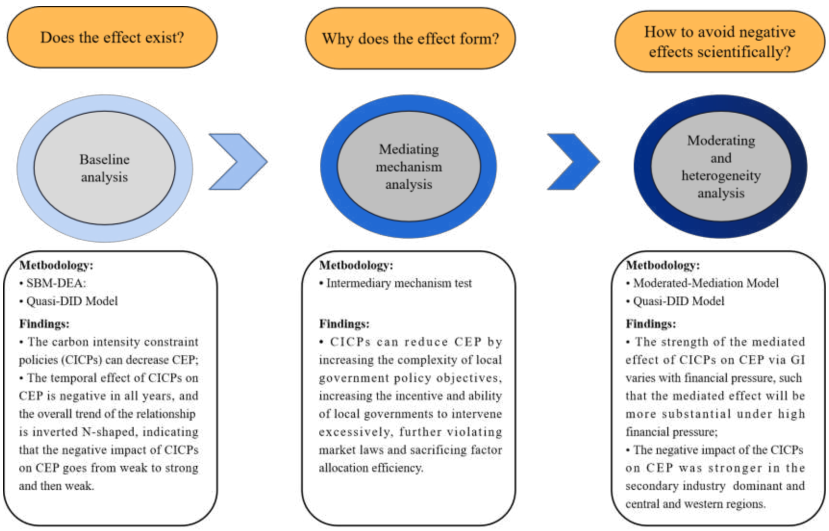
Can China's carbon intensity constraint policies improve carbon emission performance? Evidence from regional carbon emissions

Abstract: Carbon Intensity Constraint Policies (CICPs) are vital for addressing climate change challenges and advancing sustainable development. Since 2010, China has rolled out three five-year CICPs. However, there is limited understanding of their impact on carbon emission performance (CEP). Addressing this, this study pioneers the exploration of the CICP's impact on China's CEP. Drawing from government intervention and green paradox theories, this study highlights a concerning scenario: local governments achieve emission targets via excessive intervention. For deeper insights, this study melds the overall technology frontier concept with a non-radial, non-angle directional distance function, introducing a novel efficiency model rooted in the Data Envelopment Analysis (DEA) method. This offers a CEP measure across 30 Chinese provincial regions from 2002-2019. Using the quasi-difference-in-differences (quasi-DID) and moderated mediation models, this study ascertains the presence of the green paradox, uncover its reasons, and suggest mitigation strategies. The results indicate that high government intervention diminishes CEP. This negative effect intensifies under greater regional fiscal pressure. Alarmingly, local authorities' eagerness to meet targets shows a counterproductive, inverted N-shaped trend regarding CICPs' time-based influence on regional CEP. Moreover, the impact varies based on regional economic development levels and stages. This study has ensured the robustness of the findings via parallel trend tests, parallel exclusion policies, a strengthened quasi-DID framework, and diverse control variable configurations. This study underscores the need for more balanced government intervention. It offers valuable policy insights, guiding China's upcoming CICP phase to realize the ambition of peaking carbon by 2030 and achieving carbon neutrality by 2060.

Graphical Abstract:



Keywords: carbon intensity constraint policy; carbon emission performance; government intervention; green paradox; quasi-difference-in-differences

1. INTRODUCTION

With urbanization and industrialization, the consumption of various energy sources, including fossil fuels, has produced substantial amounts of greenhouse gas (GHG) (Kuang & Lin, 2021). Emissions of carbon dioxide (CO_2), a component of the GHG, trigger the global greenhouse effect (Qin et al., 2021; Luo et al., 2023). The global greenhouse effect causes temperature rises, extreme weather, natural disasters, and food crises, severely limiting the ongoing development of the global economy and society (Ren et al., 2023). Therefore, achieving sustainable CO_2 emissions reduction has become critical for global and regional sustainable development (Jin et al., 2020). China has become the world's largest energy consumer (Ma et al., 2023), with an energy consumption of almost 5.24 billion tons of standard coal in 2021, and the energy consumption per unit of gross domestic product has reached 1.4 times the world average (6.19). China has also become the world's largest carbon emission emitter (Li et al., 2021), with nearly 10 billion tons of carbon emissions accounting for 28% of the world's carbon emissions. China is confronted with the dual challenges of energy shortages and GHG emissions, which have become a critical issue for China in international climate change negotiations (Xiong et al., 2020). It is crucial for China to transform into a low-carbon economic development model that involves reducing energy consumption and carbon emissions, to contribute to the global response to climate change (Chang et al., 2023).

To achieve a low-carbon economic transformation, the Chinese central government has introduced various targeted measures and policies to develop a society that economizes resources and protects the environment (Ouyang et al., 2020; Wang et al., 2021a). The Chinese central government announced the detailed implementation planning of the 12^{th} Five-Year Plan (FYP) in 2011. For the first time, the Chinese central government insisted on a carbon emission reduction scheme as one of the top priorities, requiring national regional average carbon emissions per capita of GDP to decline by 17% within five years from 2010. The Chinese central government then assigned carbon emission reduction targets to the local governments' performance evaluation systems (Shao et al., 2019), ensuring that local governments consider the critical nature and urgent importance of energy conservation and emission control. Furthermore, the Chinese central government has set a new target to reach the peak of CO_2 emissions by 2030 and achieve carbon neutrality by 2060 (Mallapaty, 2020). Therefore, in the face of the central government's stringent and ambitious carbon emission reduction targets, local governments are bound to accomplish the tasks.

