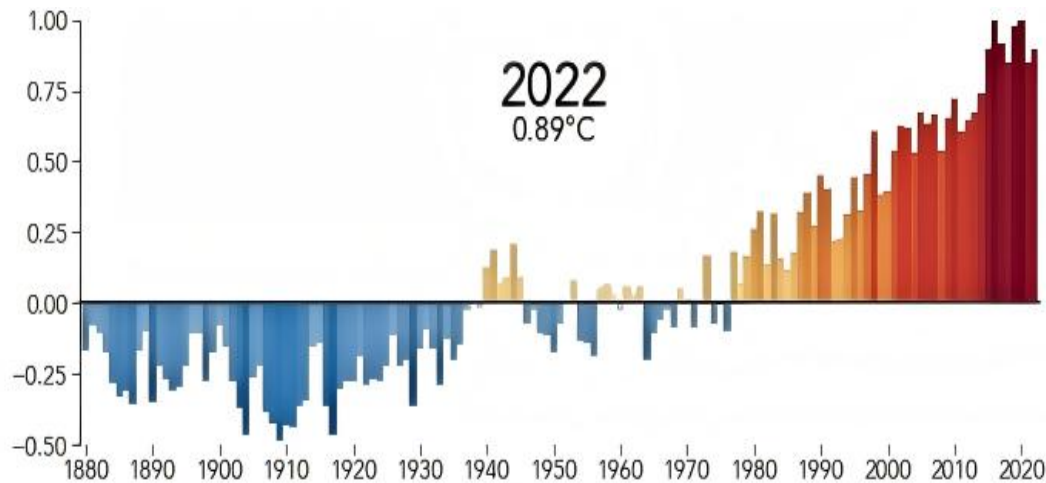
Under the guidance of the dual carbon strategy, green and low-carbon transformation has become a central pathway for promoting HQED in China (Liu et al., 2024b; Mei et al., 2024). To gain a comprehensive understanding of the institutional rationale and developmental logic behind this transition, it is essential to systematically examine multiple dimensions; namely, the trajectory of global climate change, the structural characteristics of China's carbon emissions, and the pronounced spatial disparities in regional development.

1.2.1 Evidence and Global Impact of Climate Change

Global climate change, primarily driven by the accumulation of greenhouse gases (GHGs) such as carbon dioxide (CO₂), has become a defining challenge to sustainable development. Since the Industrial Revolution, intensive fossil fuel consumption has significantly increased atmospheric CO₂ levels (Andres & Marland, 1994; Liu & Liu, 2023), contributing to a persistent rise in global temperatures. According to the National Oceanic and Atmospheric Administration (NOAA), the global average surface temperature has

increased by approximately 0.08°C per decade since 1880, with a cumulative rise exceeding 1.1°C. The past decade has recorded the highest temperatures since modern observations began. Temperature changes can be seen in Figure 1-1.

Figure 1-1: Global Temperature Anomaly (Compared to the 1951-1980 average)



Source: Climate (2023). Obtained from <https://climate.gov/news-features/understanding-climate/>

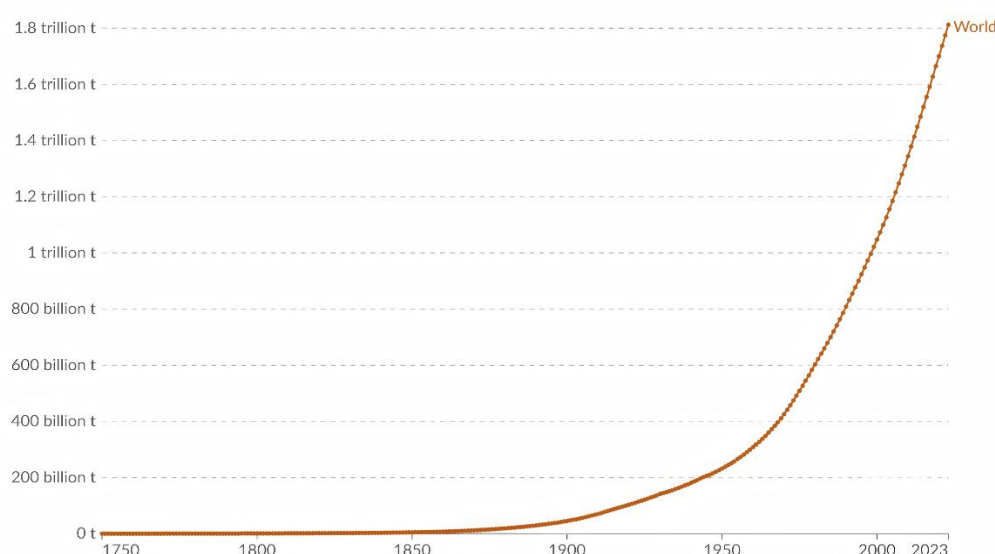
The consequences of this warming are wide-ranging. It has intensified extreme weather events, accelerated polar ice melt, and raised sea levels, threatening both ecological systems and human settlements. Climate-induced disruptions have also affected biodiversity, agricultural productivity, and food security, adding pressure to global emission control efforts (Pandit & Sharma, 2023). In this context, controlling CO₂ emissions has become central to international climate agendas. These agendas are primarily reflected in multilateral agreements such as the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol, and the Paris Agreement, which aim to limit global warming to well below 2°C while pursuing efforts to cap it at 1.5°C (UNFCCC, 2015; IPCC, 2021). Countries worldwide have committed to nationally determined contributions (NDCs), carbon neutrality targets, and market-based mechanisms to curb emissions and promote low-carbon transitions.

Against this backdrop, understanding the root causes of climate change requires an in-depth analysis of historical trends and sectoral patterns of global CO₂ emissions. This section examines the structural dynamics of global emissions to contextualize China's emission trajectory and its associated developmental challenges.

1.2.2 Global CO₂ Emission and Key Emitting Sectors

Since the onset of the Industrial Revolution, global CO₂ emissions have followed a dramatic and sustained upward trajectory. In 1950, emissions were around 23 billion tons, rising to over 85 billion tons by 1990. By 2023, cumulative emissions surpassed 18.1 trillion tons, reflecting the long-term carbon-intensive nature of global industrialization. These trends are illustrated in Figure 1-2.

Figure 1-2: Cumulative CO₂ Emissions, 1750-2023



Source: Global Carbon Budget (2024). Obtained from Cumulative CO₂ emissions

Notes:

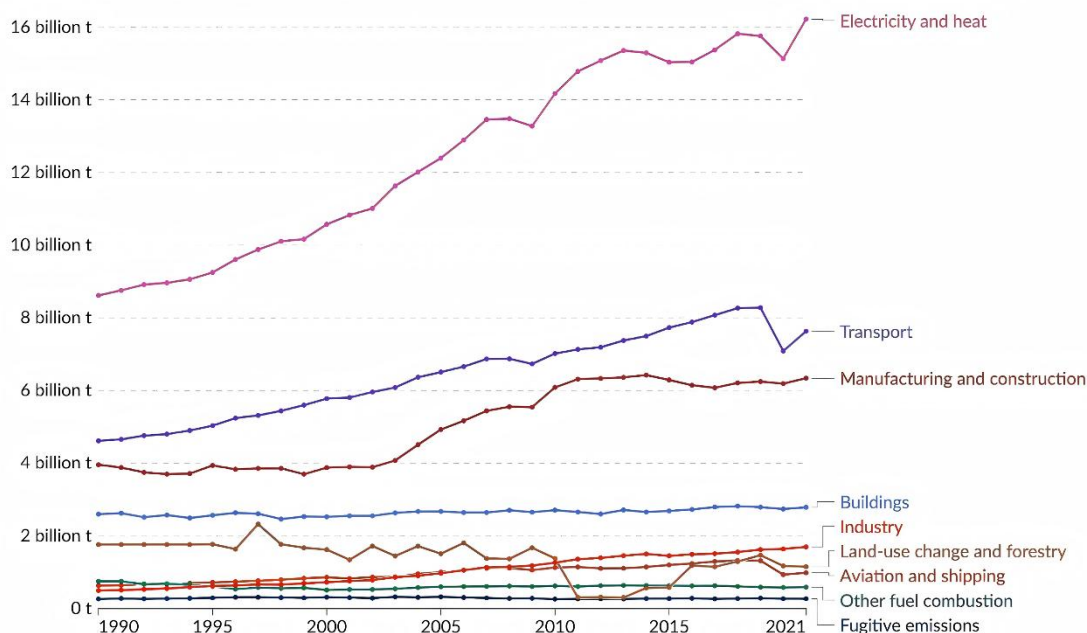
1. Running sum of CO₂ emission produced from fossil fuels and industry since the first year of recording, measured in tonnes. Land-use change is not included.
2. Fossil emissions Fossil emissions measure the quantity of carbon dioxide (CO₂) emitted from the burning of fossil fuels, and directly from industrial processes such as cement and steel production.
3. Fossil CO₂ includes emissions from coal, oil, gas, flaring, cement, steel, and other industrial processes, it does not include land use change, deforestation, soils, or vegetation.

Emissions are unevenly distributed across sectors. Electricity and heat production consistently account for the largest share, contributing approximately 35-40% of global emissions. In 2021 alone, this sector emitted 16.23 billion tons. Transportation follows as the second-largest emitter, contributing 7.63 billion tons in 2021, nearly doubling since 1990. Industrial production and construction also remain major sources, with emissions reaching 6.34 billion tons, largely driven by urbanization and global infrastructure expansion.

Notably, emission trends vary by sectoral dynamics. While electricity and transport show steady growth, industrial emissions are more sensitive to economic fluctuations. Other

sectors contribute smaller shares but exhibit persistent increases over time (Global Carbon Budget, 2024). These patterns are shown in Figure 1-3.

Figure 1-3: Global CO₂ Emissions by Sector, 1990-2021



Source: Climate Watch (2024). Obtained from <https://ourworldindata.org/grapher/co-emissions-by-sector>

Overall, the persistent rise in global CO₂ emissions reflects a systemic dependence on fossil fuel-intensive development. Understanding these structural dynamics is essential for evaluating each country's contribution and responsibility, as well as the policy space available for pursuing low-carbon transitions.

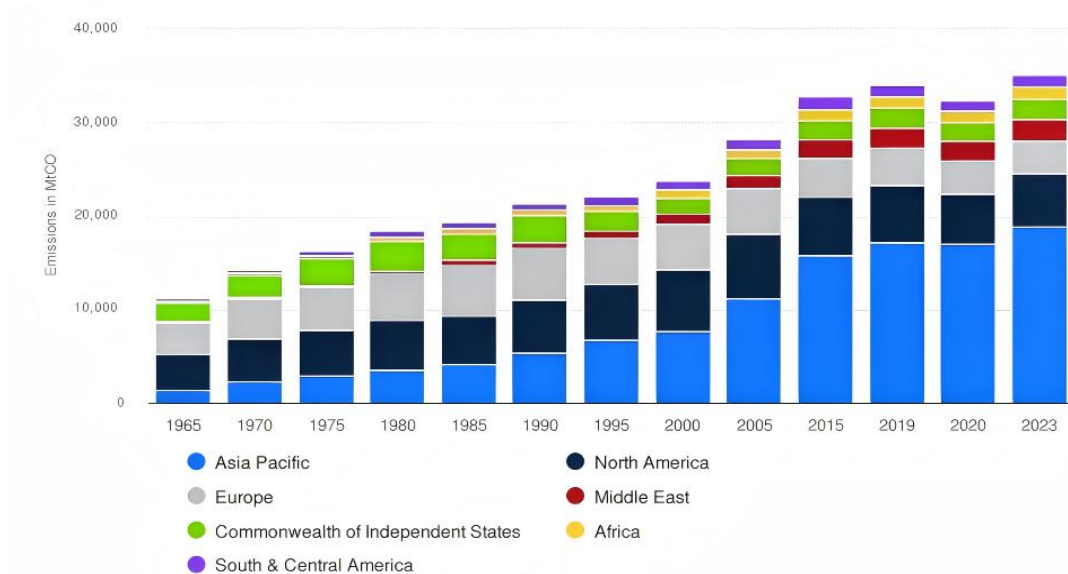
1.2.3 Major Economies' Emissions and Responsibilities

To better assess China's policy constraints and strategic options, it is essential to understand the regional distribution and historical responsibilities of CO₂ emissions. Figure 1-4 illustrates the CO₂ emissions across the world's seven major regions. Currently, the Asia-Pacific region has emerged as the largest contributor to global CO₂ emissions with total emissions reaching 18.85 billion tons in 2023. Within this region, China accounts for approximately 60% of the total emissions, while India contributes about 20%.

In contrast, North America and Europe have exhibited moderate declines in emissions, primarily due to technological advancements and the implementation of stringent environmental policies. Between 2010 and 2022, CO₂ emissions in North America and

Europe decreased by approximately 0.5% and 1.8%, respectively. Emissions from the Middle East, Africa, South America, and the Commonwealth of Independent States (CIS) remain relatively modest in terms of their share of global emissions (Statista 2024).

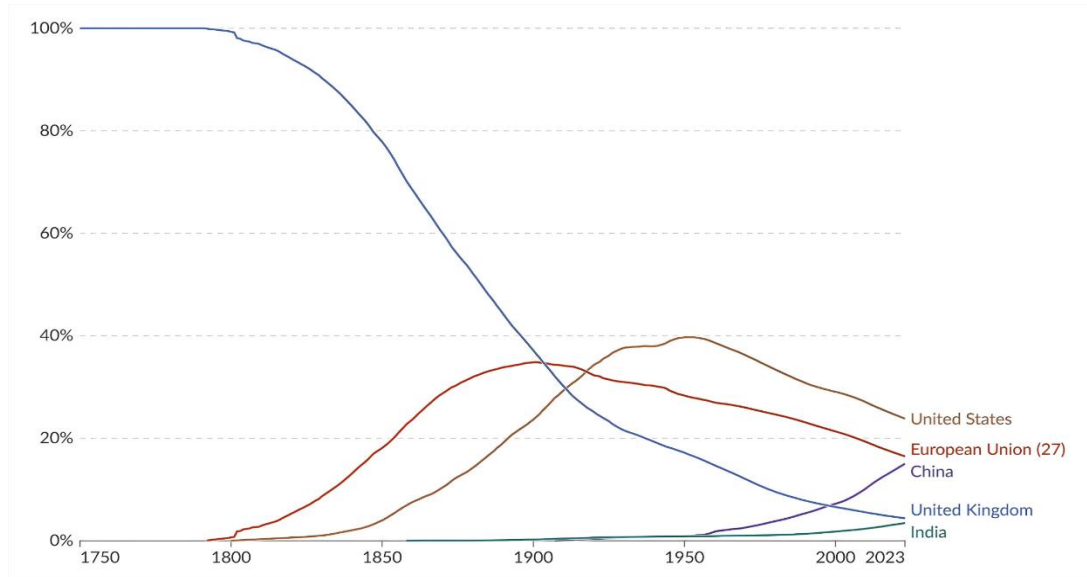
Figure 1-4: Major Regions of Global CO₂ Emissions, 1965-2023
(in million metric tons of CO₂)



Source: Statista (2024). Obtained from <https://www.statista.com/statistics/205966/world-carbon-dioxide-emissions-by-region/>

In general terms, developed countries bear the primary responsibility for the historical accumulation of carbon emissions during their industrialization processes (Dong et al., 2016; Zhang & Pan, 2022). Figure 1-5 highlights the unequal distribution of cumulative CO₂ emissions across major economies, reflecting how historical industrialization trajectories continue to shape the global carbon budget. Although current annual emissions of some developed countries have declined relative to emerging economies, their historical contributions remain disproportionately high. This historical legacy underscores the principle of “common but differentiated responsibilities” in international climate negotiations and continues to frame debates on fairness in burden-sharing for emission reduction commitments.

Figure 1-5:
Share of Global Cumulative CO₂ Emissions by Major Emitting Countries, 1750-2023



Source: Global Carbon Budget (2024). Obtained from <https://ourworldindata.org/grapher/share-of-cumulative-CO2>

Notes:

1. Running sum of CO₂ emissions produced from fossil fuels and industry¹ since the first year of recording, measured in tonnes.
2. Land-use change is not included.

As shown in Figure 1-5, developed countries, specifically the United States (US), the European Union (UN), and the United Kingdom (UK), accounted for 85.21% of global cumulative CO₂ emissions from the Industrial Revolution until 1950. In comparison, China and India contributed only 1.84%. By 2023, the cumulative share of emissions from developed nations had declined to 44.7%, while China and India combined accounted for just 18.51%. The data also reveal a gradual decline in the cumulative emission shares of the US, the EU, and the UK since 1950. This shift is largely attributed to the phenomenon of carbon leakage, whereby developed countries have outsourced carbon-intensive production activities to developing economies (Grubb et al., 2022). As a result, developing nations have borne more than 60% of the world's actual emission reduction burden (IPCC, 2021).

Despite this, developed countries have remained reluctant to fully uphold the principle of “common but differentiated responsibilities” (CBDR) in international climate negotiations (Kolmaš, 2023; Petri & Biedenkopf, 2019). At the 28th Conference of the Parties (COP28) to the United Nations Framework Convention on Climate Change held in 2023, the Loss and Damage Fund initiative, primarily advocated by the European Union and the US, called on developing countries to undertake greater emission reduction responsibilities. However, it failed to establish a corresponding compensation mechanism

for historical emissions. Such practices of environmental colonialism not only undermine the equity principles enshrined in the Paris Agreement but also constrain the development opportunities of the Global South (Cato, 2022; Ikporukpo & Ikporukpo, 2024).

For rapidly developing nations such as China, this global asymmetry presents a dual challenge. On the one hand, China must respond to increasing international pressure to reduce emissions and contribute to global climate targets. On the other hand, it must also maintain economic momentum to meet domestic development needs and narrow urban–rural and regional gaps.

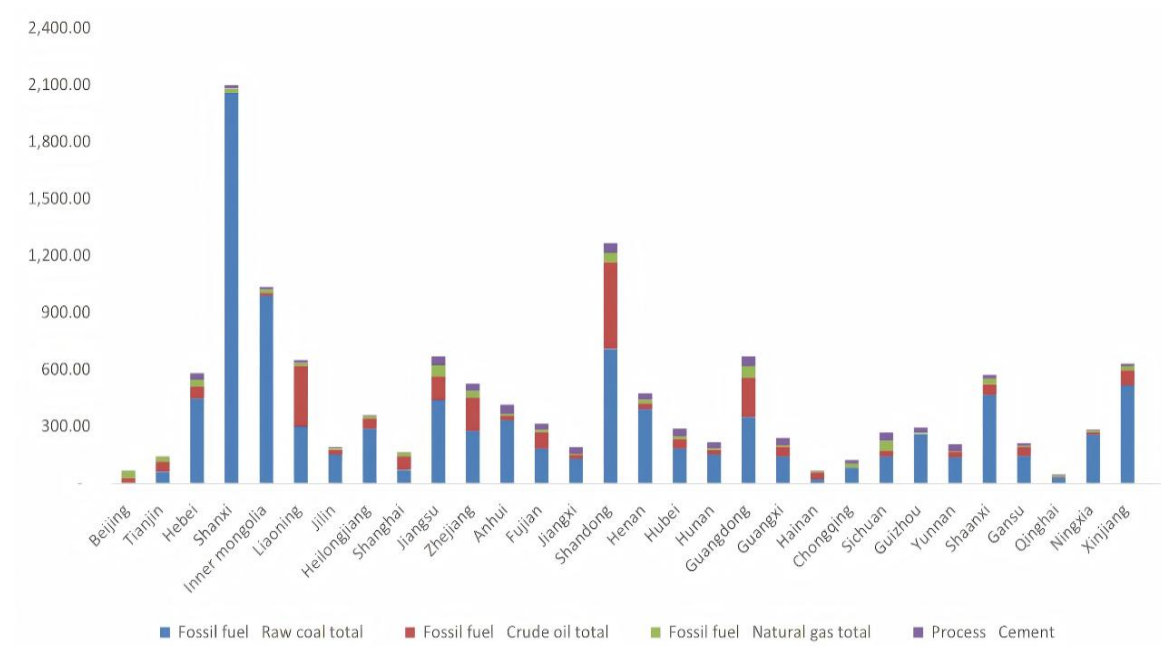
In this context, China’s emission trajectory has profound implications beyond its national borders. As the largest developing economy and a dominant emitter in recent decades, China’s success or failure in balancing growth and decarbonization will largely influence the achievement of global climate goals. Thus, achieving a balance between continued growth and environmental responsibility in China is not only a domestic priority but also a matter of global concern.

Accordingly, enhancing CP, defined as improving economic output per unit of carbon emission, has become a critical pathway for China to break its carbon-intensive growth trajectory, reduce emission intensity, and align development with sustainability objectives. A deeper understanding of CP requires not only a global perspective but also an examination of China’s internal emission structure and regional disparities. The next section therefore turns to the domestic context to illustrate why improving CP is essential and how HQED may play a pivotal role in this process.

1.2.4 Structural and Regional Disparities of CO₂ Emissions in China

Figure 1-6 presents the total CO₂ emissions of 30 provinces in mainland China for the year 2021, excluding Tibet, Hong Kong, Macao, and Taiwan. The data indicate clear disparities in emissions across provinces. Shanxi, Inner Mongolia, and Shandong are among the highest emitters, while Beijing, Tianjin, and Hainan have relatively low emission levels. These findings reflect notable regional imbalances in the structure and scale of carbon emissions.

Figure 1-6: CO₂ Emissions by Province and Source in China, 2021 (Mt)



Source: CEADs (2022). Obtained from <https://www.ceads.net/data/province/>

Provincial emissions in China can be broadly categorized into three structural patterns. First, provinces such as Shanxi, Inner Mongolia, and Shaanxi rely predominantly on coal combustion, which accounts for more than 60% of their total emissions. Their energy structure is heavily shaped by abundant coal reserves and a reliance on coal-intensive industries. Second, in provinces like Jiangsu and Guangdong, emissions originate from a more balanced mix of coal, oil, and cement production. This diversified structure reflects their complex industrial base and requires a coordinated mitigation strategy. Third, Sichuan represents a cleaner energy profile, with a significant share of emissions coming from natural gas. This reflects the province's relatively advanced energy transition supported by resource endowment and policy efforts.

In summary, variations in resource endowments, industrial composition, and energy consumption patterns have resulted in substantial regional heterogeneity in carbon emissions across China (Wu et al., 2021a; Zhao, 2023). This structural complexity necessitates region-specific decarbonization policies and highlights the difficulty of implementing uniform national standards.

Beyond spatial disparities, China also faces the broader challenge of reconciling economic development with climate commitments. In this context, CP has become a key performance indicator in assessing the effectiveness of HQED-oriented transformation.

HQED promotes technological upgrading, industrial restructuring, and institutional improvements, all of which can enhance CP. Meanwhile, improved CP signals the outcome of effective HQED practices. Therefore, exploring the dynamic linkage between HQED and CP is crucial for evaluating China's capacity to achieve green development while sustaining economic growth. This study adopts CP as an evaluative lens to examine the effectiveness of HQED across regions, forming the analytical foundation for the following chapters.

1.2.5 The Challenge of Coordinating HQED and Carbon Reduction

China faces a unique and complex set of challenges in aligning HQED with the imperative of reducing carbon emissions. These challenges can be categorized into four main dimensions:

First, the time constraint is particularly acute. China has committed to achieving carbon peaking by 2030 and carbon neutrality by 2060, leaving only 30 years for a full low-carbon transition. In contrast, many developed countries such as the EU, UK, and Japan have adopted timelines spanning 50 to 70 years (Zhao et al., 2022b). This compressed timeframe not only places immense pressure on accelerating structural adjustment and technological innovation, but also requires more intensive policy coordination, higher investment efficiency, and stronger institutional support. Compared with countries that have had decades to gradually decouple economic growth from carbon emissions, China must pursue a more concentrated and high-intensity approach to ensure that its dual carbon targets are achievable.

Second, the tension between economic growth and environmental protection remains pronounced. Despite efforts to upgrade its industrial base, China's economy still relies heavily on high-emission sectors such as steel, cement, and coal-fired power. Meanwhile, green industries and low-carbon technologies are not yet mature enough to fully support sustainable growth (Li & Deng, 2024; Wang et al., 2023a). Balancing carbon intensity reduction with stable economic performance presents a persistent policy dilemma.

Third, regional disparities in both total emissions and emission structure pose significant implementation challenges. Eastern provinces generally exhibit higher levels of CP due to advanced technologies and diversified energy mixes, while many central and western regions remain dependent on coal and other fossil fuels (Wang et al., 2024c; Yang

et al., 2021a). This uneven development pattern complicates national coordination and makes region-specific policies indispensable.

Fourth, global uncertainties further complicate the domestic policy landscape. Geopolitical tensions, energy price volatility, green trade barriers, and the restructuring of global supply chains have introduced new risks to China's green transition pathway. These external factors may disrupt progress and constrain room for maneuver, making it more difficult to design consistent and forward-looking strategies.

Taken together, these challenges highlight the extraordinary complexity of aligning HQED with carbon reduction in China. The compressed timeline magnifies the urgency of transition, the growth–environment trade-off underscores the difficulty of reconciling short-term and long-term goals, regional disparities call for differentiated but coordinated strategies, and global uncertainties add layers of risk and unpredictability. These intertwined pressures suggest that improving CP is not merely a technical issue but a systemic challenge, requiring the integration of efficiency, innovation, equity, and resilience within the HQED framework.

Given these multifaceted pressures, China must identify a development strategy that is both environmentally sustainable and economically resilient. Rather than replicating the carbon-intensive pathways of developed nations, China must pursue an approach grounded in its own institutional and developmental context (Zhang, 2021). The emphasis should be on integrating HQED with ecological principles to realize a synergistic relationship between economic growth and carbon reduction (Hon, 2013). Against this backdrop, improving CP becomes a strategic focal point. As both a performance indicator and a policy lever, CP reflects how effectively economic activities are decoupled from carbon emissions. Understanding its relationship with HQED is thus essential for evaluating the feasibility of China's dual-carbon goals. These interrelated challenges and strategic imperatives form the foundation for the research problem explored in this dissertation.

In this sense, CP not only measures the effectiveness of carbon reduction policies but also serves as a barometer of whether HQED is truly delivering sustainable and inclusive outcomes. Linking the two provides an analytical pathway to assess how China can simultaneously advance growth, equity, and ecological sustainability.

1.3 Problem Statements

The accelerating urgency of climate change has placed unprecedented pressure on economies worldwide to decouple economic growth from carbon emissions. CP has become a key indicator for evaluating the sustainability and efficiency of development. According to the IEA (2024), China alone contributed over 30% of global CO₂ emissions in 2023, making its decarbonization trajectory a pivotal concern not only domestically but also globally. As the largest developing country, China's ability to balance economic progress with environmental stewardship will significantly influence global climate outcomes.

In response, the paradigm of HQED has emerged as a central strategy to reshape China's growth trajectory. HQED emphasizes innovation, industrial upgrading, environmental sustainability, and social inclusivity, aiming to promote long-term green transformation. However, despite its growing prominence, the impact of HQED on CP remains underexplored both theoretically and empirically, limiting our understanding of whether and how development quality contributes to low-carbon transition.

First, existing studies lack a consistent and multidimensional framework to assess HQED. While various indices have been proposed, they often differ substantially in structure, weighting, and coverage, making cross-regional comparisons difficult and undermining the robustness of policy evaluation. In particular, some studies focus narrowly on economic efficiency or green total factor productivity, neglecting the broader social and institutional dimensions of HQED. This measurement inconsistency constrains empirical investigation of HQED's contribution to CP improvement and weakens the comparability of research outcomes.

Second, most empirical analyses treat HQED and CP as separate policy concerns, with limited integration in a unified analytical framework. This disconnect prevents researchers from capturing the synergistic or conflicting effects of development strategies on emission efficiency and limits evidence-based policy design. Without a comprehensive framework, it remains unclear whether HQED-driven reforms such as industrial upgrading and green finance expansion truly enhance CP, or whether they simply shift pressures across sectors and regions. A more integrated framework is therefore needed to evaluate the mechanisms through which HQED contributes to or constrains low-carbon development.

Third, the HQED-CP relationship likely involves lagged and cumulative effects shaped by long-term industrial evolution and delayed policy outcomes. Yet, temporal dynamics remain insufficiently addressed in the literature. Most existing work applies static cross-sectional or short-panel approaches, which fail to capture persistence, path dependence, and delayed responses in carbon productivity improvements. This omission raises concerns about the sustainability and consistency of HQED's influence over time, particularly given China's compressed timeframe for achieving its dual-carbon targets. Addressing temporal dynamics is critical to understanding whether HQED represents a short-term stimulus or a lasting driver of carbon efficiency.

Fourth, CP is shaped not only by local factors but also by spillover effects across provinces through industrial chains, innovation networks, and environmental coordination. Clear spatial clustering has been observed in both HQED performance and CP levels across China, but few studies explicitly incorporate these interdependencies into empirical models. Neglecting spatial transmission risks underestimating the true impact of HQED and overlooks the importance of interregional collaboration in achieving carbon reduction goals. Incorporating spatial perspectives would therefore provide a more realistic understanding of how HQED operates in a geographically diverse and interconnected economy.

In sum, China's vast regional heterogeneity, evolving policy context, and complex emission landscape necessitate an integrated research framework that captures the multidimensional nature of HQED, its dynamic effects over time, its spatial transmission mechanisms, and its interaction with institutional reforms. Only by addressing these gaps can we establish whether HQED serves as a credible and effective pathway toward a green, low-carbon transition in China. To address these gaps, this study is guided by the following research questions:

- i) How can a comprehensive and comparable index be developed to measure HQED across provinces?
- ii) What is the static relationship between HQED and CP at the provincial level?
- iii) How does the impact of HQED on CP evolve over time, and are there dynamic effects such as lag or path dependence?
- iv) Do regional differences in HQED generate spatial spillovers that influence CP performance in neighboring provinces?

1.4 Objectives of Study

1.4.1 General Objective

In general, the intention of this study is to examine the relationship between HQED and CP across China's provincial regions by developing a comprehensive measurement framework and analyzing its static, dynamic, and spatial impacts.

1.4.2 Specific Objectives

To achieve this core analytical aim, this study is guided by the following specific objectives:

- i) To construct a comprehensive HQED index grounded in theoretical principles, empirical literature, and objective weighting methods, enabling cross-regional comparison.
- ii) To examine the static relationship between HQED and CP at the provincial level.
- iii) To investigate the dynamic effects of HQED's impact on CP, including time-lagged effects and persistence over time.
- iv) To evaluate the spatial spillover effects of HQED on CP across neighboring provincial regions using spatial econometric models.

1.5 Significance of Study

This study makes a meaningful contribution to the growing body of research at the intersection of sustainable development, economic policy, and environmental efficiency. By focusing on the relationship between HQED and CP, this study addresses a pressing academic and policy gap in understanding how development strategies influence environmental outcomes in the context of carbon-constrained growth.

First, while existing studies have proposed multidimensional frameworks for HQED, most remain limited by inconsistent dimensions, or complex constructions that hinder regional comparability. This study refines and systematizes HQED measurement by

integrating economic, social, and ecological dimensions aligned with China's New Development Philosophy and the Sustainable Development Goals (SDGs). The use of entropy-based weighting enhances objectivity and replicability, offering a more robust and policy-relevant tool for regional assessment.

Second, by empirically analyzing the static, dynamic, and spatial effects of HQED on CP, this research bridges the gap between theoretical frameworks and practical policy design. The application of dynamic panel models and spatial econometrics provides a nuanced understanding of how HQED influences carbon efficiency over time and across regions, advancing methodological rigor in a field often dominated by cross-sectional or simplified analyses.

Third, the research generates actionable insights for regional policymakers in China, where significant disparities in development and emissions profiles persist. By uncovering region-specific effects and interprovincial spillovers, the findings inform differentiated and coordinated policy approaches that can better align local development goals with national carbon reduction targets.

Lastly, the study offers a transferable framework for other developing and transitional economies seeking to pursue high-quality growth without compromising environmental sustainability. As such, it holds both national and global relevance, contributing to broader discussions on how to operationalize sustainable development in practice.

1.5.1 Theoretical Contributions

a) Expanding the Theoretical Perspective

This study introduces HQED as a systemic explanatory variable into the analytical framework of CP. By moving beyond conventional approaches that rely primarily on single indicators such as Gross Domestic Product (GDP) growth or carbon intensity, the study broadens the theoretical scope of research on green and low-carbon development.

b) Enriching the Indicator System and Deepening Multidimensional Mechanism Analysis

Through the construction of a multidimensional evaluation system for HQED and the application of static, dynamic, and spatial econometric models, this study identifies

multiple transmission pathways through which economic quality influences CP. This approach enhances the theoretical understanding of the complex interaction mechanisms between economic development and carbon efficiency.

c) Strengthening the Integration Between Theory and Practice

Closely aligned with China's 14th Five-Year Plan and the dual carbon strategy, this study builds a theoretical-practical link by integrating the core goals of green development with urgent policy priorities. In doing so, it provides theoretical foundations for the coordinated advancement of economic growth and environmental sustainability.

1.5.2 Practical Contributions

a) Supporting the Alignment Between HQED and Carbon Governance

The empirical identification of the relationship between HQED and CP provides a scientific foundation for policy formulation within the dual carbon framework. It enhances the strategic coherence, effectiveness, and forward-looking nature of development and climate policies.

b) Revealing Regional Disparities to Inform Targeted Policy Design

Through the analysis of spatial effects, this study highlights how regional imbalances in economic development lead to significant differences in CP. These findings offer data-informed support for designing region-specific and differentiated low-carbon transition strategies that reflect local conditions and developmental stages.

c) Guiding Green Transformation and Industrial Upgrading

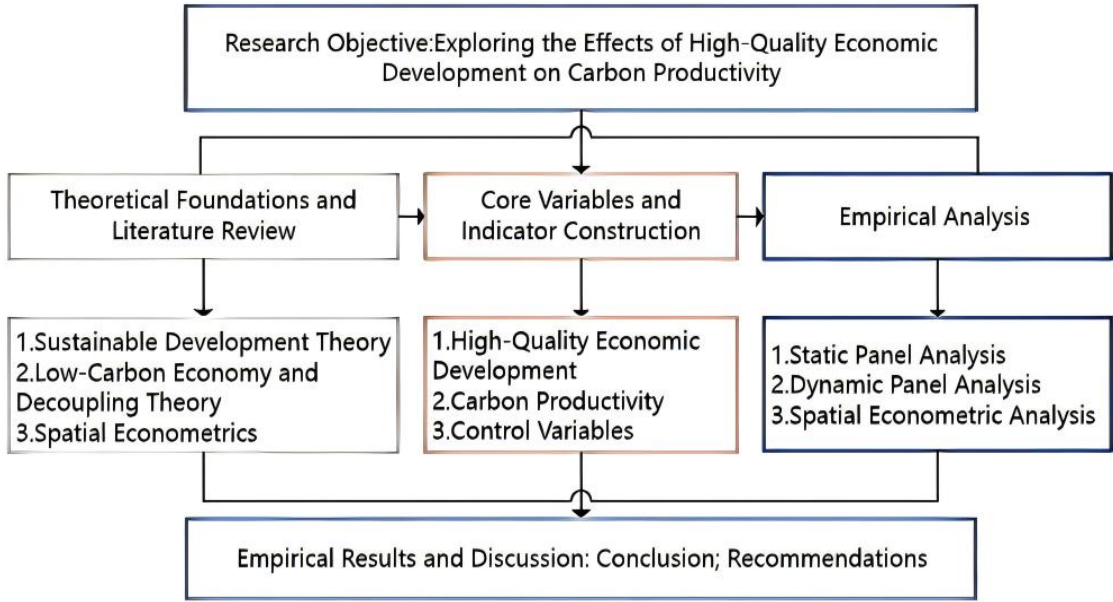
The research results provide actionable insights for local governments and policymakers in optimizing industrial structures, improving energy efficiency, and promoting green technological innovation. These measures contribute to achieving both carbon reduction and sustainable economic growth.

In conclusion, this study not only offers a robust theoretical foundation for China's ecological civilization agenda but also delivers valuable implication for global green transformation and international climate governance.

1.6 Research Framework

This section presents the overall research framework that guides the structure and logic of this study. Anchored in the core question of how HQED affects CP, the framework integrates theoretical foundations, variable construction, and empirical strategy into a coherent research pathway. It serves as a conceptual bridge between the literature-based background and the methodological design, illustrating how theoretical insights are translated into operationalized indicators and analytical models. The research process follows a structured logic of “theoretical foundation → indicator construction → empirical analysis → results and discussion.” As shown in Figure 1-7, this diagram outlines the key components and methodological flow of the study, clarifying the linkage between theoretical concepts and empirical pathways.

Figure 1-7: Research Framework



1.7 Organization of Study

To systematically address the research objectives and ensure analytical coherence, this thesis is structured into five chapters.

Chapter 1 introduces the study by outlining its background, significance, theoretical rationale, and overarching research logic. It defines the key research questions, clarifies the study objectives, and provides a roadmap of the thesis structure.

Chapter 2 offers a comprehensive literature review, covering the theoretical foundations of sustainable development, the low-carbon economy, decoupling theory, and spatial econometrics. It clarifies key concepts, synthesizes empirical findings from both domestic and international studies, identifies literature gaps, and articulates the study's scholarly positioning and theoretical innovation.

Chapter 3 details the research methodology, including data sources, variable construction, and the selection of analytical models. The chapter introduces a progressive modeling framework comprising the static panel model, the System Generalized Method of Moments (System GMM), and the Spatial Durbin Model (SDM), with clear justifications for their use in examining the relationship between HQED and CP.

Chapter 4 presents the empirical results and discussion, analyzing the impact of HQED on CP from static, dynamic, and spatial perspectives. The spatial analysis includes a decomposition of effects into direct, indirect, and total components. Comparative insights are drawn to uncover the underlying mechanisms linking HQED to CP across provinces.

Finally, Chapter 5 concludes the thesis by summarizing the main findings, proposing region-specific and policy-oriented recommendations, and reflecting on the study's limitations. It also outlines future research directions to advance understanding of the spatial and dynamic interactions between HQED and CP.

CHAPTER 2:

LITERATURE REVIEWS

2.1 Introduction

This chapter focuses on the two core variables, Carbon Productivity (CP) and High-Quality Economic Development (HQED). It aims to clarify their conceptual definitions, examine the relevant theoretical foundations, and systematically review existing research in both domestic and international contexts. Through a structured and critical literature review, this chapter seeks to identify current academic progress, highlight key research gaps, and outline the limitations of prior studies. In so doing, it underscores the theoretical contributions and innovative significance of this dissertation and establishes a solid conceptual and analytical foundation for the subsequent chapters focused on model construction and empirical analysis.

2.2 Core Concepts and Analytical Linkages

2.2.1 CP: Definitions, Measurement, and Relevance

CP refers to the amount of economic output generated per unit of CO₂ emissions. It is typically measured as the ratio of GDP to CO₂ emissions. The concept was originally proposed by Kaya and Yokobori (1997) to evaluate carbon efficiency in the context of economic growth. As a core indicator of green development performance, CP reflects the carbon cost of generating economic output, thereby capturing the trade-off between economic expansion and environmental pressure.

CP is closely related to carbon intensity, which measures the amount of CO₂ emissions per unit of GDP. Although the two are mathematical inverses, they differ in focus. Carbon intensity emphasizes emission reduction constraints and is frequently used to identify high-emission sectors or regions, thereby informing emission control policies. In

contrast, CP highlights efficiency gains and evaluates carbon performance from a productivity-oriented perspective, making it better aligned with China's strategic emphasis on HQED. Some studies have noted that CP has already been adopted by certain provincial governments as a core metric in green performance evaluations (Wang et al., 2020).

In terms of measurement, two main approaches are commonly used. The first is single-factor CP, calculated as the GDP-to-CO₂ ratio. The second is total-factor carbon productivity (TFCP), which incorporates multiple input variables such as labor, capital, and energy (Chen & Yao, 2024; Li & Feng, 2014). Although TFCP provides a more comprehensive theoretical framework, it often suffers from strong subjective assumptions, as well as inconsistencies in data standards across provinces, which may compromise the reliability and comparability of results.

Considering data accessibility, methodological applicability, and policy relevance, this study adopts single-factor CP as the core measurement indicator. On the one hand, this method is straightforward to calculate, widely comparable, and suitable for longitudinal and spatial panel analysis. On the other hand, its results can be easily integrated into national carbon policy frameworks, including the dual carbon targets. A large body of literature supports this approach (Enkvist et al., 2008; Gornall et al., 2010; Wang & Xue, 2024), offering a robust foundation for comparative research. Therefore, using the GDP-to-CO₂ ratio provides a clear and policy-relevant metric for identifying the influence mechanisms of HQED on CP.

2.2.2 HQED: Definitions and Conceptual Evolution

The report of the 19th National Congress of the Communist Party of China emphasized that high-quality development is characterized by low factor inputs, efficient resource allocation, minimal environmental and resource costs, and substantial economic and social benefits. From a functional perspective, high-quality development pertains to the broader domain of economic performance. According to Wei (2022), high-quality development constitutes a core task in building a modern socialist country. Feng et al. (2024a) argued that achieving this objective requires enhancing efficiency, optimizing economic structures, fostering innovation-driven growth, and promoting green transformation, thereby advancing toward a development model that is more sustainable, coordinated, and inclusive.

In this study, terms commonly found in existing literature, such as “quality of economic development,” “quality of economic growth,” “high-quality development,” and “macro-quality” are collectively defined as HQED.

The term “quality of economic growth” emerged as a critical response to the shortcomings of focusing solely on growth speed. It underscores the importance of balancing the quantity and quality of economic growth. However, there remains no unified academic consensus on its definition at either the domestic or international level (Ren, 2012). Research on “quality of economic development” has mainly originated in China and emphasizes multi-objective evaluation frameworks. Since the formal adoption of the concept of “high-quality development” in the 19th Party Congress, the academic focus has shifted from merely pursuing multiple goals to pursuing higher-level development, with relevant research primarily found in Chinese academic literature (Ren, 2018b).

International economists such as Solow (1956) and Jorgenson and Griliches (1967) were among the earliest to discuss the concept of economic growth quality, although they did not provide a clear definition. Their work suggested that non-growth dimensions, including efficiency and sustainability, should be incorporated into the evaluation of economic performance. Early studies primarily focused on economic efficiency (Dornbusch & Fischer, 1979), while subsequent scholars such as Lucas Jr (1988) and Thomas (2000a), expanded the analytical scope to include social development, environmental protection, and human capital. More recent studies have further examined the quality of economic growth from the perspectives of economic structural transformation, growth stability, equity, and resource–environment coordination (Barro, 2002; Castells-Quintana et al., 2018; Thomas, 2000b). However, much of the existing international literature remains fragmented and lacks an integrated framework.

Among domestic contributions, Ren Baoping’s research team has played a leading role in developing a comprehensive evaluation system for economic growth quality. Chao and Hui (2009) proposed an integrated index system that encompasses economic structure, environmental protection, equity, and stability. This framework provides a more holistic and systematic approach to evaluating the quality of economic growth.

Since President Xi Jinping formally introduced the concept of “high-quality development” at the 19th National Congress of the Communist Party of China in 2017, a

growing body of literature has emerged to explore its theoretical and practical dimensions. Jin (2018), drawing on normative economic analysis, argues that high-quality development is designed to meet the population's evolving needs and is reflected in various aspects of economic performance, structural adjustment, and developmental patterns. According to Tian (2018), this form of development emphasizes attributes such as comprehensiveness, coordination, resilience, and sustainability.

Compared with earlier expressions such as “quality of economic growth” or “quality of development,” the term HQED reflects a theoretical elevation that aligns with China's new development philosophy, strategic direction, and governance priorities in the current era (Ren, 2018a). Although the phrase HQED appears to focus on the economic domain, its proper interpretation must also encompass social, political, ecological, and cultural dimensions. Furthermore, the existing literature does not provide a clear distinction between the concepts of “high-quality development” and “HQED” and these terms are often used interchangeably without conceptual differentiation.

Since the implementation of the Reform and Opening-up policy, China has experienced remarkable economic growth. However, this progress has also given rise to a number of structural challenges, including regional development imbalances, widening income disparities, insufficient social welfare systems, and increasing environmental degradation. These issues have contributed to the formation of an economy that is large in scale but lacking in quality. In response to these constraints, scholars have enriched the conceptual framework of HQED by emphasizing its problem-oriented, context-specific, and practically relevant dimensions. Current academic research on HQED primarily focuses on three major thematic orientations:

a) Theoretical Orientation

Scholars have emphasized the multi-dimensional connotation of HQED. For example, Song and Gao (2024) highlighted the intrinsic connection between economic growth, the creation of social wealth, income distribution, and public satisfaction. Similarly, Jin (2018) stressed the alignment between HQED and the overarching objective of comprehensive human development.

b) Problem-solving Orientation

A number of studies have focused on the practical challenges of unbalanced development. For instance, Liu and Sun (2021) identified income inequality, the urban–rural divide, and regional development gaps as critical obstacles that hinder the advancement of high-quality development.

c) Pathway Orientation

Other scholars have explored the mechanisms and channels through which HQED can be realized. These include innovation-driven growth, reallocation of production factors, upgrading of industrial structures, and improvement of ecological conditions. Within the domain of innovation, Sun and Xu (2018) and Wang (2022) underscored the critical role of technological innovation as a driving force. Regarding industrial restructuring, Fang et al. (2020) and Kong et al. (2018) examined the relationship between structural adjustment and the attainment of HQED. In the ecological context, Chen and Chen (2018) analyzed the impact of PM2.5 pollution on the overall quality of economic development.

These diverse perspectives have contributed to a more comprehensive theoretical and empirical foundation for understanding and advancing HQED in China.

2.2.3 The Interconnection Between HQED and CP

Under the background of the dual carbon strategy, CP, which measures the economic value generated per unit of carbon emissions, has become a core indicator for promoting green transformation and assessing the effectiveness of low-carbon development efforts (Zhang et al., 2021). At the same time, HQED, as the overarching goal of China’s economic strategy in the new era, emphasizes development quality, structural upgrading, and green coordination. Its fundamental objective is to achieve integrated progress in economic efficiency, ecological sustainability, and social well-being (Wu et al., 2023c; Xu & Deng, 2022). From a theoretical perspective, there is strong conceptual alignment between CP and HQED. Their interaction is primarily reflected in three dimensions: economic foundation, social foundation, and ecological foundation. On this basis, HQED promotes CP through a systematic and multi-channel transmission mechanism.

