

EFFECTS OF CLIMATE POLICY ON URBAN CARBON EMISSIONS – NEW INSIGHTS FROM CHINA'S LOW-CARBON CITY PILOT POLICY

XU, X. P.* – LIU, L.

School of Business, Xiangtan University, Xiangtan 411105, China

**Corresponding author
e-mail: xuxianpu@xtu.edu.cn*

(Received 4th Dec 2024; accepted 27th Feb 2025)

Abstract. China's actions to attain sustainable, low-carbon growth are greatly assisted by the Low-Carbon City Pilot (LCCP) scheme, which also offers a viable solution into 2030 peaking carbon in the battle against climate change. In this context, grounded in the panel dataset comprising 282 Chinese cities during 2006–2021, using LCCP execution as a quasi-natural experiment, this research adopts a multi-phase difference-in-differences (DID) model and gives a detailed evaluation for the impacts of LCCP on carbon emissions. Following subsequent robustness tests, this study argues that LCCP has notably reduced urban carbon emissions. More importantly, the results of the heterogeneity test revealed that LCCP created notable benefits in curbing carbon emissions, especially in big cities, non-resource-based cities, non-old industrial base cities, and eastern regions. Mechanism results also indicated that LCCP has effectively diminished carbon emissions by cutting energy consumption in urban areas, enhancing the levels of green innovation, and fostering digital economy. Consequently, it is essential to improve LCCP scheme and customize low-carbon development strategies according to local conditions, offering empirical proofs for widening the range of pilot cities under LCCP scheme.

Keywords: *LCCP, green transformation, DID model, green innovation, digital economy*

Introduction

Climate change, exacerbated by the excessive emission of greenhouse gases, is currently a huge concern for humanity around the globe. Since the Industrial Revolution, the widespread extraction and utilization of fossil fuels have greatly elevated greenhouse gas emissions, predominantly carbon dioxide, contributing to global climate change (Shapiro, 2021). The thawing of glaciers, increasing sea levels, and various extreme natural events triggered by these changes pose a significant risk to human existence as well as to sustainable development. Therefore, lowering the detrimental effects of climate change upon the world economy, taking carbon reduction as an essential means, has evolved into the focus of the entire globe (Nordhaus, 2019; Moscona and Sastry, 2023). As a large developing country, since the reform and opening up, driven by factors and investment, China's economy has achieved rapid growth and achieved remarkable growth achievements that have attracted worldwide common attention (Wei et al., 2017). More importantly, disclosed from official statistics figures, China's total GDP in 2023 was 126 trillion yuan, ranking second in the world (Gao et al., 2024). However, the extensive growth model that emphasizes quantity over quality has achieved economic growth, even more, along with drove a series of serious resource and environmental problems such as insufficient environmental carrying capacity, low energy utilization efficiency, and sharp increase in carbon emissions, posing serious challenges to China's long-term and high-quality development. To be more specific, as a large responsible country, China actively practices its responsibility to reduce emissions and has gradually evolved into the

participant and leader in global climate and environmental governance (Yang et al., 2023). In 2020, the China's authority formally announced some ambitious plans, as a reply to regulating greenhouse gas, to strive to peaking carbon by 2030 as well as neutralizing carbon by 2060. More importantly, the 20th China National Congress, which convened at a critical stage in China's progress towards the 2nd centenary orientation, stressed the urgency of shifting towards a greener growth model and intensifying pollution control efforts. Consequently, how to greatly reduce carbon emissions while fostering economic growth, enhancing environmental quality, and building a sustainable balanced growth path has emerged as a pressing challenge that urgently needs to be studied in the academia (Wang and Zhang, 2022; Shang et al., 2023; Li and Xu, 2024).

Cities are the center of economic growth and an important contributor for greenhouse gas emissions. To best our knowledge, the attainment of urban carbon reduction goals is closely correlated with improve climate condition and its pursuit of sustainable growth principles in China (Yang et al., 2023; Wang et al., 2023). As of the end of 2023, the permanent population in China's urban areas was 93,267 million, accounting for 66.16% of national population. With the continuous advancement of urbanization in China, urban infrastructure construction, industrial activities, transportation, and residential life will all consume a large amount of fossil energy, making cities one of the main areas for carbon emissions (Lyu et al., 2023). From Cai et al. (2019), the volume of prefecture-level carbon emissions accounts for roughly 70% of the national share. Moreover, cities are also high-risk areas for climate risks, and the threat of climate disasters featuring droughts, rising sea levels, heatwaves, and extreme weather caused by climate change to cities is gradually becoming apparent. Therefore, the Chinese authority has made active efforts to enhance cities' growth potential to adapt to climate change, and launching LCCP is an important measure among them (as shown in *Figure 1*). In 2010, the Chinese government initiated a pilot scheme aimed at developing low-carbon areas and cities, as well as focused on fostering an industrial framework and consumption patterns marked with reducing carbon emissions. This initiative included Yunnan, Hubei, Liaoning, Shaanxi, and Guangdong provinces, as well as other eight cities which are Hangzhou, Tianjin, Shenzhen, Baoding, Guiyang, Nanchang, Xiamen and Chongqing. To build on this initial effort, in 2012, the government designated 29 additional cities and provinces, (including Shanghai, Beijing, Suzhou, Ningbo, Qingdao, Sanya etc.), as the 2nd wave of LCCP scheme areas. Even more, in 2017, the authority further expanded the scope of LCCP scheme execution again, and 45 cities were picked as pilot cities in the 3rd phase. Cities actually participating in LCCP projects have set carbon emission peak targets to promote low-carbon development, increase the spread of low-carbon technologies and ecologic items, along with promote low-carbon growth in key domains such as industry, construction, and transportation, and form distinctive low-carbon development models (Pan et al., 2022; Zhong et al., 2024). Meanwhile, as an active policy to improve climate environment and promote low-carbon development, China's LCCP has received widespread attention. Therefore, can LCCP significantly lower urban carbon emissions? If yes, what are the mechanisms of LCCP on carbon emissions? Resolving these issues has critical significance for further expanding the scope of LCCP projects and helping to attain the goals of peaking carbon (Liu et al., 2022; Wang et al., 2023; He et al., 2023).

The purpose of this research, LCCP being a quasi-natural experiment, aims to disclose how LCCP execution affects China's urban carbon emissions by applying a multi-phase DID model, especially revealing the impact mechanisms for LCCP on carbon emissions. Compared with existing research, there are two possible novelties in this study. First, this

research analyzes the benefits of urban low-carbon transition growth on carbon emissions from LCCP scheme, which to some extent expands the research scope of pilot policies and provides a solid basis for comprehensive evaluating the benefits of LCCP execution. More importantly, regarding the notable variations across geospatial positions, population dynamics, resource availability, and industrial foundations in cities, we delve into the diverse benefits of LCCP scheme on carbon emissions across urban areas. Particularly, this analysis yields valuable policy suggestions for local authorities aimed at reducing pollution disparities. Second, through inspection with the multi-phase DID technique, we conduct a thorough testing of how LCCP affects urban carbon emissions, confirming the presence of three key mechanisms: optimizing urban energy consumption, advancing high-quality green innovation, as well as developing digital economy. This establishes a robust basis for enhancing the LCCP framework and attaining the dual-carbon targets.

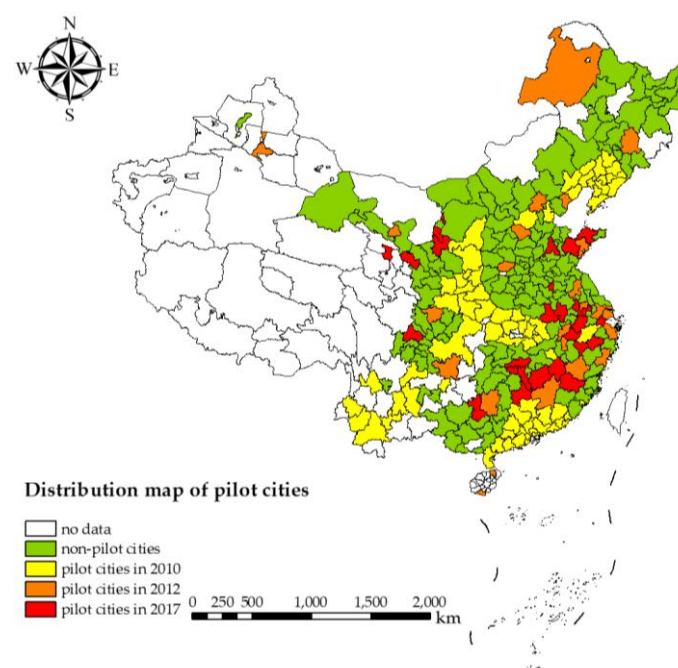


Figure 1. Spatial distribution map for LCCP scheme execution pilot cities

The rest of this research is formatted as such. Part two mentioned below is literature review, which briefly summarizes the nexus between LCCP and carbon emissions. The DID empirical framework and relevant variables are addressed in Part three, which also outlines the study design. Part four conveys the empirical analysis results. Finally, there are conclusions.

Literature review

Because carbon emissions can lead to harmful effects like rising sea levels and ocean acidification, scholars have consistently concentrated on unraveling the connection between environmental regulations and carbon emissions. The factors influencing carbon emissions, driven by both natural and human activities, have been extensively analyzed to provide valuable insights into emission trends. With the extensive discussion on the topic of LCCP in the academia, its impact is gradually becoming apparent. Besides, the

application of DID models has been elaborated upon, highlighting its methodological advantages in empirical evaluations. The literature overview, illuminated by numerous contributions from scholars across different disciplines, is outlined as below.