However, the green paradox theory indicates that stricter enforcement of environmental policies intensifies the exploitation of fossil energy and flows large amounts into the market (Sinn, 2008). Ultimately, environmental regulations increase fossil fuel energy consumption and overall carbon emissions. This implies that an imperfect design of environmental policies may lead to unexpected implementation results, deviating from the original intention of the environmental measure design (Lai et al., 2022). Given the actual conditions in China, the gap between environmental policy formulation and implementation allows more scope for economic agents to adopt strategic behavior (Zhang et al., 2017). It is essential to analyze the green paradox from the policy implementation perspective. Local environmental policies are implemented to achieve the central government's intention to reduce carbon emissions by intervening in corporate operation activities (Yin et al., 2022). However, because of the complexity of the 3E-system (economy-environment-energy system) and the dynamic and diverse external situations, the effectiveness of emission reduction policies is contingent on the degree to which local governments implement them, that is, the degree of government intervention (Zhou & Feng, 2017). Indeed, as the pressure to reduce carbon emissions intensifies, some regions have implemented extreme administrative measures to control corporate emissions, including forced power rationing (Peng et al., 2018), to stop corporate production to meet emission reduction targets in the short term. Excessive government intervention is detrimental to the long-term construction of a low-carbon economy and is inconsistent with the carbon peaking and neutrality objectives. Therefore, analyzing the effectiveness of CICPs from the perspective of local government intervention is crucial for China to achieve its carbon neutrality goal.

This study relates to two strands of the literature. One strand focuses on the determinants of carbon emissions. Special attention has been paid to the factors that affect carbon emissions from many aspects, such as scale, structure, technology, and institutional conditions (Zhang & Zhang, 2018; Sheng et al., 2020). Scholars have shown that relevant institutional conditions, such as corruption, fiscal decentralization, fiscal transfer payments, and environmental regulations, can influence carbon emission reductions (Pei et al., 2021; Yang et al., 2019; Zhou & Lin, 2023). Environmental regulations can directly influence carbon emission levels (Xu et al., 2022). Scholars have made efforts to reveal the ties between environmental regulations and carbon emissions, but have not reached a consistent conclusion (Lu et al., 2022). Some scholars have argued that environmental regulation can control carbon emissions from the endpoint, and thus contribute to carbon emission reduction. For example, Chen and Lin (2021) found that, as an effective market-oriented policy, the carbon emission trading scheme can significantly improve carbon/energy performance. Similar conclusions have been reached by Shi et al. (2022) and Gu et al. (2022). Some studies have argued that predictable carbon tax policies (Kiss et al., 2021), supportive policies for low-carbon energy (Grafton et al., 2012), environmental policy lags (Di et al., 2012; Smulders et al., 2012), and unilateral environmental policies (Daubanes et al., 2021) lead to ineffective environmental regulations that fail to curb carbon emissions and generate a green paradox (Sinn, 2008). In addition, some scholars have found uncertainty regarding the direct impact of environmental regulations on carbon emissions (Wu et al., 2020; Lu et al., 2022). Furthermore, Huang and Tian (2023) concluded that there is a nonlinear relationship between environmental regulations and net carbon emissions. However, it is unclear whether the CICP, as a constraint target environmental regulation, can influence carbon emission performance. The causal relationships and drivers between the two call for an in-depth study.

The other strand evaluates the effects of the constraint target policies. Studies on the effects of constraint target policies have primarily focused on green production performance (Yang et al., 2017) and energy consumption (Shao et al., 2019). Studies have mainly concentrated on industrial sectors at the green production performance level. For example, Yang et al. (2017) found that CICPs cause a factor substitution effect that hinders the improvement of green production performance in China's 36 industrial subsectors. Research on energy consumption has focused on whether CICPs have a positive influence on energy efficiency and energy structure (Shao et al., 2019; Yang et al., 2022). For instance, Shao et al. (2019) pointed out that the constraint policy related to energy intensity is not conducive to the total factor energy efficiency in subsectors with higher energy intensity levels. Yang et al. (2022) empirically tested that rigorous carbon regulation is detrimental to upgrading the energy structure, while appropriate carbon intensity reduction targets are conducive to increasing low-carbon energy consumption. Although the literature provides evidence of the impact of CICP policies on environmental aspects, there is a lack of empirical evidence for comprehensively evaluating the impact of such policies on carbon emissions.

The existing literature provides good references for this study but encounters the following three challenges. First, most current studies have classified policies into categories and examined the impact of heterogeneous environmental regulations on CEP (Huang & Tian, 2023), drawing inconsistent conclusions. Ahough a number of scholars have paid attention to relevant carbon reduction policies that have been introduced in recent years (Yang et al., 2022; Luo et al., 2023), few studies have examined how carbon reduction policies affect CEP.