Within the economic foundation dimension, HQED emphasizes the enhancement of economic efficiency through industrial structure upgrading and technological innovation (Jin

& Sun, 2019; Song et al., 2022). Specifically, by promoting industrial upgrading, improving industrial rationalization, and increasing the share of producer services, HQED helps reduce the proportion of traditional energy-intensive industries. This facilitates the reallocation of resources toward greener and more efficient sectors (Wu et al., 2024; Xue et al., 2022; Yang et al., 2022b). In addition, continuous progress in technological innovation—often captured by the urban innovation index—supports the development and diffusion of green technologies, thereby improving the marginal efficiency of carbon abatement (Chamchong & Boossabong, 2021; Chen et al., 2021; Yang et al., 2022b). The growth of inclusive total factor productivity also reflects improvements in the resource allocation efficiency of capital, labor, and technology (Guan et al., 2022; Sato et al., 2018). Furthermore, a higher level of openness to international trade and foreign investment contributes to the introduction of advanced green technologies and management practices, enhances the mobility of green production factors, and promotes cross-border knowledge spillovers (Song et al., 2024). Collectively, these mechanisms drive the improvement of CP from the supply-side perspective.

In the social foundation dimension, HQED emphasizes a people-centered approach and the equalization of public services, aiming to improve residents' quality of life and promote social inclusiveness (Fan & Zhang, 2019; Liu et al., 2022). On the one hand, increasing levels of per capita disposable income contribute to the formation of green consumption preferences and environmentally conscious behaviors, which generate demand-side momentum for industrial green transformation (Wei et al., 2024). On the other hand, higher investment in education and improved access to healthcare help strengthen human capital, elevate public awareness of low-carbon development, and enhance citizen engagement in environmental initiatives. These changes collectively lay a social foundation for sustainable green lifestyles (Wu et al., 2023b). Furthermore, the development of a more inclusive social security system enhances public support for environmental regulations and fosters micro-level incentives that encourage environmentally friendly behavior. These mechanisms contribute to the establishment of a stable institutional environment, which facilitates the continuous improvement of CP (Wang & Li, 2022).

In the ecological foundation dimension, HQED is guided by the concept of ecological civilization, which incorporates environmental constraints into the logic of economic planning (Zhang et al., 2022a). Efforts such as increasing the comprehensive utilization rate

of industrial solid waste, reducing sulfur dioxide emissions per unit, and lowering PM2.5 concentrations have improved regional ecosystem quality and enhanced the carrying capacity of the environment. These actions help optimize the allocation of natural resources and the utilization of environmental assets (Alli et al., 2024; Lei et al., 2022). Improvements in resource recycling efficiency not only reduce overall carbon emissions but also raise the economic output generated per unit of CO₂. A sound ecological environment also plays a supportive role in attracting green investments, clean energy, and sustainable technologies, which facilitate the replacement of traditional energy sources and the upgrading of production systems. These factors jointly contribute to sustained improvements in CP.

In summary, HQED promotes the enhancement of CP through coordinated improvements in economic efficiency, social development, and ecological quality. This integrated approach forms a composite mechanism that supports low-carbon and high-efficiency economic growth. From a theoretical standpoint, it can be reasonably inferred that HQED exerts a positive influence on CP through a structured and multidimensional transmission pathway. However, this relationship still requires empirical validation to clarify its internal mechanisms and actual effects. Based on this conceptual framework, the present study develops a multidimensional index system and conducts an empirical analysis of the static, dynamic, and spatial effects of HQED on CP across provincial regions in China. The objective is to provide a solid theoretical foundation for promoting green transformation and supporting the coordinated achievement of the dual carbon goals.

2.3 Theoretical Foundations of HQED and CP

2.3.1 Sustainable Development Theory and the Foundations of Green Growth

During the 1950s and 1960s, the world experienced rapid economic growth, accelerated urbanization, and population expansion. However, these trends brought mounting environmental pressure, triggering deep reflection on the traditional paradigm of “growth equals development.” As the path of unrestrained economic expansion faced the dual constraints of resource depletion and ecological degradation (Chang & Li, 2009), the theory of sustainable development (SD) emerged and gradually became the dominant global framework for addressing the conflict between economic progress and environmental protection.

2.3.1.1 The Concept of Sustainable Development

The concept of the sustainable development concept evolved from early awareness to institutional formulation (Tomislav, 2021). In 1972, Barbara Ward and René Dubos co-authored *Only One Earth*, the first major work to elevate human survival to a global ecological issue. That same year, the Club of Rome released *The Limits to Growth*, which argued that infinite economic expansion was unsustainable and introduced early ideas of “sustainable growth” and “balanced development” (Meadows et al., 1972).

A major breakthrough came in 1987, when the World Commission on Environment and Development (WCED) released the report *Our Common Future*, which provided a systematic and widely accepted definition of sustainable development: “Development that meets the needs of the present without compromising the ability of future generations to meet their own needs.” This definition laid the theoretical foundation for modern sustainable development and has been widely adopted by the United Nations as a central tenet of the global development agenda.

2.3.1.2 The Three-Dimensional Goals and Policy Practices of Sustainable Development

In practice, the concept of sustainable development has evolved from a focus on resource conservation to a multidimensional coordination approach. In 1992, the United Nations Conference on Environment and Development formally adopted the *Rio Declaration* and *Agenda 21*, which articulated the three foundational pillars of sustainable development: economic growth, social progress, and environmental protection. The conference also established the principle of “common but differentiated responsibilities” (Un, 1992), marking the transition from theoretical advocacy to a global governance framework.

In 2000, the United Nations launched the Millennium Development Goals (MDGs), focusing on poverty reduction and initiating a new era of development-oriented international cooperation. In 2015, building upon the MDGs, the UN adopted the Sustainable Development Goals (SDGs), comprising 17 goals and 169 sub-targets that comprehensively cover economic, social, environmental, and governance dimensions (Briant, 2015; Gao et al., 2019).

Among SDGs, the economic goals, such as Goal 8 (*Decent Work and Economic Growth*) and Goal 9 (*Industry, Innovation, and Infrastructure*), emphasize job creation, total factor productivity, technological innovation, and global cooperation. These align closely

with the dimensions of high-quality development adopted in this study, including structural optimization, efficiency improvement, technological advancement, and openness. Environmental goals, such as Goal 12 (*Responsible Consumption and Production*) and Goal 13 (*Climate Action*), directly correspond to this study's selected indicators such as industrial solid waste utilization, SO₂ emissions, and PM_{2.5} concentration. Social goals, such as Goal 10 (*Reduce inequality*), Goal 4 (*Quality Education*), and Goal 3 (*Good Health and Well-being*), reflect the equity dimension of sustainable development and align with the social equity indicators used in this study, such as per capita disposable income, per capita education expenditure, and per capita hospital beds.

This conceptual framework supports a profound shift in development logic from GDP-centric, one-dimensional growth toward a model centered on green efficiency and multidimensional sustainability. It emphasizes high-efficiency growth under resource and environmental constraints and aligns closely with the concept of high-quality development currently being promoted in China (Ma et al., 2023).

2.3.1.3 A Unified Theoretical Foundation for High-Quality Development and CP

Sustainable development theory provides a unified theoretical foundation for this study's focus on the impact of HQED on CP. On one hand, CP, which seeks to generate more economic output with lower carbon emissions, inherently reflects the green efficiency dimension of sustainable development. On the other hand, the concept of high-quality development, with its emphasis on economic, social, and environmental coordination, represents a localized application of the three-dimensional goals of the SD framework (Qi et al., 2022). Therefore, both in terms of structural alignment and development logic, improving CP is a key measure of sustainable development, while HQED serves as the strategic pillar for operationalizing this theoretical model.

2.3.2 Low-Carbon Economy and the Decoupling Hypothesis

2.3.2.1 The Concept and Evolution of the Low-Carbon Economy

In response to the intensifying global climate crisis, the concept of the low-carbon economy has gained widespread recognition as a critical pathway for advancing sustainable development (While et al., 2010). The core idea of this theoretical framework is to minimize greenhouse gas emissions while maintaining sustained economic growth. This is achieved

through optimizing the energy structure, improving energy efficiency, and fostering green technological innovation (Pan et al., 2022; Zhang et al., 2024b).

The term “low-carbon economy” was first introduced by the UK government in its 2003 white paper “*Our Energy Future: Creating a Low Carbon Economy*”, which advocated for achieving higher-quality, lower-pollution economic outputs with reduced resource inputs. Treffers et al. (2005) examined the feasibility of significantly reducing greenhouse gas emissions in Germany without sacrificing economic growth. They concluded that a low-carbon economy is both achievable and sustainable through energy restructuring and targeted policy interventions.

A low-carbon economy is an economic model characterized by low energy consumption, low emissions, and low pollution (Gbadeyan et al., 2024). Mezentseva et al. (2024) defines it as a form of economic growth that balances development needs with sustainability considerations. According to Chen et al. (2023), the essence of a low-carbon economy lies in enhancing CP—that is, producing more GDP per unit of CO₂ emissions, effectively reducing carbon intensity. Zhao et al. (2024b) argue that a low-carbon economy is a developmental model in which both CP and human development reach a certain threshold, emphasizing the pursuit of prosperity under the premise of climate and environmental protection. Chen (2012) further points out that the transition to a low-carbon economy refers to a real economic transformation that takes into account low-carbon factors such as energy use and environmental pollution.

2.3.2.2 Decoupling Theory: A Framework for Identifying the Relationship Between Economic Growth and Carbon Emissions

One of the key theoretical foundations supporting the low-carbon economy is the concept of decoupling between economic growth and carbon emissions (Naz et al., 2024; Zhao et al., 2022c). This theory originates from the Environmental Kuznets Curve (EKC) hypothesis, which posits an inverted U-shaped relationship between environmental pressure and economic development (Ajmi et al., 2023; Sarkodie & Strezov, 2019). The Organization for Economic Co-operation and Development (OECD) formally introduced the concept of decoupling, distinguishing between relative decoupling—where economic growth exceeds the rate of emissions growth—and absolute decoupling, which refers to economic growth accompanied by an actual reduction in emissions (Güngör, 2023) .

Building on the OECD's framework, Tapio (2005) proposed a more nuanced classification system based on elasticity coefficients, identifying eight distinct decoupling states, such as strong decoupling, expansive coupling, and recessive decoupling. This provided a clearer analytical framework for empirical research. Zhao et al. (2022a) applied carbon elasticity coefficients to evaluate the decoupling status of 20 major economies, finding that a country's stage of development significantly influences its capacity to achieve decoupling. Koondhar et al. (2021) further advanced the theory by constructing a mathematical linkage between the EKC turning point and decoupling trajectories, thereby strengthening its analytical foundation. Kang et al. (2021) argue that with China's commitment to peak carbon emissions before 2030 and achieve carbon neutrality before 2060, the decoupling of carbon emissions from economic growth has become an irreversible trend.

Recent studies have found that several eastern provinces in China are already exhibiting strong decoupling trends. Key driving forces include green technological innovation, environmental regulation, and industrial upgrading (Liang et al., 2022; Zhao et al., 2024a; Zhao et al., 2022a). Today, decoupling analysis is widely used in studies of CP evolution, regional green performance evaluation, and feedback mechanisms under the dual carbon policy framework.

2.3.2.3 Providing a Theoretical Foundation for Understanding the Relationship Between HQED and CP

This study uses CP as a core metric, which essentially reflects the degree of decoupling between economic growth and carbon emissions. The central objective of high-quality development is to enhance the output per unit of energy and environmental input through structural optimization, technological innovation, and efficiency improvement. This aligns closely with the achievement of a “strong decoupling” state. Therefore, the decoupling theory offers a rigorous explanatory framework for understanding the relationship between high-quality development and CP (Murshed, 2023; Qi et al., 2022).

Moreover, the decoupling process is not linear and is often affected by macroeconomic fluctuations and external shocks, which may lead to episodes of “recoupling.” Studies have shown that the improvement of CP exhibits clear stages and regional differences, and that achieving long-term gains requires sustained institutional reform and coordinated policy support (Liang et al., 2024).

2.3.2.4 Exploring a Green Decoupling Path with Chinese Characteristics

Unlike the Western model of “pollute first, clean up later” or emissions outsourcing, China is forging a distinct path of green, high-quality development (Zhang, 2023). On one hand, China remains in a transitional stage of development and continues to face pressing challenges such as reducing regional disparities, narrowing the urban–rural divide, and addressing uneven growth (Jiang et al., 2023). On the other hand, China has adopted a dual governance approach that emphasizes both ecological civilization and institutional advantages, constructing a unique policy framework in areas such as green finance, industrial policy, and carbon trading (Li, 2024).

From a historical responsibility perspective, the bulk of cumulative global carbon emissions originates from developed countries. However, since the announcement of its dual carbon targets, China has demonstrated a strong institutional capacity and confidence in transitioning toward a low-carbon economy. Recent studies also indicate that China possesses a realistic foundation for significantly improving CP through green technological innovation, low-carbon urbanization, and digital transformation (Song & Wei, 2023).

2.3.3 Spatial Econometrics: Theory and Application

Spatial econometrics is an interdisciplinary field that integrates econometrics, spatial statistics, and geographic information science. It is developed to address estimation biases in traditional econometric models that arise from ignoring spatial interdependence. The core of spatial econometrics lies in identifying and modeling spatial dependence, spatial heterogeneity, and spatial externalities among regions (Anselin & Florax, 1995a). By introducing a spatial weight matrix, the theory quantifies geographic or economic proximity between regions, allowing for a more comprehensive analysis of spatial interactions. This framework enables researchers to capture not only how regional factors influence local outcomes but also how they spill over to and are influenced by neighboring areas, thus revealing the true dynamics of regional interconnectedness.

The theoretical foundation of spatial econometrics can be traced back to American geographer Waldo Tobler’s “First Law of Geography,” proposed in 1970: “Everything is related to everything else, but near things are more related than distant things.” This principle laid the conceptual groundwork for spatial analysis. In their study, Kim and Brewer (2020) noted that Cliff and Ord (1973) were the first to incorporate spatial correlation into economic

modeling, emphasizing that ignoring spatial structures could result in residual autocorrelation and biased estimation results.

The term “spatial econometrics” was formally introduced by Paelinck and Klaassen in 1979, marking the emergence of this field as an independent area of study (Anselin & Florax, 1995b). Later, Anselin (1988) made a significant contribution with his seminal work *Spatial Econometrics: Methods and Models*, in which he systematically introduced foundational model structures such as the spatial lag model and the spatial error model. His work laid the groundwork for the formalization and widespread adoption of spatial econometric techniques.

Building on this foundation, scholars such as Lesage and Pace (2009) and Elhorst (2014) expanded the model frameworks and methodological tools, advancing the application of spatial econometrics across diverse fields including regional economics, real estate, and environmental policy.

The core of spatial econometrics consists of two fundamental dimensions: spatial dependence and spatial heterogeneity. Spatial dependence refers to the phenomenon where the development status of a given region is significantly influenced by its neighboring regions. Goodchild (1992) pointed out that adjacent areas often exhibit similar development patterns and economic behaviors. Ver Hoef and Cressie (1993) further emphasized that the non-independence of spatial data is a theoretical prerequisite for constructing spatial models. Fingleton (2003), using a spatial lag model, empirically demonstrated that spatial dependence plays a crucial role in regional economic growth, revealing a dynamic mechanism of “co-growth” across regions.

In particular, policies such as green innovation and environmental regulation tend to exhibit externalities, which may lead to interactive structures among neighboring provinces characterized by imitation, diffusion, and feedback. This type of interdependence can be quantified using spatial autocorrelation indicators such as Moran’s I (Moran, 1948) and Geary’s C (Geary, 1954). Moreover, it can be modeled through spatial lag terms in econometric models, including the Spatial Lag Model (SLM) and the Spatial Durbin Model (SDM), which help capture and interpret spatial economic effects.

Empirical studies, such as that by Ma et al. (2024), have shown that CP is influenced not only by local policy interventions but also significantly affected by institutional changes in neighboring regions, exhibiting clear positive spatial spillover effects.

Spatial heterogeneity refers to the fact that different regions, due to variations in resource endowments, institutional foundations, and stages of development, may respond differently to the same influencing factors. This results in non-stationary parameter estimates across space. Ignoring such heterogeneity can lead to biased regression results and distortions in statistical significance (Fotheringham et al., 1998). To address this issue, spatial econometric models often incorporate fixed effects or group-based modeling approaches to account for regional differences and improve the robustness of estimations. In recent years, spatial econometric techniques have been widely applied to examine the regional spillover effects of factors such as environmental regulation, green finance, and industrial upgrading on CP (Ding et al., 2022; Li et al., 2022a; Wang et al., 2021a). These studies have revealed that the impacts of such factors can vary significantly across regions, with both positive and negative effects exhibiting clear spatial heterogeneity.

In model construction, the spatial weight matrix serves as a critical bridge connecting theoretical frameworks with real-world spatial relationships. It quantifies the adjacency and interaction strength between regional units and forms the foundational tool for modeling spatial structure (Getis, 2009). Common approaches to constructing spatial weight matrices include contiguity-based matrices, such as Rook and Queen adjacency matrices, distance-based matrices, such as inverse geographic distance matrices, economically weighted matrices based on trade or GDP proximity, and nested matrices that integrate multiple dimensions ((Wang & Xue, 2024). The choice of spatial weight matrix can significantly affect both the estimation results and the explanatory power of spatial models (Lam & Souza, 2020). Therefore, constructing a matrix that accurately reflects the real interaction mechanisms among regions is essential for ensuring the validity and robustness of spatial econometric analysis (Anselin, 2022).

In recent years, scholars have also proposed the use of dynamic spatial weight matrices to capture evolving spatial relationships over time, such as shifts in policy alliances, trade networks, or interregional cooperation (Cheng et al., 2014; Yu et al., 2012). As such, the spatial weight matrix is not merely a modeling tool; it embodies the researcher's

understanding of regional structural logic and is an indispensable component of empirical spatial economic analysis.

Crucially, spatial econometrics is not merely a technical toolset but also a theoretical framework that supports the understanding of regional interconnectivity, structural heterogeneity, and policy interactions. In the context of studying HQED and CP, incorporating a spatial perspective is instrumental in uncovering patterns of regional green transformation, identifying differentiated transition pathways, and analyzing the mechanisms of spatial externalities. Accordingly, this study will apply spatial econometric theory to construct spatial panel models, aiming to empirically examine the spatial effects of HQED on CP across Chinese provinces. This approach will provide deeper insights into the spatial dynamics underlying China's green and low-carbon transition.

2.4 Empirical Research Review

2.4.1 Empirical Determinants of CP: Evidence and Models

CP reflects the dual objectives of reducing carbon emissions and promoting economic growth and has been widely adopted as a key indicator for assessing the effectiveness of green transformation strategies (Zhang & Zheng, 2015). Enhancing CP means achieving higher economic output with lower carbon emissions, making it an essential pathway for advancing green development and achieving the dual carbon goals (Lu et al., 2023). In recent years, both domestic and international scholars have conducted extensive research on the determinants of CP. These studies span a variety of theoretical perspectives, variable designs, and methodological approaches. Overall, the research can be broadly categorized into five main analytical pathways.

2.4.1.1 Studies Based on the IPAT Model and Its Extensions

The IPAT model was first proposed by Ehrlich and Holdren (1971) to describe the relationship between environmental pressure and three core factors: population, affluence, and technology. As a concise and intuitive framework, IPAT laid the theoretical foundation for subsequent studies and has been widely applied in analyses of carbon emissions and production efficiency (Shi, 2003). Dietz and Rosa (1994) later extended the model into a

stochastic regression form, known as the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT), enhancing its empirical applicability.

The STIRPAT model emphasizes the role of stochastic disturbance and model flexibility, and it has become one of the mainstream tools for analyzing carbon emissions and CP (Wu et al., 2021b). Research using this framework has found notable heterogeneity in the effects of population density (P), economic growth (A), and technological efficiency (T) on CP. For example, Zhong et al. (2024), using an extended STIRPAT model, found that in high-density regions of China, technological progress has a stronger positive effect on CP, while in low-density provinces CP is more constrained by energy structure. Yao and Jiang (2022) further incorporated structural variables, revealing that foreign direct investment, urban scale, and transportation infrastructure also significantly influence CP.

In a related study, Li et al. (2019b) used provincial panel data from 1996 to 2016 and found that per capita GDP, technological investment, and trade openness significantly improved CP, while a higher share of the secondary industry and dependence on traditional energy sources exerted negative effects. Similar findings suggest that human capital accumulation and investment in education enhance the absorption of green technologies, thereby promoting CP (Huang et al., 2021; Tao et al., 2022).

As the model has evolved, scholars have increasingly incorporated nonlinear terms, interaction effects, and mediating mechanisms into STIRPAT to improve explanatory power (Wang et al., 2023b). For instance, Zhu (2022) showed that economic structure indirectly affects CP through the mediation of green technologies. Zhang and Liu (2024) used urban panel data to explore how informatization and income inequality jointly regulate the effect of CP. These developments demonstrate that the IPAT framework and its extensions not only serve as a theoretical starting point for identifying the determinants of CP but also offer a foundational structure for uncovering underlying behavioral and structural mechanisms at the micro level.

2.4.1.2 Studies Based on the Kaya Identity and Its Extensions

The Kaya Identity is a widely used mathematical tool for analyzing the driving forces behind carbon emissions. Proposed by Japanese scholar Kaya (1990), the identity expresses carbon emissions as the product of four key factors: population (P), per capita GDP (A), energy intensity (EI), and carbon intensity (CI). While retaining the core logic of the IPAT

model, the Kaya Identity introduces disaggregated indicators of energy use and carbon emission efficiency, allowing for a more precise identification of causal pathways. Due to its simplicity, quantifiability, and clarity, the Kaya Identity has become a commonly applied analytical framework for interpreting the coupling relationship between energy systems and economic systems, and it plays an important role in CP studies (Lee et al., 2024; Lin et al., 2023).

Many scholars have extended the Kaya Identity using nonlinear functions, neural networks, and structural equation modeling to improve the explanatory and predictive capacity of CP research. For example, Browne et al. (2022) employed a Neural Ordinary Differential Equation (Neural ODE) model based on the Kaya framework to simulate the dynamic evolution of carbon emissions across countries, revealing the long-term effects of population aging and changes in carbon intensity on CP. Zhang and Liu (2024) integrated the Kaya Identity with the Logarithmic Mean Divisia Index (LMDI) method to decompose provincial-level differences in China's carbon efficiency, finding that energy intensity and technological progress were the dominant contributing factors.

Compared with the STIRPAT model, the Kaya Identity is particularly well-suited for analyzing the impacts of energy structure and carbon reduction efficiency on CP (Yu & Xu, 2023). In empirical applications, it is often used to decompose the sources of change in CP. For instance, Xu et al. (2022), from the perspective of energy configuration, used an improved LMDI method to show that adjustments in the structure of energy types have significant heterogeneous effects on CP. This is especially evident during the early stages of energy transition, when reductions in carbon intensity have stronger marginal effects on productivity gains.

In recent years, researchers have also explored the use of the Kaya Identity in regional panel and time-series analyses. Liao et al. (2019), for example, combined the Kaya framework with spatial clustering techniques to decompose changes in carbon emission efficiency within China's power sector, uncovering imbalances in regional energy structure and technological progress. Hao et al. (2022) further constructed a provincial-level CP evolution framework based on the Kaya Identity and confirmed the existence of nonlinear coupling effects between per capita GDP and energy intensity.

In general, the Kaya Identity has played a pivotal role in CP research due to its clear decomposition logic and strong interpretability of variables. While the Kaya model emphasizes structural pathway identification, the STIRPAT model focuses on enhancing statistical explanatory power. Taken together, they form a complementary analytical system that underpins much of the current theoretical research on the drivers of CP.

2.4.1.3 Studies Based on the Environmental Kuznets Curve Hypothesis

The EKC hypothesis is a widely cited theoretical framework for understanding the relationship between economic growth and environmental degradation. Its central proposition is that there exists an inverted U-shaped relationship between environmental pollution and per capita income, whereby pollution levels initially rise and then fall as income increases (Grossman & Krueger, 1991). This framework offers an alternative lens through which to analyze CP, namely, different stages of economic development may significantly influence carbon emission efficiency and resource utilization performance.

In the context of CP, the EKC hypothesis is often used to examine whether economic growth facilitates green transformation. A large body of empirical literature suggests that there is some form of nonlinear relationship between carbon emissions and per capita GDP in China, though the specific curve shapes vary significantly across regions (Huo et al., 2021; Nie et al., 2019; Zhou et al., 2021a). The EKC does not exhibit a universally inverted U-shape across countries and pollutants. Instead, N-shaped, inverted N-shaped, or even monotonic patterns have also been observed, raising doubts about the hypothesis's general applicability (Ajmi et al., 2023; Gyamfi et al., 2021).

Within the Chinese context, studies have found that the EKC relationship is more likely to hold in economically advanced eastern provinces, while many central and western regions remain in the rapid growth phase of carbon emissions and have not yet reached the “turning point.” For instance, Lu and Liu (2022) using Jiangxi Province as a case study, found that the EKC curve alternated between U-shape and inverted U-shape during different periods, with energy structure and industrial composition being the primary influencing factors. Huang (2022), based on urban panel data, showed that at different stages of development, the roles of green finance, institutional regulation, and technological diffusion significantly affect the EKC curve's shape.

Some researchers have further integrated the EKC framework with decoupling theory to investigate whether economic growth and carbon emissions have achieved “weak” or “strong” decoupling (Lv et al., 2021; Song et al., 2021; Wang & Su, 2020). Zhao et al. (2024a) observed that some eastern cities in China exhibit a “strong decoupling” pattern, characterized by declining total carbon emissions alongside continued GDP growth, resulting in rising CP. In contrast, resource-dependent cities or regions with a high concentration of energy-intensive industries have yet to reach the inflection point.

In addition, the shape of the EKC curve is widely acknowledged to be influenced by multiple factors, such as pollution type, regional economic structure, regulatory intensity, and consumer behavior (Dogan & Inglesi-Lotz, 2020; Wang et al., 2022). For example, Liu et al. (2023c) found that after controlling for variables related to energy structure and technological progress, the turning point of the EKC curve shifted significantly earlier, suggesting that policy intervention and green technology adoption can accelerate improvements in CP.

In summary, the EKC hypothesis provides a “stage-based” theoretical framework for analyzing CP. It is particularly valuable for identifying regional carbon emission inflection points and understanding the role of structural drivers. Although the EKC remains a subject of debate, it complements the Kaya Identity and STIRPAT model, together forming one of the core analytical paradigms in current CP research.

2.4.1.4 Studies on the Influencing Factors of CP Based on Index Decomposition Methods

To identify the specific sources of change in CP, several studies have adopted Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA) to systematically break down the contributing factors (Qu, 2020; Xu & Ang, 2013). Among these, IDA has become one of the most widely used tools in CP research due to its low data requirements, ease of computation, and clear interpretability (Ang & Zhang, 2000). Within IDA, the LMDI method is regarded as the most stable and widely applied form. It offers several advantages, including zero residuals, the ability to handle zero values, and suitability for intertemporal and cross-regional comparisons (Rivera-Niquepa et al., 2023). LMDI-based approaches typically decompose changes in CP or emissions into contributing factors such as economic activity intensity, energy structure, technological efficiency, and industrial composition (Moutinho et al., 2020).

In international studies, Chong et al. (2019) applied the LMDI method to analyze the drivers of carbon emission growth in Malaysia from the perspective of energy configuration. They found that improvements in energy intensity and carbon intensity were the main contributors to emission reductions. Moutinho et al. (2015) conducted a decomposition analysis of CO₂ emission drivers across four regional groups in Europe—Eastern, Western, Northern, and Southern countries. Their findings suggest that CO₂ emissions are closely linked to economic energy consumption patterns within each group, and that energy consumption itself is largely influenced by population dynamics across countries. The study emphasizes that the key to reducing CO₂ emissions lies in transforming the energy structure.

Wen and Li (2020) combined LMDI with spectral clustering to explore temporal and spatial variations in industrial carbon emissions across 30 Chinese provinces. Their findings revealed substantial asymmetries in the marginal contributions of technological progress and energy efficiency across regions. Similarly, Cao et al. (2020) employed LMDI to uncover the drivers behind carbon footprint growth in China's food system, offering policy insights into how demand-side measures can enhance CP. Zou et al. (2023) used LMDI from the perspectives of the power system and regional economies, respectively, and confirmed that improvements in technological efficiency and industrial structure optimization play decisive roles in boosting CP. Liu et al. (2023a) using a temporal-spatial production-theoretical decomposition model (TS-PDA), found that the growth of regional carbon emissions is primarily driven by economic activity and technological disparities. While improvements in energy-saving and emission-reduction technologies can effectively curb emissions and narrow regional gaps, the impact of such technologies varies significantly across different regions.

Additionally, recent research has incorporated tools such as the Theil index to measure and decompose regional disparities in CP (Tian et al., 2021; Wang et al., 2021c). Zhang et al. (2022c) proposed a comparative framework integrating convergence analysis and decoupling indicators to evaluate the dynamic evolution of China's CP. Fu et al. (2024b) developed a green CP decomposition model of CP to analyze regional disparities and their interaction with regional industrial performance. It reveals the multiple effects and underlying mechanisms driving CP differences at both the regional and sectoral levels.

Overall, index decomposition methods provide a solid analytical foundation for identifying the structural sources of CP evolution and for comparing contribution

mechanisms across regions. Given the multifactorial nature of CP, the widespread application of methods like LMDI has significantly enhanced the transparency of analysis and the precision of policy recommendations.

2.4.1.5 Studies on the Influencing Factors of CP Based on Econometric Models

In addition to decomposition methods, a growing body of recent research has adopted econometric modeling approaches to explore the determinants of CP in greater depth. Compared with structural decomposition, econometric models offer stronger causal inference and better capacity for handling dynamic structures, enabling researchers to capture both direct and indirect effects among variables while accounting for heterogeneity across regions and over time.

Building on traditional panel models, an increasing number of studies have incorporated spatial econometric models to address spatial dependence and spillover effects between regions. For example, Hu and Wang (2020) used a Spatial Durbin Model (SDM) and found significant positive spatial autocorrelation among CP levels across Chinese provinces. They also reported that the effect of environmental regulation on CP exhibits a nonlinear threshold pattern. Hou et al. (2023) further revealed a U-shaped relationship between CP and environmental regulation, where green technological progress amplifies the positive effect, while pollution transfer weakens its marginal impact.

From a digitalization perspective, Yu and Liu (2024) utilized panel data from 136 countries to construct fixed-effects and mediation-effect models, finding that digitalization significantly enhances CP through two mediating mechanisms: technological innovation and income equality. These effects were found to be strongest in countries with higher income levels and greater human capital. Their study underscores the critical role of institutional quality and factor allocation in promoting CP.

Using Dynamic Spatial Durbin Models (DSDM), Liu and Zhang (2021) analyzed provincial panel data from China and discovered an inverted U-shaped relationship between industrial agglomeration and CP. Their results confirmed that CP exhibits path dependence and spatial spillovers, with technological innovation playing a decisive role in shifting the turning point, thereby validating the existence of a nonlinear synergy between innovation and agglomeration economies.

From an urban spatial perspective, Wu et al. (2025) employed a combination of the Slack-Based Measure model (SBM) and the Seemingly Unrelated Regression model (SUR) to assess the impact of land-use efficiency on urban CP in the Yangtze River Delta. Their results indicated that over-intensive land use significantly suppresses urban carbon efficiency, while the alignment between industrial structure and land allocation was found to be a key moderating factor.

At the policy level, Liu (2023) used a Difference-in-Differences (DID) approach to evaluate the impact of China's low-carbon city pilot policy. They found that the policy significantly improved urban CP. However, fiscal pressure served as a counteracting force, dampening the effect. The analysis also revealed heterogeneous effects across cities with different development levels, suggesting that place-based policy design is essential.

In summary, econometric modeling has established a systematic analytical framework for CP research. The increasing application of spatial panel models, dynamic estimation techniques, and causal identification tools, such as DID and panel-IV have significantly enhanced explanatory power and policy relevance. This modeling approach has become instrumental in analyzing the multi-dimensional interactions among economic development, institutional design, and carbon efficiency.

2.4.2 Measuring HQED: Indicators and Frameworks

Constructing a scientifically robust measurement system is a fundamental prerequisite for conducting research on HQED. However, as the concept of HQED remains in a stage of theoretical refinement and practical exploration, a unified measurement standard has yet to be established in academic circles. Existing studies predominantly follow two measurement approaches: the use of single indicators and the construction of multidimensional indicator systems.

2.4.2.1 Single-Indicator Approaches

Although there is broad academic consensus on the multidimensional nature of HQED, some scholars still argue that it can be measured using a single core indicator. Among these, Total Factor Productivity (TFP) is frequently used as a key measure of high-quality development, as it reflects production efficiency and technological progress (Liu et al., 2019; Yang & Li, 2022). For example, Jiang and Chen (2018) pointed out that the sericitization of

the industrial structure is a major contributor to the decline in TFP, highlighting the importance of industrial structural adjustment in improving economic efficiency.

In contrast, Green Total Factor Productivity (GTFP) incorporates undesirable outputs such as pollutant emissions and resource consumption and is therefore better aligned with green development goals (Li & Dong, 2020; You et al., 2024). Lu et al. (2017) employed the DEA-based Malmquist–Leuenberger index to measure GTFP along the Yangtze River Economic Belt. Similarly, Zheng et al. (2022) used Super-Efficiency SBM models with undesirable outputs and the DEA-GML model to evaluate regional GTFP levels.

Compared to traditional TFP, GTFP places greater emphasis on the coordination between economic development and environmental sustainability, thus more accurately reflecting the core values of high-quality development. Other representative indicators include labor productivity (Chen & Chen, 2018), the Contribution Share of Total Factor Productivity (TFP) to Economic Growth (Xu et al., 2018), and the proportion of employees in the secondary and tertiary industries (Wang & Zhang, 2020).

While single-indicator approaches offer advantages such as data accessibility and methodological simplicity, they face notable limitations. Given that high-quality development is inherently a systemic and multidimensional objective, relying solely on TFP or its derivatives fails to capture the complex interplay among economic, social, and environmental dimensions. As Zhang (2020) notes, such approaches are insufficient for comprehensively evaluating the coordinated and sustainable nature of high-quality development.

2.4.2.2 Multidimensional Evaluation Frameworks

To overcome the limitations of single-indicator approaches, scholars have increasingly advocated the construction of comprehensive evaluation systems encompassing multiple dimensions and hierarchical levels to assess HQED. The International Monetary Fund (IMF) developed a measurement framework incorporating only two dimensions—economic fundamentals and social development—to evaluate the development levels of emerging economies (Mlachila et al., 2017). Building on this foundation, several Chinese scholars have adapted and expanded the IMF framework to assess the level of HQED in China. However, significant divergences remain in the selection and structure of specific indicators, which can be broadly categorized into the following three perspectives.

(i). Indicator Systems Based on the New Development Philosophy

Building upon the five pillars of China's New Development Philosophy—namely innovation, coordination, green development, openness, and sharing—this line of research further extends these principles into multidimensional evaluation systems aligned with contemporary development goals. For instance, Zhang and Zhao (2017) proposed a three-tier analytical framework, “Five Principles – Development Quality – Moderately Prosperous Society”, to measure the overall quality and sub-dimensions of China's socio-economic development. Shi and Li (2019) constructed a comprehensive index system comprising 62 indicators and applied principal component analysis to evaluate the quality of economic development in China from 2000 to 2017. Lv and Cui (2020) selected 57 foundational indicators across six dimensions to construct a provincial-level evaluation system, enabling the measurement of high-quality development levels, regional disparities, and spatiotemporal convergence. Yang et al. (2021b) developed a 47-indicator system using provincial panel data to assess the status and degree of imbalance in regional high-quality development. Zhang et al. (2022b) applied a temporal global principal component analysis method to evaluate high-quality development levels across 31 mainland provincial-level regions and examined the strength and relative importance of each development concept.

(ii). Indicator Systems Based on the Intrinsic Connotation of Development

This research perspective emphasizes the multidimensional nature of development by incorporating indicators reflecting economic performance, social welfare, and ecological sustainability (Long et al., 2020; Zhao et al., 2020). Ren and Li (2018) proposed that the assessment of high-quality development should involve six subsystems: an indicator system, policy framework, standard framework, statistical framework, performance evaluation system, and governance assessment system. Wei and Li (2018) developed a measurement framework consisting of 53 indicators across 10 dimensions and applied the entropy-weighted TOPSIS method to calculate high-quality development indices for 30 provinces in 2016. Jian and Nie (2020) constructed an index system with 63 indicators covering five dimensions—product and service quality, economic efficiency, social benefits, ecological performance, and macroeconomic stability—assessing China's high-quality development from 1978 to 2018. Lin and Xu (2022) based on China's 14th Five-Year Plan, proposed an evaluation system with 20 indicators across five dimensions: economic development, innovation-driven growth, social well-being, green ecology, and security. This framework

was used to evaluate national and provincial high-quality development performance from 2014 to 2019.

(iii). Indicator Systems Based on the People-Centered Development Philosophy

This approach emphasizes the centrality of human well-being and equitable development, constructing evaluation systems from the perspective of public happiness and balanced development. Ren and Li (2018) incorporated indicators related to healthcare, education, and elderly care to underscore the importance of livelihood-related dimensions. Li et al. (2019a) developed an index system comprising 27 indicators across five categories, grounded in the conceptual logic of “people’s aspirations for a better life” and addressing “unbalanced and inadequate development.” Chen et al. (2022) further introduced “people’s happiness” as a key dimension, proposing a measurement framework based on subjective well-being using China General Social Survey (CGSS) data, thereby expanding the scope of economic measurement to include psychosocial perspectives.

2.4.2.3 Justification for Measurement Approach in This Study

In line with the research objective of exploring the impact of HQED on CP, this study constructs a comprehensive evaluation system comprising three core dimensions: economic efficiency, ecological environment, and social equity. This framework aims to systematically and comprehensively measure the multi-dimensional performance of development quality across regions. Compared with commonly adopted frameworks in existing literature—such as the five-dimensional “integrated” structure (Zhang & Tian, 2019) or multi-level nested structures at macro, meso, and micro levels (Wang et al., 2021b)—the dimensional division adopted in this study demonstrates greater thematic specificity and empirical adaptability.

From a dimensional perspective, the economic dimension focuses on improving production efficiency, promoting technological innovation, and optimizing industrial structure, precisely addressing the technology-driven and efficiency-driven mechanisms required for enhancing CP. The ecological dimension centers on the effectiveness of environmental governance, providing a direct reflection of a region’s green transition performance. The social dimension emphasizes the equity of income distribution, access to educational resources, and public services, thereby highlighting the inclusive nature of development outcomes and enabling the identification of regions’ endogenous development capacity and foundational conditions for green transformation.

In terms of alignment with macro-level strategies, this dimensional structure is highly consistent with the systematic objectives set forth in the United Nations SDGs, particularly those related to economic growth (Goal 8), environmental protection (Goals 12 and 13), and social well-being (Goals 3, 4, and 10). Furthermore, it reflects the strategic priorities of China's ecological civilization agenda and its commitment to achieving the dual carbon goals. The current indicator system broadly aligns with the core principles of China's high-quality development agenda and the multidimensional goals of the SDGs. It effectively captures key aspects such as economic transformation, green growth, and social equity.

Regarding methodological implementation, this study applies the entropy method for indicator weighting and composite index construction. The entropy method determines indicator weights based on the degree of variation (dispersion) across observations, which enhances objectivity and robustness compared to subjective weighting approaches. This method is particularly well-suited for ensuring consistency and comparability in cross-provincial data. The composite index derived from this approach serves as the core explanatory variable in the subsequent empirical models.

2.4.3 Linking Economic Development and CP

CP, as a key indicator for evaluating the quality of a low-carbon economy, fundamentally reflects the coordination between economic growth and carbon emissions control. However, the process of achieving such coordinated development exhibits notable regional disparities and spatial spillover effects.

2.4.3.1 Regional Disparities

At the international level, developed economies typically exhibit significantly higher levels of CP than developing countries, owing to their advanced technologies and optimized industrial structures (Cao et al., 2022; Xiao et al., 2023). For example, countries in North America and Western Europe have largely achieved a relative decoupling of economic growth from carbon emissions, whereas emerging economies such as China—despite experiencing rapid improvements in CP in recent years—still operate from a much lower baseline, currently achieving only about one-fifth the CP level of developed nations (Mehmood et al., 2024; Wang & Su, 2020). One underlying reason is that international trade has played a significant role in shaping disparities in CP. Historically, labor exploitation and

the intensification of carbon emissions embedded in trade flows have widened the gap between developed and developing countries (Liu & Oka, 2024; Mahlkow & Wanner, 2023).

Within individual countries, regional differences in development stages, industrial structures, and technological capabilities give rise to pronounced spatial imbalances in CP (Zhou et al., 2021b). In China, for instance, coastal provinces in the eastern region exhibit significantly higher levels of CP than the central and western regions. The latter continue to face challenges in low-carbon development due to their resource endowments and industrial compositions (Pan & Zhang, 2011; Wang et al., 2023c). A case in point is Guangdong Province: in 2019, cities in the Pearl River Delta such as Shenzhen and Guangzhou displayed substantially higher CP than those in eastern and western Guangdong, forming a clear gradient pattern with declining CP from the urban core to peripheral areas (Di et al., 2023; Zhou et al., 2021b).

2.4.3.2 Spatial Spillover Effects

Studies have demonstrated that CP exhibits significant spatial dependence across neighboring regions (Du et al., 2022; Shen et al., 2021). Regions with high CP often contribute to the coordinated improvement of surrounding areas through channels such as technological diffusion, industrial chain transmission, and policy imitation effects (Wu et al., 2021c; Zhao et al., 2023). However, such spatial spillover effects are not uniformly positive and may also produce negative externalities. Sheng et al. (2023) found that while China's outward foreign direct investment (OFDI) has enhanced CP in eastern provinces, it has simultaneously increased carbon emission pressures in central and western regions through industrial relocation, leading to a decline in their CP. This finding highlights the existence of a "spatial scissors effect", whereby developed regions, while improving their carbon efficiency through green transformation, tend to transfer high-pollution industries to less-developed areas, resulting in a "pollution shifting" phenomenon.

In summary, the relationship between economic development and CP presents complex and multifaceted spatial characteristics on both global and national scales. Significant disparities arise between countries due to differences in development levels, while spatial imbalances persist among regions within a single country. Recognizing and understanding these dynamics, especially the positive and negative spatial spillover effects, is critical for designing context-specific carbon reduction strategies and for promoting globally coordinated green development.

2.5 Synthesis and Theoretical Implications

2.5.1 Summary of Key Literature Insights

Existing studies have conducted extensive theoretical discussions and empirical tests on the influencing factors of CP, the measurement methods of HQED, and the relationship between the two.

With regard to the influencing factors of CP, scholars have constructed a rich theoretical and empirical framework from multiple perspectives. These include micro-level extensions based on the IPAT and STIRPAT models, the Kaya identity and its modifications, phase-based identification using the EKC, and advanced applications of index decomposition and econometric modeling. These approaches have collectively identified the dynamic evolution patterns and regional disparities of CP from the perspectives of population, economy, energy, technology, and institutional arrangements.

In terms of measuring HQED, the literature has generally followed two methodological paths: the “single-indicator proxy approach” and the “multi-dimensional index construction approach.” The former, often represented by TFP or GTFP, emphasizes economic efficiency and offers operational simplicity, though with limited explanatory power. The latter places greater emphasis on comprehensive and systematic assessment. It includes measurement frameworks based on the new development philosophy, the intrinsic connotations of development, and people-centered goals—better capturing the complexity and multi-dimensional nature of “quality” in development.

Regarding the relationship between HQED and CP, existing studies have clearly revealed significant disparities across countries and within domestic regions. Furthermore, they demonstrate the presence of spatial dependence and spillover effects in CP, including both positive spillovers and negative “pollution shifting” phenomena. These findings offer a nuanced understanding of the spatial structure and driving mechanisms behind both global and regional low-carbon economic transitions.

In summary, the current body of literature has made substantial progress in terms of theoretical frameworks, methodological approaches, and variable design. These contributions provide a solid foundation for the present study.

2.5.2 Key Theoretical and Empirical Implications

Despite a growing body of research on the relationship between CP and economic development, several notable gaps remain from the perspective of this study:

a) Unclear Mechanistic Framework

Existing studies often examine the relationship between high-quality development and CP from a single dimension, lacking a unified theoretical framework. This limits the explanatory power regarding how different dimensions of development collectively influence improvements in CP.

b) Absence of a Unified Measurement System

There is no widely accepted measurement framework for HQED. The selection of variables and weighting methods varies considerably across studies, which hampers empirical comparability and weakens the foundation for robust theoretical development.

c) Insufficient Dynamic Perspective

Most current studies adopt a static analytical approach and fail to adequately account for dynamic factors such as policy implementation lags and the gradual nature of structural adjustments. This omission affects the identification of long-term trends and policy effectiveness.

d) Limited Spatial Analysis

While CP demonstrates clear spatial clustering and spillover characteristics, few studies systematically explore the positive spatial spillovers or negative externalities associated with high-quality development. The spatial effects of policy and development remain underexplored.

2.6 Identified Research Gaps and Contributions

2.6.1 Theoretical and Conceptual Gaps

In the current body of literature, HQED and CP are often explored as independent research areas. Studies on HQED typically focus on concepts such as innovation, green

transformation, and coordinated development, while those on CP emphasize the efficiency of economic output relative to carbon emissions. Although some studies have examined the relationship between HQED and total carbon emissions (Li et al., 2022b; Zhao et al., 2023), or evaluated the coupling coordination between HQED and carbon intensity (Kuang et al., 2022; Li et al., 2025), few works have directly investigated how HQED influences CP as an efficiency-based outcome variable. Theoretical integration between these two fields remains insufficient, and the mechanisms through which HQED affects CP have not been clearly identified.

Furthermore, many existing indicator systems used to evaluate HQED are overly complex, with limited regional applicability. As a result, they often fail to align effectively with the objectives of green development. This study seeks to address these shortcomings by constructing a three-dimensional evaluation system grounded in the SDGs. This design enhances both the theoretical linkage and the practicality of measurement, thereby helping to bridge the current gap in theory and indicator construction.

2.6.2 Methodological Gap

A considerable portion of the existing empirical research adopts static panel models or localized spatial econometric models, which are limited in capturing the multi-layered effects of time, space, and mechanism. Static panel models often neglect temporal dynamics, while conventional spatial models tend to overlook the structural mechanisms underlying spatial interactions. This results in a relatively narrow analytical framework that does not fully capture the complexity of the HQED–CP relationship.

In contrast, this study integrates static panel regression, the System GMM, and the SDM to investigate the effects of HQED on CP from temporal, spatial, and structural perspectives. Through effect decomposition, the study identifies direct, indirect, and total effects, revealing the presence and magnitude of spatial spillovers—whether positive or negative—among different regions. This comprehensive approach improves empirical robustness and enhances the explanatory power of the results.

2.6.3 Empirical Gap

Empirical research on the relationship between HQED and CP remains limited. Few existing studies have incorporated HQED as a core explanatory variable in CP-related empirical analysis. As a result, there is a lack of direct and robust causal evidence supporting the impact of HQED on CP. Moreover, current literature seldom investigates the spatial spillover channels through which HQED may influence the CP levels of neighboring provinces. The absence of spatial perspectives limits the understanding of how regional development interdependencies contribute to carbon efficiency outcomes.