Research on the factors affecting carbon emissions

As nations around the world become more conscious of environmental concerns in the process of economic development, research on controlling global warming has become more urgent, which has prompted the academic community to give serious consideration to carbon emissions (Candelon and Hasse, 2023; Xu and Huang, 2024). From a macro perspective, as a foundational framework for understanding complex systems, scholars have increasingly emphasized environmental concerns, primarily focusing on how economic growth, environmental regulations, industrial structure, and trade openness affect carbon emissions (Narayan and Narayan, 2010; Aslan et al., 2018). For instance, Alshehry and Belloumi (2015), who used the Johansen multivariate cointegration technique disentangling for complex problems, tested the nexus between Saudi Arabia's carbon dioxide emissions and economic growth driven by rapid industrialization and policy shifts. Their findings revealed a bidirectional causal relationship, the conclusion that was also corroborated by Kinyar and Bothongo (2024). When it comes to how industrial structure affects carbon emissions, scholars have claimed that industrial structure not only directly reduces carbon emissions but also indirectly promotes carbon reduction through technological advancement. Specifically, Tian et al. (2014) analyzed panel data from nine Chinese provinces and discovered that regional industrial structures significantly influenced local carbon emissions. They also confirmed that a shift to their resource-driven industries led to increasing carbon emissions, which posed a threat to public health nationwide. Nonetheless, several scholars have presented opposing arguments. The error correction model and data were being systematically analyzed by Jiang and Sun (2023) to uncover the intricate connections between industrial structure and carbon emissions, discovering that there was no appreciable influence of industrial structure on carbon emissions, which had been extensively studied in recent years. Drawing on Chinese data from 282 cities between 2003 and 2016, Wang and Zhang (2022) investigated how environmental regulations influenced carbon emissions. Their findings demonstrated that these regulations had successfully limited carbon emissions. Conversely, Hassan et al. (2022) argued that the environmental policies implemented in OECD nations failed to significantly rein in carbon emissions. Moreover, how trade affects carbon emissions, theoretically speaking, has received significant attention, with considerable efforts being made to mitigate their environmental impact (Kim et al., 2019). Specifically, Ertugrul et al. (2016), who used data spanning from 1971 to 2011, observed the associations between trade openness and carbon dioxide emissions of ten developing nations with a rapidly economic growth path, discovering the impact of trade openness on carbon emissions varies across countries. Wang et al. (2022) further verified the result that international trade could generate inequalities in carbon emissions globally. Additionally, some scholars have begun researching carbon emissions at a micro level, utilizing individual-level data to identify strategies for reducing emissions. To be specific, some scholars have increasingly recognized technological innovation, internal management, and environmental information disclosure as key drivers in reducing carbon emission intensity, with corporate digital transformation expected to yield significant environmental benefits (Shang et al., 2023). Using data of A-share listed firms during 2010–2019, Chen et al. (2024) explored how manufacturing enterprises' digital

transformation, a process increasingly prioritized in modern industries, contributed to reducing carbon emissions. This result was further verified by Zhang et al. (2024). Meticulously gathered data covering the period from 2010-2020, Li and Xu (2024) confirmed that corporate environmental, social, and governance rating (ESG) ratings could enhance overall environmental sustainability by alleviating corporate financing constraints and addressing institutional issues. Using a spatial econometric model for 208 cities in China, Yang and Hei (2024) further revealed that higher ESG ratings significantly lowered carbon emissions.

Research on the implementation effect for Low-Carbon City Pilot Policy (LCCP)

In recent years, ecological protection policies have become increasingly stringent and a key focus of research, particularly as the construction of sustainable and low-carbon cities with abundant renewable energy resources has gained significant attention worldwide (Yasmeen et al., 2020; Yang et al., 2023). Notably, Neves et al. (2020) and Luo et al. (2022) utilized advanced econometric techniques and investigated how green total factor productivity and environmental pollution were influenced by environmental regulations, often viewed as pivotal to achieving sustainable development, respectively. Scholars have emphasized the Low-Carbon City Pilot (LCCP) program as a critical institutional framework with significant implications for both the environment and the economy (Yang et al., 2023). Existing research on the effects of LCCP implementation can generally be divided into two categories. On the one hand, some studies argue that LCCP promotes corporate green innovation, reshapes industry structures, and fosters the digital economy. Further, they suggest that LCCP enhances the digital economy through technological innovation and industrial adjustments (Wang et al., 2023). Using data during the years 2007–2019 and a quasi-natural experimental method carefully curated to ensure accuracy, Chen et al. (2024) revealed that LCCP could promote the deployment of digital transformation strategies in A-share listed firms, which contributed significantly to China's economic landscape. This evidence was also verified by Zhao et al. (2023). Additionally, a propensity score matching DID (PSM-DID) model, frequently used in policy evaluation studies, was employed by Pan (2022) to study pilot cities selected as representatives of green pioneers, demonstrating that LCCP could promote industrial upgrading by encouraging urban innovation mechanisms. Similarly, using a time-varying DID method with a dataset covering more than a decade, Zhong et al. (2024) examined how LCCP promoted industrial structure in 283 Chinese prefecture-level cities, some of which were already major industrial hubs. Meanwhile, some scholars assert that LCCP could promote corporate green innovation by lowering policy uncertainty, particularly in sectors heavily reliant on traditional energy sources, and boosting R&D investment toward renewable technologies. Employing a staggered DID model that was specifically designed for time-varying treatments, Liu et al. (2023) concluded that LCCP fostered advancements in green technology of Chinese A-share listed companies that were publicly traded, as well as Wang et al. (2022) also supported this conclusion. As catastrophic climatic events stay more common worldwide and environmental and energy issues gain prominence in different countries, some scholars have focused on how LCCP affects energy efficiency and air pollution, particularly in countries with high levels of industrial pollution and energy consumption. As an illustration, Yang et al. (2023) identified a nonlinear association, particularly evident in urban areas, between LCCP and air quality with a geographic positional heterogeneity using the DID model. Similarly, based on a DID model, He et al. (2023) in their recent study concluded that LCCP

motivated a fall in urban PM_{2.5} levels. Guo et al. (2022) investigated how LCCP affected sulfur dioxide emissions from heavily polluting firms using the DID model, and the results showed that LCCP reduced corporate sulfur dioxide emissions. Some scholars recognize that LCCP can optimize energy efficiency through promoting urban industrial structure, emphasizing the integration of green technologies and technological innovation in pilot cities, thereby supporting long-term economic and environmental benefits (Lee et al., 2022). Using a PSM-DID model commonly used in causal inference, Wang et al. (2023) verified that LCCP enhanced urban energy efficiency, an essential driver of sustainable urbanization. This result was further supported by Zeng et al. (2023).

Research on the application of difference-in-differences (DID) model

Achieving an ideal balance between economic growth and environmental sustainability, countries worldwide typically begin with pilot trials, acquire knowledge, and then gradually expand these efforts to optimize the governance of regional low-carbon emission reductions. In this context, the DID model, a flexible framework suitable for diverse applications, has found widespread application across various fields, including medicine, economics, environment, along with sociology (Guo and Zhong, 2022; Wang, 2023). In the field of economics, the literature on using the DID model to study economic issues is quite extensive. Specifically, Fuest et al. (2018) used the DID model, a widely adopted quasi-experimental method, to analyze how wages were affected by corporate taxes, which influenced corporate behavior and labor market outcomes. They found that employees, in response to the policy changes, absorbed about half of the tax burden, particularly affecting low-skilled, younger, and female workers more heavily in Germany, which reduced their disposable income level. Ganong and Noel (2020) used the DID model to explore how borrowers' liquidity and wealth, which were crucial determinants of financial stability, affected default and consumption decisions during the Great Recession, a period characterized by widespread economic hardship. Utilizing a multi-period DID method, Guo and Zhong (2022) investigated the impact of China's smart city pilot initiative aimed at enhancing urban infrastructure and sustainability. Their outcomes exhibited that this policy significantly enhanced urban innovation performance. Using the DID model, Zhong et al. (2024) evaluated how industrial upgrading, a critical process for enhancing economic resilience and sustainability, was influenced by the LCCP program, which highlighted the benefits arising from changes in environmental regulation. In the field of environmental studies, Watanabe and Watanabe (2019) applied a DID model to evaluate how public perceptions of smog risk were impacted by China's command-and-control regulation outlined in the ambitious Air Pollution Prevention and Control Action Plan, a sweeping national strategy aimed at tackling severe air pollution. The result presented that the regulation effectively reduced the public's risk perception of smog in Tianjin, a city with long-standing air pollution challenges. Schwartz et al. (2021) applied the DID model to investigate data about the insured population, a group with relatively consistent health coverage and access to medical care, concluding that PM_{2.5}, which was capable of penetrating deep into the lungs, increased mortality rates in the United States. Moreover, employing a semi-parametric DID approach, Nenavath (2022) analyzed how fintech and green finance affected the environment in India. The results demonstrated that fintech diminished sulfur dioxide emissions, while green finance substantially lowered industrial carbon dioxide emissions. Han et al. (2024) used the DID model to demonstrate the Winter Clean Heating Plan for Northern China policy, which replaced coal-based heating systems with cleaner energy sources, decreased air pollution emissions in

Northern China, a region historically plagued by severe winter smog and high particulate matter levels. Additionally, several scholars have applied the DID model in sociological and medical research. Ionescu-Ittu et al. (2015), a seminal study in the field of social policy analysis, used a DID model to rigorously examine the long-term and significant food security effects of Canada's Universal Child Care Benefit policy, a nationwide initiative aimed at reducing the financial burden on families with young children, discovering that small monthly income subsidies generally reduced food insecurity, with a more pronounced effect on vulnerable populations. Alonso et al. (2019) took both the DID approach and a regression discontinuity method, which allowed for a more precise evaluation of local-level impacts, and indicated that crime rates linked to social instability were reduced by the United Kingdom's Neighborhood Renewal Fund program, an initiative designed to revitalize economically distressed areas. Based on China's broadband policy aiming to expand internet access nationwide, digital infrastructure construction to meet growing demand for internet services improved people's health, which was concluded by Liu et al. (2024) with a multi-period DID model.