Second, existing studies have mostly used single-factor indices, such as CO_2 emissions or carbon intensity, to test the effects of carbon reduction policies (Pei et al., 2021; Xu et al., 2021). Although CICPs are directly concerned with reducing CO_2 emissions, in the actual goal achievement process, they also affect other inputs and outputs related to production and the overall allocation efficiency of the factors. In addition to determining whether China's carbon reduction target, reflected by the single-factor index, can be achieved, the effect of the CICPs will also impact the achievement of carbon neutrality and near-zero emissions in terms of total-factor carbon efficiency. Therefore, there is a need for a more in-depth and rigorous examination of the effectiveness of CICPs in improving carbon efficiency, based on scientific measures of carbon reduction intensity.

Third, studies on CEP have mostly focused on its impact on total factor energy efficiency (Shao et al., 2019), industrial structural transformation (Zhang et al., 2018), energy structure optimization (Yang et al., 2022), corporate innovation (Huang & Zhang, 2021), and changes in corporate competitiveness and performance (Yan et al., 2021; Lu & Zhang, 2022). No studies have discussed the impact of CICPs on CEP. Scholars generally use a homogeneous empirical analysis of the relationship between CICPs and the research object. However, implementing the CICP depends on local government intervention and varies across regions. It is necessary to analyze the mechanisms and heterogeneity of policy effects in different regions.

To fill the research gap, this study calculated and analyzed the CEP of China's 30 provincial regions from 2002 to 2019 using an Overall Technology (OT) frontier DEA model that rests on a non-radial, non-angular Directional Distance Function (DDF). This method avoids the disadvantages of adopting single carbon emission efficiency. Second, this study employed the quasi-difference-in-differences (quasi-DID) technique to analyze the influence of CICPs on CEP. Accordingly, the theoretical mechanism and regional differentiation of the effects of CICPs on CEP are explored through a moderated mediation model by incorporating local government intervention (GI) and fiscal pressure (FP) into a unified analytical framework. Finally, this study conducted robustness tests on the empirical findings using concurrent exclusion policy, strength-DID, and control variable substitution analyses.

The contributions of this study are summarized as follows. First, it contributes to the literature on the green paradox theory by illustrating the policy effects of the CICPS. This study extends prior theoretical and empirical research on why current environmental policy implementation has failed to achieve the desired results. In particular, this paper details how the "green paradox" is caused by local government intervention and identifies why and how it produces effects contrary to the original intent of environmental policy from the perspective of policy implementation. Previous studies have argued that China's green paradox is caused by market segmentation (Lai et al., 2021), government decision-making competition (Li & Xu, 2020), and fiscal decentralization (Zhang et al., 2017; Chen et al., 2020). However, this study argues that the root cause of China's green paradox in CICPs is the excessive intervention by local governments. Considering market failure and the property of public goods of carbon emissions, the effectiveness of CICPs will inevitably be compromised owing to institutional distortions of government over-intervention. With the implementation of more stringent CICPs, China's overall carbon emissions have shown a downward trend, but CEP has not improved significantly. Under a system of political promotion, local governments have an incentive to over-intervene and even distort environmental regulations to gain political success in achieving a win in political competition. The under-examined CICPs are a case of green paradox generation, suggesting that the effectiveness of China's policy implementation is insufficient (Zhang et al., 2017), providing additional evidence to verify green paradox theory. Second, this study advances the understanding of the policy effect by exploring the mechanisms and heterogeneity of how the CICP impacts CEP in more detail. Specifically, most previous studies have overlooked the possible mediating role of government intervention. This study incorporated the CICPs, GI, and CEP into one analytical framework, used FP as an additional variable, and investigated heterogeneous policy effects based on two attributes of the dominant industries and economic development level to systematically analyze the influence of the CICP on CEP more comprehensively. Moreover, this study extends the existing frontier DEA model (Afsharian & Ahn, 2015) and combines the non-angle, non-radial Directional Distance Function (DDF) proposed by Zhou et al. (2012) to construct a new type of DEA efficiency measurement model to solve the problems of technological frontier setting bias and efficiency measurement bias and to provide a more accurate measurement of the CEP, which improves the single-factor index evaluation in previous literature. This will enable a more specific, accurate, and appropriate evaluation of regulations.

Subsequent sections detail the policy background, theoretical hypotheses, data sources, and methods, followed by results, conclusions, and policy recommendations.

2. POLICY BACKGROUND AND THEORETICAL HYPOTHESIS

2.1 Policy Background

China's CICPs started with the 2011 Control Greenhouse Gas Emissions Program, which originated with China's green, low-carbon development strategy. At the Copenhagen Climate Conference in 2009, China announced that it would take action to decrease its carbon intensity by 40% to 45% by 2020 on the base of the 2005 level (Xu et al., 2022). Against this background, China made a 17% reduction in carbon emissions a mandatory binding target for the first time in its 11th FYP. Most recently, China announced an 18% reduction in carbon intensity in the 14th FYP to attain the significant aim of carbon neutrality by 2060 (Mallapaty, 2020). These policies outlined the overall requirements and objectives, various emission reduction measures, incentives, constraint mechanisms, a low-carbon development strategy, and a comprehensive development plan for China's carbon emissions reduction. The implementation of CICPs is of great practical importance.