To address this gap, the present study utilizes panel data covering 30 provinces in China to conduct a comprehensive empirical analysis, which includes both the direct effects of HQED on local CP and the indirect effects on adjacent regions. This approach provides a solid empirical basis for exploring interregional coordination mechanisms and offers valuable insights for the formulation of regionally integrated low-carbon development strategies.

CHAPTER 3:

RESEARCH METHODOLOGY

3.1 Introduction

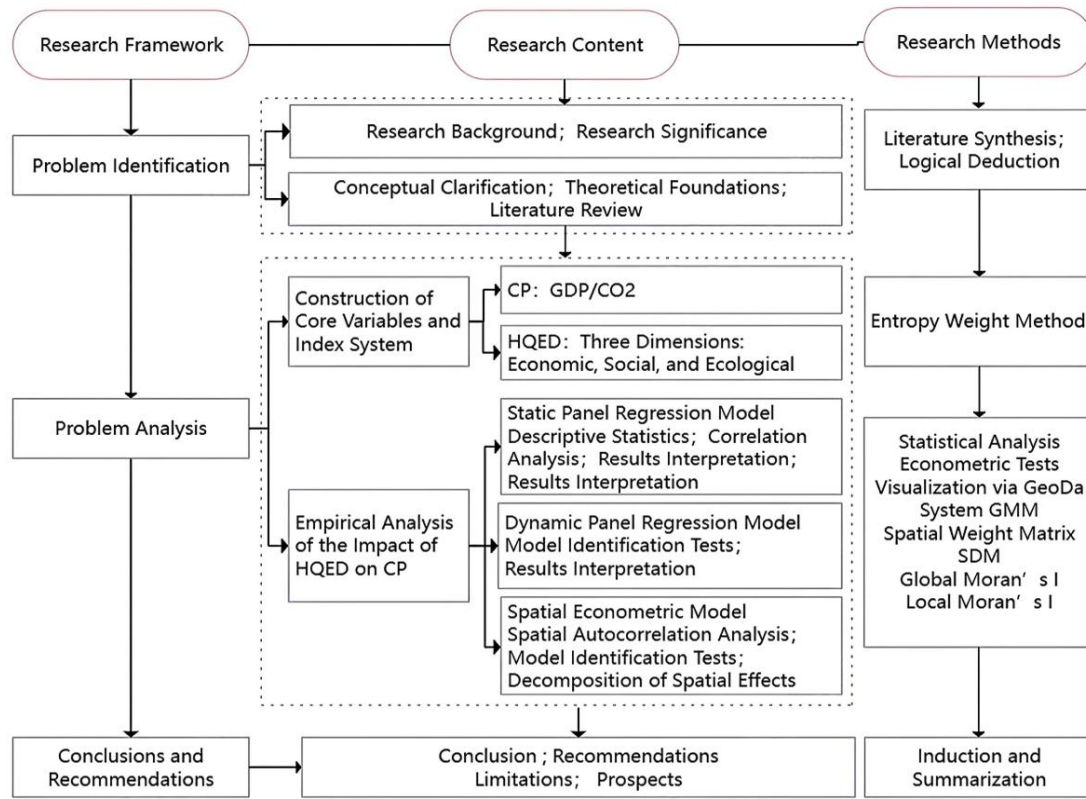
This study investigates the impact of high-quality economic development (HQED) on carbon productivity (CP) across 30 Chinese provinces by constructing a multidimensional empirical framework. To comprehensively assess this relationship, the analysis employs static panel regression, dynamic system GMM, and spatial econometric models, capturing both temporal effects and regional spillovers.

To provide a theoretical and methodological foundation for this study, an integrated framework is developed by synthesizing the principles of sustainable development, low-carbon economy and decoupling theory, and spatial econometrics. Sustainable development theory provides a normative basis for balancing economic growth, environmental sustainability, and social equity. The low-carbon economy and decoupling perspective emphasize structural upgrading and green innovation as key strategies for enhancing carbon efficiency. Spatial econometrics enables the modeling of cross-regional dependencies and spatial spillover effects, which are essential for understanding geographically heterogeneous outcomes.

Figure 3-1 illustrates the integrated analytical and empirical framework of the study, linking theoretical foundations, variable design, and methodological structure within a unified approach.

This chapter first presents the definitions and construction of key variables, followed by a detailed explanation of data sources and processing procedures. Finally, it elaborates on the design and estimation of each econometric model.

Figure 3-1: Integrated Analytical and Empirical Framework



Source: Author own illustrations.

3.2 Variable Selection and Measurement

3.2.1 Dependent Variable: CP

In this study, CP serves as the core dependent variable. The scientific validity of its measurement directly affects the robustness and explanatory power of the research conclusions. According to the definition of CP, the calculation formula is expressed as follows:

$$CP_{it} = \frac{GDP_{it}}{CE_{it}} \quad \text{Equation 3-1}$$

Where CP_{it} denotes the CP of region i in year t , GDP_{it} represents the real Gross Domestic Product, and CE_{it} refers to the amount of CO₂ emissions. To ensure comparability across different years by eliminating price effects, nominal GDP data in this study are deflated using the GDP index method with 2008 as the base year. The CO₂ emissions data

are sourced from the China Emission Accounts and Datasets (CEADs) (Guan et al., 2021; Shan et al., 2020; Xu et al., 2024).

3.2.2 Explanatory Variable: HQED

3.2.2.1 Multidimensional Indicator Framework for HQED

HQED, the core explanatory variable in this study, is essential for examining how development quality affects CP during China's transition toward sustainable growth. Building on Zhao et al. (2020) and relevant literature, this study constructs an improved multidimensional evaluation system for HQED that reflects current policy priorities and regional development characteristics, and is aligned with theoretical foundations such as the Sustainable Development Goals.

The framework maintains three main dimensions—economic, social, and ecological, while introducing two key adjustments. First, openness is included under the economic dimension to reflect the growing importance of global integration in China's development strategy, especially considering the environmental impacts of foreign direct investment. Second, per capita disposable income replaces per capita GDP under the social dimension, offering a better reflection of living standards and inclusive development across regions.

The resulting index includes six sub-indicators that capture the essential features of high-quality development, this refined framework offers a more realistic and theoretically grounded basis for assessing HQED and its influence on CP across different provinces in China, as described below.

(i). Industrial Structure

The optimization and upgrading of industrial structure is a critical driver of HQED, signaling a shift from high-pollution, high-energy-consuming industries to low-carbon, high value-added sectors. This dimension is assessed using three indicators:

Advanced industrial structure: measured by the ratio of tertiary to secondary industry output, reflects the degree of industrial upgrading toward service-oriented activities.

Rationalized industrial structure: Evaluated using the structural deviation index (E), is calculated as:

$$E = \sum_{i=1}^n \left| \frac{Y_i/Y}{L_i/L} - 1 \right| \quad \text{Equation 3-2}$$

Where Y_i and L_i denote the output value and employment in industry i , respectively, and Y and L represent the total output value and total employment. A smaller value indicates a more rational industrial structure.

Proportion of producer services: which captures the integration and influence of advanced service sectors, such as finance, logistics, and information services within traditional industrial chains. A higher proportion reflects deeper service-oriented transformation and a more advanced industrial pattern.

(ii). Technological Innovation

Technological innovation, represented by the City Innovation Index, is critical in driving carbon emission reductions and high-quality economic growth. This study adopts the City Innovation Index provided in the “China City and Industry Innovation Report 2017” (Kou & Liu, 2017), which comprehensively covers patent outputs, R&D investments, and science and technology talent, effectively reflecting urban innovation capabilities.

(iii). Inclusive Total Factor Productivity (ITFP)

To reflect the synergy between efficiency and equity, this study introduces the inclusive TFP, emphasizing the balance between resource allocation efficiency and social equity. Based on the Hicks-Moorsteen Index, considering urban-rural income disparity as an undesirable output, inclusive TFP is measured through input-output distance functions:

$$\begin{aligned} Y(y) &= [D_0(x_{hs}, y, s) D_0(x_{it}, y, t)]^{1/2} \\ X(x) &= [D_1(x, y_{hs}, s) D_1(x, y_{it}, t)]^{1/2} \end{aligned} \quad \text{Equation 3-3}$$

$$\begin{aligned} &TFP_{hs,it} \\ &= \left\{ \frac{D_0(x_{hs}, y_{it}, s)}{D_0(x_{hs}, y_{hs}, s)} \frac{D_1(x_{hs}, y_{hs}, s)}{D_1(x_{it}, y_{hs}, s)} \frac{D_0(x_{it}, y_{it}, t)}{D_0(x_{it}, y_{hs}, t)} \frac{D_1(x_{hs}, y_{it}, t)}{D_1(x_{it}, y_{it}, t)} \right\}^{1/2} \end{aligned} \quad \text{Equation 3-4}$$

Where X and Y represent input and output vectors, s and t denote time periods; $D_1(X, Y)$ and $D_0(X, Y)$ are Shepard’s input and output distance functions, respectively. The detailed data processing and method are referenced from Fan et al. (2018).

(iv). Degree of Openness

China's economic and social development over the past four decades underscores openness as a critical growth driver. Indicators such as trade dependency and foreign direct investment (FDI) openness effectively reflect economic openness and international competitiveness, facilitating a comprehensive evaluation of HQED.

(v). Living Standards

Enhancing people's welfare is the ultimate goal of HQED, aligning economic progress with social inclusivity. By meeting citizens' aspirations for a better life, HQED ensures that growth translates into tangible improvements in well-being. Indicators such as per capita disposable income, per capita educational expenditure, and per capita hospital beds are incorporated to represent different dimensions of social welfare, covering income distribution, human capital investment, and healthcare access. Collectively, these measures embody the principle of "shared" development and reflect whether developmental benefits are equitably distributed across society, thereby strengthening social cohesion and resilience.

(vi). Ecodevelopment

Ecological civilization has been repeatedly emphasized in China's national strategy, particularly since the 18th National Congress, as both the foundation and hallmark of HQED. It underscores the principle that sustainable growth must be pursued in harmony with environmental stewardship. Indicators such as the comprehensive utilization rate of industrial solid waste, sulfur dioxide emissions per unit of output, and PM2.5 concentration are used to evaluate urban environmental quality, efficiency of resource utilization, and effectiveness of pollution control efforts. Together, they reflect the degree to which the concept of green development has been implemented in practice and demonstrate the progress toward achieving sustainable, low-carbon, and environmentally friendly growth.

This multidimensional indicator system encapsulates the intrinsic logic of the new development philosophy, which emphasizes innovation, coordination, greenness, openness, and sharing, while providing a robust and quantifiable framework for assessing HQED. By employing the entropy weight method, this study assigns objective weights to each indicator and constructs a composite HQED index that minimizes subjectivity and enhances comparability. The detailed composition of indicators and their data sources are summarized in Table 3-2.

Table 3-1: Indicators of HQED

Fundamentals	Primary Indicators	Second indicators (Weight)	Indicator Description	Abbreviation (Attributes)
Economic fundamentals	Industry Structure (0.1407)	Percentage of productive service industry (0.0389)	Proportion of productive service industries in urban employment	PPS (+)
		Rationalization of industrial structure (0.0350)	Structural deviation method	RIS (+)
		Heightened industrial structure (0.0668)	Ratio of the output value of the tertiary sector to the secondary sector	HIS (+)
	Technological innovation (0.2099)	innovation index (0.2099)	Innovation index at the urban level	IN (+)
	ITFP (0.0346)	Inclusive TFP (0.0346)	Calculation using the Hicks-Moorsteen index method	TFP (+)
	Degree of Openness (0.4581)	Foreign trade openness (0.3580)	Foreign direct investment / regional GDP	FDO (+)
		Openness to foreign investment (0.1001)	Total imports and exports / regional GDP	OFI (+)
Social fundamentals	Living Standards (0.1228)	Per Disposable personal income (0.0481)	Regional GDP / total resident population	PDPI (+)
		Expenditure on education per capita (0.0452)	Local government financial education expenditure / total resident population	PCE (+)
		Hospital beds per capita (0.0295)	Number of hospital beds / total resident population	PHB (+)
Ecological fundamentals	Ecodevelopment (0.0543)	SO ₂ emissions per unit (0.0008)	SO ₂ / regional GDP	SEP (-)
		Comprehensive utilization rate of industrial solid waste (0.0389)	Comprehensive utilization / total output + storage volume	CUI (+)
		PM2.5 (0.0146)	Population-weighted PM2.5 concentration	PM (-)

Notes:

1. The attributes of indicators are marked as positive (+) or negative (-);
2. The numerical values following each indicator represent the weights calculated by the entropy weight method.

3.2.2.2 Constructing the HQED Index Using the Entropy Weight Method

The entropy weight method is widely used as an objective weighting approach in multi-indicator comprehensive evaluation systems. Its fundamental idea is to determine the contribution of each indicator to the overall system based on the variability of information entropy over the observation period. A higher entropy indicates smaller variability and lesser contribution, while lower entropy suggests higher variability and greater significance.

In this study, the entropy weight method is applied to measure the level of HQED across provinces. The calculation involves four steps:

(i). Data Standardization

Before applying the entropy weight method, standardization of each indicator is necessary due to differing dimensions. Assuming there are samples (such as regions or time points) and n sub-indicators, forming an original data matrix, where x_{ij} denotes the value of the j th indicator for the i th sample. Suppose there are m evaluated objects, each with n indicators. Consequently, an $m \times n$ judgment matrix can be constructed. After standardizing indicators, a new matrix $R = (r_{ij})_{m \times n}$ · $r_{ij} \in [0,1]$ is obtained, the formula is given as follows:

$$X = (r_{ij})_{m \times n} \quad (i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n) \quad \text{Equation 3-5}$$

if the indicator has a positive trend,

$$r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad \text{Equation 3-6}$$

if the indicator has a negative trend,

$$r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \quad \text{Equation 3-7}$$

(ii). Calculation of Entropy

We can calculate the contribution of year i under index j via the following equation:

$$\begin{aligned} e_{ij} &= -k \sum_{i=1}^n p_{ij} \ln(p_{ij}) \\ p_{ij} &= \frac{r_{ij}}{\sum_{i=1}^n r_{ij}} \\ k &= \frac{1}{\ln n} \end{aligned} \quad \text{Equation 3-8}$$

(iii). Determining the Weights

$$W_j = \frac{1 - e_j}{\sum_{j=1}^m 1 - e_j} \quad \text{Equation 3-9}$$

(iv). Comprehensive Score Calculation for HQED

$$s_i = \sum_{j=1}^n W_j \cdot P_{ij} \quad \text{Equation 3-10}$$

Where S_i denotes the comprehensive score for HQED of the i th sample, and W_j represents the weight of the j th indicator calculated using the entropy weight method. A

higher score indicates a higher level of HQED for the sample. The specific weights of each indicator obtained by the entropy weight method are presented in Table 3-1.

To ensure the validity and methodological rigor of the HQED index constructed in this study, three key considerations were emphasized. First, the indicator framework is directly grounded in the theoretical foundations proposed in this study, namely sustainable development, low-carbon economy and decoupling theory, and spatial econometrics. These theories jointly emphasize the need to balance economic growth, social equity, and environmental sustainability, which correspond to the economic, social, and ecological dimensions of the index. Second, the entropy weight method was applied to objectively assign weights based on interprovincial variation, enhancing internal consistency and avoiding subjective bias (Zhu et al., 2020). This approach ensures that each indicator's contribution reflects actual development disparities across regions. Third, the constructed HQED index integrates well with the empirical modeling strategy adopted in this study. It produces stable and interpretable results across static, dynamic, and spatial econometric models.

Compared with alternative HQED frameworks such as those based on the new development philosophy or people-centered development paradigms (Chen & Huo, 2022; Cui et al., 2024), the multidimensional structure developed here demonstrates stronger empirical applicability, cross-regional comparability, and theoretical coherence with the analytical framework of this research.

3.2.3 Control Variables

To more comprehensively and accurately evaluate the impact of HQED on CP, this study introduces several control variables in addition to the core explanatory variable, thereby minimizing potential biases due to omitted variables. These control variables are carefully selected based on existing literature and the theoretical framework of low-carbon economic development, ensuring that the empirical model adequately captures the multidimensional drivers of CP. By accounting for structural, institutional, and environmental factors that may influence CP, the inclusion of these variables not only reduces endogeneity risks but also enhances the explanatory power and robustness of the empirical results. In this way, the analysis can better isolate the independent contribution of HQED while providing a more nuanced understanding of the mechanisms through which

CP is shaped at the regional level. The specific definitions and measurement approaches of these control variables are presented as follows.

Table 3-2: List of Control Variable

Control Variable	Abbreviation	Description	Definition
Energy Intensity	ei	Reflects regional energy use efficiency. Lower intensity generally improves CP by reducing energy-related emissions (Mehmood Mirza et al., 2022).	Energy consumption per unit of GDP
Urbanization Rate	ur	Indicates the level of urban concentration. Urbanization may enhance productivity through agglomeration but also increase energy demand and pollution (Hashmi et al., 2021; Pan et al., 2024).	Urban population as a share of total population
Marketization Level	ml	Captures the extent of market-oriented reforms. Higher levels may improve CP by facilitating efficient resource allocation (Qi, 2023).	Share of employment in private and individual enterprises
Government Environmental Expenditure	env	Reflects the strength of public environmental governance. Greater investment supports emission control and ecological improvements (Liu et al., 2023b).	Environmental expenditure as share of local fiscal spending
Industrial Structure	ss	Represents the composition of economic activity. A higher share of secondary industry is often linked to greater emissions, though restructuring can mitigate this effect (Lin & Wang, 2023b).	Share of secondary industry in regional GDP
Capital-Labor Ratio	clr	Serves as a proxy for capital intensity. Higher ratios typically signal technological advancement, which supports improved energy efficiency and CP (Tao et al., 2024).	Capital stock divided by number of employed persons

3.3 Data Sources and Processing

Scientific and rational selection and processing of data are fundamental for ensuring the validity and reliability of research findings. This study has meticulously designed and rigorously implemented data selection, timeframe determination, and preprocessing procedures to establish a robust foundation for empirical analysis.

3.3.1 Data Sources and Study Period

Data used in this study are primarily derived from authoritative sources, including:

- National Bureau of Statistics of the People’s Republic of China (NBS)
- General Administration of Customs and Ministry of Commerce of China
- Statistical Communiqué of the National Economy and Social Development
- China Energy Statistical Yearbook

- Environmental Quality Bulletin
- China Industrial Statistical Yearbook
- China Environmental Statistical Yearbook
- China Statistical Yearbook
- China Emission Accounts and Datasets (CEADs)

CEADs is jointly maintained by various domestic and international research institutions, characterized by high credibility and transparency. Integrating multi-dimensional data such as energy consumption, industrial output, and carbon emission coefficients, CEADs systematically calculates carbon emissions based on IPCC methodologies and a lifecycle analysis framework, thus ensuring data consistency and scientific rigor. Its datasets are widely applied in research areas such as carbon efficiency, energy utilization, and environmental performance, recognized academically for accessibility and reliability. Given that CEADs data is available up to 2021, and considering data availability alongside the empirical requirements of this analysis, CP indicators for China's 30 provinces were constructed using carbon emissions and real GDP data from 2008 to 2021.

The study's timeframe from 2008 to 2021 aligns firstly with data availability in the CEADs database, ensuring data completeness. Additionally, the year 2008 marks China's economic shift from high-speed growth towards high-quality development, triggered by the international financial crisis, rendering this period significant both policy-wise and practically representative. Furthermore, China's statistical systems have become increasingly standardized post-2008, providing a more mature and reliable data framework essential for empirical research.

3.3.2 Data Preprocessing

Regarding data preprocessing, missing values for a limited number of indicators in certain years were addressed through the exponential smoothing method or by using the mean value of adjacent years to ensure continuity and robustness of the time series data. To mitigate the effects of differing measurement scales across variables, all indicators underwent Min-Max normalization, converting them into dimensionless standardized values. Additionally, data cleaning involved cross-validation across multiple sources, ensuring

consistency and logical integrity. These meticulous preprocessing steps provide a solid data foundation for subsequent model construction and empirical analysis.

3.4 Econometric Model Specification

To systematically evaluate the impacts of HQED on CP, this study adopts a progressive econometric strategy combining static, dynamic, and spatial panel models, each serving a distinct analytical objective. First, a static fixed effects model is employed to establish baseline correlations and control for time-invariant provincial characteristics. Second, to address potential endogeneity and capture the cumulative and lagged effects of HQED, the System GMM is applied. This dynamic model is particularly suited for short panels with potential autocorrelation and endogenous regressors. Finally, spatial econometric models, including the Spatial Durbin Model (SDM), are used to identify interregional spillover effects and spatial dependencies that are common in environmental and development indicators. Together, this multi-model approach provides a more robust and comprehensive understanding of the HQED-CP relationship, accounting for both internal dynamics and spatial interactions across provinces.

3.4.1 Static Panel Regression Model

3.4.1.1 Model Specification

To establish a benchmark relationship between HQED and CP, this study first employs a static panel regression model. Panel data, which track multiple entities over time, offer a unique advantage in controlling for unobserved heterogeneity and improving estimation efficiency. Compared to cross-sectional or time series models, panel models allow for more accurate identification of the effects of key explanatory variables, especially when provincial characteristics remain relatively stable over time. Accordingly, this study utilizes balanced panel data from 30 Chinese provinces spanning 2008 to 2021 to estimate the baseline static relationship between HQED and CP, while accounting for time-invariant regional effects. The following econometric model is specified:

$$\ln CP_{it} = \beta_0 + \beta_1 \ln HQED_{it} + \beta \ln \sum_{i=1}^6 X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad \text{Equation 3-11}$$

Where CP_{it} denotes the CP of province i in year t . $HQED_{it}$ represents the HQED index, calculated based on a multidimensional evaluation system comprising economic, social, and ecological foundations, using the entropy weight method introduced earlier. X_{it} is a vector of control variables. μ_i indicates individual fixed effects, capturing time-invariant characteristics specific to each province. φ_t denotes time fixed-effects, controlling for common shocks that vary over time but affect all provinces uniformly. ε_{it} is the idiosyncratic error term, representing unobserved random factors not explicitly modeled.

To mitigate heteroscedasticity, reduce the influence of extreme values on the estimation results, and facilitate the interpretation of regression coefficients in elasticity terms, all continuous variables, including CP, HQED, and control variables are transformed using the natural logarithm. Under this transformation, the estimated coefficients can be interpreted as elasticities, i.e., the percentage change in CP associated with a 1% change in the explanatory variable. This approach is well-established and has been widely adopted in empirical research due to its strong theoretical foundation and empirical robustness (Wooldridge, 2010).

3.4.1.2 Model Selection Tests (FE vs. RE)

To accurately evaluate the impact of provincial HQED on CP, it is essential to account for individual and time effects. Individual effects refer to unique, time-invariant characteristics specific to each entity (such as region, firm, or country), including geographical location, historical and cultural background, and economic conditions. Time effects denote common changes experienced by all entities over different time periods, usually driven by external factors such as macroeconomic fluctuations, policy shifts, and global events.

Panel data models can be classified into three types based on the presence and treatment of individual effects: the Fixed Effects model (FE), Random Effects model (RE), and Pooled Ordinary Least Squares model (OLS). FE model assumes that individual effects exist and are correlated with explanatory variables, treating these effects as time-invariant and fixed factors. Conversely, the RE model also assumes the existence of individual effects, but treats them as random, uncorrelated with explanatory variables. The pooled OLS model assumes no individual effects exist.

Choosing the appropriate model is critical to ensure the validity of estimation results. Therefore, this study sequentially employs the F-test, the Breusch–Pagan Lagrange Multiplier (BP-LM) test, and the Hausman test for model identification.

(i). F-test for Fixed Effects

The F-test assesses whether individual fixed effects significantly differ from zero, thus evaluating if the fixed effects model is superior to the pooled OLS model. The null hypothesis (H_0) posits that all individual effect coefficients are zero (no fixed effects). Rejection of H_0 suggests the fixed effects model is appropriate. The F-test statistic is given by:

$$F = \frac{(R_u^2 - R_r^2)/(n-1)}{(1-R_u^2)/(nT-n-K)} \sim F(n-1, nT-n-K) \quad \text{Equation 3-12}$$

Where R_u^2 and R_r^2 represent the coefficients of determination from unrestricted (FE) and restricted (pooled OLS) models, respectively. n is the number of cross-sectional units, T is the number of time periods, and K denotes the number of explanatory variables. A significant F-statistic (typically $p < 0.05$) indicates substantial individual fixed effects, validating the FE model. Otherwise, the pooled OLS model is appropriate.

(ii). Breusch-Pagan LM Test

The BP-LM test compares the pooled OLS and random effects models by assessing the existence of random individual effects. The null hypothesis (H_0) states that there are no random individual effects, i.e., variance components equal zero (Breusch & Pagan, 1980). The LM statistic is expressed as follows:

$$LM = \frac{NT}{2(T-1)} \left[\frac{\sum_{i=1}^N (\sum_{t=1}^T \hat{e}_{it})^2}{\sum_{i=1}^N \sum_{t=1}^T \hat{e}_{it}^2} - 1 \right]^2 \quad \text{Equation 3-13}$$

Where e_{it} denotes residuals from the pooled OLS model. If the BP-LM test rejects the null hypothesis (significant $p < 0.05$), the presence of random effects is confirmed, suggesting the random effects model is preferable over the pooled OLS model.

(iii). Hausman Test

The Hausman test is employed to determine the final choice between the FE and RE models. The null hypothesis (H_0) posits no correlation between explanatory variables and individual effects, validating the RE model. The alternative hypothesis (H_1) assumes

correlation, supporting the FE model. The Hausman test statistic is calculated as (Hausman, 1978).

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})' [Var(\hat{\beta}_{RE}) - Var(\hat{\beta}_{FE})]^{-1} (\hat{\beta}_{RE} - \hat{\beta}_{FE}) \quad \text{Equation 3-14}$$

Where $\hat{\beta}_{FE}$ and $\hat{\beta}_{RE}$ represent estimators from fixed effects and random effects models, respectively. A significant Hausman statistic (typically $p < 0.05$) rejects the null hypothesis, indicating the fixed effects model is more suitable. Otherwise, the random effects model should be adopted.

3.4.2 Dynamic Panel Regression Model

When analyzing the impact of HQED on CP, it is noted that CP exhibits a certain “inertia” characteristic. Specifically, its current level is influenced not only by external factors such as economic development but also by its own historical values. This temporal path dependency and adjustment lag endow CP with significant dynamic characteristics. Consequently, employing a static panel model may neglect the intrinsic dynamic mechanism of CP, resulting in estimation bias. To more scientifically identify the lagged effects of HQED on CP, this study introduces a dynamic panel regression model.

3.4.2.1 Model Specification

Based on the above logic, construct the following dynamic panel data model:

$$\begin{aligned} \ln CP_{it} = & \beta_0 + \beta_1 \ln HQED_{it} + \beta_2 \ln CP_{i,t-1} \\ & + \beta \ln \sum_{i=1}^6 X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \end{aligned} \quad \text{Equation 3-15}$$

The variables used in this model are consistent with those in the static panel regression, with the addition of a one-period lagged dependent variable $CP_{i,t-1}$.

In this study, the panel dataset consists of 30 provinces ($N=30$) and spans 14 years ($T=14$), constituting a typical "short panel" structure. In such panels, the cross-sectional dimension significantly exceeds the temporal dimension ($N > T$), a common scenario in empirical research within economics and finance. Although the temporal dimension is relatively short, this does not hinder the applicability of Generalized Method of Moments (GMM) estimation, as the asymptotic properties of GMM primarily rely on the increase in the number of cross-sectional units.

When the lagged dependent variable $CP_{i,t-1}$ is introduced into the model, thus forming a dynamic panel, conventional estimation methods suffer from endogeneity bias due to the correlation between the lagged dependent variable and the error term. (Nickell, 1981) pointed out that in fixed-effects estimation, the lagged dependent variable correlates with the residual component of individual effects, causing significant downward bias in the estimation of the lagged term, especially when T is small. Conversely, pooled OLS tends to produce upward-biased estimates. This phenomenon is known as the "dynamic panel bias." To address this issue, Arellano and Bond (1991) proposed the Difference GMM method. This method eliminates unobservable individual effects u_i through first differencing of the model and employs earlier-period lagged variables as instrumental variables, thereby effectively estimating the lagged dependent variable. The differenced model is specified as follows:

$$y_{it} = \alpha + \rho y_{i,t-1} + x'_{it}\beta + z'_i\delta + \mu_i + \varepsilon_{it} \quad (t = 2, \dots, T) \quad \text{Equation 3-16}$$

taking the first-order difference of it, we can obtain:

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \Delta x'_{it}\beta + \Delta \varepsilon_{it} \quad (t = 2, \dots, T) \quad \text{Equation 3-17}$$

However, $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ is still correlated with $\Delta \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$ because $\Delta y_{i,t-1}$ is inherently correlated with $\varepsilon_{i,t-1}$. Therefore, $\Delta y_{i,t-1}$ is considered an endogenous variable, and it is necessary to identify an appropriate instrumental variable to obtain consistent estimates. To address this, (Anderson & Hsiao, 1981) proposed using $y_{i,t-2}$ as an instrument for $\Delta y_{i,t-1}$. Clearly, under the assumption of no serial correlation, $y_{i,t-2}$ is uncorrelated with $\Delta \varepsilon_{it}$ but correlated with $\Delta y_{i,t-1}$, making it a valid instrument. Similarly, higher-order lagged values can also serve as effective instruments. Thus, a key condition for the validity of the difference GMM approach is that the error term sequence $\{\varepsilon_{it}\}$ is not serially correlated, i.e., $Cov(\varepsilon_{it}, \varepsilon_{is}) = 0, t \neq s, \forall i$.

Nevertheless, the Difference GMM approach has two notable limitations. First, the differencing process eliminates any time-invariant variables z_i , thereby making it impossible to estimate the coefficients associated with these variables. Second, if the autoregressive coefficient of the series $\{y_n\}$ is close to 1, then the correlation between $y_{i,t-2}$ and $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ may be weak, leading to the problem of weak instruments, which in turn reduces estimation efficiency. To overcome these issues, Arellano and Bover (1995) proposed estimating the level equation (Equation 3-17) using $\{\Delta y_{i,t-1}, \Delta y_{i,t-2} \dots\}$ as

instruments for $y_{i,t-1}$. Evidently, these are correlated with $y_{i,t-1}$. Under the assumptions that $\{\varepsilon_{it}\}$ is not serially correlated and that the instruments $\{\Delta y_{i,t-1}, \Delta y_{i,t-2} \dots\}$ are uncorrelated with individual effects, they can be used to perform GMM estimation of the level equation. This method is known as “Level GMM.” However, while Level GMM can address the weak instrument problem, it still cannot estimate the coefficients of time-invariant variables z_i .

Blundell and Bond (1998) proposed integrating the Difference GMM and Level GMM approaches by combining the differenced equation and the level equation into a unified system, thereby conducting estimation through a system of generalized method of moments (System GMM). This method offers several advantages; it enhances the identification power of instrumental variables, improves estimation accuracy and efficiency, and allows for the estimation of coefficients for time-invariant variables. Furthermore, System GMM imposes relatively weak assumptions, it does not require strict distributional specifications of the disturbance terms, nor does it rely on the absence of serial correlation or homoskedasticity. Consequently, it tends to produce parameter estimates that are closer to the true values than alternative methods. Given these advantages, this study adopts System GMM as the preferred methodology to examine the dynamic impact of HQED on CP.

3.4.2.2 Validity Tests and Estimation Diagnostics

To ensure the validity of the System GMM estimation and the reliability of its results, it is essential to test the underlying assumptions of the model. System GMM relies on two core assumptions: first, that there is no serial correlation in the model’s disturbance terms; and second, that the instrumental variables used are exogenous and uncorrelated with the error term. Accordingly, this study conducts the Arellano–Bond test for serial correlation and the over-identification test to verify the validity of these assumptions. Only when both tests are satisfied can the effectiveness of the model and the robustness of its estimations be ensured.

(i). Arellano-Bond Test

Arellano and Bond (1991) argue that in dynamic panel models, although first-order differenced disturbance terms may exhibit first-order autocorrelation (AR (1)), valid instrument specification should ensure the absence of second-order autocorrelation (AR (2)). Therefore, testing for serial correlation in the differenced residuals is a necessary step for verifying the validity of the System GMM estimator.

The null hypothesis of the Arellano–Bond test is that “there is no serial correlation $\{\varepsilon_{it}\}$ ” in the disturbance terms. The presence of first-order autocorrelation in the differenced residuals is expected because:

$$\begin{aligned} Cov(\Delta\varepsilon_{it}, \Delta\varepsilon_{i,t-2}) &= Cov(\varepsilon_{it} - \varepsilon_{i,t-1}, \varepsilon_{i,t-2} - \varepsilon_{i,t-3}) \\ &= -Cov(\varepsilon_{i,t-1}, \varepsilon_{i,t-2}) = -Var(\varepsilon_{i,t-2}) \neq 0 \end{aligned} \quad \text{Equation 3-18}$$

Differencing the disturbance terms removes individual effects but may introduce AR (1), whereas AR (2) or higher-order autocorrelation should not be present if the instruments are valid. Thus, the test examines whether AR (1) and AR (2) are present in the differenced residuals. If the p-value for AR (1) is statistically significant (e.g., AR (1) $p = 0.000$), but the p-value for AR (2) is not significant (e.g., AR (2) $p > 0.05$), this suggests the residuals exhibit first-order but not second-order autocorrelation, meeting a fundamental assumption of System GMM. In such a case, the System GMM approach is appropriate. Conversely, if the AR (2) p-value is significant, indicating the presence of second-order serial correlation, the use of System GMM would be invalid.

(ii). *Overidentification Tests*

When conducting parameter estimation using the System GMM, it is necessary to verify the validity and exogeneity of the instrumental variables to ensure the appropriateness of model specification and the reliability of estimation results. Since System GMM introduces lagged dependent variables as instruments, it often results in a large number of instruments, potentially leading to the problem of overidentification. Therefore, statistical tests for overidentifying restrictions are required, primarily including the Sargan test and the Hansen J test. Both tests construct their test statistics based on the moment conditions of GMM but differ in their assumptions regarding the distribution of the error terms.

Sargan Test: Originally proposed by Sargan (1958), the Sargan test is applicable under the assumptions of homoscedasticity and no autocorrelation in the error terms. Its core purpose is to test whether all instrumental variables used in GMM are uncorrelated with the error term, i.e., whether the exogeneity assumption holds. The test statistic is constructed as follows:

$$S = nR^2 \xrightarrow{d} \chi^2(m - r) \quad \text{Equation 3-19}$$

Where S denotes the Sargan test statistic, n is the sample size, R^2 is the coefficient of determination from an auxiliary regression of the residuals on all exogenous explanatory and instrumental variables, R is the number of endogenous regressors, and m is the total number of instruments. The test statistic follows χ^2 distribution with degrees of freedom equal to $m - r$, representing the number of overidentifying restrictions. If the p-value is significantly lower than the chosen significance level, the null hypothesis is rejected, indicating a potential endogeneity problem in the instruments; otherwise, the assumption of instrument exogeneity is accepted.

Hansen J Test: The Hansen J test builds upon the Sargan test by incorporating robust estimation methods that account for heteroskedasticity and serial correlation in the disturbance terms. Therefore, it offers greater robustness and is particularly suitable when heteroskedasticity or autocorrelation is suspected. In System GMM, where more instruments are typically used, the model is more susceptible to overfitting; the Hansen J test is thus widely favored for its robustness. The test statistic is defined as:

$$J = n \cdot (\hat{g}(\theta))' \hat{W}^{-1} \cdot \hat{g}(\theta) \quad \text{Equation 3-20}$$

Specifically, $\hat{g}(\theta)$ denotes the moment conditions constructed based on the GMM estimator, $\hat{W}^{-1}$ represents the optimal weighting matrix, and n is the sample size. The J-statistic follows a χ^2 distribution. When the p-value of the Hansen test is statistically significant, it suggests that the instrumental variables may be endogenous, indicating that the model is likely misspecified. In contrast, if the p-value is relatively high, typically greater than 0.1, it implies that the instrumental variables meet the exogeneity assumption, and the GMM estimation results are considered reliable (Roodman, 2009).

(iii). *One-Step and Two-Step Estimation Strategies*

To enhance estimation reliability, this study adopts both one-step and two-step system GMM methods. The one-step estimator constructs a weighting matrix under the assumption of homoskedasticity, which provides relatively robust standard errors in small sample settings. It serves as a stable reference point to assess the consistency of results across different specifications. The two-step estimator builds upon the one-step procedure by using the residuals from the first stage to construct an optimal weighting matrix, which improves efficiency in large samples (Arellano & Bond, 1991; Blundell & Bond, 1998). However, in small samples, the two-step method has a well-documented limitation, it tends to

underestimate standard errors, resulting in overstated statistical significance of coefficients. This downward bias can mislead inference, especially when the number of cross-sectional units is limited or when the instrument count is high relative to sample size.

To address this issue, the Windmeijer (2005) correction is applied to adjust the standard errors in the two-step estimation, improving their finite-sample properties. By reporting both estimation results, this study ensures that the final interpretation rests on consistent coefficient estimates and corrected standard errors. The one-step results serve to confirm the reliability of estimation, while the two-step results offer additional efficiency once corrected.

3.4.3 Spatial Econometric Model Framework

Theoretically, carbon emissions exhibit significant environmental externalities, with their impacts often transcending geographical boundaries. Emissions from one region may adversely affect the environmental quality of surrounding areas. Therefore, building upon the previous analytical framework, this study adopts a spatial-geographic perspective to construct a spatial econometric model to examine the spatial effects of HQED on CP. In spatial econometric modeling, the construction of a spatial weight matrix is a fundamental prerequisite for identifying and characterizing the spatial interactions among regional units.

3.4.3.1 Specification of the Spatial Weight Matrix

The spatial weight matrix serves not only as a fundamental tool for spatial autocorrelation tests and spatial regression analysis, but also as a critical link connecting spatial econometric models with real-world geographic and economic relationships. A properly specified spatial weight matrix can effectively capture the degree of spatial dependence among regions, thereby directly influencing the accuracy of model estimation and the explanatory power of economic interpretations.

In current empirical studies of spatial econometrics, three primary types of spatial weight matrices are commonly employed: contiguity-based weight matrices, geographic distance-based weight matrices, and nested economic-geographic weight matrices. These weights are typically structured as spatial cross-sectional symmetric matrices with zero diagonal elements, expressed in the following basic form:

$$W_{ij} = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1n} \\ w_{21} & 0 & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & 0 \end{bmatrix} \quad \text{Equation 3-21}$$

All elements of the matrix are assumed to be exogenous and are specified as known constants. The weights are standardized using row-normalization according to Equation 3.21, ensuring that the sum of each row equals one. Based on this formulation, various specific forms of spatial weight matrices have been developed and extended (Wang, 2013).

$$W'_{ij} = W_{ij} / \sum_j^n W_{ij} \quad \text{Equation 3-22}$$

(i). *Contiguity Matrix*

The contiguity weight matrix is one of the most fundamental and commonly used spatial weight specifications. Its mathematical form is shown in Equation 3.23.

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \quad W_{ij} = W_{ji} = \begin{cases} 1, j \in \{j\} \\ 0, j \notin \{j\} \end{cases} \quad \text{Equation 3-23}$$

Where the spatial weight matrix W is an N symmetric matrix with all diagonal elements equal to zero. In this setting, the weights are determined based on whether two regions share a common boundary: a value of 1 is assigned if the regions are adjacent, and 0 otherwise.

Based on the adjacency criterion, the matrix can be further divided into Rook contiguity and Queen contiguity. The Rook contiguity matrix assigns weights only when regions share a common border, whereas the Queen contiguity matrix treats regions as adjacent if they share either a border or a vertex. The primary advantage of contiguity matrices lies in their simplicity and computational convenience. However, they are limited in their ability to reflect variations in geographic distance or economic linkages, making them more suitable for research settings where physical adjacency is the dominant spatial relationship.

(ii). *Inverse Distance Matrix*

This matrix assigns weights based on the inverse of the straight-line geographic distance between regional centroids—the shorter the distance, the stronger the spatial influence—thereby reflecting Tobler's First Law of Geography in the spatial diffusion

process. To ensure standardization, the matrix is typically row-normalized, meaning that the sum of weights in each row equals 1. The specific formulation is as follows.

$$W = \begin{bmatrix} 0 & \frac{1}{d_{1,2}} & \cdots & \frac{1}{d_{1,n}} \\ \frac{1}{d_{2,1}} & 0 & \cdots & \frac{1}{d_{2,n}} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{1}{d_{n,1}} & \frac{1}{d_{n,2}} & \cdots & 0 \end{bmatrix} \quad \text{Equation 3-24}$$

Here, d_{ij} represents the centroid-to-centroid distance or the administrative center distance between regions i and j . Compared to the contiguity matrix, the geographic distance weight matrix takes into account the actual spatial distance between provinces, capturing the degree of spatial association from a relative distance perspective. It better reflects the attenuation of spatial influence over distance. However, it neglects the real economic interactions between regions.

(iii). *Economic-Geographic Nested Spatial Weight Matrix*

Given the significant regional disparities in China's economic development, a purely geographic matrix may be insufficient to fully capture the mechanisms of spatial interaction driven by economic linkages. Therefore, this study incorporates an economic-geographic nested spatial weight matrix, defined as follows:

$$W_{ij} = A_{ij} \cdot \left(1 - \frac{|Y_i - Y_j|}{\max|Y_i - Y_j|}\right) \quad \text{Equation 3-25}$$

In this formula, A_{ij} denotes geographic contiguity, where $A_{ij} = 1$ if regions i and j are adjacent, and $A_{ij} = 0$ otherwise. Y_i and Y_j represent the economic attributes of regions i and j , commonly measured by per capita GDP or a composite economic development index. The denominator $\max|Y_i - Y_j|$ refers to the maximum absolute difference in economic attributes across all sample regions and is used for normalization. The resulting matrix is subjected to row normalization, ensuring that the sum of each row equals one: $\sum_{j=1}^n W$. This guarantees the operability and consistency of the matrix in spatial econometric modeling.

It is important to note that the economic-geographic nested spatial weight matrix addresses the limitations of purely geographic matrices by incorporating interregional economic linkages, making it more suitable for analyzing China's regional economic coordination and the transition toward green and low-carbon development.

To ensure objectivity and appropriateness in spatial weight construction, this study employs all three types of spatial matrices—contiguity, geographic distance, and nested economic-geographic for model estimation. A comparative analysis is conducted based on model goodness-of-fit, the significance of spatial effects, and the stability and explanatory power of core variables. This multidimensional evaluation provides empirical justification for selecting the most appropriate spatial weight matrix.

3.4.3.2 Testing for Spatial Dependence

Carbon emissions are influenced by various spatial factors, including interregional environmental linkages, industrial transfers, and policy diffusion. As a result, CP across different regions exhibits spatial interdependence. Therefore, before applying spatial econometric models to investigate the impact of HQED on CP, it is essential to first examine whether spatial autocorrelation exists among the variables.

Tests for spatial effects are typically classified into two categories: global spatial autocorrelation and local spatial autocorrelation. The former assesses whether there is an overall spatial clustering pattern across the entire sample, while the latter focuses on spatial disparities and associations within specific local areas. Following prior studies (Lesage & Pace, 2009), this study conducts spatial autocorrelation tests on both CP and HQED using Global Moran's I and Local Moran's I indices.

(i). Global Moran's I Index

The Global Moran's I is a classical statistic for measuring the degree of spatial clustering across the entire sample. It is calculated using the following formula:

$$I_g = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{Equation 3-26}$$

Where, n denotes the number of spatial units, x_i and x_j are the observed values of the variable in regions i and j , $\bar{x}$ is the global mean of the variable, W_{ij} represents the spatial weight between regions i and j . The value of the Global Moran's I statistic ranges between -1 and 1. When $I > 0$, it indicates positive spatial autocorrelation, meaning that high-value regions are adjacent to other high-value regions, or low-value regions are clustered near other low-value regions. Conversely, when $I < 0$, it implies negative spatial autocorrelation, where high and low values are spatially interspersed. The closer the absolute value of

Moran's I is to 1, the stronger the degree of spatial correlation. Generally, positive spatial autocorrelation is more common than negative, and a Moran's I value near zero suggests a random spatial distribution, indicating the absence of spatial dependence.

In this study, we employ the Global Moran's I statistic in conjunction with GeoDa software to examine the spatial autocorrelation of CP and HQED across 30 Chinese provincial regions.

(ii). Local Moran's I Index

In contrast to the global test, the Local Moran's I index is used to detect the degree of spatial association between each observation unit and its neighboring areas. The Local Moran's I is calculated as follows:

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^n W_{ij} (x_j - \bar{x})}{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{Equation 3-27}$$

It measures the similarity between a specific unit and its surrounding units. If $I_i > 0$, this indicates positive spatial clustering, meaning that a high-value unit is adjacent to other high-value units or a low-value unit is surrounded by other low-value units. If $I_i < 0$, it reflects a negative spatial relationship, where a high-value unit is surrounded by low-value units or vice versa.

To further identify specific types of spatial clustering, this study combines the values of Local Moran's I with their significance levels and uses the Local Indicators of Spatial Association (LISA) cluster map to classify the study area into four typical categories: High-High (H-H): a region with a high value surrounded by other high-value regions, representing a positively correlated “hotspot” area; Low-Low (L-L): a region with a low value adjacent to other low-value regions, indicating a “cold-spot” area; High-Low (H-L): a high-value region surrounded by low-value neighbors, reflecting spatial heterogeneity; Low-High (L-H): a low-value region surrounded by high-value neighbors, also indicating spatial heterogeneity.

3.4.3.3 Spatial Model Forms and Estimation

This study extends the traditional non-spatial linear panel model by incorporating spatial variables, thereby constructing spatial econometric models. Spatial econometric models are capable of capturing spatial interaction effects among dependent variables,

independent variables, and error terms. This allows for better identification of regional spatial spillover effects, enhancing both explanatory power and policy relevance.

(i). *Evolution of Spatial Econometric Models*

Initially, spatial econometric modeling focused on two core forms: the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM). The SAR model incorporates endogenous interaction effects among the dependent variables, while the SEM model accounts for interaction effects among error terms. Each model considers only one type of spatial interaction.