In brief, despite the above literature analysis being comprehensive and well-documented, there are still four shortcomings that need to be adequately addressed. Firstly, there is a lack of accurate examinations of how carbon emissions are affected by environmental regulations, such as carbon taxes and cap-and-trade systems, especially when considering the complexities of regional variations. Second, while LCCP has aroused academic attention, there has been less discussion on how LCCP influences carbon emissions overall. Neglecting to explore the underlying mechanisms hinders a systematic analysis of the pathways for LCCP on carbon emissions. Third, although DID model has gotten research interest, it is not sufficiently efficient in identifying the policy impacts of LCCP owing to the complexity and diversity of the policy environment. Hence, it is essential to deploy the multi-period DID model to identify the sustained effects of interventions in conjunction with the PSM-DID and instrumental variable methods, which are widely recognized for addressing endogeneity issues and providing a more accurate measurement of the immediate and measurable effects of LCCP. Fourth, despite the increasing body of literature widely discussing the impacts of various policies, more in-depth research focusing on the carbon emission control effect of the LCCP scheme is still required on a broader scale.

Materials and methods

The specification of multi-period DID model

It should be noted that, under the LCCP scheme, low-carbon cities reflect pilot initiatives implemented by the Chinese government aimed at advancing ecological civilization, fostering sustainable and low-carbon growth, and accelerating the dual-carbon targets, laid down by the Chinese government in 2020, which covers peaking carbon and neutralizing carbon. To best our knowledge, from policy expectations, they should have carbon reduction effects. To argue that carbon emissions and the creation of low-carbon scheme are causally related, this paper considers LCCP as an exogenous policy shock. Considering that LCCP is initiated in three batches, referring to Pan et al. (2022), a multi-phase DID technique, as expressed in the *Equation (1)* below, is employed to assess how does LCCP matter for carbon reduction:

$$CE_{it} = \alpha + \beta \cdot Low_did_{it} + \gamma \cdot X_{it} + \eta_i + \lambda_t + \varepsilon_{it} \quad (\text{Eq.1})$$

In *Equation (1)*, i reflects the city and t reflects the year. CE_{it} is the carbon emissions level of city i in year t , which is calculated by four types of energy consumption. The constant term is denoted as α . If city i is a low-carbon pilot city at time t , the variable Low_did_{it} is 1, whereas it is 0. The variable X_{it} includes various prefecture-level control variables (*Control*): economic development ($Pgdp$), the level of industrialization ($Indus$), population density ($Dens$), financial development ($Finan$), government fiscal support ($Fiscal$), and economic openness ($Open$). γ denotes the results for control variables. More importantly, η_i , along with λ_t denotes the fixed effects of city (ID FE) and year (Time FE), respectively. ε_{it} is a random error term. In addition, the symbol β reflects how LCCP scheme affects carbon emissions. Because LCCP is to lower carbon emissions, we predict that the value for LCCP scheme β retains notably negative.

Variables declaration

Explained variable: urban carbon emissions (CE)

Since official statistics on carbon emissions have not yet been disclosed by the Chinese government, it is essential to calculate prefecture-level carbon emissions (Xu and Zhu, 2024). So far, scholars have mainly used three methods such as energy consumption method, night-time light data matching method, and high-resolution spatial grid data method to measure prefecture-level carbon emissions in China (Liu et al., 2022; Liang et al., 2022; Zeng et al., 2023). Considering the consistency, comparability, and integrity of data, this study uses energy consumption tactics to derive urban carbon emissions, covering four types of carbon emission sources. The formula is expressed as follows:

$$CE = C_g + C_p + C_e + C_h = \kappa \cdot E_g + \nu \cdot E_p + \varphi \cdot E_e + \chi \cdot E_h \quad (\text{Eq.2})$$

In *Equation (2)*, CE reflects the total carbon emissions in city, with C_g , C_p , C_e , and C_h representing carbon emissions from four types of energy consumption, including natural gas (denoted by the letter g), liquefied petroleum gas (p), total electricity consumption (e), and heating (h), respectively. E_g , E_p , E_e , and E_h represent the consumption in the above four types of energy over the years, respectively. Parameters κ , ν , φ , and χ denote the carbon conversion metric values from natural gas, liquefied petroleum gas, electricity, and raw coal. From IPCC data, natural gas has a carbon coefficient of 2.1622 kgCO₂/m³, liquefied petroleum gas 3.1013 kgCO₂/m³, and raw coal 1.9003 kgCO₂/kg. Due to the complex process of carbon emissions generated by electricity consumption, especially since 2011, China has divided the power grid into six regions, namely, East grid, North grid, Central China grid, South grid (Hainan province merged into the South grid), Northeast grid, and Northwest grid. Therefore, we assess the carbon emissions attributed to electricity use across various regions based on historical carbon dioxide emission benchmarks from China's regional power grid. In essence, we compute the overall carbon emissions (CE) for 282 cities and use logarithmic processing to the data, as illustrated in *Figure 2*. To be more specific, *Figure 2* shows that with the sustained growth of Chinese economy, the total level of urban carbon emissions continues to rise, and geographically exhibits a trend of clustering in the eastern coastal areas. Moreover, to validate the results, this study includes a robustness test that analyzes per capita carbon emissions (PCE).

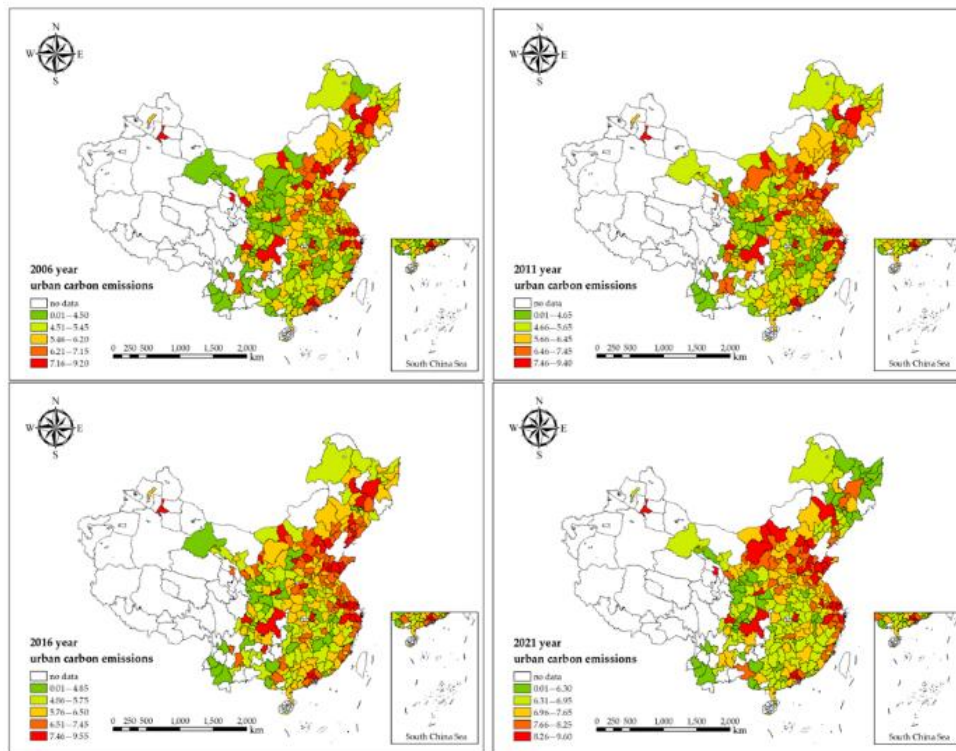


Figure 2. The geographical change patterns for Chinese carbon emissions during 2006–2021

Core explanatory variable: Low carbon city pilot (LCCP)

The research examines the influence of LCCP scheme execution on prefecture-level carbon emissions. Thus, whether a certain area belongs to LCCP is the crucial explanatory variable. When an area is selected in pilot scheme in a certain year, the value is 1, otherwise it is 0. It should be noted that there have been three batches of implementation for LCCP development initiative. To be more specific, the initial batch of LCCP chiefly encompasses 5 provinces, 2 directly governed municipalities, and 6 cities. Later, the 2nd batch for LCCP scheme entails 1 province, 2 municipalities, and 26 cities. The 3rd batch for LCCP scheme, however, entails 35 cities and 10 counties. Following Yang et al. (2023), this study defines all prefecture-level cities in the whole pilot province as pilot cities. For cases where different waves of pilot cities intersect, the earlier implementation year shall prevail. For example, although Kunming, Guangzhou, Yan'an, and Wuhan, are listed as pilot cities in the 2012 batch, their provinces have been implemented as early as 2010. Therefore, the policy execution time for these cities should be defined as 2010. In addition, as the public paperwork for the 2nd batch of LCCP scheme being released on November 26, 2012, and considering the potential period-delay in LCCP execution, 2013 was defined as the beginning year for the 2nd batch of pilot initiatives. After removing samples with missing data and inconsistent administrative levels, a total of 123 pilot city samples and 159 non-pilot city samples are selected in this study.

Control variables

Given the distinctive dynamics of China's economic growth since 2006, we incorporate a set of prefecture-level variables into our model to account for various factors that could influence urban carbon emissions. These include population density (*Dens*),

industrialization (*Indus*), financial development (*Finan*), government fiscal support (*Fiscal*), economic development (*Pgdp*), and economic openness (*Open*). Specifically, *Pgdp* is expressed as each city's per capita regional gross domestic product (GDP). *Open* is clarified, as earlier literature stated, as the role of entire import & export regarding GDP. *Indus* is defined as the proportion of value added by secondary industry in relation to regional GDP. *Finan* is expressed as the ratio of the year-end RMB deposits and loans held by financial institutions to regional GDP in each city. *Fiscal* is reflected by the share of expenses on education and science in each city relative to prefecture-level total fiscal public expenditure. Meanwhile, the figure of each city's permanent residents in its unit administrative area is represented by *Dens*.