The CICPs have distinctive features. Unlike previous command-and-control and market-based regulations, CICPs are constraint-based. The Chinese central government determined each region's award-punishment measures and mechanisms to reduce CO_2 emission intensity in 2011 and further optimized the assessment indicators in 2016. In particular, the following two mechanisms were established. First, the completion of the reduction target was included in the comprehensive evaluation system of economic social development and bureaucrat promotion evaluation system. Provincial governments and relevant departments are responsible for controlling GHG emissions in their regions and sectors. Second, the reduction of CO_2 emission intensity is incorporated in the region's economic and social development planning, the development of specific work programs, and the establishment of improved working mechanisms to control GHG emissions work to implement accountability, rewards, and punishments (Wu et al., 2020).

The quota distribution of carbon emission control targets by region in the 12th and 13th FYP is shown in Table 1. The staggered implementation of the CICPs as a plausibly exogenous shock provides significant spatial and temporal variations for studying the impact of target-bound emission reduction policies on carbon emissions.

Insert Table 1 about here

2.2 Theoretical Hypothesis

2.2.1 CICPs and Carbon Emission Performance

The China's central government allows local governments to implement CICPs according to local conditions. However, there is a gap between policymaking and implementation, and accordingly, an impact on the CEP. China’s low-carbon technology innovation has yet to balance economic goals and emission reduction targets to decouple economic growth and CO_2 emissions (Du and Li, 2019; Xu et al., 2021). Therefore, the target of CO_2 emission reduction will affect regional economic development. Previous research has found a negative correlation between environmental regulation and carbon emissions (Shi et al., 2022; Gu et al., 2022). Many other researchers have found a correlation between environmental regulations and economic output (Li et al., 2022; Chen et al., 2022). Carbon emission performance depends on the influence of both CO_2 emissions and economic output factors. However, existing studies have not explored the joint role of environmental regulation, CO_2 emissions, and economic output. Therefore, this study is a pioneer to analyze the role of CICP on CEP in terms of both CO_2 emissions and economic output.

According to green paradox theory, stakeholders' expectations of the stringency of regulations will accelerate energy extraction and the sale of energy assets, thereby accelerating energy consumption and increasing CO_2 emissions (Lai et al., 2022). To implement CICPs to meet carbon reduction targets and compensate for the increase in CO_2 emissions that stakeholders expect from the policy, local governments may close down high-emission enterprises, exacerbating the decline in economic output (Lu et al., 2021). The campaign style for the implementation of CICPs locally leads to a simultaneous decrease in the growth rates of carbon emissions and economic output. However, the effects of the two on CEP were in two different directions. Therefore, the simultaneous decrease in both counteracts the positive effect of CICPs on CEP, and may have a negative effect. Additionally, local governments reduce CO_2 emissions by reducing energy consumption, whereas economic output involves energy consumption and many other factors. The substitution relationship among factor inputs (Kumar et al., 2015) allows local governments to maintain their economic output by increasing the inputs of other factors. Particularly, a significant increase in capital (K) with high output elasticity causes the input structure of economic development to break away from the original optimal level and against the market mechanism. Therefore, the implementation distortions of CICPs may affect the market mechanism and decrease CEP.

As a result, the first hypothesis is proposed below:

H1: CICPs have negative impact on CEP.

2.2.2 The Mediating Role of Government Intervention

The green paradox points out that the speculative behavior among the relevant economic agents in the policy implementation process results in the inevitable distortion of policy (Zhang et al., 2017). Accordingly, this study presents a pioneering analysis of the causes of the green paradox from the perspective of government intervention.

The causality can be traced to the Chinese fiscal decentralization. It is effective to decentralize power of the central government to local governments to give them more autonomy. The central government simultaneously has the absolute authority to appoint local bureaucrats and can reward and punish them. The CICPs explicitly strengthened the evaluation of local bureaucrats' CO_2 emission reduction performance. In this new situation, the CO_2 binding reduction target is an essential factor that directly affects the careers of local bureaucrats. At the same time, CICPs increase the complexity of local government policy objectives; local governments need to adjust environmental policies, fiscal transfers, and other interventions according to their characteristics in the policy implementation process. Therefore, fiscal decentralization gives local governments the incentive and ability to implement undue interventions, leading to the inevitable emergence of policy implementation distortions. Specifically, the Chinese central government's policy of achieving a double carbon target means that CO_2 reduction will be a significant political achievement for local governments. Local governments' tight regulation of high-carbon industries and blind subsidies for low-carbon technologies have gained legitimacy and have borne fewer political costs and risks. Consequently, local governments have introduced strict carbon emission reduction policies to pursue short-term carbon emission targets. This kind of disregard for the actual local situation and the completion of the assessment in a non-developmental way has caused the regional economic structure to remain at a low-level, high-energy, and deformed development level. Excessive intervention by local governments has distorted the Chinese central government's policy intentions.