In 2007, researchers began to place increasing emphasis on models that included multiple types of spatial interaction effects. For instance, Kelejian and Prucha (1998) proposed that models should simultaneously account for endogenous interactions and correlated error structures. This integrated model was formally defined by Lesage and Pace (2009) as the Spatial Autoregressive Combined model (SAC). The SAC model combines the components of both the SAR and SEM models. The general form is given by:

$$Y = \alpha + \delta \sum_{j=1}^n W_{ij}Y + X\beta + \mu + v$$

$$v = \rho \sum_{j=1}^n W_{ij}v + \varepsilon$$

Equation 3-28

In this formulation, α denotes the constant term; $\sum_{j=1}^n W_{ij}Y$ represents the spatially lagged dependent variable, calculated as the weighted average of the dependent variable in neighboring regions based on the spatial weight matrix; δ is the spatial autoregressive coefficient, reflecting the degree of spatial dependence among regions; β is the $k \times n$ matrix of coefficients for the explanatory variables, and X is the matrix of observed values of the independent variables; v is the vector capturing spatially autocorrelated errors, accounting for mutual influences among regions; ρ represents the spatial error autocorrelation coefficient, indicating the strength and direction of spatial interdependence; and μ is the random disturbance term.

James LeSage advocated the use of models that incorporate both endogenous and exogenous interaction effects, analogous to the Durbin model in time series analysis. Anselin (1988) referred to this as the Spatial Durbin Model (SDM). The specific model can be expressed as follows:

$$Y = \alpha + \delta \sum_{j=1}^n W_{ij} Y + X\beta + \sum_{j=1}^n W_{ij} X\theta + \mu \quad \text{Equation 3-29}$$

The interpretation of variables remains consistent with that in Equation 3.28. $\sum_{j=1}^n W_{ij} X$ denotes the spatially lagged independent variables, calculated as the weighted average of neighboring regions' explanatory variables based on the spatial weight matrix. When all types of spatial interaction effects are considered simultaneously, a general form of spatial econometric model can be derived—commonly referred to as the General Nesting Spatial model (GNS). The specific form is expressed as follows:

$$Y = \alpha + \delta \sum_{j=1}^n W_{ij} Y + X\beta + \sum_{j=1}^n W_{ij} X\theta + \rho \sum_{j=1}^n W_{ij} v + \mu + \varepsilon \quad \text{Equation 3-30}$$

(ii). *Construction of the Spatial Autocorrelation Panel Data Model*

The aforementioned models are suitable for modeling linear spatial dependence in cross-sectional data without considering temporal effects. However, in the study of economic issues, it is essential to account for the influence of time effects. By incorporating temporal factors into the models described above, a spatial panel data model integrating individual, temporal, and spatial dimensions is constructed. The general form is as follows:

$$Y_{it} = \alpha + \delta \sum_{j=1}^n W_{ij} Y_{it} + X_{it}\beta + \sum_{j=1}^n W_{ij} X_{it}\theta + \rho \sum_{j=1}^n W_{ij} v_{it} + \varepsilon_{it} + \vartheta_{it} + \mu_i \quad \text{Equation 3-31}$$

To examine the endogenous spatial interaction effects of the dependent variable, CP, the SAR is first constructed. Its functional form is shown in Equation 3.32:

$$\ln CP_{it} = \rho \omega \ln CP_{it} + \beta_0 + \beta_1 \ln HQED_{it} + \beta_2 \ln \sum_{i=1}^6 X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad \text{Equation 3-32}$$

Here, $\ln CP_{it}$ represents the CP of region i in year t , and $HQED_{it}$ is the HQED index, serving as the core explanatory variable. $\sum_{i=1}^6 X_{it}$ denotes the set of control variables. ω is the spatial weight matrix, and ρ is the spatial autoregressive coefficient of the dependent variable. μ_i and φ_t represent region-specific and time-specific fixed effects, respectively, while ε_{it} is the error term. This model captures the spatial spillover effect of CP from neighboring regions on local CP.

(iii). *Construction of the Spatial Error Panel Model*

In addition to the spatial effects of neighboring regions' carbon emissions and HQED, carbon emissions in region *iii* may also be influenced by omitted variables that are spatially correlated due to geographic proximity. To account for this, a SEM is constructed with the following basic specification:

$$\ln CP_{it} = \beta_0 + \beta_1 \ln HQED_{it} + \beta_2 \ln \sum_{i=1}^6 X_{it} + \mu_i + \varphi_t + \lambda \omega \mu_{it} + \varepsilon_{it} \quad \text{Equation 3-33}$$

Here, μ_{it} denotes the spatially structured error term, and λ is the spatial autoregressive coefficient of the error term. This model emphasizes the spatial transmission of unobserved factors, reflecting the influence of omitted variables that exhibit spatial correlation.

(iv). *Construction of the Spatial Durbin Model*

With the deepening of spatial econometric research, scholars have increasingly recognized that explanatory variables may also exhibit spatial spillover effects. LeSage and Pace introduced the SDM, which incorporates spatial lags of both the dependent and explanatory variables into the model, thereby enhancing its explanatory power and robustness. The general form of the model is as follows:

$$\begin{aligned} \ln CP_{it} = & \rho \omega \ln CP_{it} + \beta_0 + \beta_1 \ln HQED_{it} + \lambda \omega \ln HQED_{it} \\ & + \beta_2 \ln \sum_{i=1}^6 X_{it} + k \omega \ln \sum_{i=1}^6 X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \end{aligned} \quad \text{Equation 3-34}$$

In this specification, $\omega \ln HQED_{it}$ and $\omega \ln \sum_{i=1}^6 X_{it}$ represent the spatially lagged core explanatory variable and control variables, respectively, while λ and k denote their corresponding spatial spillover effect coefficients. The SDM allows for simultaneous estimation of both direct effects (within a region) and indirect effects (from neighboring regions), capturing the full spatial interaction structure. Due to its nested structure and flexibility, the SDM is often used as a general starting point for spatial model identification. Subsequent Wald and Likelihood Ratio (LR) tests can be employed to determine whether the SDM should be simplified to a SAR or SEM model.

3.4.3.4 Model Selection and Identification Tests

In spatial econometrics, the three types of spatial interaction effects—spatial lag, spatial error, and spatial Durbin, each possess distinct characteristics. Selecting the appropriate model is fundamental to empirical analysis, and thus, it is essential to conduct systematic model identification prior to estimation. This section performs model specification testing from three aspects: (1) the Lagrange Multiplier (LM) test is used to determine whether SAR or SEM is present; (2) the Hausman test is used to determine whether to adopt FE or RE; and (3) the Wald and LR tests are applied to assess whether the SDM can be simplified to a SAR or SEM model.

(i). Identification Test for Spatial Panel Data Models

To begin, it is necessary to determine whether there is significant spatial correlation among variables. While the previous section employed Moran's I index to assess the spatial clustering of CP and HQED, Moran's I alone cannot determine which type of spatial model should be applied, since it only identifies the existence of global or local autocorrelation without specifying its structural source. Therefore, this study further adopts the LM test and its robust versions, as proposed by Anselin et al. (2008), to distinguish whether a SAR or a SEM specification is more appropriate. Specifically, four types of diagnostic tests are conducted:

LM-Lag Test: This test evaluates whether the spatially lagged dependent variable should be included, i.e., whether there exists substantive spatial autocorrelation in the dependent variable.

LM-Error Test: This test examines whether spatial correlation exists in the error term, indicating whether a SEM is appropriate.

Robust LM-Lag Test: This test assesses the independent significance of the spatial lag term under the presence of spatial dependence in the error term.

Robust LM-Error Test: This test evaluates the independent significance of the spatial error effect when the spatial lag is present. The decision criteria for model selection based on these tests are summarized in Table 3-3.

Table 3-3: Model Identification Based on LM Tests

Model Selection and Interpretation	LM-Err	LM-Lag	Robust LM-Err & Robust LM-Lag
OLS	Not significant	Not significant	-
SEM	Significant	Not significant	-
SAR	Not significant	Significant	-
SEM	Significant	Significant	Robust LM-Err > Robust LM-Lag
SAR	Significant	Significant	Robust LM-Err ≤ Robust LM-Lag

This stage of testing provides a preliminary basis for further constructing spatial econometric models. Compared with Moran's I, these tests provide a more detailed diagnostic framework by decomposing the possible sources of spatial dependence into lag and error components. This stage of testing not only validates the presence of spatial dependence but also lays the empirical foundation for selecting an appropriate spatial econometric specification in subsequent modeling.

(ii). Hausman Test

In the context of spatial panel data models, determining whether to use FE or RE remains a critical issue. To avoid estimation bias, this study applies the Hausman test to guide model selection. The null hypothesis posits that “the RE model is more efficient,” while the alternative hypothesis contends that “the FE model is more consistent.”

H_0 (null hypothesis): Individual effects are uncorrelated with the explanatory variables; adopt the RE model.

H_1 (alternative hypothesis): Individual effects are correlated with the explanatory variables; adopt the FE model.

If the Hausman test statistic is significant ($p < 0.05$), the null hypothesis is rejected, and the fixed effects model should be used.

(iii). Wald Test and LR Test

Following the LM series tests, if the Robust LM test suggests rejecting the non-spatial model in favor of a spatial lag model or spatial error model, further caution is warranted. In such cases, the more general SDM is recommended. Subsequently, the Wald test and the LR test can be used to assess whether the SDM can be simplified to either a SAR or SEM model.

If the null hypothesis $H_0: \theta = 0$ is not rejected, implying that all coefficients on the spatially lagged explanatory variables are zero, then the SDM can be simplified to the SAR.

If the null hypothesis $H_0: \rho + \theta\beta = 0$ is not rejected, implying that the combination of the spatial autoregressive coefficient ρ , the spatial lag coefficient of the explanatory variables θ , and the coefficient of the explanatory variables β equals zero. In this case, the SDM can be simplified to the SEM.

Both test statistics follow χ^2 distribution with degrees of freedom equal to the number of restrictions k . If both hypotheses are rejected, the SDM is preferred. If only one hypothesis is rejected, a simplified model may be considered. If neither hypothesis is rejected, a more parsimonious model may be adopted to enhance estimation efficiency.

In summary, prior to the formal construction of spatial econometric models, this section applies a systematic identification sequence comprising the LM series tests $\rightarrow$ Hausman test $\rightarrow$ Wald/LR tests. This provides a comprehensive assessment of the source and nature of spatial effects, thereby laying a solid foundation for model specification and empirical interpretation.

CHAPTER 4:

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the empirical results on how High-Quality Economic Development (HQED) affects Carbon Productivity (CP), using static, dynamic, and spatial analyses. The analysis is carried out in three stages. First, the static panel model uses fixed or random effects to estimate HQED's direct impact on CP, with the best model selected using the Hausman test and robustness checks. Second, the dynamic panel model introduces the lagged CP variable and applies the system GMM method to account for path dependence and address endogeneity, helping to identify causal effects. Lastly, the spatial econometric analysis explores spillover effects using Moran's I, SEM, SAR, and SDM models to assess whether HQED influences CP in neighboring regions through geographic or economic connections. This reveals how HQED supports low-carbon transformation across regions.

4.2 Spatiotemporal Evolution Characteristics of CP and HQED

To comprehensively examine the evolving trends and spatial distribution of CP in the context of HQED in China, this section analyzes their temporal dynamics and regional heterogeneity, aiming to uncover the patterns of change and spatial disparities.

4.2.1 Evolutionary Characteristics of CP in China

4.2.1.1 Temporal Trend Analysis

Based on the previously defined concept and calculation formula of CP, this study measures the CP of China from 2008 to 2021. Key data for selected years are presented in the table below to illustrate the trend over time.

Table 4-1: CP and Averages in China, 2008-2021
(Unit: 100 million RMB / 10,000 tons of CO₂)

Province	2008	2010	2012	2014	2016	2018	2020	2021
Beijing	1.2047	1.3952	1.6395	2.0429	2.7689	3.2838	3.8359	4.1048
Tianjin	0.7248	0.6843	0.8504	1.0469	1.3786	1.3940	1.5967	1.5510
Hebei	0.3322	0.3471	0.3753	0.4448	0.5156	0.6048	0.6777	0.7344
Shanxi	0.1232	0.1343	0.1278	0.0804	0.0938	0.0931	0.0878	0.0878
Inner Mongolia	0.1941	0.2031	0.1846	0.2122	0.2617	0.2522	0.2178	0.2343
Liaoning	0.3132	0.3570	0.3992	0.4790	0.4922	0.4921	0.4532	0.4768
Jilin	0.3373	0.3680	0.3991	0.5198	0.6479	0.7877	0.8735	0.8995
Heilongjiang	0.3473	0.2969	0.3278	0.4198	0.4513	0.5422	0.5738	0.5721
Shanghai	0.9742	1.0402	1.1590	1.4378	1.6262	1.9357	2.0442	2.1184
Jiangsu	0.6705	0.7184	0.7736	0.9200	1.0236	1.1856	1.3396	1.3654
Zhejiang	0.6336	0.6960	0.8026	0.9415	1.0979	1.1966	1.1699	1.0969
Anhui	0.3681	0.4048	0.4094	0.4372	0.5460	0.6198	0.6840	0.7089
Fujian	0.7899	0.7706	0.8305	0.9220	1.1496	1.1499	1.1533	1.1153
Jiangxi	0.6037	0.6698	0.7663	0.8192	0.9125	1.0396	1.1668	1.2288
Shandong	0.3720	0.4195	0.4710	0.5667	0.5988	0.6152	0.6440	0.7008
Henan	0.5444	0.3922	0.5074	0.5895	0.7170	0.8963	1.0417	1.0835
Hubei	0.5342	0.5279	0.6004	0.8966	1.0460	1.1965	1.3004	1.2405
Hunan	0.5830	0.6498	0.6866	0.8901	1.0055	1.2778	1.5250	1.7148
Guangdong	1.0309	1.0194	1.1095	1.2612	1.4462	1.5102	1.5898	1.4747
Guangxi	0.7334	0.6801	0.5919	0.7438	0.8676	0.8649	0.8956	0.8943
Hainan	0.4224	0.4336	0.4387	0.4822	0.5282	0.5832	0.6345	0.6627
Chongqing	0.4836	0.5633	0.6901	0.9228	1.1094	1.4762	2.2982	1.7869
Sichuan	0.5380	0.5856	0.7423	0.8601	1.1935	1.3652	1.4583	1.5650
Guizhou	0.1823	0.1814	0.2036	0.2280	0.2560	0.3679	0.4367	0.4440
Yunnan	0.3782	0.4065	0.4710	0.5942	0.7143	0.7650	0.8591	0.9295
Shaanxi	0.2662	0.3089	0.3023	0.2970	0.2933	0.3512	0.3535	0.4083
Gansu	0.2504	0.2692	0.2847	0.3307	0.4090	0.4188	0.4303	0.4263
Qinghai	0.3171	0.3482	0.2815	0.3189	0.4384	0.5464	0.7000	0.6647
Ningxia	0.1100	0.1009	0.1014	0.1161	0.1395	0.1294	0.1301	0.1271
Xinjiang	0.2334	0.2077	0.1882	0.2091	0.2183	0.2129	0.2024	0.1903
National Average	0.4865	0.5060	0.5572	0.6677	0.7982	0.9051	1.0125	1.0203

From a national perspective, with the exception of Shanxi and Xinjiang, most provinces in China exhibited a sustained upward trend in CP from 2008 to 2021. This overall trajectory demonstrates clear phase-based characteristics and can be reasonably divided into three stages. The classification is based on major economic and environmental policy shifts, structural transitions, and turning points in national development strategy, rather than arbitrary time intervals.

Phase I (2008-2012): Traditional growth model with emerging green signals. During this period, CP increased from 0.4865 in 2008 to 0.5572 in 2012, representing a cumulative growth of approximately 14.5%. This phase coincided with the aftermath of the 2008 global financial crisis, during which China adopted a RMB 4 trillion stimulus package primarily focused on infrastructure and energy-intensive industries. The country also surpassed the United States to become the world's largest CO₂ emitter in 2007. In response to growing international pressure, China pledged at the 2009 Copenhagen Climate Conference to reduce

CO₂ emissions per unit of GDP by 40-45% from 2005 levels by 2020. Although early efforts in energy conservation and emission reduction began to take shape, structural reforms in energy and industry remained nascent. The policy environment, situated between the Eleventh and Twelfth Five-Year Plans, was still dominated by administrative command-and-control mechanisms. As a result, CP improvement was modest and largely policy-driven rather than structurally embedded.

Phase II (2013-2017): Policy reinforcement and accelerated green transformation. This period saw CP rise rapidly from 0.5572 to 0.8564, with an average national increase of approximately 39.4%. The Twelfth Five-Year Plan formally introduced “green development” as a core concept of the New Development Philosophy. Policy instruments transitioned from pure administrative regulation toward more market-based mechanisms, including the pilot launch of carbon emissions trading systems and support for clean energy technologies. The Central China Rise strategy entered a deeper implementation stage, leading to significant CP improvements in provinces such as Anhui (36.5%) and Hubei (31.8%). Simultaneously, the Paris Agreement was signed in 2015, marking China’s stronger international commitment. Industrial upgrading and pollution control policies began to exert substantial effects, although regional disparities persisted, with Xinjiang and Shanxi lagging behind due to their resource dependency and slower transition pace.

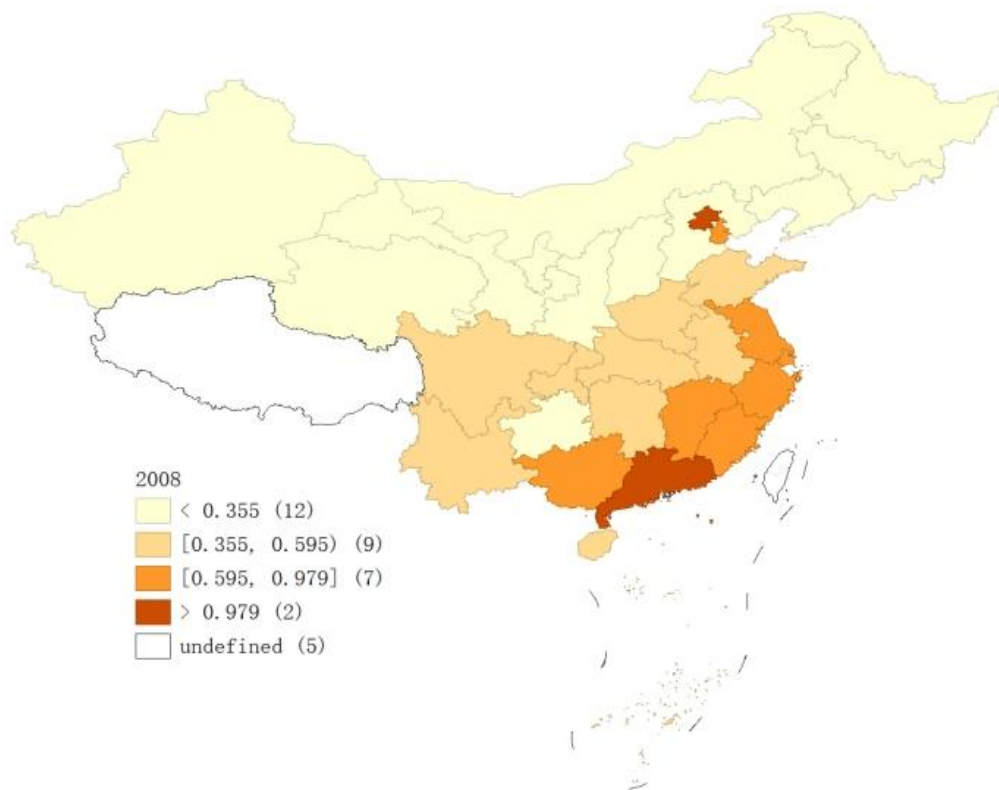
Phase III (2018-2021): Strategic reorientation and regional divergence. CP continued to grow from 0.9051 in 2018 to 1.0203 in 2021, but the annual growth rate began to decelerate. This stage marked a pivotal transition toward high-quality and low-carbon development. In 2017, the concept of “high-quality development” was officially proposed at the 19th National Congress of the Communist Party of China. Subsequent years laid the groundwork for the “dual carbon” goals, which were formally announced in 2020. National strategies during this period emphasized optimization of the energy structure, regional coordination, and the expansion of green finance. However, inter-provincial disparities became more pronounced. While eastern and central provinces with stronger economic foundations continued to improve their CP, many western and northeastern provinces experienced stagnation or decline due to entrenched reliance on coal and heavy industries. This divergence underscores the uneven regional capacity to adapt to the evolving green development agenda.

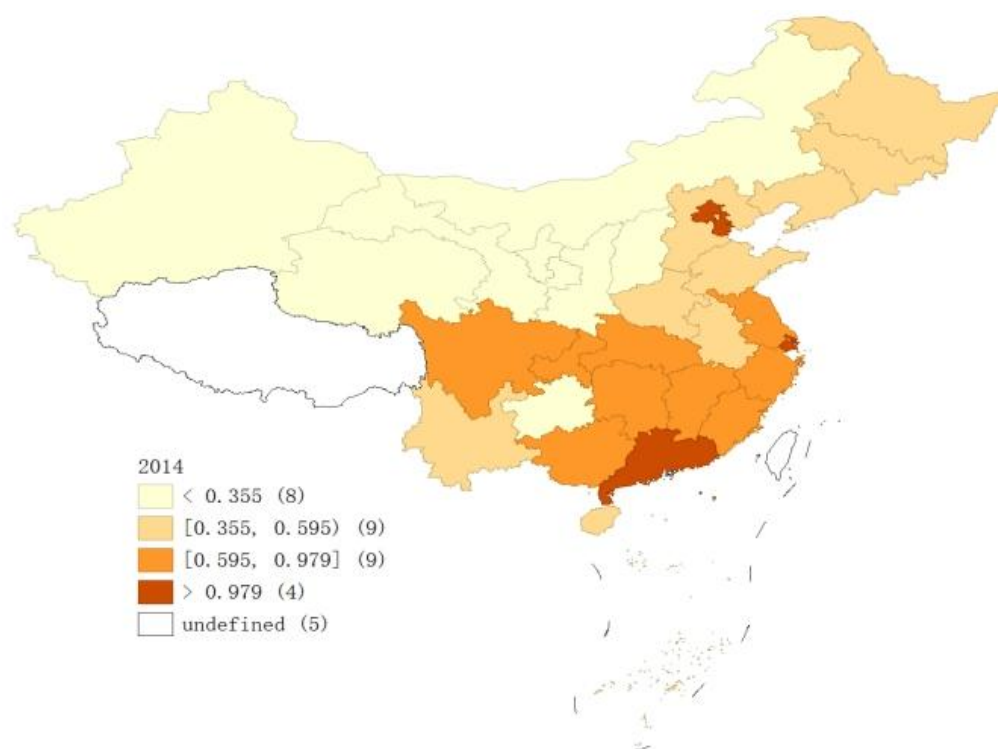
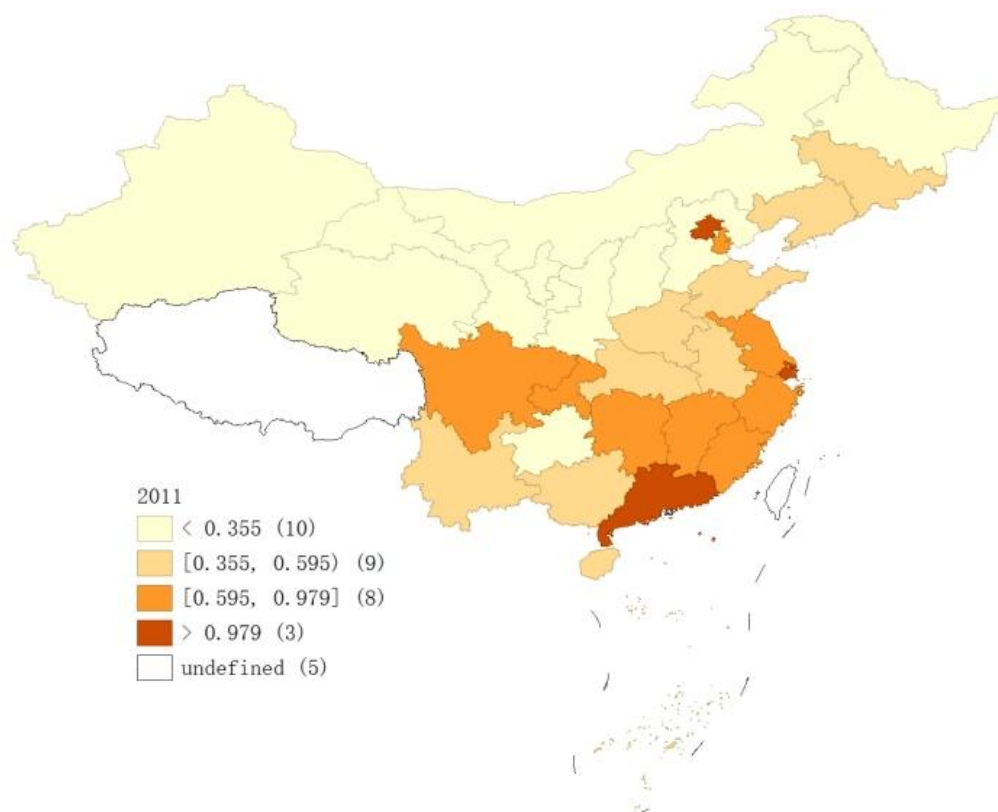
In summary, the temporal evolution of CP in China follows a trajectory of initial policy-driven improvement, followed by rapid policy reinforcement, and finally a structural transition characterized by regional divergence. These phases reflect the cumulative and differentiated effects of China's evolving green development strategies and institutional responses to global climate commitments.

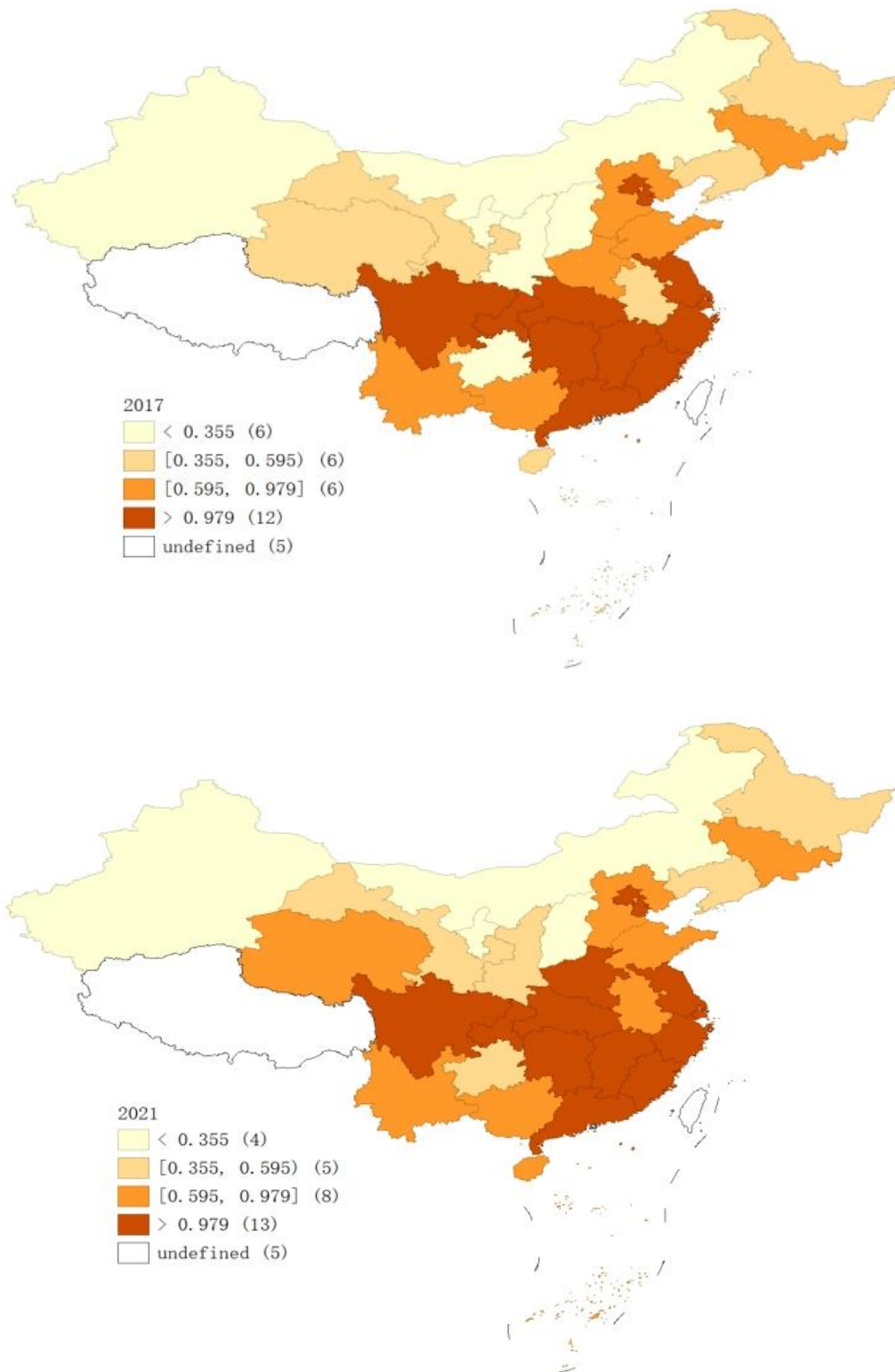
4.2.1.2 *Spatial Distribution and Evolution Analysis*

Building on the temporal analysis of national CP trends, this section explores the spatial heterogeneity and evolutionary dynamics of CP across provinces. Figure 4-1 presents the spatial distribution of CP for selected benchmark years (2008, 2011, 2014, 2017, and 2021) using a four-level natural breaks classification, which facilitates interprovincial comparison and highlights intra-year disparities in emission efficiency. This visualization provides an intuitive basis for identifying regional patterns of concentration, divergence, and transformation.

Figure 4-1: Spatial Distribution Pattern of CP, 2008-2021







Source: Authors 'own drawing, based on GeoDa 1.22.0.4 software.

Notes:

1. Source of the map of China: GeoAtlas (areas_v3). Map Review Number: GS Jing (2022) No. 1061. Obtained from https://datav.aliyun.com/portal/school/atlas/area_selector;
2. Undefined are Tibet, Hong Kong, Macau, Taiwan, and the Nansha Islands, which are not included in the study scope.

Provinces shaded in darker tones exhibit higher CP, indicating a more efficient decoupling between economic growth and carbon emissions, while lighter shades represent relatively lower CP levels. The classification adopts a natural breaks method, dividing CP into four intervals: extremely low (<0.355), low ($0.355-0.595$), medium ($0.595-0.979$), and high (>0.979), with the number of provinces in each category shown in parentheses. This visual representation helps identify temporal shifts in CP levels across space and provides an empirical basis for further spatial econometric modeling.

(i). Distinct Pattern of “Higher in the East, Lower in the West; Stronger in the South, Weaker in the North”

The phrase “higher in the East, lower in the West” refers to absolute differences in CP levels, as measured by each province’s position in the CP distribution for a given year. Eastern coastal provinces such as Beijing, Shanghai, Jiangsu, and Guangdong consistently appear in the high or medium CP intervals, due to their advanced industrial structures, high innovation, and policy-driven energy transitions. In contrast, western and some northeastern provinces including Shanxi, Xinjiang, and Ningxia tend to fall into the low or extremely low categories, reflecting structural reliance on coal-intensive and resource-dependent industries.

The notion of “stronger in the South, weaker in the North” refers to the direction and intensity of CP growth over time, rather than static levels. Southern provinces such as Fujian, Hunan, and Guangdong have shown consistent upward mobility across CP intervals, driven by early green transition efforts and participation in national low-carbon pilot programs. In comparison, northern provinces like Inner Mongolia and Heilongjiang display stagnation or even decline, despite national policy incentives. This highlights structural challenges in decarbonization and the need for deeper transformation.

(ii). Emerging Spatial Clustering and Lock-In Effects

Over time, spatial clustering in CP has intensified, forming contiguous zones of high-value performance in the Yangtze River Delta and Pearl River Delta. These “high-high” clusters indicate spatial agglomeration of green productivity, often reinforced by regional collaboration in technology, finance, and regulation. Conversely, a subset of inland and northeastern provinces exhibits “low-low” clustering, remaining persistently in the lowest CP quantile. This phenomenon reflects what is termed “low-value lock-in”, where entrenched industrial structures, limited technological spillovers, and weak institutional

enforcement hinder upward transition. These structural rigidities require not only economic transformation but also targeted governance reform to unlock CP potential.

(iii). Overall Stability with Gradual Spatial Diffusion

Although the broader CP landscape remains relatively stable, localized transitions are observable. Provinces such as Anhui, Chongqing, and Hunan have moved upward through the CP tiers, driven by green investments and industrial realignment. These shifts suggest the presence of “gradual spatial diffusion”, where improvements originating in leading provinces extend into neighboring regions via mechanisms such as supply chain relocation, policy emulation, and environmental governance spillovers. However, this diffusion remains uneven, constrained by administrative, infrastructural, and institutional boundaries.

(iv). Transition from Point-Based Hubs to Belt-Shaped Corridors

In the early years, CP improvements were highly localized in a few growth poles—what can be described as “point-based” development. Cities such as Beijing, Shanghai, and Guangzhou served as carbon-efficient nodes with limited external spillovers. Over time, however, these nodes have become anchors for broader regional development, forming spatially continuous “belt-shaped” structures, particularly along the Yangtze River Economic Belt. This transition from isolated high-performing provinces to integrated green corridors exemplifies the growing influence of regional integration and interprovincial coordination. It reflects not only economic expansion, but also the diffusion of technological standards, regulatory practices, and ecological consciousness across administrative borders.

In summary, the spatial evolution of CP in China is marked by high-value clustering in coastal regions, low-value lock-in in structurally constrained areas, and gradual spatial diffusion from advanced to lagging regions. The persistence of these patterns reflects both the advantages of technologically advanced provinces and the development bottlenecks faced by resource-dependent areas. The emergence of belt-shaped development patterns further highlights the role of spatial connectivity, industrial transfer, and coordinated governance in shaping regional dynamics. These evolutionary characteristics not only establish the empirical rationale for incorporating spatial dependence in the econometric models presented in the following sections but also provide critical insights into the mechanisms underlying green transformation across diverse regional contexts, where both market forces and policy interventions jointly influence outcomes.

4.2.2 Evolutionary Characteristics of HQED

4.2.2.1 Temporal Trend Analysis

Based on the indicator system and entropy-weighted results established earlier, this study calculates the comprehensive index of HQED for 30 provinces from 2008 to 2021. The results are presented in Table 4-2.

Table 4-2: Comprehensive Index and Average Value of HQED, 2008–2021

Province	2008	2010	2012	2014	2016	2018	2020	2021
Beijing	0.2345	0.2389	0.2612	0.2809	0.2958	0.3595	0.4136	0.4410
Tianjin	0.1157	0.1154	0.1284	0.1339	0.1510	0.1666	0.1913	0.2078
Hebei	0.0538	0.0561	0.0627	0.0727	0.0948	0.1072	0.1220	0.1335
Shanxi	0.0620	0.0720	0.0810	0.0852	0.1022	0.1142	0.1198	0.1225
Inner Mongolia	0.0567	0.0631	0.0670	0.0803	0.0913	0.0974	0.1093	0.1155
Liaoning	0.0918	0.0973	0.1107	0.1216	0.1442	0.1669	0.1796	0.1900
Jilin	0.0705	0.0771	0.0913	0.1043	0.1148	0.1257	0.1403	0.1474
Heilongjiang	0.0692	0.0851	0.0971	0.1042	0.1181	0.1432	0.1393	0.1432
Shanghai	0.2094	0.2160	0.2388	0.2390	0.2710	0.3087	0.3369	0.3469
Jiangsu	0.1284	0.1369	0.1522	0.1597	0.1898	0.2329	0.2717	0.2989
Zhejiang	0.1193	0.1277	0.1390	0.1532	0.1816	0.2192	0.2545	0.2804
Anhui	0.0582	0.0659	0.0786	0.0866	0.1018	0.1345	0.1594	0.1750
Fujian	0.0929	0.1008	0.1133	0.1141	0.1235	0.1409	0.1571	0.1650
Jiangxi	0.0505	0.0592	0.0727	0.0889	0.0872	0.1117	0.1223	0.1291
Shandong	0.0887	0.1028	0.1158	0.1244	0.1448	0.1692	0.1997	0.2163
Henan	0.0534	0.0584	0.0724	0.0882	0.0986	0.1140	0.1273	0.1433
Hubei	0.0704	0.0735	0.0849	0.0967	0.1108	0.1351	0.1500	0.1644
Hunan	0.0570	0.0697	0.0754	0.1002	0.1148	0.1361	0.1549	0.1597
Guangdong	0.1595	0.1713	0.1921	0.1979	0.2317	0.2752	0.3329	0.3778
Guangxi	0.0560	0.0766	0.0703	0.0771	0.0908	0.0982	0.1170	0.1370
Hainan	0.1117	0.1044	0.1085	0.1197	0.1295	0.1386	0.3677	0.4520
Chongqing	0.0656	0.0703	0.0977	0.1108	0.1197	0.1408	0.1559	0.1658
Sichuan	0.0592	0.0660	0.0801	0.0995	0.1116	0.1342	0.1525	0.1611
Guizhou	0.0631	0.0636	0.0803	0.0841	0.0870	0.0950	0.1101	0.1150
Yunnan	0.0636	0.0737	0.0832	0.0803	0.0956	0.1056	0.1184	0.1230
Shaanxi	0.0463	0.0506	0.0746	0.0815	0.0982	0.1135	0.1238	0.1342
Gansu	0.0584	0.0639	0.0794	0.0789	0.0955	0.1107	0.1127	0.1164
Qinghai	0.0432	0.0510	0.0699	0.0813	0.0812	0.1002	0.1037	0.1091
Ningxia	0.0507	0.0620	0.0683	0.0733	0.0802	0.0921	0.0985	0.1000
Xinjiang	0.0758	0.0736	0.0851	0.0932	0.0956	0.1178	0.1082	0.1137
National Average	0.0845	0.0914	0.1044	0.1137	0.1284	0.1502	0.1750	0.1895

As shown in Table 4-2, the national average HQED index increased steadily from 0.0845 in 2008 to 0.1895 in 2021, reflecting a gradual but consistent transformation in China's development paradigm. To ensure comparability with the CP analysis and to reflect key policy and structural shifts, the evolution of HQED is divided into three phases: 2008-2012, 2013-2017, and 2018-2021. Each phase is characterized by distinct institutional priorities, structural adjustments, and dimension-specific performance, particularly across the economic, social, and ecological components of HQED.

Phase I (2008-2012): Industrial Dominance with Early Exploratory Shifts. During this initial phase, the HQED index increased slightly from 0.0845 in 2008 to 0.0968 in 2012, reflecting the early transition efforts amid a still industrial-heavy growth model. In response to the global financial crisis, China launched a RMB 4 trillion stimulus package, which prioritized infrastructure and manufacturing investments. As a result, industry accounted for over 40% of GDP, with heavy industries such as steel and cement contributing more than 60% of total output. Coal dominated the energy mix with a share exceeding 70%, while renewables contributed less than 10%. Despite these structural constraints, this period marked the initial integration of quality-oriented development concepts. Moderate improvements emerged in education access, social services coverage, and institutional coordination, particularly in eastern provinces. These signals, though limited in scale, laid the conceptual foundation for more systematic transformation in the following years.

Phase II (2013-2017): Structural Optimization and Regional Coordination. Between 2013 and 2017, the HQED index rose from 0.1092 to 0.1374, indicating a steady institutionalization of high-quality development principles. This phase corresponded with the emergence of “new normal” economic thinking, which emphasized innovation, structural adjustment, and green transformation over pure growth targets. A landmark shift occurred in 2013, when the services sector’s share of GDP (46.7%) surpassed that of industry (44%) for the first time, signaling a gradual rebalancing of the economic structure. Policy frameworks such as the Five Major Development Concepts and supply-side structural reforms accelerated this process, while industrial relocation from coastal to inland areas fostered early forms of regional coordination. HQED improvements during this period were particularly evident in dimensions related to technological innovation, urbanization quality, and environmental investment intensity, though regional disparities remained pronounced.

Phase III (2018-2021): Institutional Deepening and Green Transition Mainstreaming. This phase saw the HQED index increase from 0.1502 in 2018 to 0.1895 in 2021, continuing the steady upward trend. While the growth rate was not significantly faster than previous stages, this period was marked by the full implementation of the New Development Philosophy, which prioritized innovation, coordination, green development, openness, and sharing across national and local governance. Structurally, the economy became increasingly service-oriented, with the services sector reaching 53.3% of GDP. Meanwhile, coal’s share in total energy consumption declined, and renewable energy capacity expanded, driven by

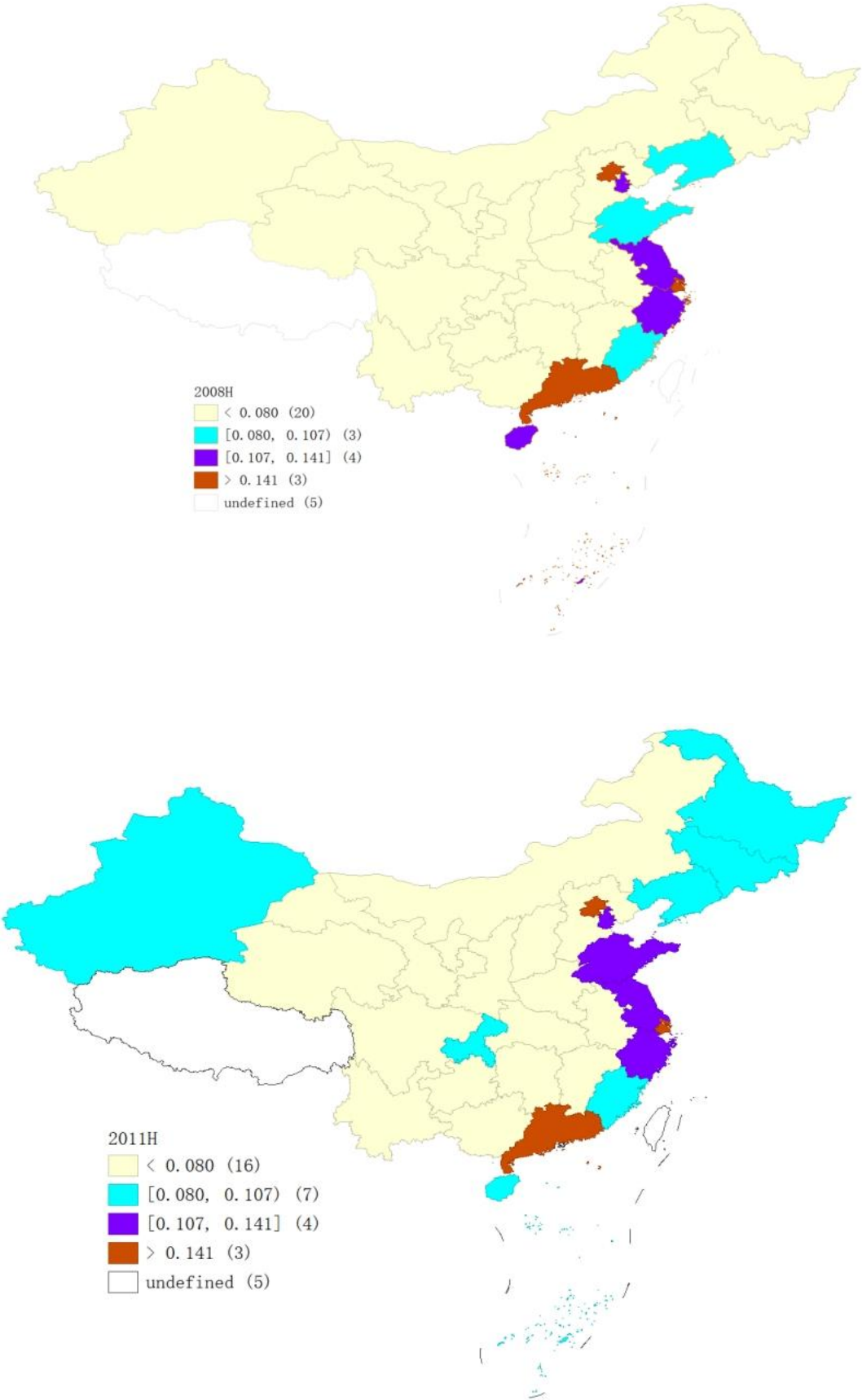
environmental regulation and green finance initiatives. HQED performance improved across all three dimensions, namely economic efficiency, social inclusiveness, and ecological sustainability, with notable gains in western provinces due to central investments and policy diffusion.