Data sources and description

To best our knowledge, the data accessibility, integrity, and comparability are required for empirical analysis. Therefore, we carefully match the LCCP directory with prefecture-level city data to construct a novel panel dataset with a sample interval of 2006–2021. Meanwhile, considering that some cities are located in provinces with many missing data, this research finally extracts 282 prefecture-level cities covering 30 Chinese provinces. The sample dataset for this study is mainly collected from China Statistical Yearbook, China Urban Statistical Yearbook, and EPS Database. More importantly, the underlying data required for calculating urban carbon emissions is obtained by crawling such yearbooks as China Urban-Rural Construction Yearbook, and China Energy Yearbook. For certain missing data stated in this study, we use linear interpolation method and ARIMA technique to fill in it. In addition, to eliminate heteroscedasticity, Winsor 2 truncation method is applied to all continuous variables at 1% quantile, resulting in 4512 prefecture-level observations, as reflected by *Table 1*.

Table 1. Descriptive statistics

Variable	Definition	The whole sample			Pilot cities		Non-pilot cities	
		Obs	Mean	SD	Mean	SD	Mean	SD
<i>CE</i>	Urban carbon emissions	4,512	6.251	1.186	6.460	1.295	6.089	1.067
<i>Low_did</i>	Low-carbon pilot policy	4,512	0.269	0.444	0.617	0.486	0	0
<i>Pgdp</i>	Economic development	4,512	10.490	0.718	10.609	0.717	10.398	0.705
<i>Indus</i>	Industrialization level	4,512	0.381	0.077	0.379	0.069	0.382	0.083
<i>Dens</i>	Population density	4,512	5.737	0.923	5.829	0.832	5.666	0.982
<i>Finan</i>	Financial development	4,512	0.631	0.250	0.691	0.279	0.585	0.214
<i>Fiscal</i>	Fiscal support	4,512	0.036	0.017	0.035	0.015	0.037	0.018
<i>Open</i>	Economic openness	4,512	0.192	0.276	0.245	0.291	0.152	0.257

Empirical results and analysis

The chronological trajectory of urban carbon emissions in China

To illustrate the overall changes of carbon emissions, we draw trend chart and kernel density map of urban carbon emissions (As evinced in *Figure 3*). To be specific, *Figure 3* reveals the formation trends and kernel density distribution of total carbon emissions in China for prefecture-level pilot and non-pilot cities under LCCP scheme execution over the period 2006–2021.

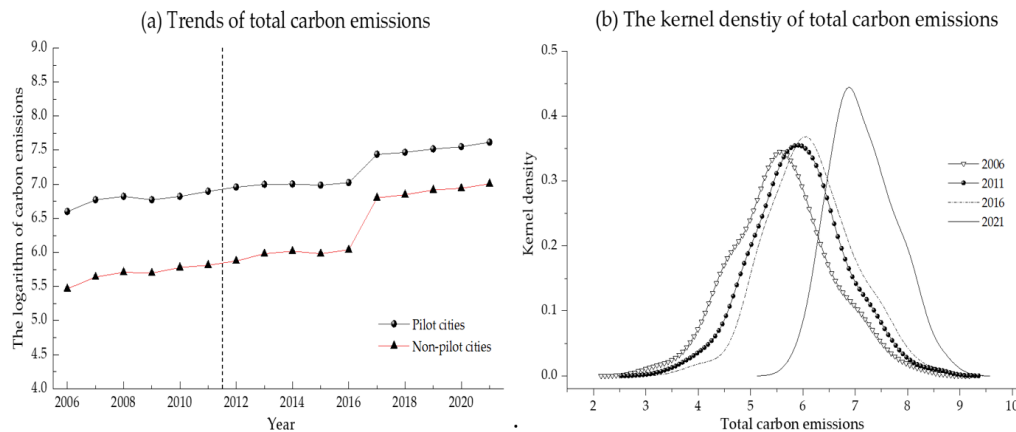


Figure 3. Trends for Chinese prefecture-level carbon emissions during 2006–2021

From the annual trends, as implied in *Figure 3(a)*, pilot cities and non-pilot cities both document an overall upward tendency in carbon emissions levels since 2006. This pattern is in line with economic intuition, implying that prefecture-level carbon emissions levels still steadily increase with recent high-speed economic growth, and realizing the goal for peaking carbon emissions by 2030 is still a hardest task. Meanwhile, as shown in *Figure 3(b)*, the distribution curves of kernel density generally shift to the right from 2006 to 2011, indicating an upward trend in urban carbon emissions, which is line with the fact reflected in *Figure 3(a)*. Moreover, the kernel density curves exhibit a peak state during 2006–2011, indicating that the gaps in carbon emissions across areas become narrowing with the advance of China’s economy, and indeed do not exhibit significant multipolar differentiation pattern.

Baseline regression results

To further clarify LCCP’s causal hyperlink to carbon emissions across urban areas, we act a regression analysis following *Equation (1)*, with the findings detailed in *Table 2*. To be more specific, when defining the dependent variable mentioned in variables notices, Columns (1) to (4) report the estimated results with total carbon emissions, along with Columns (5) to (6) reveal the estimated findings with per capita carbon emissions.

The findings outlined in *Table 2* clearly demonstrate that LCCP is essential in lowering carbon emissions in urban areas. When we contemplate the impacts for China’s LCCP scheme execution on total carbon emissions, Column (1) displays regression findings without control variables, but Column (4) incorporates those same controls. The findings from both columns clearly indicate that, at the 1% level, from a statistic position, the outcomes for LCCP (*Low_did*) are significantly negative. This result supports that LCCP may effectively reduce carbon emissions presented by Zeng et al. (2023). In addition, Column (2) outlines regression findings that eliminate both city and year fixed effects, whereas Column (3) solely excludes year fixed effects. Regardless of the consideration of these fixed effects, LCCP constantly exhibits a substantial negative influence on carbon emissions. In addition, when per capita carbon emissions stated above are chosen as the explained variable in *Equation (1)*, as illustrated in Column (5) and (6), the estimated findings of LCCP remain significantly negative, underscoring the substantial drop in prefecture-level per capita carbon emissions likewise.

Table 2. Baseline regression result of LCCP on urban carbon emissions

Variable	CE				PCE	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Low_did</i>	−0.077*** (−3.36)	−0.067*** (−2.58)	−0.085*** (−3.41)	−0.085*** (−3.87)	−0.089*** (−3.52)	−0.082*** (−3.66)
<i>Pgdp</i>		0.878*** (42.84)	0.834*** (43.15)	0.694*** (16.22)	0.824*** (42.16)	0.758*** (17.44)
<i>Indus</i>		−0.898*** (−5.13)	−3.226*** (−17.48)	−0.284 (−1.41)	−3.153*** (−16.89)	−0.359* (−1.75)
<i>Dens</i>		0.265*** (21.20)	0.393*** (2.94)	0.289** (2.54)	−0.200 (−1.48)	−0.296** (−2.55)
<i>Finan</i>		1.078*** (19.15)	0.334*** (4.98)	−0.053 (−0.81)	0.329*** (4.84)	−0.008 (−0.12)
<i>Fiscal</i>		−11.610*** (−14.31)	−3.226*** (−3.06)	1.585 (1.60)	−2.767*** (−2.60)	2.599*** (2.59)
<i>Open</i>		0.075* (1.83)	0.182*** (3.54)	−0.056 (−1.24)	0.232*** (4.46)	−0.018 (−0.39)
<i>_Cons</i>	6.272*** (751.24)	−4.402*** (−19.38)	−3.626*** (−4.81)	−2.570*** (−3.32)	0.856 (1.12)	1.104 (1.40)
ID FE	Yes	No	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	Yes	No	Yes
R ²	0.898	0.625	0.871	0.906	0.869	0.904
F statistic	11.32	1074.22	771.95	58.27	692.07	60.67
Obs	4,512	4,512	4,512	4,512	4,512	4,512

Note: t value in parentheses. Asterisk means significance: ***p<0.01, **p<0.05, *p<0.1

Robustness analysis

Parallel trend test

While DID model can mitigate endogeneity issues to a certain degree, its application relies on the experimental and control groups, from a statistical perspective, adhering to the parallel trend assumption. More precisely, this assumption posits that prior to the implementation of the policy, the overall trends in carbon emissions, either way, for both pilot and non-pilot cities are identical. Meanwhile, it is important to emphasize that the estimated findings declared above illustrate the common reaction impacts for LCCP scheme on carbon emissions. However, they do not provide a precise explanation for the variations in carbon emissions, presented in benchmark regression, between pilot and non-pilot cities over different periods before LCCP execution. Therefore, following Beck et al. (2010), as mentioned later, the research deeply analyzes the dynamic effects of LCCP by using event study method. *Figure 4* reveals the parallel trend test outcomes for LCCP scheme on total carbon emissions (CE) and per capita carbon emissions (PCE). To be more specific, the outcomes declare that the values for LCCP scheme remains all not significant in the six periods before the policy, indicating stable carbon emission trends in areas for pilots and non-pilots, and supporting the parallel trend hypothesis. Additionally, significant negative estimates for LCCP emerged from the second year after the policy, exhibiting its effectiveness in reducing urban carbon emissions.