The negative impact of government intervention imply the necessary conditions for the green paradox to occur. Government intervention has two main observable effects on regional CEP. First, the "supporting hand" of government intervention in high-carbon enterprises distorts the allocation of factors and reduces the performance of carbon emissions. The "supporting hand" refers to local governments providing policy and financial support for low-carbon projects. Financial subsidies are the most direct way for the government to intervene in enterprises and are particularly important for promoting low-carbon development (Shen et al., 2021). However, Most enterprises receive government subsidies and use them for the field of capacity projects (Yu et al., 2023) unrelated to research and development (R&D). Government subsidies are ineffective in promoting low-carbon research investment and do not lead to the spillover of regional carbon emission reduction technologies. Second, government intervention has a mandatory effect on high-carbon enterprises inevitably accompanied by economic stagnation, which is detrimental to improving CO_2 emissions performance. The "grabbing hand" is mainly manifested by legal authorization (such as formulating laws and regulations) to regulate society and the market to regulate expected emissions. Since high-carbon enterprises are the primary source of CO_2 emissions, local governments have forced the closure of high-carbon industries to reduce emissions. Production restrictions to reduce CO_2 violate economic laws and do not contribute to long-term CO_2 emission performance (Feng et al., 2023). In addition, excessive government interventions such as mandatory "pulling and limiting" of electricity disrupt the routine production rules of enterprises, destroying their means and methods of saving electricity and causing unnecessary excess energy waste. Although government interventions effectively reduce emissions in the short term, they cannot cure energy dependence, cannot fundamentally reduce CO_2 and improve performance for a long time. Hence, Hypothesis 2 is proposed as follows:

H2: Government intervention mediates the negative relationship between the CICPs and CEP.

2.2.3 The Moderating Role of Financial Pressure

Institutional factors, such as fiscal pressure, influence local government behavior, which can lead to distortions in implementing environmental policies, especially under a fiscal decentralization system and political tournaments (Chen et al., 2020; Zhang et al., 2017). This section explores how to reduce and avoid the inhibitory effect of distortions in the implementation process of CICPs on CEP, from the perspective of institutional factors. The conceptual model is illustrated in Figure 1.

Due to the mismatch between local governments' financial rights and affairs, financial pressure on local governments in China has been increasing. Faced with financial pressure, local governments seek revenue support in various ways to alleviate financial stress. Generally, local governments facing fiscal pressure will promote the growth of tax sources and increase fiscal revenue through land concessions and environmental deregulation. However, faced with the pressure on the carbon emission reduction performance of the CICPs, it is no longer the optimal choice for local governments to sacrifice resources and carbon emissions in exchange for tax revenues to relieve fiscal pressure. Local governments use non-tax revenues, such as Chinese central government subsidies, to reduce financial stress. The Chinese central government provides financial incentives to promote regional low-carbon development by selecting demonstration cities for energy efficiency and emission reduction. Therefore, under intense fiscal pressure, local governments will strengthen government interventions to balance fiscal pressure and emission reduction pressure by obtaining non-tax revenue from being selected as demonstration cities. First, incentive funds from the Chinese central government and provincial support funds directly expand local governments' financial resources, which relieve financial pressure of local governments and reduce local governments' independence on enterprises of energy-intensive consumption and high-pollution, and accordingly, increase local governments' intervention ability. Second, the performance assessment of the Chinese central government further amplifies the economic incentive effect. The government's performance assessment is a "baton". The CICPs stipulate that incentive funds will be withheld or deducted for cities that fail to meet annual targets. Under the performance appraisal, local bureaucrats will intensify government intervention to complete energy-saving and emission-reduction targets and will not deduct incentive funds. In summary, fiscal pressure exacerbates the effect of CICPs on government intervention, and this effect tends to be more prominent in regions with high fiscal pressure.

Fiscal pressure also affects local revenues and expenditures during the implementation of the CICPs, which affects the impact of government intervention on CO_2 emission performance. The "supporting hand" of local government intervention is to promote CO_2 emission reduction primarily by increasing fiscal spending on low-carbon development innovations. Fiscal pressure can change the structure of local government expenditures and deviate from the optimal level of intervention. They prefer to spend on productive projects with short investment cycles, quick results, and low risk (Grisorio and Prota, 2015). Compared with other technological innovation, low-carbon related technological innovation involves a more complex process and higher innovation costs. Therefore, an increase in fiscal pressure weakens local governments' optimal resource allocation to low-carbon technological innovation, exacerbating the negative impact of government intervention on regional CEP. In addition, local governments' grabbing hands have reduced CO_2 emissions by strengthening regulations. Simultaneously, fiscal pressure promotes discriminatory regulation enforcement by local governments to raise revenue, resulting in opportunistic corporate carbon emission reductions. Discriminatory regulatory enforcement by local governments increases fiscal revenue and restricts long-term carbon reduction performance. Discriminatory regulation is more prevalent among key firms because local government revenues and officer career opportunities are associated with large key firms that provide massive jobs and profits. Under substantial financial pressure, key firms' bargaining power reduces the deterrent effect of the regulation, and local governments may meet their carbon reduction targets by subjecting small firms to closer scrutiny. In addition, driven by the CICPs, local governments tend to favor large key firms, whereas small firms, even in non-high-carbon industries, are sometimes forced to shut down by local governments to leave room for crucial firms' carbon emissions. Thus, the negative effect of government intervention on emissions is more pronounced in regions with high fiscal pressure. Therefore, the third hypothesis is proposed (Figure 2).

H3: The strength of the mediated effect of CICPs on CEP via GI varies with financial pressure, such that the mediated effect will be more substantial under high financial pressure.