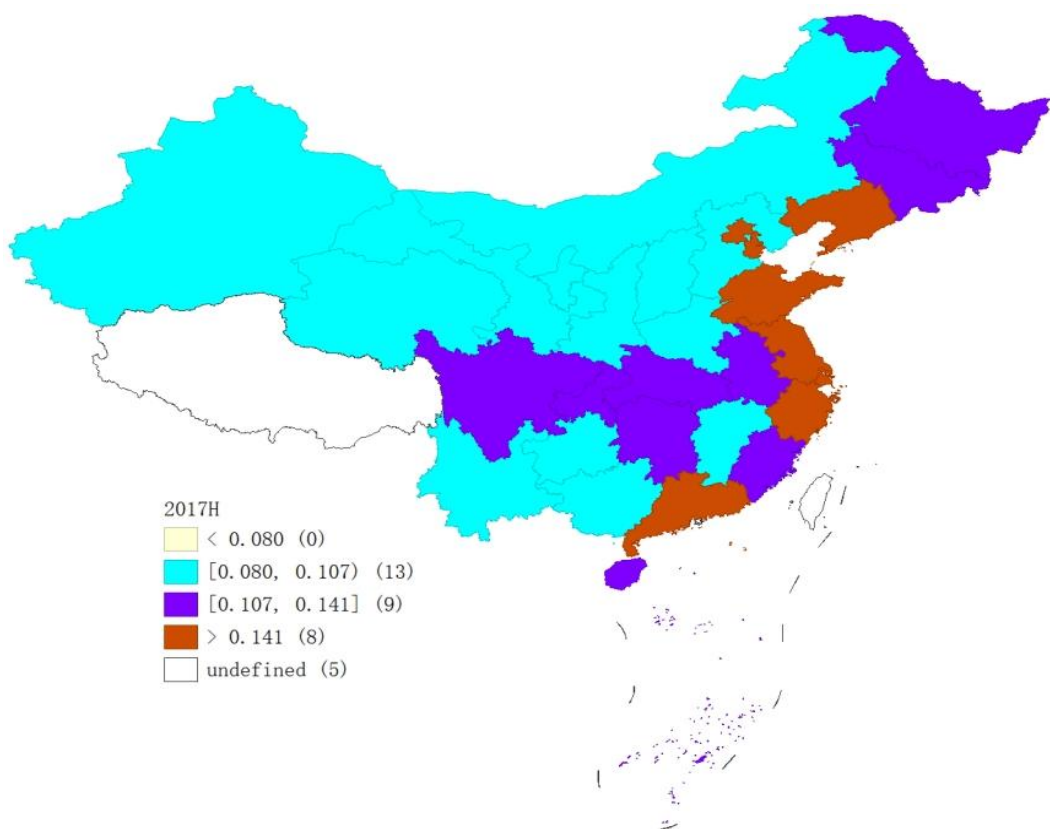
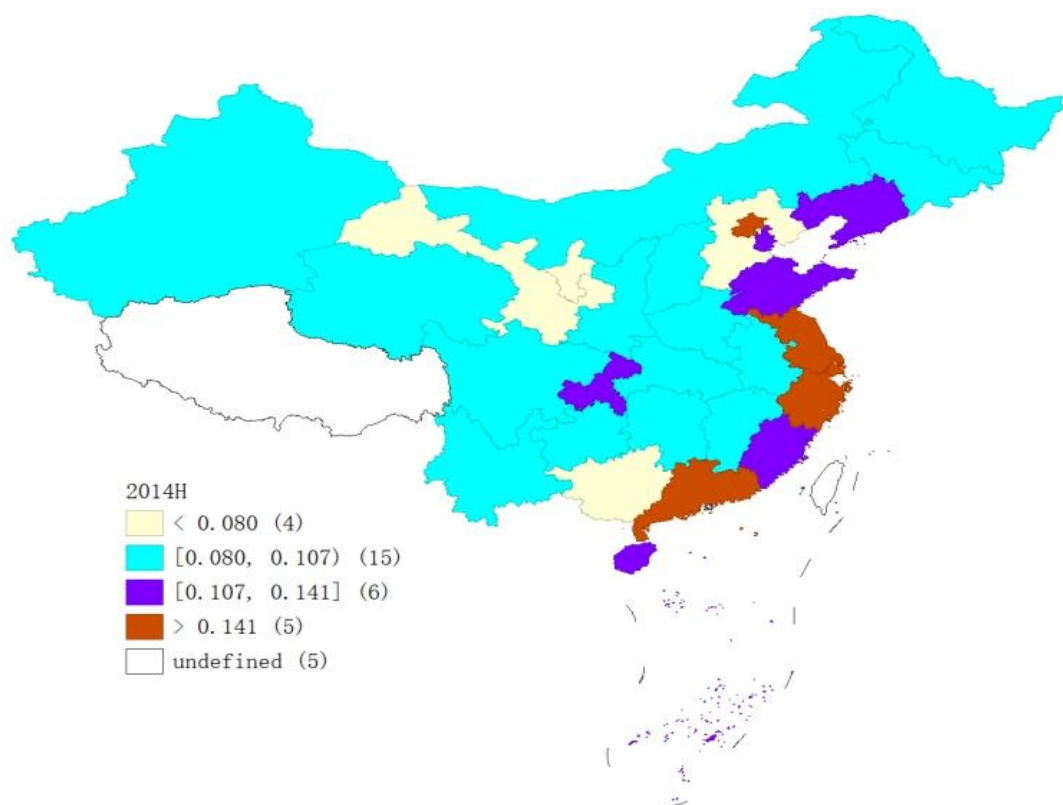
This phase reflects the mainstreaming of HQED as a national strategy, emphasizing institutional depth and interregional coordination rather than structural shifts alone. It also reinforced the foundation for CP improvements, especially through enhanced environmental governance and green innovation systems. In summary, the three-phase evolution of HQED demonstrates a gradual yet determined shift in China's development trajectory. While industrial dominance characterized the early stage, subsequent phases were defined by structural rebalancing, innovation, and green transition. These institutional and structural changes complement the spatial evolution of CP.

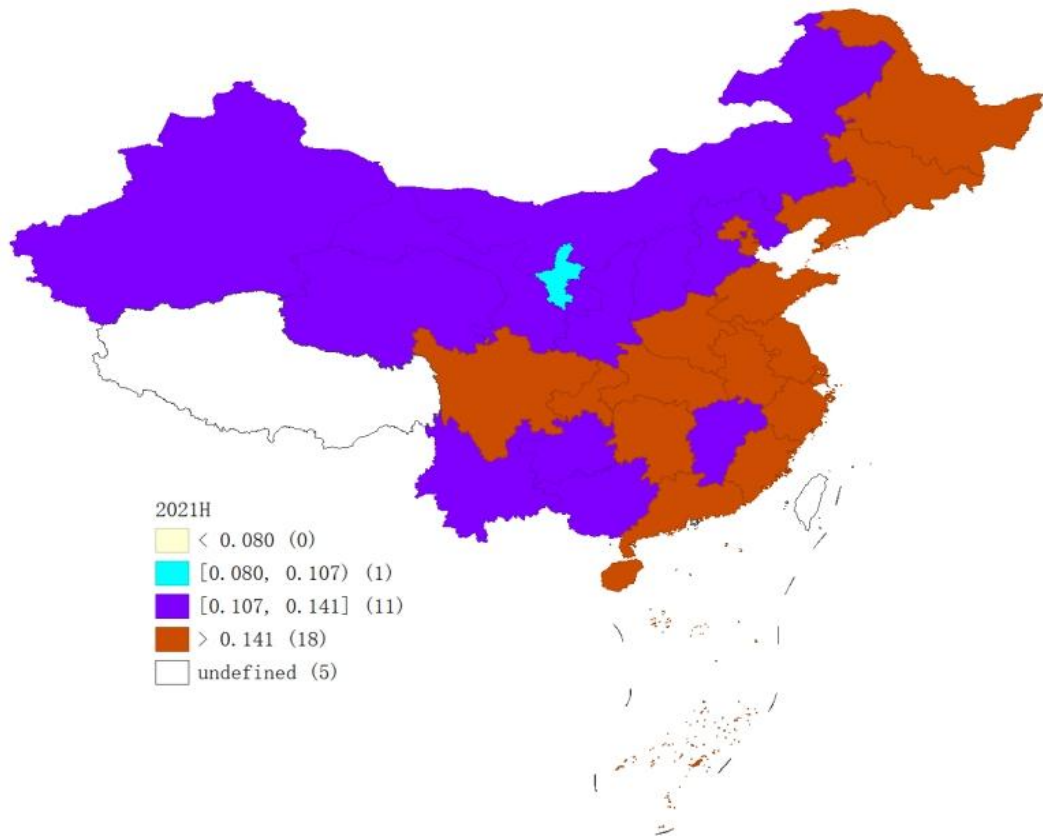
4.2.2.2 Spatial Distribution and Evolution Analysis

To further explore the spatial distribution characteristics of HQED across Chinese provinces, this study employs GeoDa software to visualize spatial distribution maps for five selected years, 2008, 2011, 2014, 2017, and 2021 (see Figure 4-2). These maps provide an intuitive representation of how HQED levels are spatially clustered and how their relative positions evolve over time. By examining the spatial patterns at different time points, it becomes possible to identify persistent high- or low-value regions, trace regional convergence or divergence trends, and assess whether policy interventions have altered the geographical landscape of HQED. In addition, comparing these snapshots across years enables the detection of dynamic trajectories, such as the east–west gap, the gradual rise of central provinces, or the relative stagnation of certain regions. This spatial visualization thus offers an essential empirical foundation for the subsequent econometric analysis of spatial dependence and heterogeneity.

Figure 4-2: Spatial distribution pattern of HQED, 2008-2021







Source: Authors 'own drawing, based on GeoDa 1.22.0.4 software.

Notes:

1. Source of the map of China: GeoAtlas (areas_v3). Map Review Number: GS Jing (2022) No. 1061. Obtained from https://datav.aliyun.com/portal/school/atlas/area_selector;
2. Undefined are Tibet, Hong Kong, Macau, Taiwan, and the Nansha Islands, which are not included in the study scope.

Provinces shaded in darker tones represent higher levels of HQED, while lighter shades indicate relatively lower HQED performance. The classification follows the natural breaks method, dividing HQED into four intervals: extremely low (<0.080), low ($0.080-0.107$), medium ($0.107-0.141$), and high (>0.141), with the number of provinces in each category shown in parentheses. Grey areas indicate provinces with missing or undefined data. These maps reveal the spatial expansion and convergence trends of HQED over time and serve as a visual foundation for subsequent spatial modeling and regional heterogeneity analysis. The progressive shift of provinces from lower to higher categories reflects the gradual diffusion of high-quality development practices, while the persistence of certain low-value clusters highlights structural and institutional constraints that require targeted policy attention.

(i). *Distinct Pattern of “Higher in the East, Lower in the West; Stronger in the South, Weaker in the North”*

In 2008, high HQED values were concentrated in eastern coastal provinces such as Shanghai, Beijing, and Jiangsu, forming a pronounced gradient of “higher in the east, lower in the west.” Western and northeastern provinces, including Gansu, Inner Mongolia, and Heilongjiang, displayed significantly lower index levels, reflecting disparities in infrastructure, innovation capacity, and industrial upgrading. By 2021, although the eastern regions remained leading, several central and western provinces, such as Hubei, Chongqing, and Sichuan—advanced to higher HQED categories, signaling a shift toward more balanced development. The “stronger in the south” trend was also visible over time, with southern provinces like Guangdong and Fujian consistently improving, while northern regions exhibited slower progress or stagnation.

(ii). *Strengthened Spatial Clustering and Regional Integration*

From 2011 to 2017, spatial clustering of HQED became more evident, particularly in urban agglomerations such as the Yangtze River Delta and Pearl River Delta. These regions demonstrated integrated progress across economic, social, and ecological dimensions, benefiting from coordinated planning and institutional alignment. In contrast, parts of the northwest and northeast remained in the lower intervals, forming persistent “low-value” clusters. The growing divergence between clustered high-performing regions and lagging areas highlights the need for targeted policy support and institutional capacity building in underdeveloped zones.

(iii). *Overall Stability with Gradual Diffusion*

Although the national HQED index steadily increased from 0.0845 in 2008 to 0.1895 in 2021, spatial disparities remained relatively stable until 2014. However, from 2014 onwards, provinces such as Anhui, Jiangxi, and Shaanxi began to move into higher development tiers. These transitions reflect the effects of industrial relocation, regional development strategies, and improved public service delivery. Yet, the pace of diffusion was uneven, constrained by administrative boundaries, fiscal capacity, and infrastructure disparities.

(iv). *Evolution from Point-Based Poles to Belt-Oriented Structures*

Early HQED development was highly localized, with progress limited to a few core cities such as Beijing, Shanghai, and Guangzhou. Over time, particularly by 2021, these

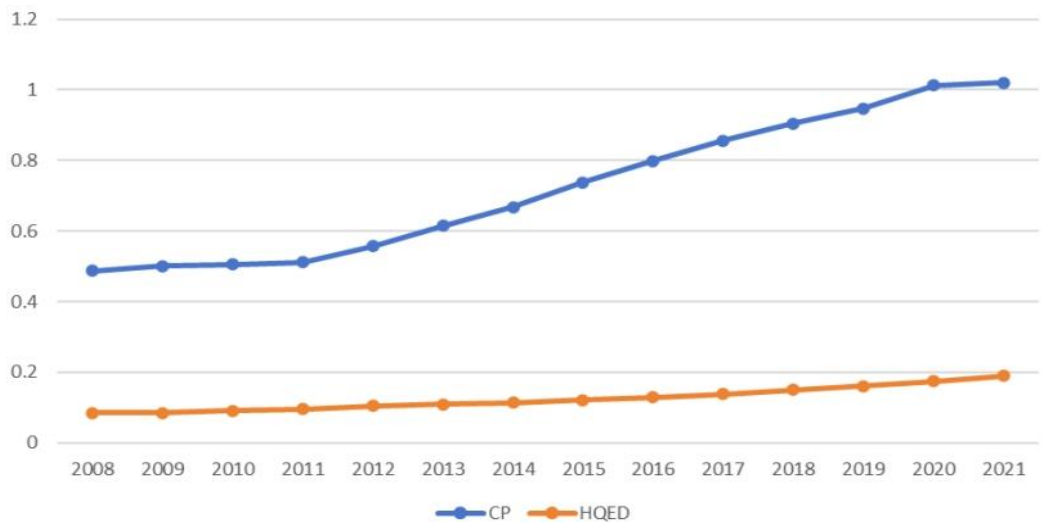
high-performing hubs became anchors for broader regional expansion, forming belt-like structures along the Yangtze River Economic Belt and parts of the Central China region. This spatial transformation illustrates how policy diffusion, interprovincial cooperation, and shared innovation ecosystems facilitated the transition from isolated excellence to more integrated regional performance.

In summary, the spatial evolution of HQED exhibits a clear trajectory of expansion from concentrated eastern nodes to broader inland diffusion, characterized by clustered development, gradual convergence, and institutional deepening. These dynamics support the empirical design of spatial econometric models and underscore the importance of regional coordination in promoting high-quality development nationwide.

4.2.3 Comparative Analysis of the Average Values of CP and HQED

Figure 4-3 illustrates the trend in national average values for CP and HQED across 30 Chinese provinces from 2008 to 2021. Overall, both indicators show a consistent upward trajectory during the study period, reflecting China’s synchronized progress in advancing green transformation and enhancing development quality.

Figure 4-3: Trends of Average Values of CP and HQED, 2008-2021



Source: Author’s calculation based on multi-source data and CEADs (2024).

China’s CP started at a relatively high level, with a national average of approximately 0.4865 in 2008, and increased to 1.0203 by 2021, representing a near 100% rise. The period from 2011 to 2020 witnessed a phase of rapid growth, driven by the initial effectiveness of

energy-saving and emission-reduction policies, industrial upgrading, and technological progress. However, the pace of improvement slowed between 2020 and 2021, suggesting diminishing marginal gains in carbon efficiency under the influence of the dual carbon strategy and highlighting the increasing difficulty of further improvements once earlier, low-hanging measures had been implemented.

In contrast, the HQED index began at a relatively low level, with a national average of only 0.0845 in 2008, but exhibited more substantial growth, reaching 0.1895 in 2021, an increase of over 124%. From 2008 to 2013, the pace of HQED improvement was relatively modest, largely constrained by the inertia of the traditional growth paradigm and the preliminary stage of indicator system development. After 2014, with the full implementation of the “new development philosophy,” key elements such as innovation, green growth, coordination, and inclusiveness were increasingly embedded into policy frameworks and development practices, resulting in a marked acceleration of HQED growth. The later surge also reflects the combined effects of central government policy support, local experimentation, and the rapid diffusion of green technologies.

From a comparative perspective, although the two indicators began at different levels and followed slightly different growth rhythms, they generally exhibit a consistent direction, dynamic coupling, and phase synchronization. As a reflection of the green performance of economic operations, improvements in CP often rely on institutional reforms, structural adjustments, and technological progress, all core elements of HQED. Conversely, the realization of high-quality development is fundamentally underpinned by improvements in energy efficiency and the transition toward green and low-carbon development.

In summary, CP and HQED exhibit strong coherence and interaction in their evolutionary trajectories, a finding that provides empirical support for the subsequent econometric analysis. It is important to note, however, that while trend analysis reveals macro-level synchronicities, it does not determine the existence of stable causal relationships or spatial spillover mechanisms. Therefore, it is necessary to employ static, dynamic, and spatial econometric models to empirically identify and analyze the mechanisms through which HQED influences CP, with the aim of obtaining more precise and policy-relevant conclusions. Such methodological rigor ensures that observed patterns are not coincidental but are grounded in robust statistical evidence, thereby strengthening the credibility of policy implications.

4.3 Empirical Analysis of the Static Panel Model

This section empirically examines the impact of HQED on CP through the construction of a static panel regression model. The analysis begins with descriptive statistics of the variables to provide a foundational understanding of the data and to support subsequent model estimation. Descriptive analysis helps assess the central tendency, dispersion, and range of each variable, and also provides a preliminary view of possible heterogeneity across provinces and over time.

4.3.1 Descriptive Statistics

Table 4-3 presents the mean, standard deviation, maximum, and minimum values for each variable. These statistics offer insight into the overall distribution and variation in CP, HQED, and relevant control variables across the sample period.

Table 4-3: Summary of Descriptive Statistics

Variable		Mean	Std. dev.	Min	Max
lncp	overall	0.5039	0.2719	0.0774	1.6302
	between		0.2481	0.0983	1.1934
	within		0.1194	0.1011	0.9919
lnhqed	overall	0.1158	0.0573	0.0423	0.3729
	between		0.0481	0.0749	0.2646
	within		0.0323	0.0451	0.3429
lnei	overall	0.5803	0.2346	0.1625	1.3035
	between		0.2087	0.2864	1.1090
	within		0.1133	0.3045	0.9452
Lnur	overall	0.4517	0.0815	0.2555	0.6397
	between		0.0741	0.3485	0.6372
	within		0.0364	0.3588	0.5372
lnml	overall	0.2925	0.1357	0.0614	0.7566
	between		0.1052	0.1862	0.5915
	within		0.0877	0.0624	0.5644
lnenv	overall	1.3616	0.2427	0.6764	2.0559
	between		0.1881	0.9970	1.7056
	within		0.1570	0.8011	2.2908
lnss	overall	0.3346	0.0639	0.1475	0.4704
	between		0.0576	0.1805	0.4127
	within		0.0295	0.2545	0.4463
lnclr	overall	3.1249	0.5916	1.3049	4.6726
	between		0.4085	2.4465	4.1049
	within		0.4339	1.8495	4.0917

The descriptive statistics reveal several key insights: The mean of lncp is 0.5039 with a standard deviation of 0.2719, indicating considerable regional disparities in CP across provinces. The mean value of lnhqed is 0.1158, reflecting an overall low level of HQED during the sample period. However, its relatively small standard deviation suggests a more balanced distribution among regions. Control variables such as energy intensity (lnei),

urbanization rate (lnur), marketization level (lnml), government environmental expenditure (lnenv), industrial share (lnss), and capita-labor ratio (lnclr) also show notable cross-regional variation. In particular, lnclr exhibits a high within-group standard deviation (0.4339), suggesting dynamic internal adjustments in production input structure over time.

For most variables, the between-group standard deviation is significantly greater than the within-group standard deviation, indicating that interprovincial differences are the primary source of variation. This reflects considerable heterogeneity across provinces in terms of carbon efficiency, energy utilization, institutional conditions, and industrial structure. Such disparities suggest that regional context plays a decisive role in shaping development outcomes, and they provide an empirical rationale for adopting econometric approaches that account for spatial and structural heterogeneity. In particular, the observed variation underscores the necessity of further examining how high-quality economic development exerts differentiated impacts on carbon productivity across distinct provincial settings.

4.3.2 Correlation Analysis Among Variables

Table 4-4 reports the Pearson correlation coefficients among the key variables, providing a preliminary assessment of the strength and direction of linear relationships. The correlation coefficient ranges from -1 to 1, where values approaching 1 indicate a strong positive linear relationship, while values near -1 suggest a strong negative linear association.

Table 4-4: Summary of Correlation Analysis

	lncp	lnhqed	lneci	lnur	lnml	lnenv	lnss	lnclr
lncp	1							
lnhqed	0.752***	1						
lneci	-0.802***	-0.629***	1					
lnur	0.626***	0.791***	-0.518***	1				
lnml	0.652***	0.797***	-0.562***	0.774***	1			
lnenv	-0.191***	-0.172***	0.335***	-0.192***	-0.085*	1		
lnss	-0.243***	-0.386***	0.146***	-0.365***	-0.252***	-0.113**	1	
lnclr	0.370***	0.535***	-0.333***	0.7813***	0.657***	-0.082*	-0.378***	1

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

The results indicate that $\ln cp$ is significantly and positively correlated with $\ln hqed$ ($r = 0.752, p < 0.01$), suggesting that HQED may contribute to the improvement of CP. This provides initial evidence in support of the hypothesis that enhancing development quality plays a central role in decoupling economic growth from carbon emissions. In addition, $\ln cp$ shows significant positive correlations with $\ln ml$, $\ln ur$, and $\ln clr$, implying that marketization, urbanization, and capital-labor ratio may create favorable conditions for CP improvement through mechanisms such as efficiency gains, agglomeration effects, and technological upgrading.

In contrast, $\ln cp$ is significantly negatively correlated with $\ln ei$ ($r = -0.802, p < 0.01$), indicating that higher energy consumption per unit output substantially suppresses CP. Furthermore, CP also shows negative correlations with $\ln env$ and $\ln ss$, which may reflect the constraining effects of traditional industrial structures and short-term fiscal priorities on CP improvement. Specifically, the negative relationship with environmental investment ($\ln env$) could be attributed to the fact that in the short run, increased expenditure on pollution control and environmental protection tends to increase costs rather than immediately translating into productivity gains. Similarly, a higher proportion of secondary industry ($\ln ss$) is often associated with resource- and energy-intensive production, which inhibits efficiency improvements in CP. It is also worth noting that the relatively high correlations among certain variables suggest the potential presence of multicollinearity, which needs to be further examined through variance inflation factor (VIF) tests in the subsequent regression models. This step is essential to ensure that the explanatory power of each variable can be accurately distinguished without bias.

Overall, most correlation coefficients fall within a reasonable range, supporting the validity of the selected explanatory variables for regression modeling. Nevertheless, correlation analysis is limited in scope and cannot reveal causal relationships or dynamic linkages. In addition, the presence of spatial and institutional heterogeneity across provinces suggests that simple bivariate correlations may overlook important interregional interactions. Therefore, econometric modeling with spatial considerations will be employed in the following sections to rigorously assess the causal impact of HQED and other determinants on CP, while also identifying potential spillover effects and diffusion mechanisms across regions.

4.3.3 Static Panel Model Selection and Empirical Analysis

To ensure the effectiveness and robustness of the panel data regression, this study first conducted several diagnostic tests prior to model estimation. These included tests for multicollinearity using the VIF, the BP-LM test for spatial dependence, the Hausman test for model specification, and tests for heteroskedasticity and serial correlation. Conducting these preliminary checks is essential to avoid biased or inefficient estimators, since ignoring multicollinearity, omitted effects, or error structure problems may distort the validity of the empirical results. The corresponding regression diagnostics are presented in Table 4-5, providing the basis for selecting the most appropriate panel estimation strategy in the subsequent analysis.

**Table 4-5: Results of Static Panel Data Models
(Dependent Variable: ln_{ncp})**

	Pooled OLS	REM	FEM	FEM (Clustered by province)
ln_{hqed}	1.3267*** (5.36)	1.4181*** (8.98)	1.3558*** (8.58)	1.3558** (2.05)
ln_{ei}	-0.6505*** (-16.96)	-0.5310*** (-9.14)	-0.5051*** (-7.74)	-0.5051*** (-3.32)
ln_{ur}	0.6637*** (3.57)	-0.9607*** (-3.90)	-1.4558*** (-5.33)	-1.4558* (-1.78)
ln_{ml}	0.1470 (1.54)	0.3520*** (4.99)	0.3767*** (5.34)	0.3767* (1.96)
ln_{env}	0.0820*** (2.74)	0.0821*** (3.82)	0.0799*** (3.72)	0.0799*** (3.39)
ln_{ss}	-0.0781 (-0.65)	0.1204 (0.90)	0.1191 (0.86)	0.1191 (0.63)
ln_{clr}	-0.0785*** (-4.00)	0.0282 (1.33)	0.0709*** (3.03)	0.0709 (1.24)
_cons	0.5448*** (5.74)	0.7387*** (6.10)	0.8174*** (6.42)	0.8174*** (3.55)
BP-LM test		1451.60 (0.0000) ***		
Hausman test			73.62 (0.0000) ***	
Multicollinearity (VIF)		3.07		
Heteroskedasticity test			1911.04 (0.0000) ***	
Serial Correlation (F-stat)			21.039 (0.0001) ***	
Observations	420	420	420	420

Notes:

- Figures in the parentheses are t-statistics, except for BP-LM test, Hausman test, Heteroskedasticity and Serial Correlation tests, which are p-values.
- *p < 0.1; **p < 0.05; ***p < 0.01.

4.3.3.1 Model Specification Test Results

BP-LM Test: A comparison between the pooled OLS model and the REM shows that the BP-LM test statistic is 1451.60, with a p-value of 0.0000, indicating significance at the 1% level. This suggests that the null hypothesis should be rejected and that the REM is preferable to the pooled OLS model.

Hausman Test: Further comparison between the REM and the FEM yields a Hausman test statistic of 73.62 with a p-value below 0.01, strongly rejecting the null hypothesis. This result indicates that the FEM is more appropriate than the REM.

Multicollinearity Test: The VIF across variables is 3.07, which is well below the commonly accepted threshold of 10, suggesting that multicollinearity is not a serious concern in this model.

Heteroskedasticity and Serial Correlation Tests: The White test for heteroskedasticity reports a χ^2 statistic of 1911.04 ($p = 0.0000$), while the F-statistic for serial correlation is 21.039 (also with $p < 0.01$), indicating the presence of heteroskedasticity and first-order autocorrelation in the data.

In light of these diagnostic results, this study adopts the fixed effects model and applies clustered robust standard errors at the provincial level using the specification “FE vce (cluster id)”, to correct for potential disturbances and enhance the robustness of the estimations.

4.3.3.2 Empirical Results Analysis

Across the four static panel models (Pooled OLS, REM, FEM, and FEM with clustered), the estimated coefficient of the core explanatory variable, the HQED index (lnhqed), is positive and statistically significant at the 1% or 5% level. The coefficient values fall within the range of 1.3267 to 1.4181, suggesting that HQED has a strong and significant effect on improving CP. This result aligns with theoretical expectations. Although the level of statistical significance slightly declines after applying clustered standard errors at the provincial level, the estimated effects remain robust, indicating that the relationship between HQED and CP is both statistically stable and economically meaningful. With respect to the control variables:

The coefficient of Government Environmental Expenditure ($\ln env$) exhibits a consistently positive and statistically significant coefficient across all model specifications, highlighting the critical role of fiscal investment in environmental protection in enhancing CP. This underscores the importance of government-led green initiatives in promoting sustainable development.

Marketization level ($\ln ml$) exhibits a positive and significant effect in both the REM and FEM models, while remaining insignificant in the OLS model. This suggests that, after controlling for individual and time effects, market mechanisms more effectively facilitate resource optimization and improve carbon efficiency.

The estimated impact of urbanization rate ($\ln ur$) demonstrates mixed effects: it is significantly positive in the OLS model but turns significantly negative in the REM and FEM specifications. The significance persists under FEM with clustered standard errors, indicating that urbanization may exert both facilitating and constraining effects on CP through varying channels, such as infrastructure expansion, energy consumption patterns, and spatial agglomeration effects.

Energy intensity ($\ln ei$) is negatively and significantly associated with CP across all models, confirming that greater energy use per unit of GDP undermines carbon efficiency. This finding reinforces the urgency of energy-saving and emission-reduction strategies to enhance CP.

Share of the secondary industry ($\ln ss$) yields no significant effect in any specification. This may be attributed to the internal heterogeneity within the secondary sector, where opposing impacts from high-tech and heavy industries potentially offset one another suggesting the need for more disaggregated sectoral analysis.

Capital-labor ratio ($\ln clr$) is significantly negative in the OLS model but turns positive and insignificant under the FEM specification. This result implies a potentially non-linear or regionally contingent relationship between factor inputs and CP, possibly influenced by local variations in capital intensity, labor quality, and technological adoption.

In summary, the static panel model results indicate that HQED has a consistently positive effect on CP. Moreover, control variables such as energy intensity, environmental

fiscal expenditure, and marketization level exert significant influences, providing important insights into the multifaceted drivers of CP improvement.

4.4 Empirical Analysis of the Dynamic Panel Model

In the preceding static panel regression, HQED showed a significant positive impact on CP. However, static models fall short in capturing the dynamic characteristics of CP and addressing potential endogeneity. On the one hand, CP as a cumulative indicator, exhibits strong path dependence, meaning that its previous levels can influence current performance. On the other hand, HQED may also be subject to reverse causality from CP, thereby giving rise to endogeneity concerns. In addition, the significant results from the heteroskedasticity and serial correlation tests further highlight the limitations of static model specifications. The results show in Table 4-6.

**Table 4-6: Results of Dynamic Panel Data Models
(Dependent Variable: lncp)**

	SYS GMM one-step	SYS GMM Robust	SYS GMM Two-step	SYS GMM Robust two-step
L.lncp	0.8654*** (19.75)	0.8654*** (14.09)	0.8935*** (25.33)	0.8935*** (15.74)
lnhqed	1.6512*** (4.17)	1.6512* (1.86)	1.9815*** (3.47)	1.9815** (2.18)
lnei	-0.1319* (-1.87)	-0.1319* (-1.73)	-0.1237** (-2.17)	-0.1237 (-1.14)
lnur	-0.2061 (-0.81)	-0.2061 (-0.42)	-0.4338 (-1.18)	-0.4338 (-0.71)
lnml	-0.2671*** (-4.06)	-0.2671** (-2.00)	-0.3449*** (-3.60)	-0.3449** (-2.28)
lnenv	0.0411*** (3.20)	0.0411 (1.61)	0.0480*** (3.11)	0.0480** (2.06)
lnss	0.1693*** (2.79)	0.1693 (0.70)	0.3313* (1.92)	0.3313 (1.33)
lnclr	-0.0207 (-0.50)	-0.0207 (-0.26)	0.0357 (0.58)	0.0357 (0.36)
_cons	0.8654*** (19.75)	0.8654*** (14.09)	0.8935*** (25.33)	0.8935*** (15.74)
years	yes	yes	yes	yes
Number of observations	390	390	390	390
Number of instruments	29	29	29	29
Number of groups	30	30	30	30
Degree of freedom	20	20	20	20
AR (1) p-value	0.000	0.007	0.011	0.012
AR (2) p-value	0.491	0.357	0.295	0.314
Sargan test p-value	0.333	0.333	0.333	0.333
Hansen J test p-value		0.515	0.515	0.515

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

To enhance the robustness and reliability of the estimation results, this study employs the System GMM to conduct dynamic panel model analysis. System GMM not only accommodates the dynamic nature of models with lagged dependent variables but also effectively addresses potential endogeneity issues through the use of instrumental variables. This approach is particularly suitable for panel data structures characterized by small T and large N. The dynamic panel model is estimated using STATA 18.0. Table 4-6 presents results from four System GMM estimation strategies: one-step System GMM, robust one-step System GMM, two-step System GMM, and robust two-step System GMM. All models control for year fixed effects.

4.4.1 Model Specification Validity Tests

To verify the validity of the model specification, several diagnostic tests were conducted. The Arellano-Bond autocorrelation tests show that the p-values for AR (1) are all below 0.05, while those for AR (2) are above 0.1. This confirms the presence of first-order serial correlation and the absence of second-order serial correlation, satisfying the core assumptions of the dynamic GMM framework.

Regarding the validity of instrumental variables, the Sargan test produces a p-value of 0.333, and the Hansen J test yields a p-value of 0.515. Both results fail to reject the null hypothesis, indicating that the instruments are valid and the model does not suffer from over-identification. In addition, the regression coefficients of the core explanatory variable remain consistent across different estimation methods, including the robust one-step, two-step, and robust two-step GMM, confirming the robustness of the empirical results.

To mitigate the risk of instrument proliferation, particular attention was given to the ratio between the number of instruments and cross-sectional units. In this study, 29 instruments were used for 30 provinces. This specification was established after repeated testing. Attempts to reduce the number of instruments to 25 or 26 resulted in estimation failure, invalid Hansen tests, or convergence issues. Therefore, the selected instrument count represents the minimum feasible configuration that balances diagnostic validity and estimation reliability, in line with recommended practices in the GMM literature (Roodman, 2009).

Taken together, the test results demonstrate that the System GMM model is correctly specified, the instruments are valid, and the estimates are statistically and economically reliable. These findings provide strong assurance that the dynamic relationships identified in the model are not driven by specification errors or weak instruments. Moreover, the robustness of the estimation across multiple GMM variants further enhances the credibility of the results and lends confidence to the interpretation of HQED's impact on CP. This reliability is essential, as the subsequent analysis draws upon these validated specifications to explore more nuanced mechanisms, including regional heterogeneity and mediating pathways, thereby ensuring that policy implications are grounded in a sound econometric framework.

4.4.2 Empirical Results Analysis

4.4.2.1 Dynamic Persistence of CP

The coefficient of the lagged dependent variable, $L.lncp$, is consistently positive and statistically significant at the 1% level across all models, with a value of 0.8935 in the robust two-step estimation. This result confirms a strong path dependence in CP, indicating that provinces with historically higher CP are more likely to retain their relative advantage over time. Such persistence reflects cumulative mechanisms, including technological accumulation, long-term policy commitment, and stable institutional capacity for green governance. Similar findings have been reported by Grubb et al. (2024), who argue that historical investment patterns and environmental institutions play a central role in shaping regional trajectories of low-carbon transition. Compared with static models, the inclusion of dynamics reveals that improvements in CP are not instantaneous responses to external shocks but emerge through gradual adjustments. This implies that short-term interventions may be insufficient and that sustained, coordinated policy frameworks are essential to support long-term improvements.

4.4.2.2 Dynamic Relationship Between HQED and CP

The coefficient for $lnhqed$ is positive and statistically significant at the 5% level, with a magnitude of 1.9815 in the robust two-step model. This finding confirms that HQED has a strong and lasting positive impact on CP. The effect is notably larger than that observed in static estimations, suggesting that the benefits of HQED may not be immediately realized but instead compound over time. This aligns with the theoretical expectation that high-

quality development promotes long-term synergies between economic efficiency and environmental sustainability through mechanisms such as structural upgrading, innovation diffusion, and improvements in regulatory effectiveness (Feng et al., 2024b; Hariram et al., 2023), which may underestimate the delayed and path-dependent effects. By contrast, this study highlights that HQED not only initiates immediate gains in CP but also serves as a strategic trajectory that continuously reinforces carbon efficiency. These results echo the broader policy framework of sustainable transition under China's New Development Philosophy, which emphasizes coordinated, green, and innovation-driven growth (Yao & Li, 2022).

4.4.2.3 Dynamic Effects of Control Variables

The dynamic model results also provide new insights into the role of control variables in shaping CP.

Energy intensity ($\ln ei$) shows a negative coefficient (-0.1237), though it is statistically insignificant. This contrasts with the static FEM results, where energy intensity had a significant and negative impact on CP. The attenuation of its significance in the dynamic setting may indicate that the negative environmental consequences of energy consumption are partially offset over time by energy efficiency improvements or structural upgrading. Similar conclusions were reached by Tang et al. (2025), who found that energy-related constraints on productivity may weaken as technological innovation and cleaner energy adoption increase.

Urbanization rate ($\ln ur$) remains insignificant across all dynamic specifications. This result suggests that the effects of urbanization on CP are more nuanced and context-dependent than previously assumed. While some studies argue that urbanization can drive green development through infrastructure modernization and knowledge spillovers (Tan et al., 2023), others emphasize the adverse effects associated with increased energy demand, land use pressure, and industrial agglomeration in less-developed areas (Wang, 2023). The present finding reinforces the need to distinguish between types and qualities of urbanization rather than treating it as a uniformly positive or negative factor.

Marketization level ($\ln ml$) exhibits a consistently negative and statistically significant effect on CP in the dynamic models, with a value of -0.3449 and significance at the 5% level. This finding differs from the static model, where marketization showed a

positive coefficient. The shift in sign indicates that while private sector participation may initially boost output, its long-term effect on carbon efficiency could be detrimental, especially in the absence of effective regulatory oversight. This supports the argument by Liu et al. (2024a) that profit-oriented behaviors among private enterprises can undermine green transition unless guided by strong institutional frameworks and environmental accountability mechanisms.

Government environmental expenditure ($\ln env$) retains its positive and significant effect (0.0480), suggesting that sustained public investment in environmental protection contributes to long-run improvements in CP. This finding aligns with previous empirical evidence showing that fiscal support not only finances pollution control infrastructure but also signals regulatory commitment, encouraging firms to adopt low-carbon technologies (Xia et al., 2022)

The share of secondary industry ($\ln ss$) is positively signed (0.3313) but fails to reach statistical significance. This result deviates from expectations based on earlier studies that associate secondary industry dominance with higher emissions and lower CP (Lin & Wang, 2023a). However, it may reflect ongoing structural upgrading within China's industrial sector, where cleaner production processes and green manufacturing initiatives have started to decouple traditional industry from carbon intensity (Yang et al., 2022a). Yet the lack of significance suggests that the transformation is still uneven across provinces.

Capital-labor ratio ($\ln clr$) remains insignificant, with unstable coefficient signs across specifications. This implies that capital deepening alone is not a decisive factor for CP enhancement, possibly due to mismatches between investment direction and green productivity objectives. The heterogeneity of capital allocation across sectors may also dilute its measurable effect, as noted by Wang et al. (2024a) in their sector-level analysis.

Overall, the System GMM results confirm the robust and cumulative impact of HQED on CP, reinforcing the dynamic feedback mechanisms that support the green transition. Compared with static models, the dynamic approach more effectively captures temporal persistence, corrects for endogeneity, and reflects the lagged effects of policy and institutional change. The diminished significance of conventional growth drivers, such as energy intensity and urbanization, further suggests that improvements in CP are increasingly driven by structural and institutional transformations rather than input-led expansion.

4.5 Empirical Analysis of the Spatial Econometric Models

In the previous section employing the System GMM approach, this study fully accounted for the dynamic path dependence of CP and the potential endogeneity of HQED, confirming a significant and positive relationship between the two. However, neither the static nor the dynamic panel models incorporated potential spatial dependencies across regions. In reality, economic activities are highly interconnected across regions, and changes in CP within one province may influence neighboring areas through channels such as technology diffusion, industrial relocation, and coordinated environmental policies. Ignoring these interdependencies may lead to biased estimates and obscure important spillover effects.

To deepen the analysis, it is therefore necessary to introduce spatial econometric models to explore the spatial effects of HQED on CP. These models allow not only for the identification of direct impacts within a province but also for the estimation of indirect or spillover effects across provinces, thereby providing a more comprehensive understanding of the spatial dynamics. Prior to formally establishing the spatial models, we must first assess whether the key variables exhibit spatial correlation. Accordingly, this section begins with an analysis of spatial autocorrelation, conducted at both global and local levels, which forms the empirical foundation for selecting appropriate spatial econometric specifications in subsequent subsections.

4.5.1 Spatial Autocorrelation Analysis

4.5.1.1 Global Spatial Autocorrelation Analysis

To examine whether CP and HQED exhibit spatial clustering patterns, this study employs the Global Moran's I index to assess the spatial autocorrelation of both variables. The analysis is conducted using three types of spatial weight matrices: W1, a contiguity matrix that captures adjacency between provinces; W2, an inverse distance matrix where interaction strength declines with geographic distance; and W3, a nested economic-geographic matrix that integrates both physical proximity and economic similarity (e.g., per capita GDP). These matrices represent alternative assumptions about how spatial dependence operates across regions and thus provide a comprehensive framework for testing spatial interconnections.

By comparing results across W1, W2, and W3, the analysis enhances robustness and ensures comparability under different spatial interaction frameworks. The results, presented

in Table 4-7 and Table 4-8, not only offer a preliminary empirical basis for detecting spatial effects but also provide important guidance for the choice of appropriate econometric models.

Table 4-7 presents the Global Moran's I results for CP. The findings indicate that from 2008 to 2021, all annual Moran's I values are positive and statistically significant at the 1% or 5% level. This suggests that CP in China exhibits significant positive spatial autocorrelation at the provincial level, reflecting a clear spatial clustering pattern whereby regions with high (or low) CP tend to be geographically proximate to others with similar CP levels. In other words, improvements in CP are not randomly distributed but rather display strong spatial dependence, implying that carbon efficiency in one province may be influenced by the performance of its neighbors. This provides preliminary evidence of spatial spillover mechanisms, thereby justifying the application of spatial econometric models to capture interregional linkages in subsequent analyses.

Table 4-7: Global Moran's I of CP, 2008-2021

Year	Moran's I (W1)	P-value	Moran's I (W2)	P-value	Moran's I (W3)	P-value
2008	0.4141	0.0003	0.0795	0.0016	0.2879	0.0005
2009	0.4341	0.0001	0.0859	0.0008	0.3233	0.0001
2010	0.4129	0.0002	0.0755	0.0021	0.2987	0.0003
2011	0.3952	0.0004	0.0732	0.0024	0.3136	0.0001
2012	0.4056	0.0003	0.0795	0.0015	0.3200	0.0001
2013	0.3720	0.0008	0.0710	0.0032	0.3020	0.0003
2014	0.3786	0.0007	0.0738	0.0026	0.3133	0.0002
2015	0.3364	0.0024	0.0595	0.0088	0.2763	0.0008
2016	0.3459	0.0017	0.0626	0.0065	0.2984	0.0003
2017	0.3339	0.0023	0.0528	0.0139	0.2749	0.0007
2018	0.3310	0.0026	0.0526	0.0144	0.2534	0.0017
2019	0.3326	0.0024	0.0485	0.0197	0.2224	0.0051
2020	0.3207	0.0034	0.0400	0.0367	0.2033	0.0096
2021	0.3199	0.0032	0.0406	0.0336	0.1911	0.0132

Table 4-7 shows the Moran's I results for HQED, which also demonstrate significantly positive spatial autocorrelation across all years and weight matrices. Notably, under W3, the Moran's I values are substantially higher than those obtained under W1 and W2, indicating that HQED's spatial clustering is more strongly associated with economic linkages and development similarity rather than mere geographic proximity. This finding underscores the fact that high-quality development tends to cluster among provinces with comparable economic structures, industrial upgrading trajectories, and innovation capacities, even if they are not directly adjacent geographically.

Table 4-8: Global Moran's I of HQED, 2008-2021

Year	Moran's I (W1)	P-value	Moran's I (W2)	P-value	Moran's I (W3)	P-value
2008	0.3085	0.0030	0.0554	0.0081	0.4973	0.0000
2009	0.2981	0.0043	0.0524	0.0111	0.4689	0.0000
2010	0.2859	0.0055	0.0537	0.0093	0.485	0.0000
2011	0.2442	0.0153	0.0430	0.0218	0.4823	0.0000
2012	0.2284	0.0222	0.0377	0.0327	0.4769	0.0000
2013	0.2194	0.0277	0.0435	0.0214	0.4739	0.0000
2014	0.2250	0.0228	0.0377	0.0312	0.4503	0.0000
2015	0.2326	0.0208	0.0417	0.0250	0.4548	0.0000
2016	0.2537	0.0136	0.0516	0.0122	0.448	0.0000
2017	0.2395	0.0188	0.0501	0.0136	0.4424	0.0000
2018	0.2312	0.0229	0.0490	0.0150	0.4176	0.0000
2019	0.2496	0.0145	0.0502	0.0132	0.4029	0.0000
2020	0.4092	0.0002	0.0426	0.0291	0.2709	0.0008
2021	0.4372	0.0001	0.0444	0.0251	0.2277	0.0039

When comparing the performance of different weight matrices, W2 yields relatively weaker Moran's I value and significance levels, suggesting its limited applicability in capturing China's regional development characteristics, where spatial interaction is not driven purely by physical distance. W1, which captures geographic adjacency, performs relatively better in the CP analysis, implying that carbon productivity outcomes are more dependent on geographic spillovers such as shared natural resources, environmental conditions, and policy diffusion across neighboring areas. By contrast, W3 provides the strongest performance in the HQED analysis and also maintains robust explanatory power in the CP analysis, reflecting its ability to integrate both geographical proximity and economic connectivity. Taken together, these results highlight the importance of adopting a multidimensional spatial weight structure that aligns with China's complex regional dynamics. Therefore, this study adopts W3 as the unified spatial weight matrix in the subsequent spatial econometric analyses, as it offers greater empirical relevance, robustness, and explanatory power for capturing the dual spatial characteristics of CP and HQED.

4.5.1.2 Local Spatial Autocorrelation Analysis

While the global spatial autocorrelation analysis captures the overall spatial distribution pattern across the country, it cannot reveal the localized spatial clustering characteristics of specific regions. Therefore, this study further employs the Local Moran's I index and Local Indicators of Spatial Association (LISA) cluster maps to analyze the local spatial clustering of CP and HQED across China's provinces from 2008 to 2021. This allows

for the identification of hotspot regions (high–high clusters), cold-spot regions (low–low clusters), and potential spatial heterogeneity.

(i). *Local Spatial Autocorrelation Analysis – CP*

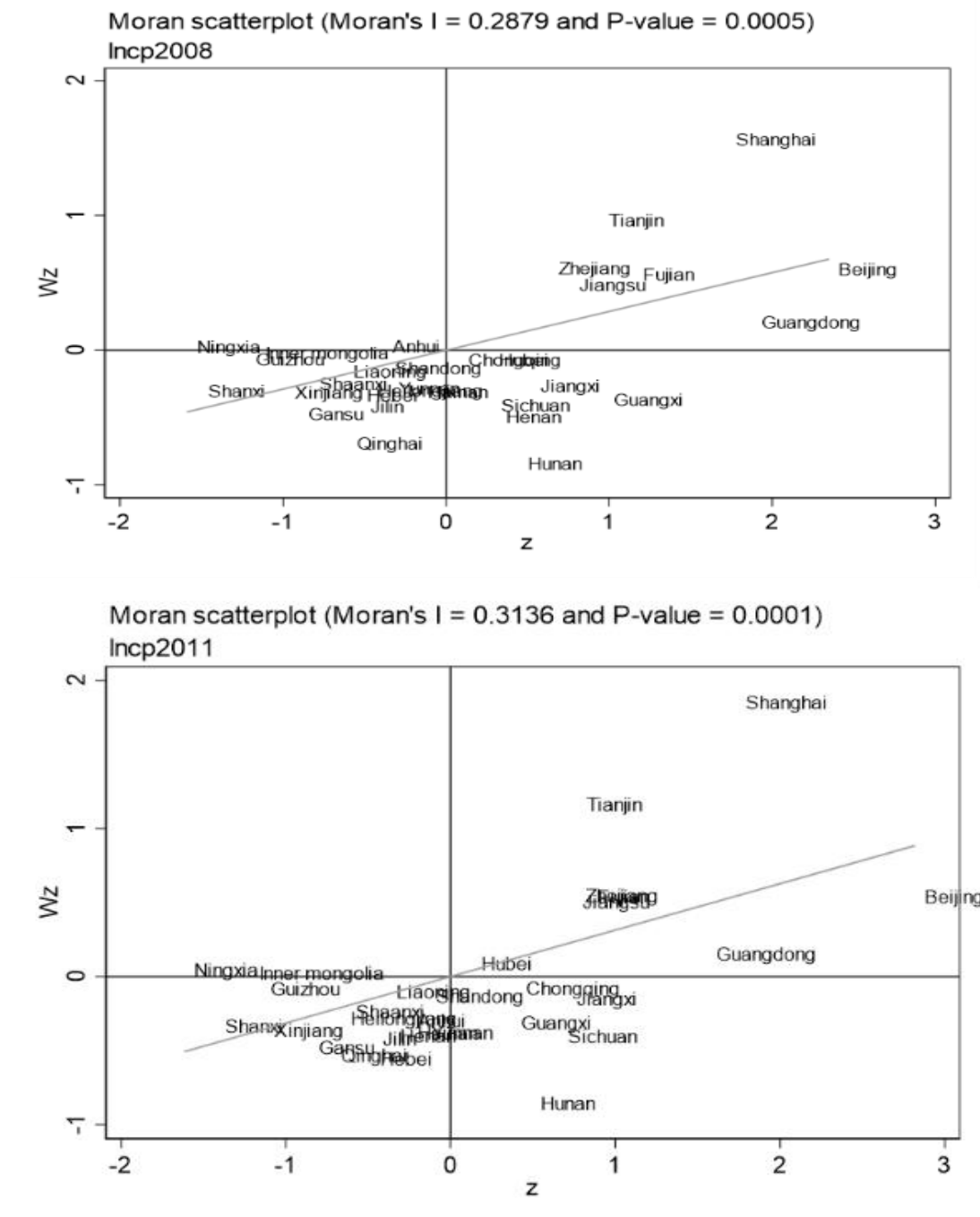
The computed results of the Local Moran’s I index for CP from 2008 to 2021 are presented in Table 4-9. Based on Table 4-9, significant disparities are observed in the Local Moran’s I indices across provinces. Some provinces did not pass the significance test, indicating no evident spatial correlation between these regions and their neighboring areas. In contrast, several provinces exhibit highly significant Local Moran’s I values, clearly rejecting the null hypothesis of spatial randomness. This suggests strong spatial dependence between these regions and their adjacent provinces, resulting in localized clusters.