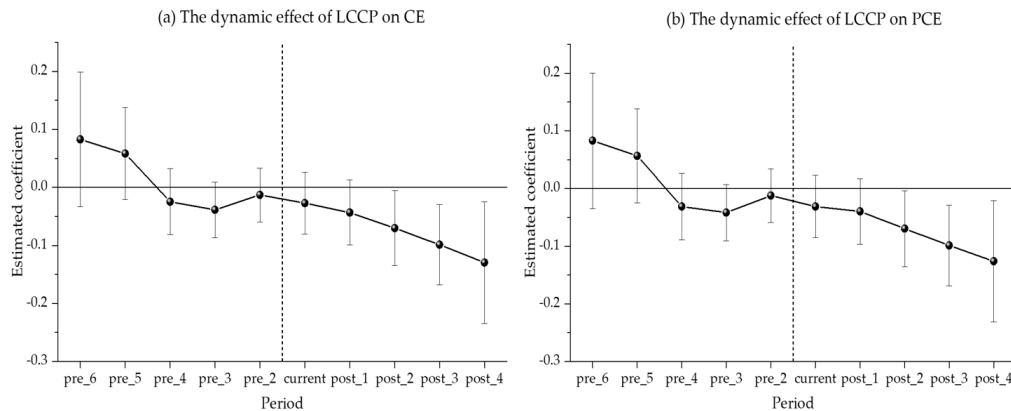


Figure 4. Parallel trend test charts for LCCP on CE and PCE

Placebo test

Even after handling fixed effects and introducing pertinent control variables, certain unobservable components unrelated to LCCP may still influence urban carbon emissions across the sample period. By selecting the treatment unit at random from the entire sample, more precisely, we use a placebo test to further alleviate the threat concerning estimation bias caused by missing some important variables in *Equation (1)*, and seeking to remove the impacts of extra oblique elements on the estimated outcomes. In theory, if the pilots are assigned at random as pseudo treatment groups, it is expected that the treatment effect of LCCP will not be tested (Wang et al., 2023). Therefore, using prefecture-level empirical data spanning 2006–2021, 123 areas are selected at random from the entire specimen to act as the pseudo-experimental units, with policy years assigned randomly for the purpose of re-estimation. More importantly, to further enhance the identification effect, the sampling procedure stated ahead has been repeated 500 times, and the probability and kernel density distribution charts of estimated coefficients for LCCP on CE and PCE are shown in *Figure 5*. It can be observed that the values of the treatment effects are mostly far from the benchmark regression results, and are concentrated on both sides of 0, basically following a normal distribution. In the meantime, the majority of estimated values for LCCP scheme execution with P-values remain higher than 0.1. The findings also reveal that lowering urban carbon emissions, to a greater extent, can be directly attributed to LCCP, rather than being influenced by other unpredictable elements. Thus, the placebo tests confirm the reliability for the above baseline estimation results.

Policy uniqueness test

Considering the fact that other policies may affect urban carbon emissions, it easily causes estimation bias in the benefits evaluation for LCCP execution. Therefore, we also examine four additional policies affecting urban carbon emissions during our study period: the environmental protection tax policy (*Tax_did*) enacted by Chinese government in 2018, the smart city pilot initiative (*City_did*) launched by Chinese government in 2012, the Broadband China strategy (*Broad_did*) from 2014, and the big data experimental zone policy (*Data_did*) introduced in 2016. To remove the threats from these policies on emissions reduction benefits of LCCP, we also add these four policies into *Equation (1)*, with the estimated findings displayed in *Table 3*.

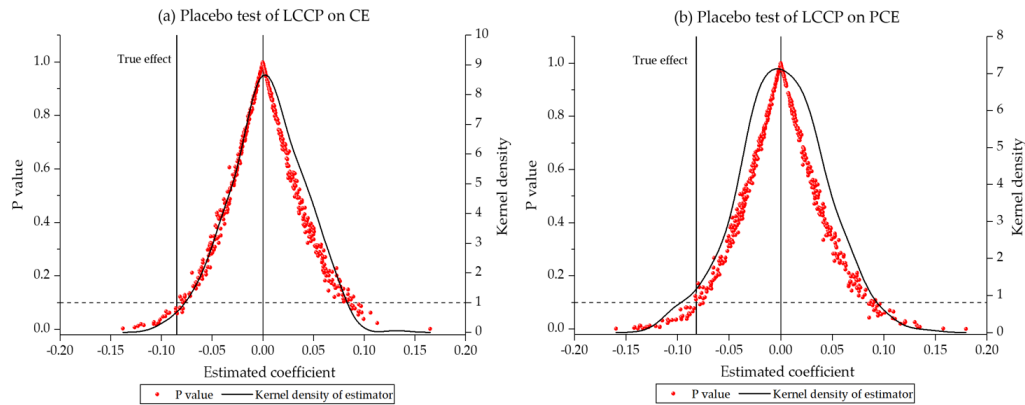


Figure 5. Placebo test charts for LCCP on CE and PCE

Table 3. The outcomes for LCCP policy uniqueness tests

Variable	CE					PCE
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Low_did</i>	−0.094*** (−4.27)	−0.077*** (−3.48)	−0.078*** (−3.59)	−0.084*** (−3.83)	−0.079*** (−3.65)	−0.075*** (−3.39)
<i>Tax_did</i>	−0.166*** (−6.50)				−0.154*** (−6.01)	−0.165*** (−6.33)
<i>City_did</i>		−0.113*** (−3.34)			−0.082** (−2.44)	−0.103*** (−3.02)
<i>Broad_did</i>			−0.189*** (−8.58)		−0.183*** (−8.23)	−0.197*** (−8.72)
<i>Data_did</i>				−0.062** (−2.39)	−0.055** (−2.13)	−0.056** (−2.13)
<i>_Cons</i>	−3.499*** (−4.46)	−2.396*** (−3.09)	−2.569*** (−3.34)	−2.601*** (−3.36)	−3.333*** (−4.28)	0.314 (0.40)
Control	Yes	Yes	Yes	Yes	Yes	Yes
ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.907	0.906	0.908	0.906	0.909	0.907
F statistic	56.77	52.51	61.06	51.76	49.54	52.87
Obs	4,512	4,512	4,512	4,512	4,512	4,512

Note: t value in parentheses. Asterisk means significance: ***p<0.01, **p<0.05

Table 3, to be specific, outlines the estimated findings for LCCP after excluding the threats from other related policies. In particular, Column (1) displays the test outcomes for LCCP, taking into consideration the environmental protection tax policy correlated with carbon emissions. The significantly negative estimation result for LCCP (*Low_did*) suggests that the benchmark findings hold strong. Column (2) illustrates the outcomes of the LCCP in light of the smart city pilot policies. More importantly, from the outcomes, even when the influence of these policies is discounted, LCCP retains its effectiveness in reducing carbon emissions. Column (3) details the LCCP results under the Broadband China strategy policy, revealing that its capacity to curb carbon emissions remains unchanged once this policy’s impacts are excluded. Meanwhile, Column (4) offers insights into LCCP findings concerning pilot initiatives in big data zones. Remarkably,

even after accounting for the big data programs, LCCP persists in emphasizing a noteworthy adverse impact on carbon emissions. Additionally, Column (5) introduces dummy variables for the previously mentioned four policies, confirming that the initial regression outcomes remain consistent. Lastly, the analysis shifts to per capita carbon emissions shown in Column (6) of Table 3, which confirms that carbon emissions are still greatly impacted negatively by LCCP scheme execution.

Other robustness tests

To confirm the reliability for the estimation outcomes mentioned above, with the findings presented in Table 4, this study conducts robustness tests from the following six directions.

Table 4. Robustness test results

Variable	PSM-DID	Carbon intensity	2008–2019	Lagged Control	Modify sample	IV estimation
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Low_did</i>	−0.066*** (−2.95)	−0.042*** (−5.32)	−0.063** (−2.46)	−0.075*** (−3.24)	−0.051** (−2.10)	−0.085* (−1.85)
<i>_Cons</i>	−4.742*** (−5.64)	1.035*** (3.75)	−0.724 (−0.73)	−2.881*** (−3.48)	−3.845*** (−4.72)	— —
Control	Yes	Yes	Yes	Yes	Yes	Yes
ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.901	0.762	0.911	0.905	0.889	—
F statistic	58.60	21.07	20.99	49.19	56.42	12.11
KP-rk-LM						188.539
CD-Wald-F						1.0e+06
Obs	4,192	4,512	3,384	4,230	4,032	4,512

Note: t value in parentheses. Asterisk means significance: ***p<0.01, **p<0.05, *p<0.1

Firstly, this study conducts PSM-DID testing. Assuming that the cyclical change between pilot and non-pilot areas may hinder the empirical findings, this research employs propensity score matching (PSM) technique to further lessen the sample choice bias, with the estimated findings presented in Column (1). The outcomes indicate that the estimated findings of LCCP is notably negative, being same as the benchmark regression results.

Secondly, replace the carbon emissions gauges for test. To avoid such risks caused by the choice of the dependent variable on the benchmark results, we also select the carbon emission intensity, with the way depicted in Xu and Huang (2024) using the role of carbon emissions against GDP, as the dependent variable. In a similar way, the outcomes are disclosed in Column (2). To be more specific, LCCP is −0.042 at the 1% level, proving that renovation in gauging mode for the dependent variable does not alter the benchmark findings.

Thirdly, shorten the data period for test. The effectiveness of a policy after implementation may be influenced by various complex factors in the current year. There may be a time lag from receiving policy information to producing policy effects. To lessen the risk posed by endpoint values on the empirical outcomes, we recalibrated the sample

period to span from 2008 to 2019 and conducted a re-estimation. The outcomes, being fully displayed in Column (3), disclose that the negative influence for LCCP on carbon emissions remains greatly, more importantly, reinforcing the reliability for our benchmark regression analysis.

Fourthly, modify the control variables listed in *Equation (1)* to lag by one period. as, in order to improve estimation accuracy and further mitigate endogeneity, this research lags all control variables by one period to alleviate the reverse causality relation between LCCP and carbon emissions during the same period. As detailed in Column (4), after excluding the lagged effects from the control variables, the negative estimation result of LCCP on carbon emissions remains significant at 1% level, that is to say, demonstrating the robustness of the benchmark findings utterly mentioned above in this study.

Fifthly, exclude data from municipalities and provincial capital cities for test. Owing to the notable economic, political, and technological advantages of municipalities and provincial capital cities, this study excludes Beijing, Tianjin, Shanghai, Chongqing, and 26 provincial capitals for re-estimation. The results can be observed in Column (5), proving that LCCP still exhibit a notable effect in decreasing urban carbon emissions.

Finally, use instrumental variables (IV) to overcome potential endogeneity. Following Xu and Huang (2024), the air circulation factor across cities has been selected as the IV for LCCP. Specifically, assuming total carbon emissions across cities remain unchanged, the lower the air circulation coefficient across different prefecture-level cities, the greater the observed air pollution concentration. The government increases its environmental regulation efforts, and the area has a greater likelihood of being chosen as a pilot, meeting the correlation hypothesis. In addition, the air circulation factors also greatly fulfill the exogeneity criterion well. The IV estimation outcomes, as stated in Column (6), reveal that the coefficient for LCCP remains notably negative, arguing that after overcoming potential endogeneity, LCCP can still effectively reduce urban carbon emissions.