Insert Figure 1 about here

Insert Figure 2 about here

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3. RESEARCH DESIGN AND METHODS

3.1 Data Sources and Indicators Processing

Considering the availability and completeness of the data, this study included data from China's 30 provincial regions during 2002-2019, excluding Tibet, Taiwan, Macao, and Hong Kong, due to their missing data. Following the criteria made by the National Bureau of Statistics, this paper classifies the 30 provinces into three main regions:

the eastern region covers Hainan, Guangdong, Fujian, Jiangsu, Zhejiang, Shandong, Hebei, Liaoning, Shanghai, Tianjin, and Beijing, and the western and central regions cover the rest of the 19 provincial regions.

3.1.1 Part I: Input and Output Data in the DEA Model for Measurement of CEP

The provincial data used in the CEP indicator include the desired output of industrial output (GDP), non-desired output of carbon emissions (CE), and input factors, including energy input (E), labor input (L), and capital input (K). The ideal industrial exportation (GDP) is deflated using year 2000 as the base period to derive a comparable series. According to Shao et al. (2011), the unexpected output measurement uses the physical energy consumption of all 17 fossil energy sources reported in the energy balance sheet multiplied by a conversion coefficient. Capital inputs (K) are characterized using capital stock, which is calculated through the perpetual inventory method (Goldsmith, 1951) and deflated to a comparable series based on prices in year 2000. The labor input (L) takes the average annual employment and counts in 10,000. Energy input (E) takes the total energy consumption as a proxy variable in units of 10,000 tons. The data are collected from the "China Industrial Economic Statistics Yearbook (CIESY)", "China Economic Census Yearbook (CECY)", "China Energy Statistical Yearbook (CESY)", besides statistical yearbooks of various provinces.

3.1.2 Part II: Data Used in Quasi-DID Model

The CICPs were implemented in 2011, with 2010 as the policy intervention period. This study sets 2011 to 2019 as the years of implementation of CICPs and 2002 to 2010 as the period before the policies were issued. In addition to the CEP calculated by the DEA model, the original data of mediating variables, moderating variables, and control variables in the quasi-DID model were obtained from the China Industrial Economic Statistics Yearbook (CIESY), China Statistical Yearbook (CSY), China Financial Statistical Yearbook (CFSY), besides statistical yearbooks of various provinces.

3.2 Measures

3.2.1 Dependent Variables

Carbon Emission Performance (CEP). The Malmquist-Luenberger index proposed by Chung et al. (1997) and depended on the Shephard distance function has three apparent shortcomings: it does not have a circularity feature while has biased angular and radial efficiency measures (Du et al., 2018). This study sets up a DEA measurement model as the environmental total factor productivity (TFP) growth index based on the strength of non-angle, non-radial DDF, incorporating environmental non-desired outputs proposed by Zhou et al. (2012) and the aggregate technology proposed by Afsharian and Ahn (2015) as follows:

$$P^0(x^t)=\bigcup_{t=1}^{T}P^t=\left\{\begin{array}{l}(y,b):(\sum_{k=1}^{k}z_k^1y_{km}^1\geq y_{km}^t,\sum_{k=1}^{k}z_k^1b_{ki}^1=b_{ki}^t,\sum_{k=1}^{k}z_k^1x_{kn}^1\leq x_{kn}^t)or...or\\(\sum_{k=1}^{k}z_k^Ty_{km}^T\geq y_{km}^t,\sum_{k=1}^{k}z_k^Tb_{ki}^T=b_{ki}^t,\sum_{k=1}^{k}z_k^Tx_{kn}^T\leq x_{kn}^t);\\z_k^t\geq 0,\forall m,\forall i,\forall n,\forall k\end{array}\right\} \tag{1}$$

$$\vec{D}^0(x,y,b;g)=\sup\{\mathbf{W}^T\beta:(x,y,b)+g\times diag(\beta)\in P^0(x)\} \tag{2}$$

$$\vec{D}^0(x^t,y^t,b^t;g^t)=\max\left\{\left\{\begin{array}{l}\max w_m^y\beta_{my}^{O,t}+w_i^b\beta_{ib}^{O,t}+w_n^x\beta_{nx}^{O,t}\\s.t.\sum_{k=1}^{K}z_k^ty_{km}^t\leq y_m^t+\beta_{my}^{O,t}g_{my}^t,\forall m;\\\sum_{k=1}^{K}z_k^tb_{ki}^t=b_i^t-\beta_{ib}^{O,t}g_{ib}^t,\forall i\\\sum_{k=1}^{K}z_k^tb_{kn}^t\geq x_n^t-\beta_{nx}^{O,t}g_{nx}^t,\forall n;z_k^t\geq 0\end{array}\right\}\right\} \tag{3}$$

where $x=(x_1......x_N)\in\circ^+{}_N$ represents the input of N elements for each decision-making unit (DMU), $y=(y_1......y_M)\in\circ^+{}_M$ represents the M expected outputs produced, $b=(b_1.....b_I)\in\circ^+{}_I$ represents I kind of no-expected production output, $t=1,......,T$ represents each period, and (y_k^t,b_k^t,x_k^t) represents the output input vector of $DMU_k=(k=1,......,K)$. Compared with the technology frontier, the overall technology frontier can comprehensively consider the input and output information of multiple periods and ensure that the benchmark technology for efficiency measurement in each period is uniform, thus enhancing the comparability of the measurement results. Compared with the technology frontier, the overall technology frontier can comprehensively consider the input and output information of multiple periods and ensure that the benchmark technology for efficiency measurement in each period is entirely uniform, thus enhancing the comparability of the measurement results. Based on a study by Zhou et al. (2012), Zhang et al. (2013), and the Luenberger productivity indicator (Chambers et al., 1996), the CEP in t+1 is as follows:

$$TFCEP=\vec{D}^O(x^t,y^t,b^t;g^t)-\vec{D}^O(x^{t+1},y^{t+1},b^{t+1};g^{t+1}) \tag{4}$$