Table 4-9: Local Moran’s I of CP, 2008-2021

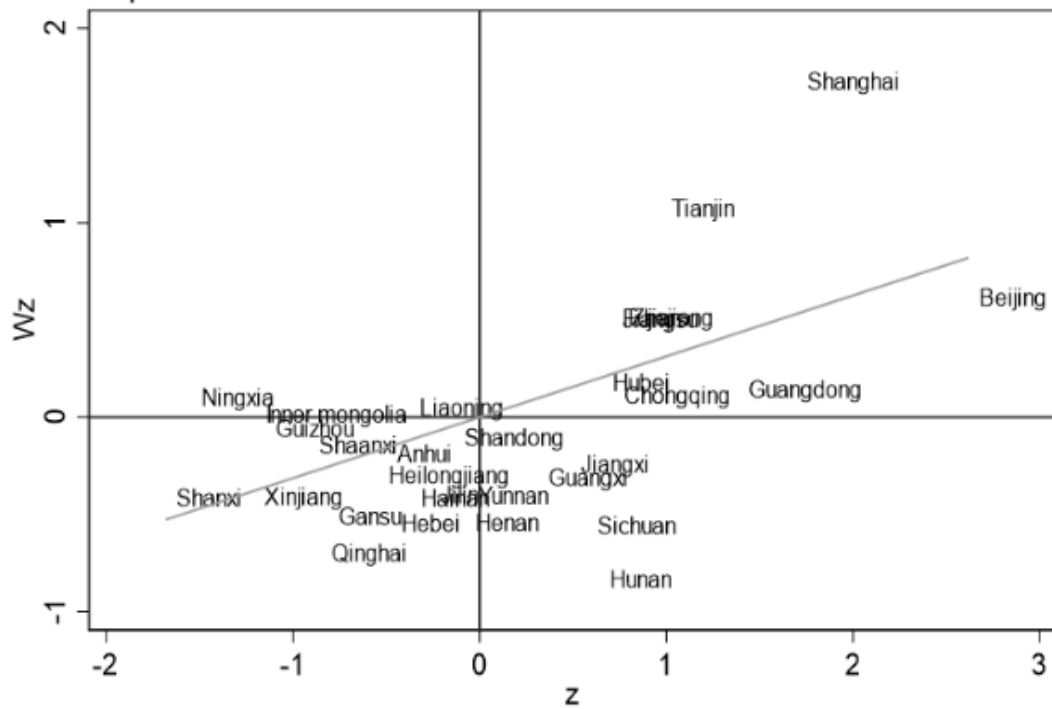
Province	2008		2011		2014		2017		2021	
	Ii	P-value	Ii	P-value	Ii	P-value	Ii	P-value	Ii	P-value
Beijing	1.4616	0.0004	1.5762	0.0001	1.6712	0.0000	1.7856	0.0000	1.5814	0.0001
Tianjin	0.9376	0.0121	0.9208	0.0125	1.0827	0.0038	1.2323	0.0009	1.0436	0.0046
Hebei	0.1875	0.6184	0.2776	0.4778	0.2668	0.4969	0.1559	0.6647	0.1029	0.7536
Shanxi	0.4732	0.3057	0.4930	0.2805	0.7174	0.1273	0.3144	0.4749	0.1642	0.6829
Inner Mongolia	0.0240	0.7585	0.0309	0.9849	-0.0219	0.9471	0.0103	0.8134	0.0587	0.6233
Liaoning	0.1012	0.5975	0.0408	0.7677	-0.0209	0.9576	0.0475	0.9592	0.1113	0.7625
Jilin	0.2248	0.2281	0.2024	0.2686	0.1089	0.5044	0.0796	0.5939	0.0034	0.8592
Heilongjiang	0.1482	0.3666	0.1935	0.2585	0.1670	0.3188	0.1409	0.3844	0.1018	0.4988
Shanghai	2.7753	0.0000	3.3158	0.0000	3.0357	0.0000	2.8731	0.0000	2.8267	0.0000
Jiangsu	0.3795	0.0975	0.3903	0.0867	0.3685	0.1058	0.2789	0.2060	0.2439	0.2603
Zhejiang	0.3957	0.1034	0.4300	0.0761	0.4006	0.0984	0.2784	0.2319	0.1145	0.5683
Anhui	0.0116	0.9660	0.0798	0.8289	0.0949	0.8083	0.0624	0.8544	0.0168	0.9732
Fujian	0.6718	0.0105	0.4653	0.0675	0.3771	0.1344	0.2828	0.2454	0.0942	0.6367
Jiangxi	0.1422	0.7938	0.1090	0.8547	-0.1195	0.8358	0.0050	0.9422	0.0042	0.9404
Shandong	0.0513	0.5980	0.0201	0.7383	0.0147	0.7628	0.0269	0.7071	0.0420	0.6403
Henan	0.1563	0.8043	0.1493	0.7045	0.0440	0.8724	0.0270	0.8990	0.1066	0.8812
Hubei	0.0199	0.9694	0.0123	0.9012	0.1215	0.6812	0.1294	0.6632	0.1748	0.5768
Hunan	0.3891	0.4541	0.4360	0.3900	-0.5503	0.2736	0.4051	0.4271	0.8757	0.0704
Guangdong	0.4068	0.0592	0.2450	0.2293	0.2078	0.2992	0.1399	0.4529	0.0336	0.7690
Guangxi	0.3667	0.2258	0.1186	0.7570	-0.0972	0.8186	0.0537	0.9437	0.0032	0.8894
Hainan	0.0534	0.7335	0.1023	0.5933	0.1577	0.4551	0.1622	0.4422	0.1480	0.4748
Chongqing	0.0056	0.9451	0.0332	0.9975	0.0847	0.7756	0.0477	0.8427	0.0441	0.8490
Sichuan	0.1190	0.8581	0.2731	0.6087	-0.3299	0.5299	0.4771	0.3419	0.3254	0.5307
Guizhou	0.0857	0.7292	0.0976	0.7002	0.0660	0.7713	0.0544	0.7954	0.0153	0.8842
Yunnan	0.1012	0.7163	0.0699	0.7772	0.0276	0.8675	0.0345	0.8515	0.0124	0.9521
Shaanxi	0.2139	0.1327	0.1545	0.2543	0.1361	0.3027	0.1147	0.3686	0.0387	0.6595
Gansu	0.4439	0.0319	0.4271	0.0373	0.4286	0.0374	0.3336	0.0967	0.3033	0.1270
Qinghai	0.4338	0.4003	0.3967	0.4320	0.6139	0.2416	0.3001	0.5416	0.2411	0.6138
Ningxia	0.0418	0.9882	0.0744	0.9350	-0.1660	0.7898	0.0886	0.9118	0.6131	0.2344
Xinjiang	0.3187	0.2771	0.4237	0.1539	0.5115	0.0916	0.4604	0.1232	0.4194	0.1562

To more intuitively visualize the spatial clustering patterns of regional CP, this study employs Moran scatter plots to depict the spatial association structure of CP, as shown in Figure 4-4. These plots not only illustrate the degree of spatial dependence but also classify provinces into different spatial association quadrants (High-High, Low-Low, High-Low, and Low-High), thereby revealing heterogeneous clustering tendencies across regions. This visual evidence provides an important complement to the Global Moran's I results and offers deeper insights into the localized mechanisms of CP clustering.

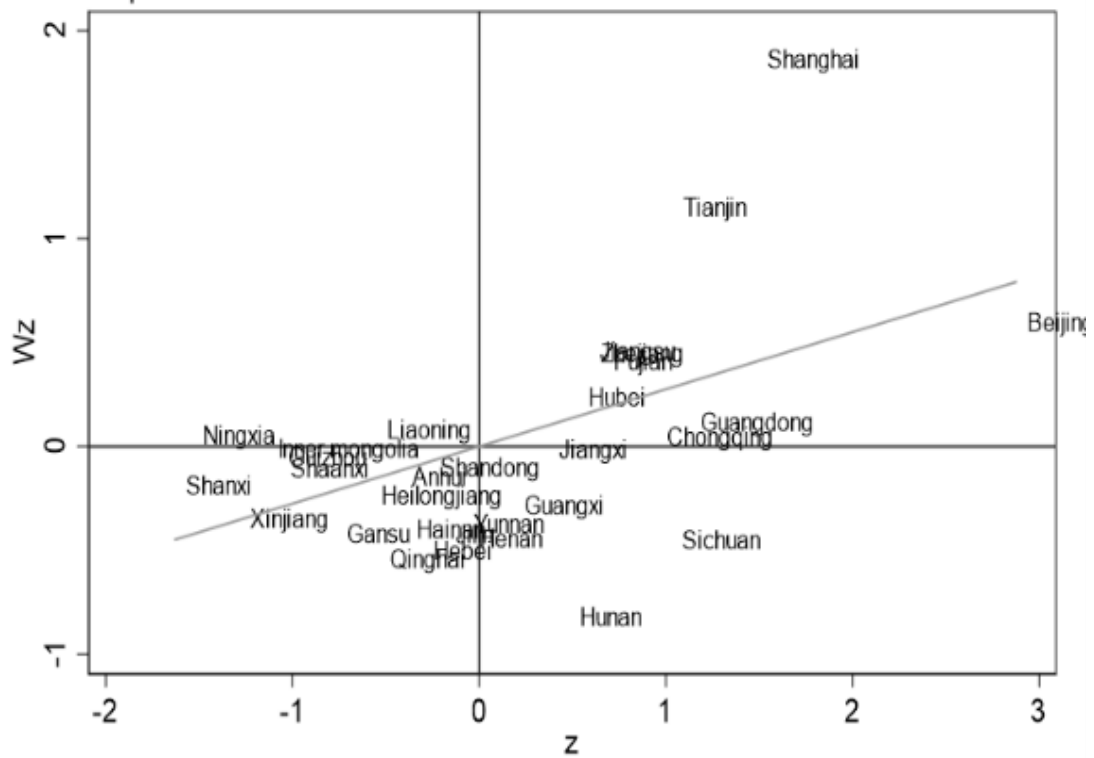
Figure 4-4: Local Moran's I Scatter Plots of CP, 2008-2021

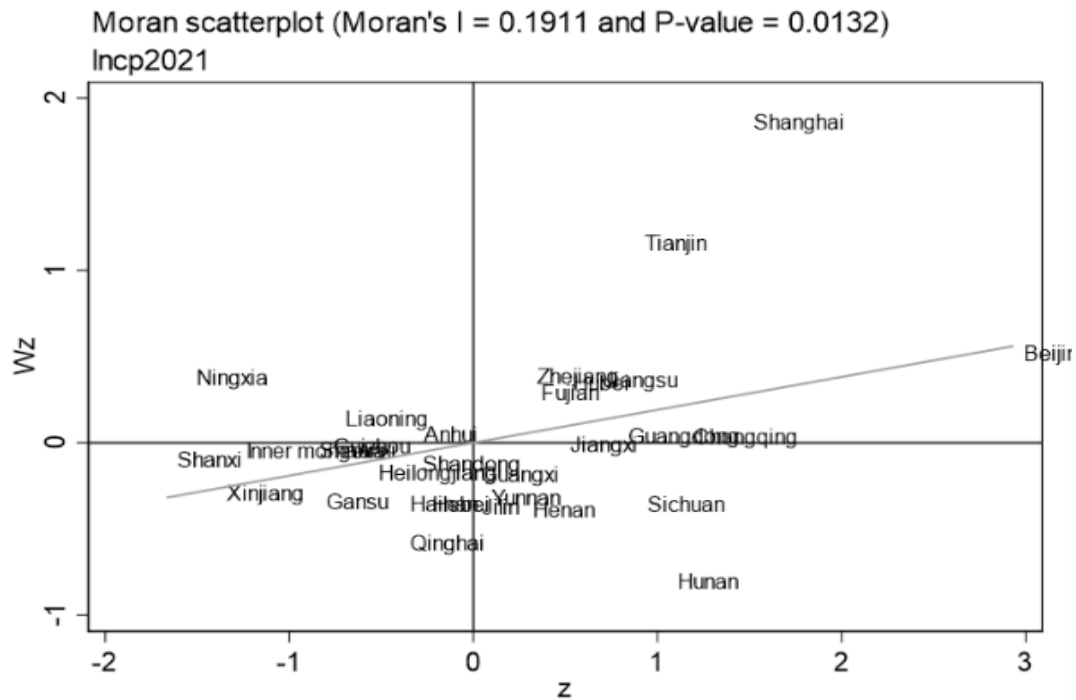


Moran scatterplot (Moran's $I = 0.3133$ and $P\text{-value} = 0.0002$)
Incp2014



Moran scatterplot (Moran's $I = 0.2749$ and $P\text{-value} = 0.0007$)
Incp2017





The four quadrants of the Moran's I scatterplot represent different types of spatial association patterns: Quadrant I (H-H): regions with high CP surrounded by neighbors also exhibiting high CP; Quadrant II (L-H): regions with low CP surrounded by neighbors with high CP. Quadrant III (L-L): regions with low CP surrounded by neighbors also exhibiting low CP. Quadrant IV (H-L): regions with high CP surrounded by neighbors with low CP. 错误!未找到引用源。 illustrates the provincial distribution of CP across the four quadrants of Local Moran's I scatterplots from 2008 to 2021. The classification reveals evolving patterns of spatial association, offering deeper insights into regional heterogeneity and spatial spillover dynamics.

Beyond global patterns, local spatial dependence reveals more nuanced regional heterogeneity, as discussed below.

H-H: Between 2008 and 2021, eastern coastal provinces, including Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, and Guangdong consistently fell into the H-H quadrant. This indicates that these regions maintained high levels of CP and were surrounded by neighboring provinces with similarly high CP, demonstrating strong spatial positive clustering. The pattern is primarily attributed to the region's advanced economic development, optimized industrial structure, and robust technological innovation, which collectively enhanced resource efficiency and regional CP levels. Notably, Hubei (post-2011)

and Chongqing (post-2014) transitioned into the H-H quadrant, suggesting that regions with stronger HQED have expanded high CP clusters through spatial spillovers and demonstration effects. This trend is consistent with the observed increase in the Global Moran's I over time.

Table 4-10: Provincial Distribution of CP by Local Moran's I Quadrants

Quadrant	Types	2008	2011	2014	2017	2021
Quadrant I	H-H	Beijing	Beijing	Beijing	Beijing	Beijing
		Tianjin	Tianjin	Tianjin	Tianjin	Tianjin
		Shanghai	Shanghai	Shanghai	Shanghai	Shanghai
		Jiangsu	Jiangsu	Jiangsu	Jiangsu	Jiangsu
		Zhejiang	Zhejiang	Zhejiang	Zhejiang	Zhejiang
		Fujian	Fujian	Fujian	Fujian	Fujian
		Hubei	Hubei	Hubei	Hubei	Hubei
Quadrant II	L-H	Guangdong	Guangdong	Guangdong	Guangdong	Guangdong
			Chongqing	Chongqing	Chongqing	Chongqing
		Anhui	Inner Mongolia	Inner Mongolia	Liaoning	Liaoning
		Ningxia	Ningxia	Liaoning	Ningxia	Anhui
				Ningxia		Ningxia
		Hebei	Hebei	Hebei	Hebei	Hebei
		Shanxi	Shanxi	Shanxi	Shanxi	Shanxi
Quadrant III	L-L	Inner Mongolia	Liaoning	Inner Mongolia	Inner Mongolia	Inner Mongolia
		Jilin	Jilin	Jilin	Jilin	Jilin
		Heilongjiang	Heilongjiang	Heilongjiang	Heilongjiang	Heilongjiang
		Anhui	Anhui	Anhui	Anhui	Anhui
		Shandong	Shandong	Shandong	Shandong	Shandong
		Henan	Henan	Henan	Henan	Guangxi
		Hainan	Hainan	Hainan	Hainan	Hainan
		Guizhou	Guizhou	Guizhou	Guizhou	Guizhou
		Yunnan	Yunnan	Yunnan	Yunnan	Yunnan
		Shaanxi	Shaanxi	Shaanxi	Shaanxi	Shaanxi
		Gansu	Gansu	Gansu	Gansu	Gansu
		Qinghai	Qinghai	Qinghai	Qinghai	Qinghai
		Xinjiang	Xinjiang	Xinjiang	Xinjiang	Xinjiang
		Jiangxi	Jiangxi	Jiangxi	Jiangxi	Jiangxi
Quadrant IV	H-L	Henan	Hunan	Hunan	Hunan	Henan
		Hubei	Guangxi	Guangxi	Guangxi	Hunan
		Hunan	Chongqing	Sichuan	Sichuan	Sichuan
		Guangxi	Sichuan			Sichuan
		Chongqing				Sichuan
		Sichuan				Yunnan

L-H: Provinces such as Anhui, Ningxia, Liaoning, and Inner Mongolia intermittently appeared in the L-H quadrant. These provinces exhibited relatively low CP levels while being adjacent to high-CP neighbors, indicating potential to benefit from positive spatial spillovers. With appropriate industrial transfers, technological inflows, and coordinated regional policy support, such areas may serve as key nodes for upward CP convergence in the future.

L-L: Hebei, Shanxi, Jilin, Heilongjiang, Gansu, Qinghai, and Xinjiang consistently appeared in the L-L quadrant. As resource-dependent regions with heavy reliance on high-emission and energy-intensive industries, these provinces have experienced persistently low

CP. However, the implementation of structural reforms and environmental governance in recent years has started to yield visible improvements, enabling some provinces to begin transitioning out of persistent L-L clusters. This signals the initial narrowing of regional disparities in CP, especially within the central and western regions.

H-L: Jiangxi, Hunan, Henan, Sichuan, and Yunnan were frequently located in the H-L quadrant, reflecting relatively high CP levels despite being surrounded by low-CP neighbors. These provinces typically benefit from stronger economic fundamentals but exhibit limited outward spillover capacity. The gradual reduction in the number of provinces within this quadrant over time suggests that some high-performing regions are increasingly generating positive spatial externalities, thereby enhancing regional CP balance.

In summary, from 2008 to 2021, China's CP exhibited a pronounced "high in the east, low in the west" spatial distribution, accompanied by persistent yet gradually diminishing regional disparities. The expansion of H-H clusters, the contraction of L-L clusters, and the transformation of some H-L provinces into H-H clusters collectively reflect progress in industrial restructuring, technological upgrading, and low-carbon transition. These dynamics highlight a trend toward more synergistic and balanced interregional development in CP.

(ii). Local Spatial Autocorrelation Analysis of HQED

To further examine spatial dependence in HQED, Local Moran's I indices were calculated for the years 2008, 2011, 2014, 2017, and 2021. Unlike the global measure, which captures overall spatial association, the local indicator of spatial association (LISA) helps identify specific provinces that form statistically significant clusters of high or low HQED values, as well as potential outliers. By analyzing local patterns, this method reveals spatial heterogeneity that might be obscured in the global index. The corresponding results are presented in Table 4-11, offering insight into the evolving local spatial association patterns of HQED across provinces.

Table 4-11 reveals that from 2008 to 2021, the majority of Chinese provinces exhibited positive values of Local Moran's I for HQED, indicating strong spatial homogeneity in the distribution of HQED. Provinces with higher HQED levels are generally surrounded by others with similarly high levels, forming stable "H-H" clusters; conversely, provinces with lower HQED levels tend to be spatially proximate to other low-performing regions, forming "L-L" clusters. This pattern reflects the spatial diffusion and spillover

effects of development quality, particularly in areas characterized by close economic linkages and institutional proximity.

Table 4-11: Local Moran's I of HQED, 2008-2021

Province	2008		2011		2014		2017		2021	
	Ii	P-value	Ii	P-value	Ii	P-value	Ii	P-value	Ii	P-value
Beijing	2.3633	0.0000	2.1597	0.0000	2.0483	0.0000	1.8233	0.0000	0.9202	0.0202
Tianjin	1.0121	0.0046	0.7757	0.0277	0.6688	0.0546	0.4935	0.1559	0.2729	0.4184
Hebei	0.3831	0.3240	0.4593	0.2417	0.4443	0.2534	0.3854	0.3252	0.2448	0.5223
Shanxi	0.3819	0.3756	0.4036	0.3494	0.3632	0.3926	0.4022	0.3569	0.4527	0.3153
Inner Mongolia	-0.0582	0.9002	-0.0963	0.7439	-0.0928	0.7578	-0.1239	0.6365	-0.0955	0.7477
Liaoning	-0.0518	0.9447	-0.0609	0.9155	-0.0348	0.9989	-0.0789	0.8594	-0.0098	0.9226
Jilin	0.1065	0.5051	0.0730	0.6111	0.0566	0.6659	0.1257	0.4501	0.1333	0.4322
Heilongjiang	0.1197	0.4409	0.0924	0.5259	0.0610	0.6326	0.0743	0.5874	0.1540	0.3493
Shanghai	5.5935	0.0000	5.6117	0.0000	5.6077	0.0000	5.2747	0.0000	2.8023	0.0000
Jiangsu	0.5070	0.0258	0.4742	0.0359	0.4945	0.0286	0.6899	0.0030	0.5119	0.0270
Zhejiang	0.4193	0.0762	0.4466	0.0595	0.4254	0.0706	0.5922	0.0148	0.4103	0.0880
Anhui	0.3648	0.4317	0.3927	0.3982	0.3026	0.5022	0.1924	0.6578	0.0542	0.8657
Fujian	0.1129	0.5804	0.1173	0.5683	0.0177	0.8437	-0.0414	0.9795	-0.1539	0.6606
Jiangxi	0.4334	0.2329	0.4142	0.2510	0.2310	0.4944	0.2683	0.4437	0.2406	0.4958
Shandong	-0.0106	0.8849	-0.0285	0.9710	-0.0221	0.9405	-0.0246	0.9522	-0.0358	0.9934
Henan	0.4044	0.3464	0.4483	0.2984	0.3313	0.4277	0.3219	0.4483	0.1596	0.6866
Hubei	0.1023	0.7069	0.1029	0.7047	0.0515	0.8115	0.0380	0.8431	0.0439	0.8341
Hunan	0.3456	0.3978	0.2754	0.4889	0.1648	0.6541	0.1117	0.7471	0.1579	0.6782
Guangdong	-0.0671	0.8865	-0.1024	0.7660	-0.1322	0.6676	-0.1557	0.5971	-0.0430	0.9708
Guangxi	0.2116	0.3534	0.2892	0.2211	0.3272	0.1699	0.3644	0.1346	0.0985	0.6230
Hainan	-0.2959	0.2965	-0.1107	0.7603	-0.0724	0.8791	0.0613	0.7035	-1.3837	0.0000
Chongqing	0.1238	0.6922	0.0968	0.7417	0.0121	0.9063	0.0278	0.8771	0.0485	0.8403
Sichuan	0.4123	0.3193	0.4229	0.3060	0.1705	0.6443	0.1967	0.6093	0.1854	0.6347
Guizhou	0.2119	0.4582	0.1913	0.4951	0.3315	0.2663	0.4337	0.1615	0.3427	0.2686
Yunnan	0.2184	0.4781	0.2118	0.4882	0.3813	0.2392	0.3897	0.2376	0.3379	0.3096
Shaanxi	0.3222	0.0331	0.2825	0.0584	0.2175	0.1331	0.1785	0.2023	0.1742	0.2091
Gansu	0.3022	0.1234	0.2714	0.1611	0.3648	0.0667	0.3523	0.0777	0.4047	0.0470
Qinghai	0.5008	0.3097	0.4491	0.3568	0.3385	0.4743	0.3953	0.4188	0.4603	0.3635
Ningxia	0.4089	0.3457	0.2947	0.4822	0.3062	0.4640	0.2727	0.5171	0.3117	0.4757
Xinjiang	0.0410	0.8087	0.1106	0.6406	0.1461	0.5591	0.2311	0.3973	-0.3703	0.2932

In terms of statistical significance, eastern provinces such as Beijing, Shanghai, and Jiangsu consistently recorded p-values below the 0.05 threshold, confirming that their spatial clustering is non-random and statistically robust. These provinces function as regional growth poles, exerting positive externalities on neighboring areas through mechanisms such as innovation diffusion, infrastructure integration, and coordinated policy environments. In contrast, interior provinces like Inner Mongolia and Ningxia displayed higher p-values and

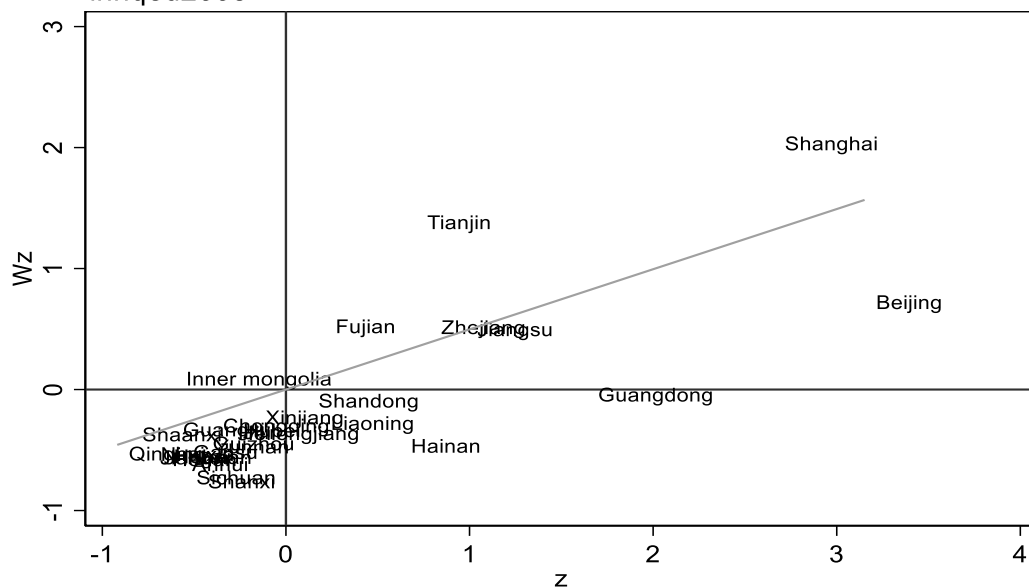
weaker spatial dependence, suggesting a fragmented development structure and limited interregional transmission of HQED.

To provide a more intuitive understanding of these spatial interaction patterns, Figure 4-5 presents the Local Moran's I scatterplot for HQED. This visual tool highlights the types and intensities of local spatial associations, offering clear insights into the degree and direction of development clustering across provinces.

Figure 4-5: Local Moran's I Scatter Plots of HQED, 2008-2021

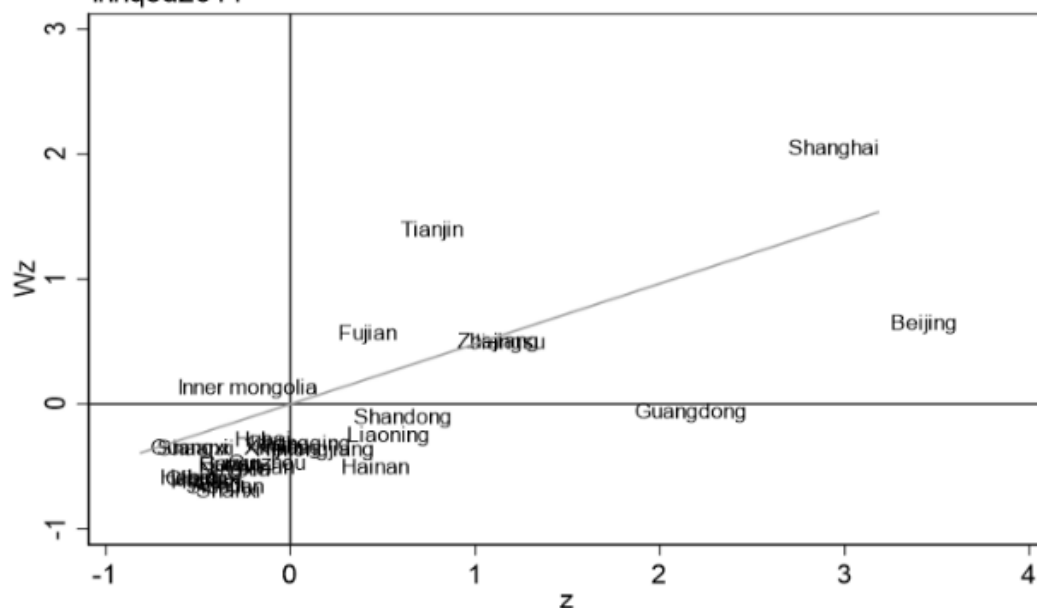
Moran scatterplot (Moran's I = 0.4973 and P-value = 0.0000)

Inhqed2008

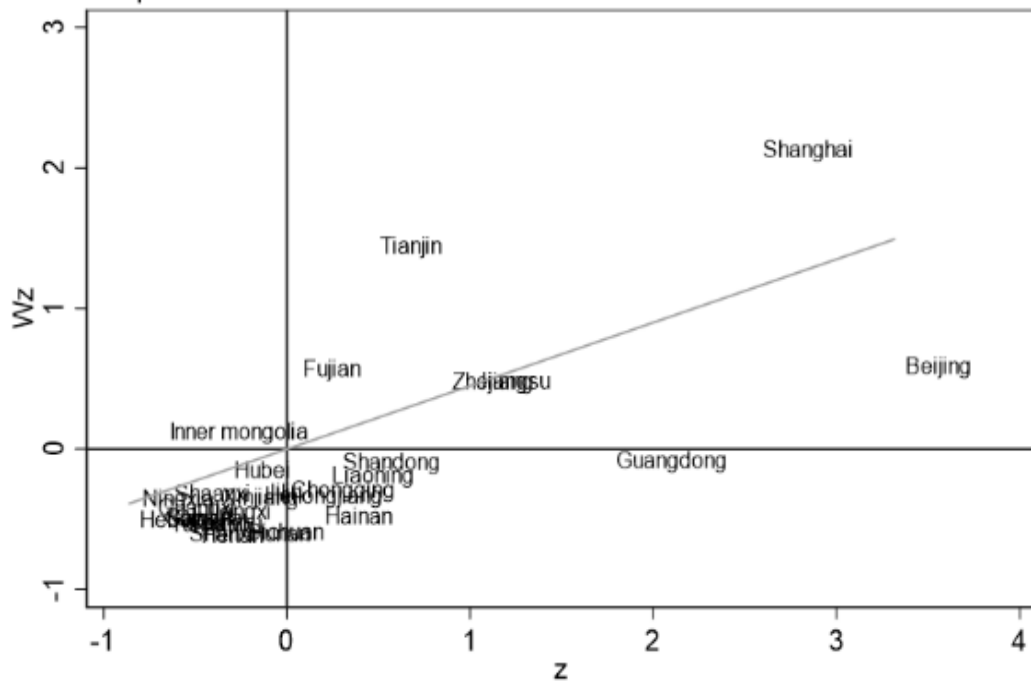


Moran scatterplot (Moran's I = 0.4823 and P-value = 0.0000)

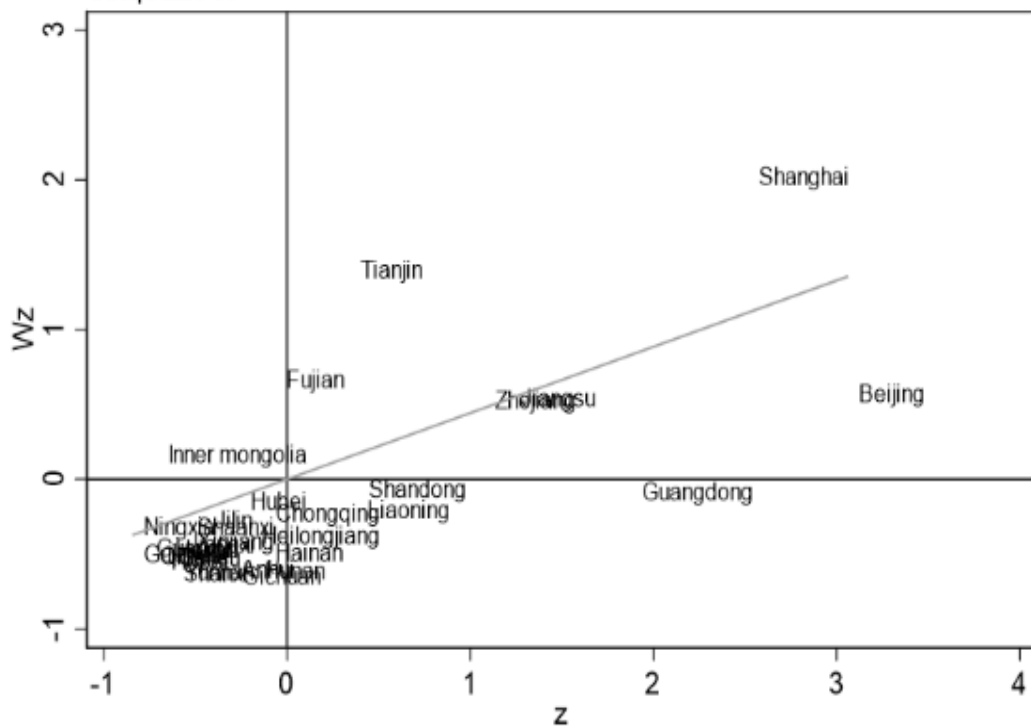
Inhqed2011

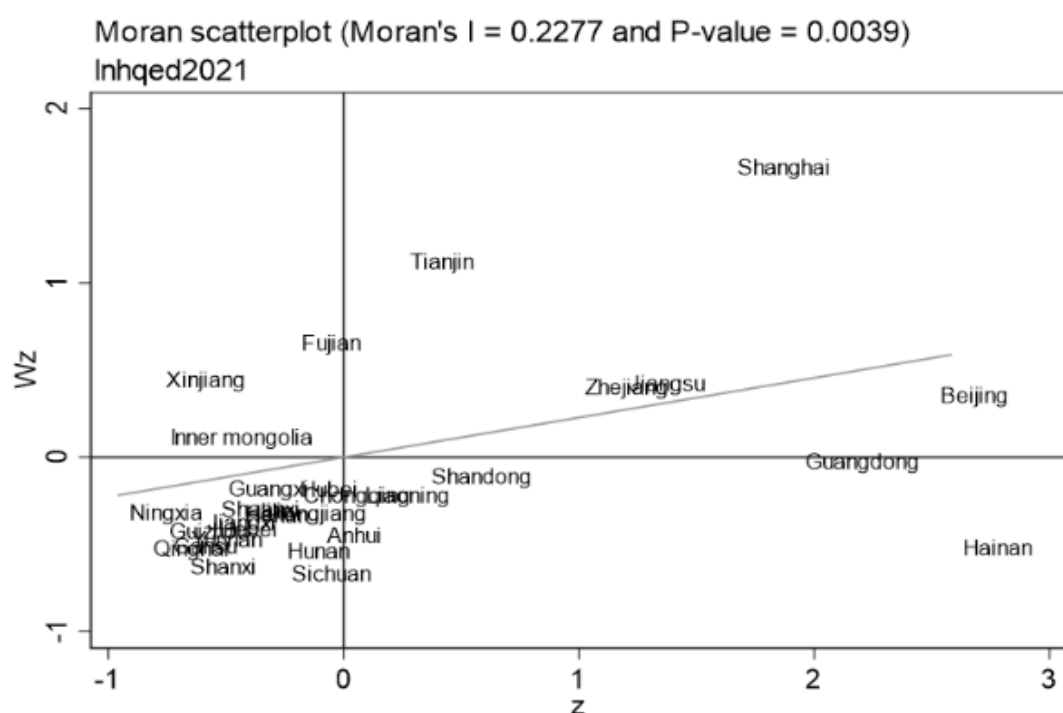


Moran scatterplot (Moran's I = 0.4503 and P-value = 0.0000)
Inhqed2014



Moran scatterplot (Moran's I = 0.4424 and P-value = 0.0000)
Inhqed2017





Based on the local Moran's I result, Table 4-12 summarizes the spatial association patterns of HQED across provinces.

Table 4-12: Spatial Classification of HQED Based on Moran's I Scatterplot

Quadrant	Spatial Pattern Description
Quadrant I (H-H)	The region and its neighboring regions both exhibit high levels of HQED.
Quadrant II (L-H)	The region has a low level of development, while neighboring regions have high levels of development.
Quadrant III (L-L)	Both the region and its neighboring areas show low levels of HQED.
Quadrant IV (H-L)	The region has a high level of development, but its neighboring regions are underdeveloped.

Based on the scatterplot, Table 4-13 summarizes the spatial clustering patterns of HQED across selected years from 2008 to 2021, offering insights into how HQED is concentrated, diffused, or isolated geographically. This classification provides a basis for understanding the spatial evolution of HQED and the potential for interregional policy spillovers. By tracking how these spatial clusters evolve across time, the analysis provides an empirical lens to evaluate whether HQED in China has moved toward convergence or divergence. This also informs the later heterogeneity analysis, offering a spatial foundation for examining why some regions have benefited disproportionately from HQED while others remain lagging.

Table 4-13: Provincial Distribution of HQED by Local Moran's I Quadrants

Quadrant	Types	2008	2011	2014	2017	2021
Quadrant I	H-H	Beijing	Beijing	Beijing	Beijing	Beijing
		Tianjin	Tianjin	Tianjin	Tianjin	Tianjin
		Shanghai	Shanghai	Shanghai	Shanghai	Shanghai
		Jiangsu	Jiangsu	Jiangsu	Jiangsu	Jiangsu
		Zhejiang	Zhejiang	Zhejiang	Zhejiang	Zhejiang
Quadrant II	L-H	Inner Mongolia	Inner Mongolia	Inner Mongolia	Fujian	Fujian
					Inner Mongolia	Inner Mongolia
						Xinjiang
		Hebei	Hebei	Hebei	Hebei	Hebei
		Shanxi	Shanxi	Shanxi	Shanxi	Shanxi
Quadrant III	L-L	Jilin	Jilin	Jilin	Jilin	Jilin
		Heilongjiang	Heilongjiang	Heilongjiang	Heilongjiang	Heilongjiang
		Anhui	Anhui	Anhui	Anhui	Anhui
		Jiangxi	Jiangxi	Jiangxi	Jiangxi	Jiangxi
		Henan	Henan	Henan	Henan	Henan
		Hubei	Hubei	Hubei	Hubei	Hubei
		Hunan	Hunan	Hunan	Hunan	Hunan
		Guangxi	Guangxi	Guangxi	Guangxi	Guangxi
		Chongqing	Chongqing	Chongqing	Chongqing	Chongqing
		Sichuan	Sichuan	Sichuan	Sichuan	Sichuan
		Guizhou	Guizhou	Guizhou	Guizhou	Guizhou
		Yunnan	Yunnan	Yunnan	Yunnan	Yunnan
		Shaanxi	Shaanxi	Shaanxi	Shaanxi	Shaanxi
		Gansu	Gansu	Gansu	Gansu	Gansu
		Qinghai	Qinghai	Qinghai	Qinghai	Qinghai
		Ningxia	Ningxia	Ningxia	Ningxia	Ningxia
		Xinjiang	Xinjiang	Xinjiang	Xinjiang	Xinjiang
Quadrant IV	H-L	Liaoning	Liaoning	Liaoning	Liaoning	Liaoning
		Shandong	Shandong	Shandong	Shandong	Shandong
		Guangdong	Guangdong	Guangdong	Guangdong	Guangdong
		Hainan	Hainan	Hainan	Hainan	Hainan

The local spatial clustering patterns identified through the Moran scatter plots reveal substantial regional differentiation in HQED. A more detailed analysis of these local spatial clustering patterns is presented as follows:

H-H: From 2008 to 2021, Beijing, Tianjin, Shanghai, Jiangsu, and Zhejiang consistently remained in the H-H quadrant. These provinces exhibit outstanding levels of HQED, with optimized industrial structures and strong innovation-driven capacities. They play a significant role in regional spillover and driving effects, forming stable high-value clusters. Fujian gradually exited this quadrant after 2017, possibly because its growth pace did not keep up with the core coastal regions. This may indicate a divergence in regional coordinated development and industrial upgrading trends.

L-H: Inner Mongolia was stably located in the L-H quadrant during 2008–2014, while Fujian and Xinjiang successively entered this quadrant from 2017 to 2021. These provinces have relatively low HQED levels but benefit from spillover effects from adjacent high-value areas. Xinjiang's later inclusion may be attributed to the implementation of the

Belt and Road Initiative, which has strengthened trade and economic cooperation with neighboring countries and regions. Though Xinjiang's own HQED level remains low, enhanced spatial spillovers from economically active neighboring regions have shifted it from the previous L-L quadrant to L-H.

L-L: Most provinces in central, western, and northeastern China have long remained in the L-L quadrant, including Hebei, Shanxi, Jilin, Heilongjiang, Anhui, Sichuan, Yunnan, Shaanxi, Gansu, and Qinghai. These regions tend to have a relatively homogeneous industrial structure, weak innovation capacity, and slow HQED progress. They often fall into spatial clusters of under-development alongside neighboring low-performing regions, with significant spatial dependence and limited regional coordination. For instance, Shanxi is highly dependent on coal-related industries and faces challenges such as resource reliance and environmental degradation, which hinders effective regional collaboration.

H-L: Liaoning, Shandong, and Guangdong have remained in the H-L quadrant for extended periods, with Hainan appearing occasionally. These provinces enjoy high levels of HQED themselves, but their neighboring areas have yet to form effective regional synergies, highlighting intra-regional development imbalances. Taking Guangdong as an example, while the Pearl River Delta is highly developed, the eastern, western, and northern parts of the province lag behind, limiting the overall spatial spillover effect.

Overall, the spatial distribution of HQED in China during 2008-2021 exhibits a pronounced “east-high, west-low” pattern. The eastern provinces have maintained their leading status, while central, western, and northeastern regions have lagged but shown signs of gradual improvement. With the strengthening of regional economic interlinkages, the increasing emergence of L-H type regions suggests that the spatial spillover effects of HQED are gradually materializing, thereby enhancing regional synergies and reducing the risk of persistent low-value lock-in in underdeveloped areas.

These findings highlight that HQED not only contributes to improvements in CP within individual provinces but also generates positive externalities for neighboring regions through channels such as industrial upgrading, technology diffusion, and policy imitation. Based on this observation, the following hypothesis is proposed for empirical testing in the subsequent spatial econometric analysis: HQED exerts a significant spatial spillover effect on regional CP.

4.5.2 Spatial Model Estimation and Effect Decomposition

a) *Testing for Spatial Effects*

Before constructing the spatial econometric models, it is essential to test whether the data exhibit significant spatial dependence to determine the appropriate model specification. As the theoretical foundations and model structures have been introduced earlier, this section focuses on the application of the LM test and Robust LM test to identify spatial autocorrelation in the panel data. The test results, as summarized in Table 4-14, provide clear statistical evidence supporting the presence of spatial effects in the data, validating the need to adopt spatial econometric models in the subsequent empirical analysis.

Table 4-14: Spatial Effect Test Results of the Spatial Panel Data Model

Test	Statistic	p-value
Spatial error:		
Lagrange multiplier	181.068	0.000
Robust Lagrange multiplier	91.693	0.000
Spatial lag:		
Lagrange multiplier	96.681	0.000
Robust Lagrange multiplier	7.306	0.007

The test statistics for LM-Lag, Robust LM-Lag, LM-Error, and Robust LM-Error are all significant at the 1% level, indicating the presence of both spatial lag dependence and spatial error dependence in the model. This suggests that provincial CP is not only influenced by its own characteristics and those of its neighbors (endogenous interaction effects) but is also subject to unobserved shocks and omitted variables that are spatially correlated (error dependence). Such findings provide strong preliminary evidence supporting the adoption of the SDM, which is capable of simultaneously addressing spatial autocorrelation and capturing spatial spillover effects transmitted through both the dependent and explanatory variables. Retaining the SDM at this stage ensures that the subsequent analysis incorporates the most comprehensive form of spatial dependence, thereby enhancing the robustness and credibility of the empirical results.

b) *Suitability Test for the Spatial Durbin Model*

To further determine whether the SDM can be simplified into a SEM or a SAR, Wald tests and Likelihood Ratio (LR) tests were conducted. These diagnostic tests help evaluate the necessity of retaining both the spatially lagged dependent and independent variables in the model structure. The detailed results are presented in Table 4-15, providing a basis for selecting the most appropriate spatial econometric specification.

Table 4-15: Test on the Applicability of Spatial Durbin Model

Examination Method	Parameter	P-value
Wald spatial lag	46.01	0.0000
LR spatial lag	62.16	0.0000
Wald spatial error	62.17	0.0000
LR spatial error	57.72	0.0000

As shown in Table 4-15, both the Wald and LR test statistics are highly significant ($p < 0.001$), strongly rejecting the null hypotheses that the SDM can be simplified into either a SEM or SAR. This indicates that the inclusion of both the spatial lag of the dependent variable and the spatially lagged explanatory variables is necessary to adequately capture spatial dependence. Consequently, the SDM is retained as the most appropriate specification for subsequent spatial effect estimation, ensuring that both endogenous interaction effects and exogenous spillover effects are properly accounted for.

c) Selection of Fixed versus Random Effects

To determine the appropriate model specification, a Hausman test was conducted to compare FEM and REM estimators. The test evaluates whether the unobserved individual effects are correlated with the explanatory variables, which would render the REM estimator inconsistent and biased. As shown in Table 4-16, the test yields a chi-square statistic of 20.27 ($p = 0.0161$), indicating that the null hypothesis of no correlation is rejected at the 5% significance level. Therefore, the FEM is statistically preferred.