Heterogeneity tests

From the earlier analysis, LCCP execution has significant carbon reduction benefits. Given distinct differences in the carbon reduction, with the estimated outcomes presented in *Table 5*, this paper performs the heterogeneity test on the effect of LCCP scheme.

Table 5. Heterogeneity test results

Variable	Location attribute		Population attribute		Resource attribute		Industrial attribute	
	East	Others_L	Large	Others_P	Non-res	Others_R	Non-base	Others_I
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Low_did</i>	-0.143** (-2.22)	-0.060 (-0.92)	-0.123** (-2.24)	-0.016 (-0.24)	-0.113** (-2.07)	0.007 (0.09)	-0.099* (-1.83)	-0.078 (-1.33)
<i>_Cons</i>	1.928 (0.71)	-5.828*** (-3.03)	2.205 (0.91)	-9.981*** (-4.35)	4.176* (1.68)	-11.370*** (-4.27)	2.085 (0.85)	-3.577 (-1.64)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ID FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.925	0.879	0.939	0.851	0.926	0.869	0.921	0.883
F statistic	10.23	10.85	5.30	13.71	5.45	15.79	8.68	17.59
Obs	1,600	2,912	2,208	2,304	2,688	1,824	2,992	1,520

Note: t value in parentheses. Asterisk means significance: ***p<0.01, **p<0.05, *p<0.1

Firstly, in terms of geographical location, cities located in different regions, to a greater extent, exhibit significant differences in transportation convenience, degree of openness, and policy preferences, showing significant spatial differences in carbon emissions. Then, we categorize the entire sample into two distinct groups: the eastern areas (which entails 100 cities) and the geographic central and western areas (which entails 182 cities), and carry out regression analysis separately. Specifically, Column (1) of *Table 5* shows the regression results in the eastern regions (East), and Column (2) of *Table 5* shows the estimated results in the geographic central and western regions (Others_L). It turns out that the estimated outcome of LCCP scheme in eastern cities is significantly -0.143 , while the outcome of LCCP execution on urban carbon emissions is not essential across central and western cities. The possible reason is that due to rapid economic growth along with high population density of cities in eastern cities, coupled with abundant higher education resources, advanced and mature low-carbon technologies, and relatively complete low-carbon supporting measures, LCCP has always been in a leading position in the course of renovating industrial structure, and has a high awareness of low-carbon city construction. That being the case, the carbon reduction effects for LCCP scheme are relatively ideal. In the central and western cities, the benefits for LCCP scheme on carbon emissions remain minimal. More importantly, this can be attributed to their relatively lower economic development and outdated pollution management technologies, coupled with their acceptance of heavy-polluting, high-energy industries migrating from eastern regions.

Secondly, in terms of population size, demographic factors can affect technological progress and energy consumption structure, causing notable variations in carbon emissions among cities. Therefore, complying with Lee et al. (2022), this study splits the entire data set into two teams given whether the permanent population of urban areas exceeded 1 million in 2014, namely, 138 large areas (Large) and 144 other small and medium-sized areas (Others_P), and conducted regression analysis on each team. As stated in Columns (3) and (4), the associated outcomes certainly exhibit the effects of LCCP for different population size cities. To be more specific, Column (3) displays the regression outcomes for large cities, while Column (4) outlines the results for smaller and medium-sized urban areas. Compared to small and medium-sized areas, we conclude that LCCP scheme greatly hampers carbon emissions in large areas. The possible explanation is that densely populated cities tend to attract a concentration of scientific and technological talent, leading to robust capabilities in technological innovation. Meanwhile, population agglomeration reduces the cost of energy infrastructure, promotes efficient use of energy, and thus forms a comparative advantage in scale. Consequently, the benefits of LCCP in lowering carbon emission are particularly noticeable in populated urban areas.

Thirdly, in terms of resource endowment, the pollution control decisions of firms will be affected regarding natural resource endowment in cities, resulting in noticeable differences in the carbon emissions of cities due to different levels of resource abundance. Therefore, we divide the whole set into two distinct teams: 168 non-resource-based areas (Non-res) and 114 other areas that are resource-based (Others_R), and re-estimate them separately. In *Table 5*, with the estimation outcomes stated in Columns (5) and (6), it reveals that LCCP scheme greatly hampers carbon emissions in non-resource-based areas, whereas the impacts are not notable in resource-rich areas. The potential explanation is that non-resource-based areas flourish in a sound industrial structure and a favorable innovation environment, mainly relying on the tertiary industry to develop

economies, and it is easier to achieve carbon reduction under LCCP. However, resource-based cities are prone to falling into the trap of resource curse and rely more on high-energy consumption industries, making it more tough to attain carbon emissions reduction.

Fourthly, in terms of industrial endowment, the air pollution situation of a city is largely influenced by its industrial endowment, leading to significant differences in carbon reduction effect of LCCP execution. Thus, based on the criterion of whether a city is an old industrial base, we split the sample set into two distinct teams: 187 non-old industrial base areas (Non-base) along with 95 old industrial base areas (Others_I), and re-estimate them separately. The findings can be observed in Columns (7) and (8). To be more specific, Column (7) presents the outcomes for cities with a non-old industrial base, while Column (8) details the outcomes for old industrial base cities. It can be observed that, as reflected in estimated coefficients, LCCP has a noticeable influence in lowering carbon emissions in non-old industrial areas, yet its control efficacy is minimal in old industrial areas. To our knowledge, we can conclude that in old industrial base areas, due to their industrial development leaning towards the industrial sector, especially the heavy industry sector, the demand for traditional energy is relatively high, resulting in serious environmental pollution and carbon emissions. In Non-base areas, their industrial structures are relatively reasonable, and economic development pays more attention to cultivating the tertiary industry with relatively low demand for traditional energy, thus confirming that LCCP promotes carbon reduction across cities.

Transmission mechanism analysis

As detailed in *Table 6*, we perform mechanism tests to elaborate the impact channels for LCCP scheme in lowering carbon emissions primarily focusing on urban energy consumption intensity, green innovation across cities, as well as prefecture-level digital economy levels.

First, by selecting the ratio of energy use to GDP (*Energy*), this study certainly inspects the effect of urban energy intensity mechanism. To be specific, as presented in Columns (1) to (2), the estimated value for LCCP scheme in Column (1) is -0.012 , being notable at the 5% level, displaying that LCCP execution can accelerate the innovation vitality of energy development and utilization technology, improve urban energy utilization efficiency in various industrial sectors, and thus reduce urban energy intensity. Further, with the estimated outcomes outlined in Column (2), from a statistic position, the interaction term between LCCP and energy intensity ($Low_did \times Energy$) remains notably positive at 1% level. By the same token, this demonstrates that decreasing energy intensity could boost how well urban green projects work to lower carbon emissions. This conclusion bolsters the notion that LCCP facilitates urban carbon reduction through diminished energy intensity.

Second, to assess how effectively green technology innovation is influenced, this research employs the total volume of prefecture-level green patent applications (*Green*) authorized by China State Intellectual Property Administration (CSIPA) to fully gauge the extent of green innovation vitality across cities in China, followed by deeply conducting empirical tests. As documented in Columns (3) and (4), from a statistic position, the estimated coefficient for LCCP scheme in Column (3) is 0.149 at the 1% level, proving that LCCP scheme execution properly promote urban green technology innovation. Likewise, at the 1% level, Column (4) portrays a noticeably negative interaction coefficient ($Low_did \times Green$) between LCCP and green innovation. This

suggests that advancements in green technology boost the benefits of LCCP in curbing urban carbon emissions, which posits that LCCP fosters green innovation and mitigates carbon footprints.

Table 6. The results of mechanism test for LCCP on urban carbon emissions

Variable	Energy intensity		Green innovation		Digital economy	
	(1)	(2)	(3)	(4)	(5)	(6)
	Energy	CE	Green	CE	Dige	CE
<i>Low_did</i>	−0.012** (−1.98)	−0.169*** (−3.14)	0.149*** (5.12)	0.149*** (3.09)	0.004*** (2.78)	0.050 (0.82)
<i>Low_did</i> × <i>Energy</i>		1.407*** (2.58)				
<i>Energy</i>		4.338*** (6.61)				
<i>Low_did</i> × <i>Green</i>				−0.299*** (−4.95)		
<i>Green</i>				−0.085 (−1.05)		
<i>Low_did</i> × <i>Dige</i>						−1.948*** (−2.77)
<i>Dige</i>						0.665 (0.88)
<i>_Cons</i>	0.317 (1.62)	−4.632*** (−3.29)	−0.071 (−0.05)	−3.658** (−2.05)	0.286 (1.39)	−2.891 (−1.56)
Control	Yes	Yes	Yes	Yes	Yes	Yes
ID FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.666	0.943	0.870	0.911	0.890	0.907
F statistic	3.39	24.67	14.94	15.29	4.79	11.25
Obs	4,512	4,512	4,512	4,512	4,512	4,512

Note: t value in parentheses. Asterisk means significance: ***p<0.01, **p<0.05

Third, to see the benefits from digital economy advance in cutting China’s prefecture-level carbon emissions, along with that, we employ the digital economy development index (*Dige*), derived using the entropy technique, to reflect the extent of the digital economy across cities, enabling us to conduct thorough empirical analyses. The estimated outcomes are reported in Columns (5) to (6). As being plainly evident, the estimated value for LCCP in Column (5) is 0.004, asserting that LCCP has created favourable conditions for promoting digital economy by accelerating the digital construction of urban statistics and governance systems on carbon emission. In a similar way, the interaction term (*Low_did*×*Dige*) between LCCP and digital economy, from a statistic view, is notably greatly negative at the 1% level, with the outcome observed in Column (6), proving that improving the share for digital economy can enhance the emissions reduction benefits of urban green transformation. Thus, it can be asserted that the essence of LCCP scheme execution in fostering digital economy and expediting carbon emission cuts across cities is indisputable.