This study chooses GDP(Y) and carbon emissions (C) as the expected and unexpected outputs, respectively, and take energy consumption (E), labor (L), and capital stock (K) as input factors. Then, the vector system was set, and the expected output, undesired output, and input factors were assigned 1/3 weights. Subsequently, the weights were equally distributed according to the types and quantities of the expected output, unexpected output, and input factors; namely, the weight vector was set as (1/3, 1/3, 1, 9, 1/9, 1/9). Therefore, CEP>0 (CEP<0) demonstrates the melioration (deterioration) of CEP. Using the above method, this study has calculated the CEP of all of China's provinces from 2002 to 2019. The regional CEP average is illustrated in Figure 3.

Insert Figure 3 about here

3.2.2 Independent Variables

Carbon Intensity Constraint Policies (CICPs). In the context of the 12th and 13th FYPs, a quasi-natural experiment was set up by applying the quasi-DID method to assess the influence of the CICPs on the CEP. Where, $CI_{it} \times Post_{it}$ is the key independent variable. First, a dummy variable $Post_{it}$ was constructed to implement the CICPs, which takes the value of 1 in the year when implementing the CICPs and each subsequent year, and 0 otherwise. Second, the CI_{it} variable measures the carbon emission. With a view to the carbon emission target raised in the CICPs, this study uses the emissions per unit of GDP to measure. In addition, Eq. (1) is a quasi-DID model as carbon emission intensity is a continuous type variable.

3.2.3 Mediating Variable

Government Intervention (GI). In the method described by Shao et al. (2022), local government intervention was measured by the ratio of fiscal expenditure for environmental protection to GDP. This ratio reflects the level of government intervention among the low-carbon transition of the economy as a whole.

3.2.4 Moderating Variable

Financial Pressure (FP). The management authority of local governments has not been reduced in line with the decrease in the tax sharing of corporate income tax and value added tax (VAT) system, which has put enormous financial pressure on local governments (Kou and Han, 2021). FP comes from fiscal deficits, durative out-of-balance between routine and financial powers (Hui et al., 2022). Based on this, Yang and Peng (2022) measured fiscal stress from the perspective of fiscal gap, using the per capita fiscal gap = (fiscal expenditure − fiscal revenue)/total population of an area at the end of the year to calculate fiscal pressure (FP). Higher ratio means higher FP. This paper mainly discusses the impact mechanism of CICPs on CEP under FP; therefore, the FP indicator is reflected in the interaction term with CICPs in Eq. (10) and Eq. (11).

3.2.5 Control Variables

Based on related previous studies and considering data availability, This study includes five significant control variables of CEP in the quasi-DID model: foreign direct investment (FDI), financial development scale (FDS), industrial structure (IND), economic growth level (GDP), and labor per capital stock (KL), apart from the CICP.

Foreign Direct Investment (FDI). FDI facilitates access to advanced green technologies that drive economic growth. Foreign investment brings about technology spillover effects and increases energy consumption intensity, which leads to "*the pollution haven effect or halo effect*" (Wang et al. 2021). Therefore, FDI is an essential factor that affects carbon emissions. This study estimates FDI by adopting "*the product of the actual use of foreign investment and the annual average exchange rate as a proportion of GDP"* (Hui et al., 2022).

Financial Development Scale (FDS). The ability of financial development to reduce the cost of capital is a vital indicator of the causal relationship between economic investment and energy efficiency (Al-Mulla and Sab, 2018). Financial development exacerbates energy consumption and carbon emissions by encouraging productive activities (Feng and Wu, 2022). This study uses the loans of financial institutions to GDP to characterize the scale of financial development.

Industrial Structure (IND). Industrial structure is crucial for economic sustainability and carbon emissions because of the difference in energy consumption between the secondary and tertiary sectors (Zhang et al., 2019). Considering that the existing indicators cannot reflect the trend of industrial structure change, this study adopts the ratio of the value-added of the secondary industry to that of the tertiary industry.

Economic Growth Level (GDP). Regional economic development results in increased energy demand and promotes carbon emissions. This study considers the size of the economy and population and uses the logarithm of real GDP per capita to measure per capita GDP.

Labor per capita stock (KL). Optimizing the factor input structure is an essential strategy for achieving low-carbon development in China. As capital and labor are undoubtedly the two most essential factors of production, this study uses the actual capital stock to the annual average labor force as a measure of factor structure to examine the impact of the relative abundance of capital and labor on carbon emissions (Shao et al., 2022). Table 2 defines the aforementioned variables.