The adoption of fixed effects is also consistent with the theoretical expectation that provinces differ in unobservable structural characteristics, such as resource endowments, institutional quality, and industrial composition. These factors are not only persistent over time but are also likely to correlate with HQED and CP, thereby influencing the estimation results if not properly controlled. By absorbing these unobserved heterogeneities, the FEM provides more reliable and consistent estimates, enhancing the validity of the empirical findings.

For this reason, the REM results are excluded from Table 4-16 due to their inconsistency, and all subsequent spatial econometric analyses are conducted under the fixed effects framework. This choice ensures that the estimated spatial spillover effects are robust to unobserved provincial characteristics, thereby strengthening the credibility of the policy implications derived from the results.

Table 4-16: Spatial Econometric Models with Different Fixed Effects

	Spatial fixed	Time fixed	Both fixed
Main			
lnhqed	0.914*** (0.1698)	1.194*** (0.2436)	0.413** (0.1791)
lneci	-0.778*** (0.0654)	-0.639*** (0.0386)	-0.814*** (0.0632)
lnur	-2.170*** (0.3833)	0.725*** (0.2678)	-1.735*** (0.3644)
lnml	0.124 (0.0764)	0.0218 (0.0963)	0.0592 (0.0751)
lnenv	0.00689 (0.0207)	0.0965*** (0.0296)	0.0199 (0.0202)
lnss	0.335** (0.1302)	-0.212* (0.1176)	0.293** (0.1299)
lnclr	0.0742*** (0.0250)	-0.162*** (0.0306)	0.0342 (0.0250)
Wx			
lnhqed	0.701** (0.3247)	0.754 (0.6463)	-1.994*** (0.5450)
lneci	0.452*** (0.1316)	0.656*** (0.1249)	-0.0383 (0.1827)
lnur	1.497** (0.6900)	5.247*** (0.6651)	-2.529*** (0.9185)
lnml	0.0489 (0.1389)	-0.485** (0.2413)	-0.157 (0.1815)
lnenv	0.141*** (0.0411)	0.0524 (0.0777)	0.0994** (0.0468)
lnss	-1.048*** (0.3091)	0.825*** (0.3187)	-0.455 (0.4124)
lnclr	-0.0763 (0.0517)	-0.667*** (0.0834)	-0.203*** (0.0726)
	Hanuman	20.27** P=0.0161	
R2	0.5459	0.2751	0.0943
Log likelihood	627.5392	307.0770	658.6556
sigma2_e	0.00293***	0.0136***	0.00254***

Note: *** p<0.01, ** p<0.05, * p<0.1.

d) Selection of Fixed Effects Dimensions

To further identify the optimal form of fixed effects, the study compares three model configurations: spatial fixed effects, time fixed effects, and two-way fixed effects. These specifications respectively control for region-specific, period-specific, and combined unobservable factors. As reported in Table 4-16, the spatial fixed effects model achieves an R² of 0.5459 and a Log-likelihood of 627.5392, while the time fixed effects model yields an R² of 0.2751 and Log-L of 307.0770. The two-way fixed effects model, although associated with a relatively low R² (0.0943), records the highest Log-likelihood (658.6556), indicating superior overall model fit. Based on this comparison, the two-way fixed effects specification

is selected for the subsequent SDM estimation, as it offers the most comprehensive control of unobservable influences over space and time.

e) Estimation Results of the Spatial Econometric Model

Table 4-16 presents the diagnostic results used to determine the appropriate fixed-effects structure for the SDM. By comparing spatial, time, and two-way fixed effects, and conducting a Hausman test, this step identifies the optimal model specification for consistent estimation. Based on these results, the two-way fixed-effects specification is selected for subsequent analysis.

Following this specification decision, Table 4-17 presents the final SDM estimation results. In contrast to conventional panel models, the SDM captures spatial dependence by incorporating spatial lags of both the dependent and independent variables. This enables a more comprehensive understanding of how HQED influences CP, both locally and through interregional spillovers.

A key analytical feature of the SDM is its ability to decompose the estimated effects into three distinct components. The direct effect measures the impact of an explanatory variable, such as HQED, on CP within the same province, reflecting intra-regional influence. The indirect effect, or spatial spillover effect, captures how a province's HQED affects CP in neighboring provinces through channels such as policy diffusion, industrial coordination, or environmental governance. The total effect combines both components, representing the overall spatial impact of the variable across all regions.

This decomposition is essential for capturing the spatially heterogeneous transmission mechanisms of HQED. By distinguishing between internal and external effects, it provides a more accurate interpretation of policy impacts and supports the formulation of coordinated, region-specific strategies for low-carbon development.

To enhance the model's robustness and realism, the SDM is estimated using the W3 spatial weight matrix, which integrates geographic proximity and economic similarity. This approach more accurately reflects the complex spatial linkages characterizing provincial development patterns in China. Table 4-17 reports the results of SDM.

Table 4-17: Direct Effect, Indirect Effect and Overall Effect of SDM, 2008-2021

	SDM Direct	SDM Indirect	SDM Total
lnhqed	1.0583*** (5.945)	1.0116*** (3.048)	2.0698*** (5.926)
lneci	-0.7557*** (-12.949)	0.3169** (2.159)	-0.4388*** (-2.800)
Lnur	-1.5616*** (-4.467)	1.3271* (1.860)	-0.2344 (-0.387)
lnml	0.1528** (2.069)	0.1246 (0.724)	0.2774 (1.616)
lnenv	0.0197 (0.946)	0.1472*** (2.921)	0.1669*** (3.069)
lnss	0.2399* (1.826)	-1.0933*** (-2.855)	-0.8535** (-2.036)
lnclr	0.0558** (2.151)	-0.1327** (-2.314)	-0.0769 (-1.145)
rho		0.1932** (2.425)	
sigma2_e		0.0032*** (13.799)	

Note: *** p<0.01, ** p<0.05, * p<0.1.

The results confirm that HQED exerts statistically significant and economically meaningful impacts on CP through both direct and spillover channels. Specifically, improvements in a province's HQED not only enhance its own CP but also generate positive externalities that benefit surrounding regions. This dual mechanism highlights the spatially interconnected nature of green development in China.

(i). Core Variable: HQED

The estimation results of the SDM confirm that HQED has statistically significant impacts on CP through both direct and spatial spillover effects. This indicates that improvements in local HQED not only raise local CP but also contribute positively to neighboring regions. Detailed effect decomposition results are presented in Table 4-18.

These findings highlight that the impact of HQED on CP extends beyond local boundaries, generating substantial positive spillovers across regions. This underscores the strategic importance of designing coordinated regional policies that leverage interregional synergies. To maximize the contribution of HQED to China's low-carbon transition and sustainable development goals, policy frameworks should explicitly incorporate spatial interactions and cross-regional cooperation mechanisms.

Table 4-18: Effect Decomposition of HQED on CP in the SDM

Direct Effect	The estimated coefficient for the direct effect is 1.0583, significant at the 1% level ($p < 0.01$). This result indicates that a 1% increase in the local level of HQED leads to a 1.0583% rise in local CP. It suggests that HQED enhances CP primarily through structural upgrading, technological innovation, and efficiency improvement, thereby improving the sustainability of economic output within provinces.
Indirect Effect	The indirect effect coefficient is 1.0116, also significant at the 1% level ($p < 0.01$). This implies that a 1% improvement in HQED in neighboring provinces can indirectly increase a given province's CP by 1.0116%, indicating a strong spatial spillover effect. This highlights that HQED contributes to regional carbon efficiency through channels such as policy diffusion, industrial collaboration, and institutional alignment.
Total Effect	The total effect, as the sum of the direct and indirect effects, is 2.0698, significant at the 1% level ($p < 0.01$). This shows that HQED has an overall impact of 2.0698% on CP. Notably, the indirect effect is nearly equal to the direct effect, underscoring the importance of regional synergy and spatial interaction in amplifying the benefits of HQED across provinces.

(ii). Analysis of Control Variables

The interpretations below are based on the SDM results reported in Table 4-17. Each control variable demonstrates distinct patterns of local and spatial effects, shedding light on the mechanisms through which structural factors shape CP across provinces.

Energy Intensity (Inei): Energy intensity exhibits a significantly negative direct effect on CP (-0.7557 , $p < 0.01$), indicating that higher energy consumption per unit of output inhibits carbon efficiency improvement within provinces. The indirect effect is significantly positive (0.3169 , $p < 0.05$), suggesting that reductions in energy intensity in one region may benefit neighboring areas, possibly through industrial relocation or cleaner production spillovers. However, the total effect remains significantly negative (-0.4388 , $p < 0.01$), highlighting the dominant obstructive role of energy intensity in overall CP performance.

Urbanization Level (Inur): Urbanization exerts a strongly negative direct effect on CP (-1.5616 , $p < 0.01$), which may reflect inefficient urban expansion, energy-intensive infrastructure, or mismatched urban–industrial systems. Its indirect effect is weakly positive and marginally significant (1.3271 , $p < 0.1$), indicating some diffusion of urban-driven improvements to surrounding provinces, potentially through labor mobility or interregional trade. However, the total effect is statistically insignificant (-0.2344), suggesting that the urbanization–CP relationship is highly context-dependent and exhibits spatial heterogeneity.

Marketization Level (lnml): The direct effect of marketization is positive and significant (0.1528, $p < 0.05$), reflecting the role of market mechanisms in enhancing resource allocation, stimulating innovation, and encouraging low-carbon practices. Nonetheless, both the indirect (0.1246) and total effects (0.2774) are statistically insignificant, indicating that the influence of marketization remains largely local, with limited spatial externalities across provincial boundaries.

Government Environmental Expenditure (lnenv): Although the direct effect of environmental expenditure is statistically insignificant (0.0197), its indirect effect is significantly positive (0.1472, $p < 0.01$), demonstrating strong spatial spillovers. This result suggests that government-led environmental investments promote carbon efficiency in adjacent regions, likely via cross-border collaboration, knowledge sharing, and demonstration effects. The total effect is also significant (0.1669, $p < 0.01$), confirming the broader regional benefits of public environmental spending.

Share of Secondary Industry (lnss): The direct effect is positive and weakly significant (0.2399, $p < 0.1$), indicating that industrial upgrading or green transformation in manufacturing provinces may enhance local CP. However, the indirect effect is significantly negative (-1.0933, $p < 0.01$), revealing that the relocation of pollution-intensive industries to neighboring provinces worsens their carbon performance. The total effect is significantly negative (-0.8535, $p < 0.05$), emphasizing the need for coordinated structural adjustment to prevent adverse spillovers from industrial restructuring.

Capital-Labor Ratio (lnclr): The capital-labor ratio shows a significantly positive direct effect (0.0558, $p < 0.05$), suggesting that capital-intensive development may promote CP through technological upgrading and energy-saving investment. The indirect effect is significantly negative (-0.1327, $p < 0.05$), implying that capital reallocation or industrial concentration in one province may crowd out investment in others, thus constraining their CP improvement. The total effect is statistically insignificant (-0.0769), indicating that capital intensity's regional benefits do not extend evenly across space.

Spatial Dependence Indicators: The estimated spatial autoregressive coefficient (ρ) is 0.1932 ($p < 0.05$), confirming the presence of significant spatial dependence in CP across provinces. This supports the existence of regional diffusion or demonstration effects in

carbon efficiency enhancement. The estimated error variance (σ^2_e) is 0.0032 ($p < 0.01$), indicating good model fit and reliability of the SDM estimation.

Overall, the SDM results reveal that HQED promotes CP through both direct and spatial channels, whereas energy intensity and industrial structure exert overall negative effects. Urbanization and marketization display mixed and region-specific impacts, while environmental investment generates substantial interregional synergy. These findings reinforce the importance of regionally differentiated policies, targeted structural adjustments, and coordinated environmental governance in enhancing CP.

4.6 Comparative Analysis and Scholarly Contribution

Building upon prior empirical findings, this section compares the results of the current study with those of related literature and elaborates on its incremental contributions. Three key aspects are highlighted:

4.6.1 Design and Applicability of the HQED Index

The HQED index developed in this study adopts a concise yet policy-oriented framework, offering a more practical alternative to existing measurement approaches. While some prior studies have constructed deeply nested and overly complex indicator systems (Shi et al., 2023; Tang et al., 2024), others rely on simplified proxies such as TFP or GTFP (Gong & Zhang, 2023; Guo et al., 2023) which may inadequately reflect the multifaceted nature of high-quality development.

In contrast, this study proposes a three-dimensional evaluation system encompassing economic performance, social equity, and ecological sustainability. This framework not only aligns with the strategic logic of China's development agenda but also corresponds directly to the SDGs, thereby reinforcing its international relevance. By integrating these dimensions, the index achieves a balance between theoretical robustness and empirical applicability, allowing for cross-provincial comparability while avoiding excessive complexity in indicator construction. Moreover, the practical orientation of the index enhances its policy utility, enabling it to serve as a diagnostic tool for monitoring progress and guiding differentiated development strategies.

4.6.2 Empirical Integration of the HQED-CP Relationship

The adoption of a progressive modeling strategy that combines static panel models, System GMM, and SDM provides a more comprehensive understanding of the HQED–CP relationship. While existing studies generally confirm a positive association between green innovation, industrial upgrading, or regional development and CP (Gao et al., 2022; Guo et al., 2024; Wang et al., 2024b), few have systematically evaluated HQED as a unified multidimensional driver (Fu & Tang, 2024). This study advances the literature in several ways. First, it demonstrates that HQED exerts a consistently positive influence on CP across both static and spatial frameworks, thereby validating the robustness of the relationship. Second, the dynamic analysis reveals that the long-run effect of HQED exceeds its short-run impact, highlighting the cumulative benefits of sustained institutional reform and structural upgrading. Third, the spatial econometric results identify significant direct and indirect spillover effects, indicating that improvements in HQED not only raise local CP but also diffuse positive impacts to neighboring provinces through mechanisms such as technology diffusion, policy coordination, and interregional industrial linkages.

Taken together, these findings extend prior work by uncovering both the temporal path dependence and spatial transmission channels of the HQED-CP nexus. This integrated perspective enriches theoretical understanding of how high-quality development fosters green transformation and provides empirical evidence for policy frameworks that emphasize cross-regional coordination and long-term institutional design.

4.6.3 Control Variable Differences Across Models

The estimated effects of control variables exhibit notable heterogeneity across different model specifications. For instance, urbanization and marketization, which reflect structural and institutional characteristics unique to China, demonstrate varying signs and statistical significance in the static, dynamic, and spatial models (Grubb et al., 2024; Long et al., 2024; Wang & Salman, 2022). These inconsistencies suggest that the influence of such variables is highly context-dependent, potentially shaped by regional development stages, governance structures, and resource endowments. From a methodological perspective, this variability underscores the importance of employing a multi-model strategy. While single-model studies may produce partial or even misleading interpretations of control variables, the comparative framework adopted here allows for a more nuanced assessment of their

conditional effects. Although this study does not conduct in-depth mechanism analysis of each control variable, the observed divergence in their estimated impacts reinforces the credibility of the main results, namely the consistent and positive role of HQED in driving CP.

Overall, the analysis highlights that the relationship between structural and institutional factors and CP cannot be generalized without considering regional and temporal contexts. At the same time, the robustness of the HQED coefficient across models confirms its central role in explaining green productivity dynamics. By triangulating results from multiple econometric approaches, this study not only strengthens the empirical validity of its core findings but also enriches the methodological toolkit available for future research on HQED and sustainability transitions.

In conclusion, this study advances the literature by establishing a streamlined yet comprehensive HQED index, deploying an integrated empirical strategy, and identifying robust spatial and dynamic impacts of HQED on CP. It provides new evidence supporting the policy relevance of HQED as a multidimensional catalyst for green economic transition, offering empirical insights for spatial coordination and sustainable development planning in China. Building on these findings, the next chapter summarizes the key conclusions of this research and puts forward corresponding policy recommendations to enhance CP through regionally coordinated HQED.

CHAPTER 5:

CONCLUSIONS

5.1 Introduction

This chapter builds upon the previous empirical analysis to systematically summarize the patterns and mechanisms through which High-Quality Economic Development (HQED) influences Carbon Productivity (CP). It highlights the study's theoretical contributions and empirical innovations, underscoring both its academic significance and practical value. Based on the integrated research findings, the chapter proposes feasible policy recommendations aimed at enhancing China's CP and advancing HQED, thereby providing both theoretical support and actionable pathways. In addition, the study reflects on its inherent limitations and offers directions for future research in this domain.

5.2 Summary of Key Research Findings

Drawing upon panel data for 30 Chinese provinces from 2008 to 2021, this study constructs a multi-layer empirical framework rooted in sustainable development theory, the low-carbon economy and decoupling hypothesis, and spatial econometrics. By sequentially applying fixed-effects static panel models, the system GMM estimator, and the SDM, the study provides a comprehensive assessment of the mechanisms and spatial dynamics through which HQED affects CP. The major findings are summarized as follows.

a) Spatiotemporal Evolution Patterns

During the study period, China's provincial CP followed a steadily increasing trajectory, reflecting progressive improvements in energy efficiency, technological advancement, and ecological transition. However, substantial regional disparities persist, characterized by a distinct spatial pattern of "higher in the east, lower in the west." Provinces such as Jiangsu, Zhejiang, and Guangdong consistently outperformed inland regions like

Gansu and Guizhou, due to differences in industrial bases, innovation capacity, and environmental governance effectiveness.

HQED likewise exhibits regional imbalance, with eastern provinces performing better than central and western regions across all three HQED dimensions: economic efficiency, ecological sustainability, and social inclusiveness. The observed strong positive correlation between CP and HQED suggests that provinces adopting more advanced development models tend to achieve superior carbon efficiency.

Global Moran's I coefficients for both CP and HQED are significantly positive throughout the sample period, confirming persistent spatial autocorrelation. Additionally, spatial visualization results (Figures 4-3 and 4-4) and LISA analyses reveal H-H and L-L clustering patterns, reflecting regional development path dependencies and the presence of positive spatial externalities. For example, high-CP provinces are often geographically proximate to one another, indicating localized synergy effects.

These findings underscore the strategic role of HQED in driving regional CP not only through internal mechanisms, but also by shaping the broader spatial landscape of sustainable development. They also point to the importance of adopting regionally differentiated and spatially coordinated policy strategies to reduce disparities and support the national dual-carbon agenda.

b) Static Analysis Results

The results from the static panel model, estimated using fixed effects with province-clustered robust standard errors, confirm that HQED has a statistically significant and positive impact on CP. As shown in Table 4-5, the coefficient of $\ln hqed$ is 1.3558 ($p < 0.01$), indicating that a 1% increase in HQED is associated with approximately a 1.36% increase in CP, holding all other factors constant.

This result highlights the critical role of HQED in enhancing carbon efficiency. The HQED index, developed using the entropy method to objectively weigh its dimensions, reflects integrated efforts across economic, ecological, and social domains. The magnitude of the coefficient indicates that these improvements in development quality translate into substantial gains in CP at the provincial level.

With regard to control variables, the model reveals that energy intensity ($\ln ei$) has a significantly negative effect on CP, reaffirming that higher energy consumption per unit of output is a key constraint on efficiency. Government environmental expenditure ($\ln env$) is positively and significantly associated with CP, illustrating the importance of public ecological investment. Urbanization ($\ln ur$) shows a marginally significant negative effect, potentially due to infrastructure expansion and industrial clustering during early urbanization phases. Other controls, including the capital-labor ratio ($\ln clr$), the share of secondary industry ($\ln ss$), and the marketization level ($\ln ml$), are not statistically significant, indicating a relatively limited independent contribution to CP when HQED is included.

Overall, the static model provides robust empirical support for HQED as a fundamental driver of CP, reinforcing the importance of promoting high-quality development pathways to achieve environmental and economic coordination.

c) Dynamic Effects of HQED

Dynamic panel estimation using the System GMM approach further validates the significant and persistent impact of HQED on CP, while shedding light on the temporal adjustment process.

The coefficient of the lagged dependent variable $L.\ln cp$ is 0.8935 ($p < 0.01$), suggesting strong path dependence in CP. This reflects the cumulative and historically embedded nature of technological upgrading, industrial transformation, and institutional evolution across regions.

HQED remains a significant contributor to CP, with a coefficient of 1.9815 ($p < 0.05$) in the robust two-step specification, substantially larger than in the static model. This difference implies that the long-term benefits of HQED accumulate and intensify over time, reinforcing the importance of sustained improvements in economic structure, innovation capacity, and ecological governance.

The model passes key robustness checks: the Arellano-Bond test confirms no second-order serial correlation ($AR(2) p = 0.314$), and the Sargan test supports instrument validity ($p = 0.333$). These results affirm the reliability of the dynamic estimation and substantiate the argument that long-term, stable implementation of HQED-oriented reforms is essential for sustained CP improvement.

d) *Spatial Spillover and Feedback Effects*

The results of the SDM indicate that HQED not only enhances local CP, but also exerts substantial spatial spillover and feedback effects across provincial borders.

As shown in Table 4-17, HQED significantly enhances CP both locally and regionally. The direct effect reaches 1.0583 ($p < 0.01$), while the spillover effect is 1.0116 ($p < 0.01$), underscoring HQED's regional transmission through mechanisms such as industrial coordination and policy diffusion. The total impact (2.0698) confirms HQED's systemic role in promoting green development across provinces.

Control variables exhibit diverse spatial dynamics. Energy intensity and the share of secondary industry negatively affect CP overall, despite some localized or spillover compensation. Environmental expenditure shows no significant local impact but yields strong positive spillovers, highlighting the importance of cross-regional ecological investment. Urbanization and marketization demonstrate mixed effects, while the capital-labor ratio enhances local CP but lacks regional transmission. The spatial autoregressive coefficient ($\rho = 0.1932$, $p < 0.05$) confirms significant spatial dependence in CP outcomes, reinforcing the need for coordinated regional strategies. The spatial model demonstrates that HQED functions not merely as a provincial driver but as a regional accelerator of CP, reinforcing the urgency of inter-provincial coordination and joint low-carbon governance.

e) *Overall Summary*

The empirical findings derived from static, dynamic, and spatial econometric models collectively confirm that HQED is a statistically significant and policy-relevant driver of CP in China. The static model demonstrates a robust average effect, while the dynamic panel estimation reveals that the impact of HQED intensifies over time, reflecting strong path-dependent characteristics. The spatial model further illustrates that HQED generates substantial spillover and feedback effects across provincial boundaries, amplifying its influence beyond local jurisdictions.

These results underscore the importance of development strategies that are not only high in quality, but also sustained in the long term, regionally coordinated, and systematically integrated. Policies aiming to enhance CP should prioritize sustained investment in innovation, ecological sustainability, and industrial restructuring under the broader framework of HQED. By leveraging its cumulative and spatial transmission

mechanisms, HQED can serve as a foundational pillar for achieving China's dual carbon goals and fostering a green, inclusive, and resilient development trajectory.

Overall, this study successfully fulfills its research objectives. The HQED index was constructed based on theoretical foundations and empirical weighting, allowing for cross-provincial comparisons (Objective i). Static regression confirms the average effect of HQED on CP (Objective ii), while dynamic analysis reveals its persistent and time-lagged impacts (Objective iii). Finally, spatial econometric results provide strong evidence of spillover effects across neighboring regions, validating HQED's broader regional role (Objective iv).

5.3 Policy Recommendations

a) Comprehensively Promote HQED to Steadily Enhance CP

As confirmed by the empirical results, HQED serves as a fundamental and multi-dimensional driver of CP improvement. This effect stems not only from the coordinated advancement of economic efficiency, ecological protection, and social well-being, but also from the internal synergies among industrial structure optimization, technological innovation, and green institutional transformation. Recent studies have emphasized that integrated development strategies can yield substantial gains in both environmental performance and carbon efficiency (Işık et al., 2025).

China is encouraged to firmly commit to a green and low-carbon development pathway, embedding HQED principles into its macroeconomic policy framework and long-term growth strategies. Priority should be given to accelerating industrial upgrading, fostering innovation ecosystems, and strengthening environmental governance mechanisms. Institutional consistency is also vital, as the cumulative benefits of HQED emerge through gradual structural and behavioral changes over time.

In particular, the central government should continue to guide the transition from factor and investment-driven development toward innovation and quality-driven growth, aligning fiscal, technological, and regulatory instruments with HQED objectives. By doing so, HQED can become a systemic enabler of CP, fostering an economy that is efficient, equitable, and ecologically sustainable.

b) Facilitate Industrial Structural Upgrading to Strengthen the “Structural Effect” of HQED

The empirical findings highlight that industrial structure plays a pivotal role in shaping both HQED and CP, acting as a core transmission channel for green and high-quality growth. To reinforce the “structural effect” of HQED, greater policy attention should be directed toward accelerating industrial transformation and upgrading, with an emphasis on reducing dependence on energy-intensive and high-emission sectors while expanding low-carbon, high-value-added, and service-oriented industries. On one hand, traditional manufacturing sectors should be encouraged to pursue intelligent, digital, and green transformation, thereby reducing carbon intensity and improving production efficiency (Cao et al., 2024). On the other hand, strategic support should be channeled toward emerging industries, including renewable energy, advanced equipment manufacturing, green materials, and modern service sectors, which are vital for driving both economic quality and environmental performance (Ding et al., 2024). Empirical studies have shown that a shift toward advanced manufacturing and services significantly improves green total factor productivity and carbon efficiency.

Regionally differentiated strategies are essential. Eastern coastal provinces should deepen their industrial base upgrading and foster high-end, green niche markets while avoiding structural homogeneity and overconcentration in traditional sectors. Central and western provinces, meanwhile, should promote the development of localized service industries and clean manufacturing, tailored to their resource endowments and comparative advantages. Avoiding redundant investment in outdated heavy industries is critical to achieving HQED at lower environmental cost and higher ecological returns.

Ultimately, industrial structure optimization not only enhances the economic dimension of HQED but also serves as a key lever to improve CP by fostering a more resilient, innovative, and resource-efficient industrial ecosystem.

c) Optimize the Energy Structure to Enhance the “Green Effect” of HQED

The empirical analysis confirms that energy intensity has a significantly negative effect on CP, underscoring the urgent need to improve energy efficiency and transition toward a cleaner, low-carbon energy structure. The “green effect” of HQED can be further strengthened by reshaping the energy mix to favor renewable and clean energy sources, thereby decoupling economic growth from carbon emissions.

Both governmental institutions and enterprises must take proactive steps to reduce reliance on fossil fuels, particularly coal, and accelerate the deployment of renewable energy technologies such as solar, wind, and hydropower. In addition, promoting energy-saving technologies, enhancing industrial energy management systems, and improving the efficiency of energy utilization across sectors are crucial for reducing energy consumption per unit of GDP. Research has shown that cleaner energy structures not only contribute directly to CP enhancement but also exert positive spillover effects on neighboring regions (Shi et al., 2024).

Particular attention should be paid to the central and western regions of China, where resource endowments are favorable for the expansion of solar, wind, and hydropower capacity. Encouraging these regions to adopt decentralized, renewable-centered energy development models will support HQED while fostering a virtuous cycle between carbon reduction and economic growth. Moreover, improving energy-related infrastructure and facilitating inter-provincial grid integration can help maximize the systemic efficiency of clean energy deployment.

Ultimately, optimizing the energy structure is not only a core requirement of green transformation but also a practical and effective mechanism to reinforce the environmental dimension of HQED and unlock sustainable gains in CP.

d) Promote Green Urbanization to Mitigate Local Pressures and Enhance Spatial Benefits

This study finds that urbanization has a significant negative direct effect on local CP, while generating modest positive spatial spillovers. These complex results reflect the dual role of urbanization in China's development. On one hand, rapid urban expansion increases energy demand across industry, transportation, and buildings, often relying on fossil fuels. Infrastructural development also contributes to short-term carbon surges with limited immediate economic returns. Furthermore, lifestyle transitions, such as higher consumption of electricity, private vehicles, and resource-intensive goods add to carbon pressure (Wang, 2023).

On the other hand, urbanization also contributes indirectly to CP improvement through mechanisms such as industrial upgrading, technological innovation, and human capital accumulation. Urban areas serve as hubs for green industries and advanced services,

promote innovation spillovers, and cultivate a more skilled and environmentally conscious workforce. These positive effects, however, often emerge over time and vary across regions depending on policy capacity and urban maturity.

To manage these diverging effects, China's urbanization policy should shift from expansion-focused planning to an integrated, low-carbon, and innovation-driven approach.

First, optimize the energy structure in urban areas by accelerating the deployment of renewable energy, promoting distributed energy systems, and improving building energy efficiency. Energy conservation programs and green infrastructure should be embedded into urban planning and public service systems.

Second, promote green industrial transformation in cities by phasing out high-emission sectors and encouraging the growth of low-carbon and circular economy industries. Strategic investments should target green tech clusters, clean mobility, and smart logistics.

Third, enhance urban innovation capacity by increasing public R&D investment in low-carbon technologies and strengthening collaboration between governments, firms, and research institutions. Support mechanisms should be built to accelerate the commercialization and diffusion of green innovations.

Fourth, invest in human capital development by expanding access to quality education and vocational training in green technologies and sustainable practices. Cultivating a skilled workforce with environmental awareness can boost low-carbon production and consumption patterns.

Fifth, improve urban planning and governance by integrating CP targets into land-use zoning, transportation design, and construction standards. Robust environmental assessments and carbon budgeting tools should be adopted to guide cities toward low-emission pathways.

e) Foster State-Market Synergy to Unlock the CP Potential of Marketization

The empirical results suggest that while marketization has improved CP in the short term through resource reallocation, its long-term and spillover effects remain weak or insignificant. This indicates structural deficiencies in the current market system, particularly the disconnect between private firms' short-term profit orientation and the strategic low-

carbon role of state-owned enterprises (SOEs). To address these asymmetries, the following strategies are proposed to align market incentives with the green transformation of China's economic system.

First, strengthen market mechanisms to steer SOEs toward low-carbon innovation. This includes expanding mixed-ownership reform in carbon-intensive sectors such as energy and transport to integrate private capital and technology. SOEs should take the lead in forming low-carbon industry alliances and technical standard systems, thereby lowering coordination costs across fragmented markets. Furthermore, carbon pricing mechanisms, such as carbon emissions trading scheme and green taxation, should be improved to reflect environmental costs more accurately and create effective signals for both SOEs and private actors (Wu et al., 2023a).

Second, establish collaborative platforms that promote SOE-private sector innovation. Green joint ventures, collaborative R&D programs, and shared intellectual property platforms can foster technological diffusion, particularly in sectors where SOEs dominate green infrastructure. Policy tools such as a “Low-Carbon Innovation Fund” or a “Carbon Credit Exchange System” could support the commercialization and market circulation of SOE-generated green technologies, enabling private firms to adopt and scale them (Chen, 2024).

Third, enhance performance evaluation systems to reward market-aligned low-carbon behavior. SOEs should be assessed based on their collaboration with private enterprises, the degree of market-based technology transfer, and improvements in CP relative to private sector benchmarks. Public ranking, peer comparison, and carbon-efficiency KPIs can foster competition, institutional learning, and more agile responses to market signals (Fu et al., 2024a).

These strategies reflect the broader logic of combining an “effective market” with a “capable government.” Rather than fully liberalizing carbon governance or relying solely on administrative mandates, China should adopt a dual-track approach: using market signals to guide state-owned enterprises toward greener investment, while leveraging SOEs' innovation capacity and institutional reach to empower private sector participation (Shang et al., 2024). This alignment between market incentives and public capacity can gradually transform the mixed effects of marketization into a positive-sum pathway for CP.

f) Leverage Fiscal Environmental Investment to Promote HQED and CP

The policy pathways proposed in Sections a) to e), including structural upgrading, energy reform, urban transformation, and market incentives—require strong and well-targeted financial backing to ensure full implementation. This study finds that environmental fiscal expenditure is not only a direct driver of CP, but also a key enabling mechanism for delivering the goals of HQED. However, fragmented frameworks and limited coordination have weakened its full potential. The following steps are proposed towards a remedy.

First, a stable growth mechanism for local environmental spending should be established. As local governments lead in applying HQED-oriented policies, they need stronger fiscal incentives and clearer mandates. Increasing the share of local budgets allocated to low-carbon programs, while improving spending efficiency, will help meet national carbon targets and support policy execution across sectors.

Second, environmental fiscal policy should act as a catalyst for industrial structure upgrading, as discussed in Section b). Local governments can use targeted spending to support clean industrial parks, green technology zones, and low-carbon value chains. These investments promote synergy among firms and facilitate innovation diffusion, accelerating the transition to green and high-productivity industries (Zhang et al., 2024a).

Third, environmental investment must better support green urbanization, complementing the urban strategies outlined in Section d). Public spending should prioritize low-carbon urban infrastructure, such as green transport, energy-efficient buildings, and urban ecological restoration. Third-party project evaluation and dynamic budgeting can ensure that investments directly boost CP in urban areas.

Fourth, spatial coordination should be enhanced to amplify the indirect and spillover effects of HQED, echoing findings from the spatial model. Interregional cooperation funds, ecological compensation mechanisms, and shared infrastructure platforms should be developed to internalize regional externalities and promote joint governance.

In sum, environmental fiscal policy is the financial foundation that enables and magnifies the effects of the structural, spatial, and institutional strategies outlined in Sections a) to e). Improving the structure, scale, and coordination of local environmental spending is essential to transforming HQED into sustained gains in CP.

g) Construct a Spatial Cooperation Mechanism for Coordinated Regional Development to Promote CP Synergies

The spatial analysis in this study shows that HQED generates significant spillover effects on CP across regions. These externalities highlight the need for stronger interregional coordination to avoid fragmented governance and unlock broader low-carbon synergies. While local initiatives are important, a spatially integrated strategy is essential to maximize the collective impact of HQED.

First, regional policy coordination should be institutionalized through cross-provincial platforms and cooperation mechanisms, such as joint development zones, integrated infrastructure planning, and shared green investment projects. Provinces with stronger fiscal and technological capacity, particularly those in the east, should facilitate technology transfer, collaborative innovation, and financial support for central and western regions (Sheng et al., 2024).

Second, a differentiated policy framework should be implemented according to regional development stages, resource endowments, and governance capacity (Lin et al., 2025). Tailored targets and policy instruments can minimize mismatches in implementation capacity and enable each region to contribute to national carbon goals in a realistic and efficient manner.

Third, a horizontal fiscal compensation mechanism should be established to internalize the costs and benefits of spatial spillovers. Regions that provide environmental public goods or bear the costs of early decarbonization should be compensated by those that benefit from these efforts. Such a system would better align incentives, mitigate local resistance, and promote balanced development.

By enhancing regional coordination, China can transform HQED from a localized initiative into a spatially distributed and mutually reinforcing low-carbon development strategy. This complements the fiscal, structural, and institutional reforms discussed in Sections a) to f), and lays the groundwork for a nationally integrated path toward CP improvement.

5.4 Research Limitations

Although this study has yielded a series of valuable findings, it is not without limitations. The main limitations are as follows.

a) Data Limitations

The carbon emissions data used in this study, obtained from the CEADs database, are available only through 2021. As a result, the analysis does not reflect more recent developments related to carbon governance and green transition initiatives introduced after that period.

b) Model Limitations

Although static, dynamic, and spatial econometric models were sequentially applied to ensure robustness, there may still be unobserved factors that influence the relationship between HQED and CP. The selected variables and empirical models inevitably simplify the complexity of real-world economic systems and may not fully capture all relevant dynamics.

c) Lack of Region-Specific Analysis

The study does not conduct separate regressions for eastern, central, and western provinces. While the national-level approach ensures overall comparability, it may overlook region-specific heterogeneity in transmission mechanisms and policy responses.

5.5 Future Research Directions

Building on the current findings and in response to the identified limitations, future research could be extended in the following directions.

a) Expand Data Scope

Future studies should incorporate more recent and longer-span data to improve the timeliness and credibility of empirical conclusions. Extending the data period beyond 2021 would allow for a more accurate identification of long-term trends and the evolving effects of national low-carbon strategies.

b) Improve Models

Employing more refined and flexible econometric models can help better account for potential influencing factors and enhance the accuracy of empirical results. Future research may consider using advanced modeling techniques to more effectively capture the complex, evolving, and spatially heterogeneous nature of the HQED–CP relationship.

c) Conducting Regionally Differentiated Analyses

Future research should consider conducting subgroup regressions across eastern, central, western, and northeastern provinces to better capture regional variation in development patterns. This approach can reveal localized drivers of CP and inform more precise and effective policy design.

REFERENCES

- Ajmi, A. N., Bekun, F. V., Gyamfi, B. A., & Meo, M. S. (2023). A bibliometric review analysis into environmental kuznets curve phenomenon: A retrospect and future direction. *Heliyon*, 9(11), 2-19.
- Alli, Y. A., Bamisaye, A., Bamidele, M. O., Etafo, N. O., CHKIRIDA, S., Lawal, A., Hammed, V. O., Akinfenwa, A. S., Hanson, E., & Nwakile, C. (2024). Transforming waste to wealth: Harnessing carbon dioxide for sustainable solutions. *Results in Surfaces and Interfaces*, 100321.
- Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, 76(375), 598-606.
- Andres, R., & Marland, G. (1994). Historic patterns of CO₂ emissions from fossil fuels: Implications for stabilization of emissions (No. CONF-940632-25). *Oak Ridge National Lab., TN (United States); Oak Ridge Inst. for Science and Education, TN (United States)*.
- Ang, B. W., & Zhang, F. Q. (2000). A survey of index decomposition analysis in energy and environmental studies. *Energy*, 25(12), 1149-1176.
- Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis*, 20(1), 1-17.
- Anselin, L. (2022). Spatial econometrics. *Handbook of Spatial Analysis in the Social Sciences*, 101-122.
- Anselin, L., & Florax, R. J. (1995a). New directions in spatial econometrics: Introduction. In *New Directions in Spatial Econometrics* (pp. 3-18). Springer Berlin Heidelberg.
- Anselin, L., & Florax, R. J. (1995b). New directions in spatial econometrics: Introduction. In *New Directions in Spatial Econometrics* (pp. 3-18). Springer.
- Anselin, L., Gallo, J. L., & Jayet, H. (2008). Spatial panel econometrics. In *The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice* (pp. 625-660). L. Matyas and P. Sevestre, eds.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277-297.
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29-51.
- Barro, R. J. (2002). *Quantity and Quality of Economic Growth*. Banco Central de Chile.
- Besada, H., Denton, F., & O'Bright, B. (2013). Development and Sustainability in a Warming World: Measuring the Impacts of Climate Change. *Background Research*

Paper, Submitted to the High Level Panel on the Post-2015 Development Agenda, United Nations.

- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115-143.
- Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, 47(1), 239-253.
- Briant, J. (2015). *Development goals for the new millennia: discourse analysis of the evolution of the 2001 millennium development goals and 2015 sustainable development goals*. Arizona State University.
- Browne, P., Lima, A., Arcucci, R., & Quilodr  n-Casas, C. (2022). Forecasting emissions through Kaya identity using Neural Ordinary Differential Equations. *arXiv preprint arXiv*, 2201.02433.
- Cao, B., Li, L., Zhang, K., & Ma, W. (2024). The influence of digital intelligence transformation on carbon emission reduction in manufacturing firms. *Journal of environmental management*, 367, 121987.
- Cao, P., Li, X., Cheng, Y., & Shen, H. (2022). Temporal-spatial evolution and driving factors of global carbon emission efficiency. *International Journal of Environmental Research Public Health*, 19(22), 14849.
- Cao, Y., Chai, L., Yan, X., & Liang, Y. (2020). Drivers of the growing water, carbon and ecological footprints of the Chinese diet from 1961 to 2017. *International Journal of Environmental Research Public Health*, 17(5), 1803.
- Castells-Quintana, D., del Pilar Lopez-Urbe, M., & McDermott, T. K. (2018). Adaptation to climate change: A review through a development economics lens. *World Development*, 104, 183-196.
- Cato, M. S. (2022). The Chequered History of Climate Finance. *Sustainable Finance: Using the Power of Money to Change the World*, 39-59.
- Chamchong, P., & Boossabong, P. (2021). Innovative city index and its application for stimulating inclusive, sustainable and connected innovative city development. *Journal of Housing the Built Environment*, 36, 191-213.
- Chang, G., & Li, Z. (2009). The Historical Evolution of the Concept of Development and Its Contemporary Destination. *Journal of Liaoning Administration College*, 8(6), 37-39.
- Chao, x., & Hui, k. (2009). Measurement of the Quality of China's Economic Growth. *The Journal of Quantitative & Technical Economics*, 26, 75-86.
- Chen, C. (2024). Can reverse mixed-ownership reform promote green transformation of private enterprises? *Heliyon*, 10(22), 2-17.
- Chen, L., & Huo, C. (2022). The measurement and influencing factors of high-quality economic development in China. *Sustainability*, 14(15), 9293.

- Chen, M., Li, D., & Wu, J. (2022). Construction of the Evaluation Index System of High - quality Development Based on the Connotation of "Needs for a Better Life". *Management Science Engineering*, 11, 444.
- Chen, M., Sinha, A., Hu, K., & Shah, M. I. (2021). Impact of technological innovation on energy efficiency in industry 4.0 era: Moderation of shadow economy in sustainable development. *Technological Forecasting Social Change*, 164, 120521.
- Chen, S. (2012). Evaluation of the Low - carbon Economic Transformation Process in Various Regions of China. *Economic Research Journal*, 8, 32-44.
- Chen, S., & Chen, D. (2018). Haze Pollution, Government Governance and High-quality Economic Development. *Economic Research Journal*, 53(02), 20-34.
- Chen, W., Han, M., Bi, J., & Meng, Y. (2023). China can peak its energy-related CO2 emissions before 2030: Evidence from driving factors. *Journal of Cleaner Production*, 429, 139584.
- Chen, W., & Yao, L. (2024). Evaluating the carbon total factor productivity of China: based on Cobb-Douglas production function. *Environmental Science and Pollution Research International*, 31(9), 13722-13738.
- Cheng, T., Wang, J., Haworth, J., Heydecker, B., & Chow, A. (2014). A dynamic spatial weight matrix and localized space–time autoregressive integrated moving average for network modeling. *Geographical Analysis*, 46(1), 75-97.
- Chong, C. H., Tan, W. X., Ting, Z. J., Liu, P., Ma, L., Li, Z., & Ni, W. (2019). The driving factors of energy-related CO2 emission growth in Malaysia: The LMDI decomposition method based on energy allocation analysis. *Energy Renewable Sustainable Energy Reviews*, 115, 109356.
- Cui, Y., Tian, H., An, D., & Jia, Y. (2024). Quality of life and regional economic development: Evidence from China. *PLoS One*, 19(5), e0298389.
- Di, K., Chen, W., Zhang, X., Shi, Q., Cai, Q., Li, D., Liu, C., & Di, Z. (2023). Regional unevenness and synergy of carbon emission reduction in China's green low-carbon circular economy. *Journal of Cleaner Production*, 420, 138436.
- Dietz, T., & Rosa, E. A. J. H. e. r. (1994). Rethinking the environmental impacts of population, affluence and technology, *Human Ecology Review*, 1(2), 277-300.
- Ding, J., Liu, B., & Shao, X. J. E. E. (2022). Spatial effects of industrial synergistic agglomeration and regional green development efficiency: Evidence from China. *Energy Economics*, 112, 106156.
- Ding, S., Li, R., Liu, Z., Li, Y., & Geng, S. (2024). Sustainable potential of the strategic emerging industries: Insights from technological innovation, economy, and ecology. *Journal of Cleaner Production*, 434, 140038.
- Dogan, E., & Inglesi-Lotz, R. (2020). The impact of economic structure to the environmental Kuznets curve (EKC) hypothesis: evidence from European countries. *Environmental Science Pollution Research*, 27, 12717-12724.

- Dong, W., Huang, J., Guo, Y., & Ren, F. (2016). Responsibility for Historical Climate Change Induced from Developed and Developing World Anthropogenic Carbon Emissions. *Atlas of Climate Change: Responsibility and Obligation of Human Society*, 185-191.
- Dornbusch, R., & Fischer, S. (1979). Sterling and the external balance. In: National Bureau of Economic Research Cambridge, Mass., USA.
- Du, Q., Deng, Y., Zhou, J., Wu, J., & Pang, Q. (2022). Spatial spillover effect of carbon emission efficiency in the construction industry of China. *Environmental Science Pollution Research*, 29(2), 2466-2479.
- Ehrlich, P. R., & Holdren, J. P. (1971). Impact of Population Growth: Complacency concerning this component of man's predicament is unjustified and counterproductive. *Science*, 171(3977), 1212-1217.
- Elhorst, J. P. (2014). Spatial panel data models. *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, 37-93.
- Enkvist, P., Nauclér, T., & Riese, J. (2008). What countries can do about cutting carbon emissions. *McKinsey Quarterly*, 2, 34.
- Fan, G., & Zhang, X. (2019). Toward high-quality development in the People's Republic of China.
- Fan, J., Yu, X., & Zhou, L. (2018). Urbanization, Urban-Rural Gap and Inclusive Growth in China. *Quantitative & Technological Economics Research*, 35(4), 41-60.
- Fang, M., Yang, S., Zhou, J., & Lei, Y. (2020). Research on the Innovation - Driven Development Path of Industrial Agglomeration in the Yangtze River Economic Belt under the Background of High - Quality Development. *China Soft Science* (05), 137-150.
- Feng, G., Sulaiman, N., Karim, Z. A., & Sieng, L. W. (2024a). Innovation, Industrial Structure Upgrading, and Environmental Regulation: A Literature Review on Drivers of High-Quality Economic Development in China. *Journal of Ecohumanism*, 3(8), 8117–8130.
- Feng, S., Shafiei, M. W. M., Ng, T. F., Ren, J., & Jiang, Y. (2024b). The intersection of economic growth and environmental sustainability in China: Pathways to achieving SDG. *Energy Strategy Reviews*, 55, 101530.
- Fingleton, B. (2003). Externalities, economic geography, and spatial econometrics: conceptual and modeling developments. *International Regional Science Review*, 26(2), 197-207.
- Fotheringham, A. S., Charlton, M. E., & Brunsdon, C. (1998). Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. *Environment Planning A*, 30(11), 1905-1927.