Conclusion and policy recommendations

As a critical holistic ecological plan to combat climate change and inspire low-carbon transition progress, LCCP scheme implemented by China provides valuable and essential wisdoms for attaining the great dual-carbon goal proposed by the President Xi Jinping in 2020. In this context, the execution for LCCP scheme being a quasi-natural experiment, employing a prefectural dataset covering 282 cities during 2006–2021, we deeply analyze the impacts of LCCP scheme on China's prefectural carbon emissions by using a multi-phase DID technique. To be more precise, the findings from baseline regression illustrate that, as against non-pilot cities, LCCP scheme has significantly reduced carbon emissions across pilot cities, which is further confirmed by parallel trend test, placebo test, along with other robustness testing. From heterogeneity tests, the findings demonstrate that the carbon reduction benefits for LCCP scheme execution range considerably within different geographies, populations, resource endowments, and industrial distributions. In particular, LCCP scheme execution exerts a notably stronger mitigating benefit on carbon emissions for the eastern areas, large cities, non-resource-based cities, and non-old industrial base cities. More importantly, from mechanism tests, the findings reveal that LCCP scheme execution greatly reduced urban carbon emissions through channels such as reducing urban energy consumption, improving green innovation levels, and advancing digital economy. Thus, we propose the following policy measures.

Firstly, fully capture the experience gained from creating low-carbon cities, gradually broaden the range of pilot cities, and persistently and profoundly advance the creation of ecological civilization. The findings of the research reveal that LCCP has effectively reduced urban carbon emissions, arguing that LCCP could enjoy a vital part in aiding the shift into a low-carbon urban economy. Therefore, it would be prudent for the policymakers in China to systematically broaden the range for LCCP scheme pilot cities by studying and applying the common traits identified in the development strategies of the initial pilot areas. Meanwhile, as an environmental regulatory measure at the city level, the central government should give local governments some autonomy and allow pilot cities to create plans for the implementation of low-carbon construction that are tailored to specific development circumstances. By the same token, it is imperative that the government provide unified supervision and clear guidance through policy execution to ensure the fulfilment of dual-carbon goals. Moreover, for low-carbon pilot cities, existing successful experiences should be summarized, and more reasonable and effective green production mode and lifestyle should be adopted through optimizing energy structure, improving green innovation level, and promoting digital economy development. Establishing a standard that directs the nation towards low-carbon and sustainable growth is essential, ranging from targeted programs to more comprehensive plans.

Secondly, the positive actions of optimizing energy structures, promoting green technological innovations, and advancing the digital economy must be fully leveraged to effectively reduce carbon emissions across cities. To be more precise, the local authorities should actively encourage citizens, businesses, and other market participants to minimize their fossil fuel consumption to continually enhance the urban energy framework. Market-driven strategies including raising consumer awareness of green purchasing, giving tax incentives, and extending financial assistance might help achieve this. The creation of sources of clean and cost-effective energy such as solar, wind, as well as nuclear energy should deserve more of attention. Encouraging this shift from fossil fuels to more environmentally friendly energy sources may also drastically enhance the efficiency of

urban energy consumption. Meanwhile, the government should continuously improve green innovation capacity at the city level, especially enhancing urban R&D investment in green technology, improving the environment for technological innovation, along with focusing on cultivating superior technical skills aimed at green and low-carbon technology, essentially assuring R&D, usage, together with commercialization of low-carbon technologies. In addition, to promote Digital China, the government should invest more in digital infrastructure, focusing on cutting-edge information technology that adapts to international forefront including artificial intelligence, 5G, big data, cloud computing, which will enhance the digitalization and greening of traditional industries, fostering urban low-carbon, high-quality development.

Thirdly, closely focus on regional differences and timely implement differentiated low-carbon development strategies subject to local conditions. Heterogeneity tests reveal marked differences in how LCCP affects urban carbon emissions. For each city, the authority should design scientific and suitable carbon reduction schemes tailored to its unique development context and choose appropriate pathways for sustainable low-carbon growth. In particular, the local decision-makers should encourage the orderly transfer of green technologies and skilled workers from the east to the west to assist low-carbon transitions in underdeveloped areas. Additionally, boosting the radiation effects of huge cities is crucial for balanced growth and enhanced carbon emissions reduction through LCCP. For resource-based cities, attempts must be committed to expand low-carbon input and fund aid. When formulating carbon reduction policies, full consideration should be given to the heterogeneity of their resource endowments. More importantly, for old industrial base cities, while implementing LCCP scheme, it is necessary to enhance the financial support for actively transforming cities to promote carbon reduction.

Finally, steadily foster energy cooperation across regions and sectors, as well as pursue a collaborative mechanism for carbon reduction aimed at promoting energy efficiency. In China, fossil fuel consumption predominantly occurs in economically booming areas near the eastern coast, whereas carbon sink, as well as renewable energy exploitation is largely concentrated in underdeveloped western regions, particularly in the northwest. In this regard, it's essential to create a collaborative framework for regional carbon reduction. We should leverage the influential role of low-carbon pilot cities to deeply and virtually foster cooperation in carbon mitigation efforts across the region. It's crucial to keep a firm hold on the overarching goals at lowering carbon emissions, thereby maximizing the benefits for LCCP in lowering carbon emissions. Building a regional carbon reduction cooperation mechanism can break through geographical limitations, generate spatial spillover effects, and thus help reduce carbon emissions in various regions, allowing central cities to play a leading role and not fight alone. Moreover, building a regional carbon reduction cooperation mechanism can provide more governance tools for urban managers. Local governments should not only focus on carbon reduction in their governance process, but also comprehensively consider political, economic, and welfare issues when reducing carbon emissions. Building a regional carbon reduction cooperation mechanism can not only effectively control carbon emissions, but also bring more choices for local governments. In this process, we should respect the government's leadership role in this process and strive for low-carbon, environmentally friendly development founded on the idea of mutually beneficial cooperation. Therefore, we can continuously expand the range of LCCP and leverage the positive externality of carbon reduction.

To clarify, it must be admitted that there are two notable limitations in this research. Firstly, prefecture-level city administrative units make up the empirical sample. Due to

limitations in data availability, this paper is unable to perform more detailed empirical inquiry at the county or firm level. Thus, for more robust estimation, county-level data or corporate data will be collected for analysis at the micro level in the future. Secondly, the spatial ripple benefits for LCCP scheme on carbon emissions reduction are overlooked in the empirical model. To be specific, this research employs a multi-period DID technique to deeply explore how carbon emissions react to LCCP scheme. Given that urban carbon emissions undeniably exhibit significant geographical interconnections, to quantify the environmental effects of LCCP scheme, the spatial spillover effects should be thoroughly considered. In the future, we will incorporate a spatial multi-period DID technique for a more comprehensive and detailed assessment.

Acknowledgements. This study was financially supported by the National Social Science Foundation of China (19BRK036) and the Humanities and Social Science Youth Foundation of the Ministry of Education in China (18YJC840047). The authors thank the reviewers of this paper for their insights and comments.

REFERENCES

- [1] Alonso, J. M., Andrews, R., Jorda, V. (2019): Do neighbourhood renewal programs reduce crime rates? Evidence from England. – *Journal of Urban Economics* 110: 51-69.
- [2] Alshehry, A. S., Belloumi, M. (2015): Energy consumption, carbon dioxide emissions and economic growth: The case of Saudi Arabia. – *Renewable and Sustainable Energy Reviews* 41: 237-247.
- [3] Aslan, A., Destek, M. A., Okumus, I. (2018): Sectoral carbon emissions and economic growth in the US: Further evidence from rolling window estimation method. – *Journal of Cleaner Production* 200: 402-411.
- [4] Beck, T., Levine, R., Levkov, A. (2010): Big bad banks? The winners and losers from bank deregulation in the United States. – *Journal of Finance* 65: 1637-1667.
- [5] Cai, B. F., Cui, C., Zhang, D., Cao, L. B., Wu, P. C., Pang, L. Y., Zhang, J. H., Dai, C. Y. (2019): China city-level greenhouse gas emissions inventory in 2015 and uncertainty analysis. – *Applied Energy* 253: 113579.
- [6] Candelon, B., Hasse, J. B. (2023): Testing for causality between climate policies and carbon emissions reduction. – *Finance Research Letters* 55: 103878.
- [7] Chen, J., Guo, Z. G., Lei, Z. J. (2024): Research on the mechanisms of the digital transformation of manufacturing enterprises for carbon emissions reduction. – *Journal of Cleaner Production* 449: 141817.
- [8] Chen, X. M., Huang, Y. H., Gao, Y. J. (2024): Can urban low-carbon transitions promote enterprise digital transformation? – *Finance Research Letters* 59: 104807.
- [9] Ertugrul, H. M., Cetin, M., Seker, F., Dogan, E. (2016): The impact of trade openness on global carbon dioxide emissions: Evidence from the top ten emitters among developing countries. – *Ecological Indicators* 67: 543-555.
- [10] Fuest, C., Peichl, A., Sieglösch, S. (2018): Do Higher Corporate Taxes Reduce Wages? Micro Evidence from Germany. – *American Economic Review* 108: 393-418.
- [11] Ganong, P., Noel, P. (2020): Liquidity versus Wealth in Household Debt Obligations: Evidence from Housing Policy in the Great Recession. – *American Economic Review* 110: 3100-3138.
- [12] Gao, S. Q., Cuffey, J., Li, G. C., Li, W. Y. (2024): Diet in China during substantial economic growth: Quality, inequality, trends, and determinants. – *China Economic Review* 86: 102208.