- Fu, G., & Tang, J. (2024). Simulation and Regulation of High-Quality Economic Development Based on System Dynamics and DPSIR Model. *Sustainability*, 16(14), 6130.
- Fu, H.-C., Zeng, S., Sun, D., & Lin, J. (2024a). Mixed-Ownership Reform and Innovation: An Examination of State-Owned Enterprises. *IEEE Transactions on Engineering Management*, 71, 14450-14471.
- Fu, M., Mei, Y., Tian, L., & Zhang, C. (2024b). Analysis of regional carbon productivity differences and influencing factors—based on new green decomposition model. *Frontiers in Physics*, 12, 1398261.
- Gao, L., Ma, C., Zeng, J., Wang, B., & Li, Y. (2019). How did poverty reduction in China contribute to the world? Viewing from the implementation of the UN MDGs and SDGs. *Chinese Journal of Urban Environmental Studies*, 7(01), 1940007.
- Gao, P., Wang, Y., Zou, Y., Su, X., Che, X., & Yang, X. (2022). Green technology innovation and carbon emissions nexus in China: Does industrial structure upgrading matter? *Frontiers in Psychology*, 13, 951172.
- Gbadeyan, O. J., Muthivhi, J., Liganiso, L. Z., & Deenadayalu, N. (2024). Decoupling economic growth from carbon emissions: a transition toward low-carbon energy systems—a critical review. *Clean Technologies*, 6(3), 1076-1113.
- Geary, R. C. (1954). The contiguity ratio and statistical mapping. *The Incorporated Statistician*, 5(3), 115-146.
- Getis, A. (2009). Spatial weights matrices. *Geographical Analysis*, 41(4), 404-410.
- Gong, M., & Zhang, N. (2023). Drivers of China's high-quality development: The role of intangible factors. *Economic Modelling*, 124, 106294.
- Goodchild, M. F. (1992). Geographical information science. *International Journal of Geographical Information Systems*, 6(1), 31-45.
- Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., & Wiltshire, A. (2010). Implications of climate change for agricultural productivity in the early twenty-first century. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554), 2973-2989.
- Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American free trade agreement. In: National Bureau of economic research Cambridge, Mass., USA.
- Grubb, M., Jordan, N. D., Hertwich, E., Neuhoﬀ, K., Das, K., Bandyopadhyay, K., Van Asselt, H., Sato, M., Wang, R., Pizer, B., & Oh, H. (2022). Carbon Leakage, Consumption, and Trade. *Annual Review of Environment and Resources*, 47(1), 753-795.
- Grubb, M., Poncia, A., & Pasqualino, R. (2024). Dynamics of the Energy Transition: Innovation, Transition Economics, Path Dependency, and Decision Making. *World Bank Working Paper*, 7(11), 2024.

- Guan, Y., Shan, Y., Huang, Q., Chen, H., Wang, D., & Hubacek, K. (2021). Assessment to China's recent emission pattern shifts. *Earth's Future*, 9(11), e2021EF002241.
- Guan, Y., Wang, H., Guan, R., & Ding, L. (2022). Measuring inclusive green total factor productivity from urban level in China. *Frontiers in Environmental Science*, 10, 966246.
- Güngör, S. (2023). *Assessment of Energy Efficiency Related Indicators and Comparing Selected Countries by Scoring Their Energy Efficiency* Middle East Technical University (Turkey)].
- Guo, L., Tan, W., Xu, Y., & Tang, Q. (2024). Curbing regional carbon emissions through green technology innovation: an empirical analysis in China. *Environment, Development and Sustainability*, 1-24.
- Guo, X., Li, M., Wang, Y., & Mardani, A. (2023). Does digital transformation improve the firm's performance? From the perspective of digitalization paradox and managerial myopia. *Journal of Business Research*, 163, 113868.
- Gyamfi, B. A., Adedoyin, F. F., Bein, M. A., & Bekun, F. V. (2021). Environmental implications of N-shaped environmental Kuznets curve for E7 countries. *Environmental Science Pollution Research*, 28, 33072-33082.
- Hao, J., Gao, F., Fang, X., Nong, X., Zhang, Y., & Hong, F. (2022). Multi-factor decomposition and multi-scenario prediction decoupling analysis of China's carbon emission under dual carbon goal. *Science of the Total Environment*, 841, 156788.
- Hariram, N., Mekha, K., Suganthan, V., & Sudhakar, K. (2023). Sustainalism: An integrated socio-economic-environmental model to address sustainable development and sustainability. *Sustainability*, 15(13), 10682.
- Hashmi, S. H., Fan, H., Fareed, Z., & Shahzad, F. (2021). Asymmetric nexus between urban agglomerations and environmental pollution in top ten urban agglomerated countries using quantile methods. *Environmental Science Pollution Research*, 28(11), 13404-13424.
- Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, 1251-1271.
- Hon, K. (2013). The Implications of Western Ecological Socialism for Ecological Civilization in China. *Journal of the Northwest Normal University*, 12, 32678.
- Hou, S. B., Yu, K. K., & Fei, R. L. (2023). How does environmental regulation affect carbon productivity? The role of green technology progress and pollution transfer. *Journal of Environmental Management*, 345, 118587., Article 118587.
- Hu, W., & Wang, D. (2020). How does environmental regulation influence China's carbon productivity? An empirical analysis based on the spatial spillover effect. *Journal of Cleaner Production*, 257, 120484, Article 120484.

- Huang, C., Zhang, X., & Liu, K. (2021). Effects of human capital structural evolution on carbon emissions intensity in China: A dual perspective of spatial heterogeneity and nonlinear linkages. *Renewable Sustainable Energy Reviews*, 135, 110258.
- Huang, D. (2022). Green finance, environmental regulation, and regional economic growth: from the perspective of low-carbon technological progress. *Environmental Science Pollution Research*, 29(22), 33698-33712.
- Huo, T., Cao, R., Du, H., Zhang, J., Cai, W., & Liu, B. (2021). Nonlinear influence of urbanization on China's urban residential building carbon emissions: New evidence from panel threshold model. *Science of the Total Environment*, 772, 145058.
- Ikporukpo, C., & Ikporukpo, N. N. (2024). Loss and Damage Financing in the Climate Justice Debate. *Advances in Social Sciences Research Journal*, 4(10), 1365-1370.
- Işık, C., Ongan, S., & Islam, H. (2025). Global environmental sustainability: the role of economic, social, governance (ECON-SG) factors, climate policy uncertainty (EPU) and carbon emissions. *Air Quality, Atmosphere & Health*, 18(3), 851-866. <https://doi.org/10.1007/s11869-024-01675-3>
- Jian, X., & Nie, C. (2020). Measurement of China's High-quality Development: 1978-2018. *The Economist*, 1(6), 49-58.
- Jiang, Y., & Chen, A. (2018). The Influence Mechanism of the Servitization of Industrial Structure on the Growth Rate of Total Factor Productivity. *Reform* (05), 87-96.
- Jiang, Y., Zheng, Y., & Zhu, L. (2023). *Unequal transition: The Widening Wealth Gap Amidst China's Rapid Growth* (No. 955). Working Paper.
- Jin, B. (2018). The Institutional Logic and Governance Thinking of China's 40 - year Reform and Opening - up. *Economic Management*, 6, 5-16.
- Jin, W., & SUN, B. (2019). The Digital Economy Promotes High-quality Economic Development: A Theoretical Analysis Framework. *The Economist*, 2(2), 66-73.
- Jing, C., & Iván, N. G. (2023). A bibliographic review of China's economic development from 1949 to 2023. *Ekonomicko-Manazerske Spektrum*, 17(1), 87-103.
- Jorgenson, D. W., & Griliches, Z. (1967). The explanation of productivity change. *The Review of Economic Studies*, 34(3), 249-283.
- Kang, W., Liang, B., Xia, K., Xue, F., & Li, Y. (2021). Decoupling of carbon emissions from economic growth: an empirical analysis based on 264 prefecture-level cities in China. *Chinese Journal of Urban Environmental Studies*, 9(03), 2150017.
- Kaya, Y. (1990). Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios. *Intergovernmental Panel on Climate Change/Response Strategies Working Group*, May.
- Kaya, Y., & Yokobori, K. (1997). *Environment, energy, and economy: strategies for sustainability* (Vol. 4). Tokyo, Japan: United Nations University Press.

- Kelejian, H. H., & Prucha, I. R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The journal of real estate finance economics*, 17, 99-121.
- Kim, K., & Brewer, S. C. (2020). Spatial Econometrics. In *Advanced Quantitative Research Methods for Urban Planners* (pp. 216-260). Routledge.
- Kolmaš, M. (2023). The Failure of CBDR in Global Environmental Politics. *Global Environmental Politics*, 23, 11-19.
- Kong, Q., Wang, Z., & Cai, M. (2018). Advantage - Shaping for the Quality and Efficiency Improvement of China's Modern Service Industry in the New Era. *Reform* (10), 82-89.
- Koondhar, M. A., Shahbaz, M., Memon, K. A., Ozturk, I., & Kong, R. (2021). A visualization review analysis of the last two decades for environmental Kuznets curve “EKC” based on co-citation analysis theory and pathfinder network scaling algorithms. *Environmental Science Pollution Research*, 28, 16690-16706.
- Kou, Z., & Liu, X. (2017). FIND Report on City and Industrial Innovation in China (2017). *Fudan Institute of Industrial Development, School of Economics, Fudan University*.
- Kuang, C. e., Li, W., LI, & Huang, X. (2022). Spatial-temporal evolution and driving factors of coupling coordination between carbon emission intensity and high-quality economic development in urban agglomerations in the middle reaches of the Yangtze River. *Economic Geography*, 42(8), 30-40.
- Lam, C., & Souza, P. C. (2020). Estimation and selection of spatial weight matrix in a spatial lag model. *Journal of Business Economic Statistics*, 38(3), 693-710.
- Lee, K., Yun, S. J., & Park, S. (2025). Varied drivers for reducing CO2 emissions in countries with legislated carbon neutrality targets: a Kaya identity clustering analysis: Lee et al. *Environment, Development and Sustainability*, 1-23.
- Lei, G., Guo, S., & Yuan, Z. (2022). Study on the Effect and Mechanism of Circular Economy Promotion Law on the Utilization Rate of Industrial Solid Waste in Resource-Based Cities. *Sustainability*, 14(16), 9878.
- LeSage, J. P., & Pace, R. K. (2009). Spatial econometric models. In *Handbook of applied spatial analysis: Software tools, methods and applications* (pp. 355-376). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Li, C., & Deng, W. (2024). Green Finance, Green Technology Innovation, Green Tax, and Energy-Economy-Carbon Emissions - A China Provincial-Based Analysis. *Polish Journal of Environmental Studies*, 5 (34), 6251-6262.
- Li, C., Fan, X., Hu, Y., Yan, Y., Shang, G., & Chen, Y. (2022a). Spatial spillover effect of green finance on economic development, environmental pollution, and clean energy production across China. *Environmental Science Pollution Research*, 29(58), 87858-87873.

- Li, H., & Dong, Y. (2020). Research on the Measurement and Trend Evolution of the Equalization of Basic Public Services in China: Based on the Dimension of High - quality Development. *China Soft Science*, 10, 74-84.
- Li, J. (2024). Another Way to Green: China's 'Ecological Civilization' Approach to Environmental Governance.
- Li, J., Shi, L., & Xu, A. (2019a). Discussion on the Evaluation Index System of High - quality Development. *Statistical Research*, 36(1), 4-14.
- Li, L., Arip, M. A., & Hong, P. C. (2025). Spatiotemporal evolution patterns of the coupling of carbon productivity and high-quality economic development in China. *Scientific Reports*, 15(1), 9114.
- Li, Q., & Feng, B. (2014). Growth and Convergence Analysis on the Carbon Total Factor Productivity of China's Provinces. *Journal of Beijing Institute of Technology*.
- Li, W., Lin, X., Wang, H., & Wang, S. (2022b). High-quality economic development, green credit and carbon emissions. *Frontiers in Environmental Science*, 10, 992518.
- Li, Z., Li, Y., & Shao, S. J. E. (2019b). Analysis of influencing factors and trend forecast of carbon emission from energy consumption in China based on expanded STIRPAT model, *Energies*, 12(16), 3054.
- Liang, D., Lu, H., Guan, Y., & Feng, L. (2022). Drivers for decoupling carbon footprint pressure from economic growth in China's provinces. *Geography Sustainability*, 3(3), 258-267.
- Liang, L. A., Wang, H. J., Huai, H. J., & Tang, X. M. (2024). Study of the Decoupling Patterns between Agricultural Development and Agricultural Carbon Emissions in Beijing Tianjin Hebei Region from 2000 to 2020. *Land*, 13(6), 839.
- Liao, M. L., Chen, Y., Wang, Y. J., & Lin, M. S. (2019). Study on the coupling and coordination degree of high-quality economic development and ecological environment in Beijing-Tianjin-Hebei region. *Applied Ecology & Environmental Research*, 17(5), 11069-11083.
- Lin, B., & Wang, C. (2023a). Does industrial relocation affect regional carbon intensity? Evidence from China's secondary industry. *Energy Policy*, 173, 113339.
- Lin, B., & Wang, C. (2023b). Does industrial relocation affect regional carbon intensity? Evidence from China's secondary industry. *Energy Policy*, 173, 113339.
- Lin, S., & Xu, K. (2022). Measurement and Evaluation of China's High-quality Development: Regional Differences and Dynamic Evolution. *Modern Economic Research*, 2, 33-43.
- Lin, Y., Ma, L., Li, Z., & Ni, W. J. E. (2023). The carbon reduction potential by improving technical efficiency from energy sources to final services in China: An extended Kaya identity analysis. *Energy*. 263, 125963.
- Lin, Z., Cai, C., Zhang, Y., Zhu, X., Peng, F., Guo, R., Peng, K., Huang, X., Zhang, Y., & Chen, G. (2025). Coordinating Interprovincial Scrap Supply for Technology Transition

to Minimize Carbon Emissions of China's Iron and Steel Industry. *Environmental Science Technology Analysis & Strategic Management*, 59(12), 6004-6015.

- Liu, B., Meng, L., Nie, B., Shi, J., & Li, Y. (2023a). Regional disparities and drivers of carbon emissions in China: A temporal-spatial production-theoretical decomposition analysis. *Science Progress*, 106(1), 00368504231163145.
- Liu, B., & Sun, P. (2021). Perspectives on Major Issues of High - quality Development of Chinese Cities under the New Development Pattern. *Journal of Xi'an Jiaotong University*, 41(3), 1-8.
- Liu, B., Yang, X., Sun, Q., & Luan, F. (2024a). Does the business environment inhibit or promote corporate greenwashing? Empirical evidence from China. *Environment, Development Sustainability*, 1-27.
- Liu, C., & Liu, T. (2023). Fossil Fuel, Greenhouse Gas and Global Warming. *Global Journal of Human-Social Science*, 16(4), 659-665.
- Liu, F. (2023). The impact of China's low-carbon city pilot policy on carbon emissions: based on the multi-period DID model. *Environmental Science Pollution Research*, 30(34), 81745-81759.
- Liu, J., & Oka, T. (2024). The decomposition of carbon productivity under the context of international trade. *Ecological economics*, 225, 108337.
- Liu, S., Zhang, S., & Zhu, H. (2019). Research on the Measurement of National Innovation - driven Force and Its Effect on High - quality Economic Development *The Journal of Quantitative & Technical Economics*, 36(4), 3-23.
- Liu, W., Yang, J., Gong, Y., & Cheng, Q. (2022). An Evaluation of Urban Renewal Based on Inclusive Development Theory: The Case of Wuhan, China. *ISPRS International Journal of Geo-Information*, 11(11), 563.
- Liu, X., Cifuentes-Faura, J., Zhao, S., & Wang, L. (2023b). Government environmental attention and carbon emissions governance: Firm-level evidence from China. *Economic Analysis Policy*, 80, 121-142.
- Liu, X., & Zhang, X. (2021). Industrial agglomeration, technological innovation and carbon productivity: Evidence from China. *Resources Conservation and Recycling*, 166, 105330.
- Liu, X. P., Cheng, S. D., Li, Z. B., Li, P., Wang, T., Guo, X. Y., Miao, Z. Y., Zhang, N. C., & Cao, Y. X. (2023c). Study on the Coupling Relationship between Carbon Emission from Sewage Treatment and Economic Development in Industrial Parks. *Water*, 15(19), 3358.
- Liu, Z.-H., Yuan, Q.-L., Li, C., Gao, L., & Xu, J.-W. (2024b). Research on the Synergistic Effect of Low-carbon Economy and High-quality Development Under the "Dual-carbon" Strategy: A Case Study of Beijing-Tianjin-Hebei Urban Agglomeration. *Huan jing ke xue*, 45(11), 6301-6312.

- Long, b., Wang, Q., Zhu, Y., & Liu, Z. (2024). The Impact and Mechanism of New-Type Urbanization on High-Quality Forestry Development: A Case Study of the Yellow River Basin in China. *Diversity*, 17(1), 7.
- Long, X., Yu, H., Sun, M., Wang, X.-C., Klemeš, J. J., Xie, W., Wang, C., Li, W., & Wang, Y. (2020). Sustainability evaluation based on the Three-dimensional Ecological Footprint and Human Development Index: A case study on the four island regions in China. *Journal of Environmental Management*, 265, 110509.
- Lu, L., Song, D., & Huang, C. (2017). Measurement of green total factor productivity of cities in the Yangtze River economic belt: A case study of 108 cities in the Yangtze river economic belt. *Urban Problems*, 1, 61-67.
- Lu, Y., Chen, L., & Meng, Y. (2023). How does science and technology innovation improve carbon productivity? —Evidence at China's province level. *Environmental Science and Pollution Research*, 30(45), 101296-101316.
- Lu, Y., & Liu, R. (2022). An Empirical Analysis of Jiangxi Province's Financial Development, Economic Growth, and Environmental Pollution. *Wireless Communications Mobile Computing*, 2022(1), 3327318.
- Lucas Jr, R. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1), 3-42.
- Lv, C., & Cui, Y. (2020). Research on Regional Disparities and Temporal-spatial Convergence of China's High-quality Development. *The Journal of Quantitative & Technical Economics*, 37(9), 62-79.
- Lv, D., Wang, R., & Zhang, Y. (2021). Sustainability assessment based on integrating EKC with decoupling: Empirical evidence from China. *Environmental Science and Pollution Research International*, 13(2), 655.
- Ma, M., Ke, S., Li, Q., & Wu, Y. (2023). Towards carbon neutrality: a comprehensive analysis on total factor carbon productivity of the Yellow River Basin, China. *Sustainability*, 15(8), 6591.
- Sun, Y., & Tang, X. (2024, August). A Spatio-Temporal Evolution Model of Carbon Productivity in Large Regions for Dual Carbon Target. In *International Conference on Smart Electrical Grid and Renewable Energy* (pp. 782-788). Singapore: Springer Nature Singapore.
- Mahlkow, H., & Wanner, J. (2023). The carbon footprint of global trade imbalances.
- Meadows, D. H., Meadows, D. L., Randers, J., & Behrens III, W. W. (1972). The limits to growth-club of rome. *Available at SSRN 3491590*.
- Mehmood, K., Hassan, S. T., Qiu, X., & Ali, S. J. G. F. (2024). Comparative analysis of CO₂ emissions and economic performance in the United States and China: Navigating sustainable development in the climate change era. *Geoscience Frontiers*, 15(5), 101843.

- Mehmood Mirza, F., Sinha, A., Rehman Khan, J., Kalugina, O. A., & Wasif Zafar, M. (2022). Impact of energy efficiency on CO2 Emissions: Empirical evidence from developing countries. *Gondwana Research*, 106, 64-77.
- Mei, K., Zhang, J., & Guo, J. (2024). Mechanism of ESG System Construction Promoting Sustainable Financial Development under the "Dual Carbon" Goals. *Advances in Economics, Management and Political Sciences*, 119, 58-64.
- Mezentseva, E., Baysaeva, M., & Fayzullaev, N. (2024). The Impact of Sustainable Development on Economic Growth: Balancing Environmental, Social and Economic Factors. *Reliability: Theory & Applications*, 19(SI 6 (81)), 1269-1274.
- Mlachila, M., Tapsoba, R., & Tapsoba, S. J. (2017). A quality of growth index for developing countries: A proposal. *Social Indicators Research*, 134, 675-710.
- Moran, P. A. (1948). The interpretation of statistical maps. *Journal of the Royal Statistical Society. Series B*, 10(2), 243-251.
- Moutinho, V., Moreira, A. C., & Silva, P. M. (2015). The driving forces of change in energy-related CO2 emissions in Eastern, Western, Northern and Southern Europe: The LMDI approach to decomposition analysis. *Renewable Sustainable Energy Reviews*, 50, 1485-1499.
- Moutinho, V., Santiago, R., Fuinhas, J. A., & Marques, A. C. (2020). The driving forces of energy-related carbon dioxide emissions from South Latin American countries and their impacts on these countries' process of decoupling. *Environmental Science Pollution Research*, 27, 20685-20698.
- Murshed, M. (2023). Can using energy resources productively and promoting good governance boost carbon productivity? An economic growth-environmental degradation decoupling analysis on 116 global countries. *Environmental Science Pollution Research*, 30(35), 84537-84562.
- Naz, F., Tanveer, A., Karim, S., & Dowling, M. (2024). The decoupling dilemma: examining economic growth and carbon emissions in emerging economic blocs. *Energy Economics*, 138, 107848.
- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, 21, 1417-1426.
- Nie, Y., Li, Q., Wang, E., & Zhang, T. (2019). Study of the nonlinear relations between economic growth and carbon dioxide emissions in the Eastern, Central and Western regions of China. *Journal of Cleaner Production*, 219, 713-722.
- Pan, J., & Zhang, L. (2011). Research on the Regional Differences of Carbon Productivity in China. *China Industrial Economics*, 8(05), 47-57.
- Pan, J., Zhuang, G., Zheng, Y., Zhu, S., & Xie, Q. (2022). Clarification of the Concept of a Low-carbon Economy and the Analysis of Its Core Elements. In *Political Economy of China's Climate Policy* (pp. 179-198). Springer.

- Pan, Y., Teng, T., Wang, S., & Wang, T. (2024). Impact and mechanism of urbanization on urban green development in the Yangtze River Economic Belt. *Ecological Indicators*, 158, 111612.
- Pandit, J., & Sharma, A. K. (2023). A comprehensive review of climate change's imprint on ecosystems. *Journal of Water and Climate Change*, 14(11), 4273-4284. <https://doi.org/10.2166/wcc.2023.476>
- Petri, F., & Biedenkopf, K. (2019). Common but Differentiated Responsibility in International Climate Negotiations: The EU and Its Contesters. *Norm Research in International Relations*, 35-54.
- Qi, W. H., Song, C. X., Sun, M., Wang, L. G., & Han, Y. C. (2022). Sustainable Growth Drivers: Unveiling the Role Played by Carbon Productivity. *International Journal of Environmental Research and Public Health*, 19(3), 1374.
- Qi, Y. (2023). Marketization, Industrial Structure Upgrading and Carbon Emission Intensity: Evidence from China. In Asia Conference on Environment and Sustainable Development (pp. 381-393). Singapore: Springer Nature Singapore.
- Qu, S. (2020). The decomposition analysis of carbon emissions: Theoretical basis, methods and their evaluations. *Chinese Journal of Urban Environmental Studies*, 8(04), 2050020.
- Ren, b. (2012). The Quality of Economic Growth: Theoretical Explanation, Basic Propositions and Ethical Principles. *Academic Monthly*, 5(2), 63-70.
- Ren, B. (2018a). The Judgment Criteria, Determinants and Realization Paths of the High-quality Development of China's Economy in the New Era. *China Post*, 7(10), 8-11.
- Ren, B. (2018b). The Transformation of China's Economy from High-speed Growth to High-quality Development in the New Era: Theoretical Explanation and Practical Orientation. *Academic Monthly*, 50(03), 66-74+86.
- Ren, B., & Li, Y. (2018). Construction of the Evaluation System for China's High-quality Development in the New Era and Its Transformation Path. *Journal of Shaanxi Normal University*, 47(3), 105-113.
- Rivera-Niquepa, J. D., Rojas-Lozano, D., De Oliveira-De Jesus, P. M., & Yusta, J. M. (2023). Methodology for selecting assessment periods of Logarithmic Mean Divisia Index decomposition techniques. *Energy Strategy Reviews*, 50, 101241.
- Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, 9(1), 86-136.
- Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the Econometric Society*, 393-415.
- Sarkodie, S. A., & Strezov, V. (2019). A review on environmental Kuznets curve hypothesis using bibliometric and meta-analysis. *Science of the Total Environment*, 649, 128-145.

- Sato, M., Tanaka, K., & Managi, S. (2018). Inclusive wealth, total factor productivity, and sustainability: an empirical analysis. *Environmental Economics Policy Studies*, 20, 741-757.
- Shan, Y., Huang, Q., Guan, D., & Hubacek, K. (2020). China CO2 emission accounts 2016–2017. *Scientific data*, 7(1), 54.
- Shang, D., Dongliang, Y., Libo, F., & and Wu, X. (2024). Mixed-ownership reform and green innovation: based on the perspectives of capital effect and governance effect. *Technology Analysis & Strategic Management*, 1-15.
- Shen, N., Peng, H., & Wang, Q. (2021). Spatial dependence, agglomeration externalities and the convergence of carbon productivity. *Socio-Economic Planning Sciences*, 78, 101060.
- Sheng, S., Li, Y., & Zhao, Z. (2024). How does regional policy coordination help achieve the low-carbon development?: a study of theoretical mechanisms and empirical analysis from China. *Environment, Development Sustainability*, 1-33.
- Sheng, X., Yi, R., Tang, D., Lansana, D. D., & Obuobi, B. (2023). The severity of foreign direct investment components on China's carbon productivity. *Journal of Cleaner Production*, 424, 138929.
- Shi, A. (2003). The impact of population pressure on global carbon dioxide emissions, 1975–1996: evidence from pooled cross-country data. *Ecological economics*, 44(1), 29-42.
- Shi, D., & Li, P. (2019). Measurement and International Comparison of China's High - quality Economic Development. *Southeast Academic Research*, 5, 169-180.
- Shi, X.-H., Chen, X., Han, L., & Zhou, Z.-J. (2023). RETRACTED ARTICLE: The mechanism and test of the impact of environmental regulation and technological innovation on high quality development. *Journal of Combinatorial Optimization*, 45(1), 52.
- Shi, Z., Loh, L., Wu, H., & Han, D. (2024). Smarter and cleaner: How does energy digitalization affect carbon productivity? *Energy Strategy Reviews*, 52, 101347.
- Solow, R. M. J. T. q. j. o. e. (1956). A contribution to the theory of economic growth. *The quarterly journal of economics*, 70(1), 65-94.
- Song, J., & Gao, C. (2024). Research on the Coordination between the Quality of Social Security and High-quality Economic Development: From the Perspectives of Decoupling and Coupling *Journal of Xi'an Jiaotong University*, 44(2), 116-129.
- Song, M., Anees, A., Rahman, S. U., & Ali, M. S. E. (2024). Technology transfer for green investments: exploring how technology transfer through foreign direct investments can contribute to sustainable practices and reduced environmental impact in OIC economies. *Environmental Science Pollution Research*, 31(6), 8812-8827.
- Song, M., Tao, W., & Shen, Z. (2022). Improving high-quality development with environmental regulation and industrial structure in China. *Journal of Cleaner Production*, 366, 132997.

- Song, S., & Wei, X. (2023). The Construction of Low-carbon Cities, Green Technological Innovation and Inclusive Low-carbon Growth. *Economic Survey*, 5(3), 14-25.
- Song, Y., Zhang, M., & Zhou, M. (2021). Study on the decoupling relationship between CO2 emissions and economic development based on two-dimensional decoupling theory: A case between China and the United States. *Ecological Indicators*, 102, 230-236.
- Sun, Z., & Xu, X. (2018). Industrial Innovation and Consumption Upgrade: An Empirical Study from the Perspective of Supply-side Structural Reform. *China Industrial Economics*, 11(07), 98-116.
- Tan, F., Yang, S., & Niu, Z. (2023). The impact of urbanization on carbon emissions: Both from heterogeneity and mechanism test. *Environment, Development Sustainability*, 25(6), 4813-4829.
- Tang, J., Shan, R., Wang, P., Chen, W.-Q., Gu, D., Li, G., Rao, P., Wang, J., & Lu, J. (2025). Deciphering decarbonization trajectories in China by spatiotemporal-accumulation modeling of electricity carbon footprint. *iScience*, 28(3), 111963.
- Tang, L., Bian, L., Zhiang, Zhao, G., & Wang, Q. (2024). Construction of High-quality Economic Development Indicator System Based on Unsupervised Learning. *Proceedings of the 3rd International Conference on Big Data Economy and Digital Management, BDEDM 2024, January 12–14, 2024, Ningbo, China*, 8(11), 98-117.
- Tao, H., Tao, M., & Wang, R. (2022). Do education human capital and environmental regulation drive the growth efficiency of the green economy in China? *Sustainability*, 14(24), 16524.
- Tao, M., Wen, L., Sheng, M. S., Yan, Z. J., & Poletti, S. (2024). Dynamics between energy intensity and carbon emissions: What does the clustering effect of labor and capital play? *Journal of Cleaner Production*, 452, 142223.
- Tapio, P. (2005). Towards a theory of decoupling: degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transport policy*, 12(2), 137-151.
- Thomas, C. (2000a). *Global governance, development and human security: the challenge of poverty and inequality*. Pluto Press.
- Thomas, V. (2000b). *The quality of growth*. World Bank Publications.
- Tian, Q. (2018). The Theoretical Connotation and Practical Requirements of High-quality Development. *Journal of Shandong University (Philosophy and Social Sciences)*, 6(06), 1-8.
- Tian, Q., Zhao, T., & Yuan, R. (2021). An overview of the inequality in China's carbon intensity 1997–2016: A Theil index decomposition analysis. *Clean Technologies Environmental Policy*, 23, 1581-1601.
- Tomislav, K. (2021). The concept of sustainable development: From its beginning to the contemporary issues. *Zagreb International Review of Economics Business*, 21(1), 67-94.

- Treffers, D., Faaij, A. P., Spakman, J., & Seebregts, A. (2005). Exploring the possibilities for setting up sustainable energy systems for the long term: two visions for the Dutch energy system in 2050. *Energy Policy*, 33(13), 1723-1743.
- Un, I. (1992). Convention on biological diversity. *Treaty Collection*, 11, 79.
- Ver Hoef, J. M., & Cressie, N. (1993). Multivariable spatial prediction. *Mathematical Geology*, 25, 219-240.
- Wang, D., Yu, Z., Liu, H., Cai, X., & Zhang, Z. (2024). Impact of capital and labor based technological progress on carbon productivity. *Journal of Cleaner Production*, 467, 142827.
- Wang, F., Wang, R., & He, Z. (2021a). The impact of environmental pollution and green finance on the high-quality development of energy based on spatial Dubin model. *Resources Policy*, 74, 102451.
- Wang, G. (2023). *Research on Population Urbanization and Carbon Emission Reduction in China*. Science Press.
- Wang, G., & Salman, M. (2022). The impacts of heterogeneous environmental regulations on green economic efficiency from the perspective of urbanization: a dynamic threshold analysis. *Environment, Development and Sustainability*, 25, 9485-9516.
- Wang, J., Ren, S., Chen, D., & Li, S. (2023a). Research on the Mechanism of Green Finance on Economic Growth. *Frontiers in Humanities and Social Sciences*, 7(11), 33-45.
- Wang, J., Zhu, J., & Wang, Y. (2024b). The impact of development zone upgrading on carbon emission reduction: examining China's regional development policies. *Environment, Development and Sustainability*, 9(2), 87-90.
- Wang, J. M., & Li, Y. Q. (2022). Soft Economic Incentives and Soft Behavioral Interventions on the Public's Green Purchasing Behaviour-The Evidence from China. *Psychology Research Behavior Management*, 2477-2499.
- Wang, L., & Xue, W. (2024). A study of the pathway to peak carbon in China. *Environment Protection Engineering*, 50(1), 71-89.
- Wang, Q. (2022). Innovation-driven Development Strategy. *China Soft Science*, 33(7), 1578-1595.
- Wang, Q., Ding, Y., & Guo, X. (2021b). Construction of the Index System for the High - quality Development of China's County - level Economy. *Soft Science*, 35(1), 115-119.
- Wang, Q., & Su, M. (2020). Drivers of decoupling economic growth from carbon emission—an empirical analysis of 192 countries using decoupling model and decomposition method. *Environmental Impact Assessment Review*, 81, 106356.
- Wang, Q., Yang, T., & Li, R. (2023b). Economic complexity and ecological footprint: the role of energy structure, industrial structure, and labor force. *Journal of Cleaner Production*, 412, 137389.

- Wang, R., Deng, X., Gao, Y., & Chen, J. (2024c). Does regional economic development drive sustainable grain production growth in China? Evidence from spatiotemporal perspective on low-carbon total factor productivity. *Socio-Economic Planning Sciences*, 98, 102129.
- Wang, R., Wang, Q., & Yao, S. (2021c). Evaluation and difference analysis of regional energy efficiency in China under the carbon neutrality targets: Insights from DEA and Theil models. *Journal of Environmental Management*, 293, 112958.
- Wang, S. (2013). The Types and Selection of Weight Matrices in Spatial Econometric Models. *Journal of Quantitative Economics*, 30(3), 57-63.
- Wang, X., Wang, S., & Zhang, X. (2023c). Heterogeneity and influence factors of carbon productivity: Evidence from Chinese manufacturing enterprises. *Journal of Cleaner Production*, 404, 136938.
- Wang, X., Zhang, T., Nathwani, J., Yang, F., & Shao, Q. (2022). Environmental regulation, technology innovation, and low carbon development: Revisiting the EKC Hypothesis, Porter Hypothesis, and Jevons' Paradox in China's iron & steel industry. *Technological Forecasting Social Change*, 176, 121471.
- Wang, Y., Yang, S., Liu, C., & Li, S. (2020). How would economic development influence carbon productivity? A case from Hubei in China. *International Journal of Environmental Research Public Health*, 15(8), 1730.
- Wang, Z., & Zhang, X. (2020). The Path Selection for the High-quality Development of Small Towns in China in the Post-industrialization Period. *China Industrial Economics*, 1, 62-80.
- Wei, L. J. F. o. E. i. C. (2022). The Next Five Years (2022–2027) Will Be Crucial for Building a Modern Socialist Country in All Respects: Implications from the Report to the 20th National Congress of the CPC. *Frontiers of Economics in China*, 17(4), 88-101.
- Wei, M., & Li, S. (2018). Research on the Measurement of the Level of China's High-quality Economic Development in the New Era. *The Journal of Quantitative & Technical Economics*, 35(11), 3-20.
- Wei, Z., Wan, L., Zheng, Q., Chen, Z., & Wang, S. (2024). Will large-scale low-carbon guidance activities improve residents' green living standards? Evidence from China. *Heliyon*, 10(19).
- Wen, L., & Li, Z. (2020). Provincial-level industrial CO₂ emission drivers and emission reduction strategies in China: combining two-layer LMDI method with spectral clustering. *Science of the Total Environment*, 700, 134374.
- While, A., Jonas, A. E., & Gibbs, D. (2010). From sustainable development to carbon control: eco-state restructuring and the politics of urban and regional development. *Transactions of the Institute of British Geographers*, 35(1), 76-93.
- Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1), 25-51.

- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT press.
- Wu, B., Wang, Z., Tian, Y., & Zheng, S. (2024). The impact of industrial transformation and upgrading on fossil energy elasticity in China. *Journal of Cleaner Production*, 434, 140287.
- Wu, L., Sun, L., Qi, P., Ren, X., & Sun, X. (2021a). Energy endowment, industrial structure upgrading, and CO2 emissions in China: Revisiting resource curse in the context of carbon emissions. *Resources Policy*, 5(22), 32-43.
- Wu, R., Wang, J., Wang, S., & Feng, K. (2021b). The drivers of declining CO2 emissions trends in developed nations using an extended STIRPAT model: A historical and prospective analysis. *Renewable Sustainable Energy Reviews*, 149, 111328.
- Wu, X., Qiu, W., & Guo, S. (2023a). Assessing the effectiveness of emissions trading schemes: evidence from China. *Climate Policy*, 24, 545-557.
- Wu, X., Zhong, S., Chen, G., Wu, C., Han, J., & Qian, Z. (2025). Influence of land use intensity on urban carbon efficiency under a carbon neutrality target: Evidence from the Yangtze River Delta urban agglomeration, China. *Environmental Impact Assessment Review*, 110, 107689.
- Wu, Y., Wan, J., & Yu, W. (2023b). Impact of environmental education on environmental quality under the background of low-carbon economy. *Frontiers in Public Health*, 11, 1128791.
- Wu, Y., Zheng, H., Li, Y., Delang, C. O., & Qian, J. (2021c). Carbon Productivity and Mitigation: Evidence from Industrial Development and Urbanization in the Central and Western Regions of China. *The Lancet Planetary Health*, 13(16), 9014.
- Wu, Z., Huang, W., Ge, Y., Dai, Y., & Zu, F. (2023c). Research on the impact of technical progress on the carbon productivity in China's service industry. *Frontiers in Environmental Science*, 11, 1143057.
- Xia, J., Zhan, X., Li, R. Y. M., & Song, L. (2022). The relationship between fiscal decentralization and China's low carbon environmental governance performance: The malmquist index, an SBM-DEA and systematic GMM approaches. *Frontiers in Environmental Science*, 10, 945922.
- Xiao, Y., Ma, D., Zhang, F., Zhao, N., Wang, L., Guo, Z., Zhang, J., An, B., & Xiao, Y. (2023). Spatiotemporal differentiation of carbon emission efficiency and influencing factors: From the perspective of 136 countries. *Science of the Total Environment*, 879, 163032.
- Xu, C., Wang, B., Chen, J., Shen, Z., Song, M., & An, J. (2022). Carbon inequality in China: novel drivers and policy driven scenario analysis. *Energy Policy*, 170, 113259.
- Xu, J., Guan, Y., Oldfield, J., Guan, D., & Shan, Y. (2024). China carbon emission accounts 2020-2021. *Applied Energy*, 360, 122837.
- Xu, X., & Ang, B. W. (2013). Index decomposition analysis applied to CO2 emission studies. *Ecological Economics*, 93, 313-329.

- Xu, X., Li, S., Wang, X., & Bi, Q. (2018). The Choice of China's Economic Growth Target: Putting an End to the "Collapse Theory" with High - quality Development. *The Journal of World Economy*, 8(10), 3-25.
- Xu, Y., & Deng, H. (2022). Green total factor productivity in Chinese cities: Measurement and causal analysis within a new structural economics framework. *Journal of Innovation Knowledge*, 7(4), 100235.
- Xue, L., Li, H., Xu, C., Zhao, X., Zheng, Z., Li, Y., & Liu, W. (2022). Impacts of industrial structure adjustment, upgrade and coordination on energy efficiency: Empirical research based on the extended STIRPAT model. *Energy Strategy Reviews*, 43, 100911.
- Yang, H., Lu, Z., Shi, X., Mensah, I., Luo, Y., & Chen, W. (2021a). Multi-region and multi-sector comparisons and analysis of industrial carbon productivity in China. *Journal of Cleaner Production*, 279, 123623.
- Yang, M., Zhu, M., & Yin, T. (2021b). Research on the Evaluation of High-quality Economic Development at the Provincial Level in China and the Measurement of Imbalance. *Review of Industrial Economics*, 5(11), 5-21.
- Yang, W., & Li, D. (2022). Spatial Differences and Formation Mechanisms of the Quality of Economic Development in China's Eight Major Regions. *Modern Economic Science*, 44(2), 33-40.
- Yang, Y., Wei, X., Wei, J., & Gao, X. (2022a). Industrial structure upgrading, green total factor productivity and carbon emissions. *Sustainability*, 14(2), 1009.
- Yang, Y., Wei, X., Wei, J., & Gao, X. (2022b). Industrial structure upgrading, green total factor productivity and carbon emissions. *Climate Change and Environmental Sustainability*, 14(2), 1009.
- Yao, L., & Jiang, Y. (2022). An empirical study on the influencing factors of carbon emissions in East China based on the STIRPAT model. In *Advances in Petrochemical Engineering and Green Development* (pp. 310-315). CRC Press.
- Yao, Y., & Li, B. (2022). On the Transformation of China's Economic Growth Drivers in the New Development Stage: Logic, Direction and Path. *Journal of East China Normal University (Philosophy and Social Sciences)*, 54(3), 161-171.
- You, Z., Chen, D., Fang, C., Gao, M., & Cheng, J. (2024). How green governance empowers high-quality development: An EKC framework-based analysis of ESG and green total factor productivity. *Science Progress*, 107(4), 00368504241288782.
- Yu, H., & Liu, H. (2024). Impact of digitization on carbon productivity: an empirical analysis of 136 countries. *Scientific Reports*, 14(1), 5094.
- Yu, J., de Jong, R., & Lee, L.-f. (2012). Estimation for spatial dynamic panel data with fixed effects: The case of spatial cointegration. *Journal of Econometrics*, 167(1), 16-37.
- Yu, Y., & Xu, Y. (2023). The roles of carbon trading system and sustainable energy strategies in reducing carbon emissions—an empirical study in China with panel data. *International Journal of Environmental Research Public Health*, 20(8), 5549.

- Zhang, C., & Zheng, J. (2015). VAR Model for Relations of China's Carbon Productivity and Social Electricity Consumption. *International Journal of Applied Mathematics & Statistics*, 53(2), 36-45.
- Zhang, J., Zhang, N., & Bai, S. (2021). Assessing the carbon emission changing for sustainability and high-quality economic development. *Environmental Technology & Innovation*, 22, 101464.
- Zhang, L., & Tian, Y. (2019). Construction of a Multi - dimensional Evaluation Index System for High - quality Economic Development. *China Statistics*, 9(6), 17-19.
- Zhang, L., Wang, H., Zhang, W., Wang, C., Bao, M., Liang, T., & Liu, K.-d. (2022a). Study on the development patterns of ecological civilization construction in China: An empirical analysis of 324 prefectural cities. *Journal of Cleaner Production*, 367, 132975.
- Zhang, S., & Liu, X. (2024). Tracking China's CO2 emissions using Kaya-LMDI for the period 1991–2022. *Gondwana Research*, 133, 60-71.
- Zhang, T. (2020). Research on the Theoretical Interpretation and Measurement Method of High-quality Development. *The Journal of Quantitative & Technical Economics*, 37(5), 23-43.
- Zhang, X., He, S., & Ma, L. (2024a). Local environmental fiscal expenditures, industrial structure upgrading, and carbon emission intensity. *Frontiers in Environmental Science*, 12, 1369056.
- Zhang, Y. (2021). China's Green Urbanization in the Perspective of Ecological Civilization. *Chinese Journal of Urban and Environmental Studies*, 9(1), 2150001.
- Zhang, Y. (2023). Reshaping the relationship between environment and development: A theoretical framework under the paradigm of eco-civilization and its policy implications. *Social Sciences in China*, 44(1), 44-72.
- Zhang, Y., Hao, F., & Li, J. (2022b). Research on the Spatial Distribution of the Coupling and Coordination of China's High-quality Development Level Based on the New Development Concept. *Journal of Guizhou University of Finance and Economics*, 40(02), 23.
- Zhang, Y., & Pan, B. (2022). Shared responsibility of carbon emission for international trade based on carbon emission embodied between developing and developed countries. *Environmental Science and Pollution Research International*, 30, 19367-19379.
- Zhang, Y., Wang, X., & Feng, N. (2024b). The path of green finance to promote the realization of low-carbon economic transformation under the carbon peaking and carbon neutrality goals: Theoretical model and empirical analysis. *International Review of Financial Analysis*, 94, 103227.
- Zhang, Y., Yu, Z., & Zhang, J. (2022c). Research on carbon emission differences decomposition and spatial heterogeneity pattern of China's eight economic regions. *Environmental Science Pollution Research*, 1-17.

- Zhang, Y., & Zhao, J. (2017). The Quality of China's Economic and Social Development and Its Impact on the Full Completion of a Moderately Prosperous Society in All Respects: Theoretical and Empirical Analysis Based on the Five New Development Concepts. *Finance & Trade Research*, 28(3), 1-10.
- Zhao, G., Guo, Y., & Bo, L. (2023). High-quality economic growth and carbon emissions in Chinese cities: The moderating role of fiscal policies. *Digital Economy Sustainable Development*, 1(1), 19.
- Zhao, J., Chen, W., Liu, Z., Liu, W., Li, K., Zhang, B., Zhang, Y., Yu, L., & Sakai, T. (2024a). Urban expansion, economic development, and carbon emissions: Trends, patterns, and decoupling in mainland China's provincial capitals (1985–2020). *Ecological Indicators*, 169, 112777.
- Zhao, J., Zhang, Y., He, X., Axmacher, J. C., & Sang, W. (2024b). Gains in China's sustainability by decoupling economic growth from energy use. *Journal of Cleaner Production*, 448, 141765.
- Zhao, T. (2023). The impact of financial inclusion and natural resource endowment on China's carbon emissions in the post-covid-19 period. *Resources Policy*, 86, 104198.
- Zhao, T., Zhang, Z., & Liang, S. (2020). Digital Economy, Entrepreneurial Activity, and High-Quality Development: Empirical Evidence from Chinese Cities. *Management World*, 36(10), 65-76.
- Zhao, X., Jiang, M., & Zhang, W. (2022a). Decoupling between economic development and carbon emissions and its driving factors: evidence from China. *International Journal of Environmental Research Public Health*, 19(5), 2893.
- Zhao, X., Ma, X., Chen, B., Shang, Y., & Song, M. (2022b). Challenges toward carbon neutrality in China: Strategies and countermeasures. *Resources, Conservation and Recycling*, 176, 105959.
- Zhao, Y., Su, Q., Li, B., Zhang, Y., Wang, X., Zhao, H., & Guo, S. (2022c). Have those countries declaring “zero carbon” or “carbon neutral” climate goals achieved carbon emissions-economic growth decoupling? *Journal of Cleaner Production*, 363, 132450.
- Zheng, C., Zhu, Y., & Cheng, F. (2022). Does Urbanization Improve Green Total Factor Productivity? - An Empirical Test Based on the Yangtze River Economic Belt. *Modern Economic Research*(05), 110-115.
- Zheng, L., Fu, J., & Cai, Z. (2012). Evaluate regional low-carbon economy competitiveness in China. In *World Automation Congress 2012* (pp. 1-4). IEEE.
- Zhong, F., Yin, Y., Tian, J., Jiang, D., & Mao, Y. (2024). Carbon Reduction Pathways for Chinese Provinces: Considering Carbon Intensity Convergence, Regional Development Plans, and Shared Socioeconomic Pathways. *Atmosphere*, 15(8), 918.
- Zhou, C., Wang, S., & Wang, J. (2021a). Examining the influences of urbanization on carbon dioxide emissions in the Yangtze River Delta, China: Kuznets curve relationship. *Science of the Total Environment*, 675, 472-482.

- Zhou, Y., Shan, Y., Liu, G., & Guan, D. (2021b). Emissions and low-carbon development in Guangdong-Hong Kong-Macao Greater Bay Area cities and their surroundings. *Applied Energy*, 228, 1683-1692.
- Zhu, X. J. E. S. (2022). Have carbon emissions been reduced due to the upgrading of industrial structure? Analysis of the mediating effect based on technological innovation. *Environmental Science Pollution Research*, 29(36), 54890-54901.
- Zhu, Y., Tian, D., & Yan, F. J. M. p. i. E. (2020). Effectiveness of entropy weight method in decision-making. *Mathematical Problems in Engineering*, 2020(1), 3564835.
- Zou, X., Li, J., & Zhang, Q. (2023). CO2 emissions in China's power industry by using the LMDI method. *Environmental Science Pollution Research*, 30(11), 31332-31347.