- [13] Guo, Q. B., Zhong, J. R. (2022): The effect of urban innovation performance of smart city construction policies: Evaluate by using a multiple period difference-in-differences model. – *Technological Forecasting and Social Change* 184: 122003.
- [14] Guo, P., Li, J., Kuang, J. S., Zhu, Y. F., Xiao, R. R., Duan, D. H., Huang, B. C. (2022): Low-Carbon Governance, Fiscal Decentralization and Sulfur Dioxide Emissions: Evidence from a Quasi-Experiment with Chinese Heavy Pollution Enterprises. – *Sustainability* 14: 3220.
- [15] Han, D. R., Yan, S., Sun, X. M. (2024): Research on the air pollution reduction effect of winter clean heating policy. – *Urban Climate* 53: 101760.
- [16] Hassan, T., Khan, Y., He, C. L., Chen, J., Alsagr, N., Song, H. M., Khan, N. (2022): Environmental regulations, political risk and consumption-based carbon emissions: Evidence from OECD economies. – *Journal of Environmental Management* 320: 115893.
- [17] He, Y., Lai, Z. Y., Liao, N. (2023): Evaluating the effect of low-carbon city pilot policy on urban PM_{2.5}: evidence from a quasi-natural experiment in China. – *Environment, Development and Sustainability* 26: 4725-4751.
- [18] Ionescu-Ittu, R., Glymour, M. M., Kaufman, J. S. (2015): A difference-in-differences approach to estimate the effect of income-supplementation on food insecurity. – *Preventive Medicine* 70: 108-116.
- [19] Jiang, W., Sun, Y. F. (2023): Which is the more important factor of carbon emission, coal consumption or industrial structure? – *Energy Policy* 176: 113508.
- [20] Kim, D. H., Suen, Y. B., Lin, S. C. (2019): Carbon dioxide emissions and trade: Evidence from disaggregate trade data. – *Energy Economics* 78: 13-28.
- [21] Kinyar, A., Bothongo, K. (2024): The impact of renewable energy, eco-innovation, and GDP growth on CO₂ emissions: Pathways to the UK's net zero target. – *Journal of Environmental Management* 368: 122226.
- [22] Lee, C. C., Feng, Y., Peng, D. Y. (2022): A green path towards sustainable development: The impact of low-carbon city pilot on energy transition. – *Energy Economics* 115: 106343.
- [23] Li, J. L., Xu, X. G. (2024): Can ESG rating reduce corporate carbon emissions? An empirical study from Chinese listed companies. – *Journal of Cleaner Production* 434: 140226.
- [24] Liang, X. Y., Fan, M., Xiao, Y. T., Yao, J. (2022): Temporal-spatial characteristics of energy-based carbon dioxide emissions and driving factors during 2004–2019, China. – *Energy* 261: 124965.
- [25] Liu, X., Li, Y. C., Chen, X. H., Liu, J. (2022): Evaluation of low carbon city pilot policy effect on carbon abatement in China: An empirical evidence based on time-varying DID model. – *Cities* 123: 103582.
- [26] Liu, B., Gan, L., Huang, K., Hu, S. Y. (2023): The impact of low-carbon city pilot policy on corporate green innovation: Evidence from China. – *Finance Research Letters* 58: 104055.
- [27] Liu, Y. W., Liu, K. S., Zhang, X. L., Guo, Q. Y. (2024): Does digital infrastructure improve public Health? A quasi-natural experiment based on China's Broadband policy. – *Social Science & Medicine* 344: 116624.
- [28] Luo, Y. S., Mensah, C. N., Lu, Z. G., Wu, C. (2022): Environmental regulation and green total factor productivity in China: A perspective of Porter's and Compliance Hypothesis. – *Ecological Indicators* 145: 109744.
- [29] Lyu, J., Liu, T. L., Cai, B. F., Qi, Y., Zhang, X. L. (2023): Heterogeneous effects of China's low-carbon city pilots policy. – *Journal of Environmental Management* 344: 118329.
- [30] Moscona, J., Sastry, K. A. (2023): Does Directed Innovation Mitigate Climate Damage? Evidence from U.S. Agriculture. – *Quarterly Journal of Economics* 138: 637-701.
- [31] Narayan, P. K., Narayan, S. (2010): Carbon dioxide emissions and economic growth: Panel data evidence from developing countries. – *Energy Policy* 38: 661-666.

- [32] Nenavath, S. (2022): Impact of fintech and green finance on environmental quality protection in India: By applying the semi-parametric difference-in-differences (SDID). – *Renewable Energy* 193: 913-919.
- [33] Neves, S. A., Marques, A. C., Patrício, M. (2020): Determinants of CO₂ emissions in European Union countries: Does environmental regulation reduce environmental pollution? – *Economic Analysis and Policy* 68: 114-125.
- [34] Nordhaus, W. (2019): Climate Change: The Ultimate Challenge for Economics. – *American Economic Review* 109: 1991-2014.
- [35] Pan, A., Zhang, W. N., Shi, X. P., Dai, L. (2022): Climate policy and low-carbon innovation: Evidence from low-carbon city pilots in China. – *Energy Economics* 112: 106129.
- [36] Schwartz, J., Wei, Y. G., Yitshak-Sade, M., Di, Q., Dominici, F., Zanobetti, A. (2021): A national difference in differences analysis of the effect of PM_{2.5} on annual death rates. – *Environmental Research* 194: 110649.
- [37] Shang, Y. P., Raza, S. A., Huo, Z., Shahzad, U., Zhao, X. (2023): Does enterprise digital transformation contribute to the carbon emission reduction? Micro-level evidence from China. – *International Review of Economics & Finance* 86: 1-13.
- [38] Shapiro, J. S. (2021): The Environmental Bias of Trade Policy. – *Quarterly Journal of Economics* 136: 831-886.
- [39] Tian, X., Chang, M., Shi, F., Tanikawa, H. (2014): How does industrial structure change impact carbon dioxide emissions? A comparative analysis focusing on nine provincial regions in China. – *Environmental Science & Policy* 37: 243-254.
- [40] Wang, H. P., Zhang, R. J. (2022): Effects of environmental regulation on CO₂ emissions: An empirical analysis of 282 cities in China. – *Sustainable Production and Consumption* 29: 259-272.
- [41] Wang, T. H., Song, Z., Zhou, J., Sun, H. P., Liu, F. Q. (2022): Low-Carbon Transition and Green Innovation: Evidence from Pilot Cities in China. – *Sustainability* 14: 7264.
- [42] Wang, Y. H., Xiong, S. Q., Ma, X. M. (2022): Carbon inequality in global trade: Evidence from the mismatch between embodied carbon emissions and value added. – *Ecological Economics* 195: 107398.
- [43] Wang, M. L. (2023): Effects of the green finance policy on the green innovation efficiency of the manufacturing industry: A difference-in-difference model. – *Technological Forecasting and Social Change* 189: 122333.
- [44] Wang, L. H., Shao, J., Ma, Y. T. (2023): Does China's low-carbon city pilot policy improve energy efficiency? – *Energy* 283: 129048.
- [45] Wang, Z. Y., Liang, F. Y., Li, C. M., Xiong, W. Z. X., Chen, Y. S., Xie, F. B. (2023): Does China's low-carbon city pilot policy promote green development? Evidence from the digital industry. – *Journal of Innovation & Knowledge* 8(2): 100339.
- [46] Watanabe, R., Watanabe, T. (2019): Effects of environmental policy on public risk perceptions of haze in Tianjin City: A difference-in-differences analysis. – *Renewable and Sustainable Energy Reviews* 109: 199-212.
- [47] Wei, S. J., Xie, Z., Zhang, X. B. (2017): From "Made in China" to "Innovated in China": Necessity, Prospect, and Challenges. – *Journal of Economic Perspectives* 31: 49-70.
- [48] Xu, X. P., Huang, L. Y. (2024): How Does Environmental Protection Tax Affect Urban Energy Consumption in China? New Insights from the Intensity Difference-in-Differences Model. – *Sustainability* 16: 4141.
- [49] Xu, X. P., Zhu, Y. Q. (2024): Towards Green Development: Identifying the Impact of Population Aging on China's Carbon Emissions Based on the Provincial Panel Data Analysis. – *Polish Journal of Environmental Studies* 33: 4861-4877.
- [50] Yang, S. B., Jahanger, A., Hossain, M. R. (2023): How effective has the low-carbon city pilot policy been as an environmental intervention in curbing pollution? Evidence from Chinese industrial enterprises. – *Energy Economics* 118: 106523.

- [51] Yang, Z. F., Yuan, Y. N., Tan, Y. (2023): The impact and nonlinear relationship of low-carbon city construction on air quality: Evidence from a quasi-natural experiment in China. – *Journal of Cleaner Production* 422: 138588.
- [52] Yang, W. W., Hei, Y. Y. (2024): Research on the Impact of Enterprise ESG Ratings on Carbon Emissions from a Spatial Perspective. – *Sustainability* 16: 3826.
- [53] Yasmeen, H., Tan, Q. M., Zameer, H., Tan, J. L., Nawaz, K. (2020): Exploring the impact of technological innovation, environmental regulations and urbanization on ecological efficiency of China in the context of COP21. – *Journal of Environmental Management* 274: 111210.
- [54] Zeng, S. B., Jin, G., Tan, K. Y., Liu, X. (2023): Can low-carbon city construction reduce carbon intensity? Empirical evidence from low-carbon city pilot policy in China. – *Journal of Environmental Management* 332: 117363.
- [55] Zhang, C., Fang, J. M., Ge, S. L., Sun, G. L. (2024): Research on the impact of enterprise digital transformation on carbon emissions in the manufacturing industry. – *International Review of Economics & Finance* 92: 211-227.
- [56] Zhao, S., Zhang, L. Q., An, H. Y., Peng, L., Zhou, H. Y., Hu, F. (2023): Has China's low-carbon strategy pushed forward the digital transformation of manufacturing enterprises? Evidence from the low-carbon city pilot policy. – *Environmental Impact Assessment Review* 102: 107184.
- [57] Zhong, Z. Q., Zheng, C. Y., Chen, Z. G. (2024): Low-carbon cities pilot and industrial structure upgrading: enabling or negative? Evidence from a quasi-natural experiment in China. – *Journal of Environmental Planning and Management*.
<https://doi.org/10.1080/09640568.2024.2319267>.