Insert Table 2 about here

3.3 Empirical Strategy

The empirical framework comprises the following two parts. The first part constructs the panel data model of the quasi-DID assessment model to quantify the effects of implementing the CICPs on CEP. Then, the annual dynamic changes in implementing the CICPs on CEP were tested. The second part of this study investigates the channels of the CICPs effects from the perspective of government intervention. Deep empirical analysis of the inhibitory effect of CICPs on CEP by considering and identifying the moderating effects of financial pressure that significantly impede CEP.

3.3.1 Quasi-DID Model for Investigating The CICPs Policy-Induced Effect

The implementation of the CICPs, as raised in China's 12th FYP, is bound to have different effects on various regions with different levels of CEP. Thus, such a policy can be deemed as a natural experiment, allowing to adopt the DID method to evaluate the actual effect of the policy. Considering that carbon emission intensity and emission performance are continuous treatment variables, this study regards 2009 as the shock year of policy implementation and use the Quasi-DID method (Yang et al., 2017) to capture the influences of CICP on CEP. Thus, a quasi-did model is established as follows.

$$CEP_{it} = \alpha_0 + \alpha_1 CI_{it} \times Post_{it} + \alpha_2 X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{5}$$

where i denotes a province level, and t represents a year. The dependent variable CEP_{it} refers to CEP. CI_{it} represents continuous carbon-intensity data. $Post_{it}$ is a dummy variable equal to 1 if $t \geq t_{i0}$, where t_{i0} refers to the year the CICP was implemented and 0 otherwise; thus, $CI_{it} \times Post_{it}$ stands for the implementation of the CICPs, where X_{it} denotes the control variables, and u_i and λ_t represent the fixed effects of province and time, respectively, which absorb all provinces and time-level characteristics invariant across time. ε_{it} is the error term. 0 controls for potential heteroskedasticity and serial correlation of the error term, standard errors are clustered at the provincial level.

Unlike the standard DID, which artificially sets the treatment group and the control group, the quasi-DID model objectively evaluates the impact of implementation of CICPs on CEP through continuous measures of treatment variables (CI_{it}) with interaction terms of policy dummy variables. Therefore, the parameter α_1, associated with the variable $CI_{it} \times Post_{it}$ provides a quasi-DID estimation of the net impact of the CICPs on CEP. That is, it captures the variation in carbon emissions performance to province in years when the CICPs were implemented relative to pre-implementation. Three scenarios exist for the estimated values of α_1. First, a significantly negative α_1 indicates that the CEP violates the original policy intentions, known as the green paradox (Sinn, 2008). Second, the significantly positive α_1 indicates that the CICP boosts CEP, which confirms that the CICPs are effective. Third, the insignificance indicates that the CICPs cannot affect the CEP, which is contrary to the original intention of environmental policies.

Next, since equation (5) is a static model, which examines the net effect of CICPs on CEP, it lacks a decomposition of the change in induced impacts over time of CICPs. Hence, to capture the annual effects of CICPs and CEP more comprehensively and accurately, a series of yearly dummy variables interacting with policy variables are created based on equation (5), and the dynamic effects are observed by estimating the interaction term "coefficients". Thus, the final dynamic panel model used to test the impact of the CICPs on the CEP is as follows:

$$CEP_{it} = \omega_0 + \sum_{t}^{2002} \omega_t CI_{it} \times Post_{it} + \omega_2 X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{6}$$

3.3.2 Moderated-Mediation Model for Investigating the Mechanism Effect of CICPs

Since implementing the Chinese central government's CICPs, local governments have faced changes in the political environment brought about by target assessment regulations. In response, local governments have made behavioral choices to achieve their carbon emission reduction targets. One of their choices is to alter the degree of government intervention, based on which the mechanisms of action between emission reduction policies and CEP are analyzed. The mechanism of action was tested according to the method of Baron and Kenny (1986). The practical test steps were as follows. First, the dummy variables of CICPs and GI were regressed; if the coefficient is significant, it means that the CICPs promote local government intervention. Second, GI was regressed on CEP. Government intervention is not conducive to improving carbon emissions performance if the coefficient is significant. Third, the dummy variables of CICPs and GI indicators were put into the model and regressed with CEP. The coefficients of the dummy variables of CICPs are the same as those of the main coefficients above. In this case, GI plays a role in mediating the effect of CICPs on CEP. The mechanism validation model estimation is specified as follows:

$$GI_{it} = \beta_0 + \beta_1 CI_{it} \times Post_{it} + \beta_2 X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{7}$$

$$CEP_{it} = \lambda_0 + \lambda_1 GI_{it} + \lambda_2 X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{8}$$

$$CEP_{it} = \mu_0 + \mu_1 CI_{it} \times Post_{it} + \mu_2 GI_{it} + \mu_3 X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{9}$$

where GI_{it} represents government intervention. The remaining variables are the same as those in equation (5).

Technically, the α_1, β_1, λ_1 and μ_1 validate the action mechanism of implementation of CICPs.

From the local government's perspective, meeting public finance needs is the primary goal of its operations. It is hoped that local governments draw fiscal revenue directly from the market through various means, especially from productive projects with a strong marginal return on investment. However, productive projects usually suffer from high energy consumption, emissions, and pollution. Implementing CICPs regulate productive projects. It is precisely the best choice for local government behavior to strengthen government intervention to meet carbon reduction targets to obtain corresponding financial subsidies and accomplish the primary goal. The effect of CICPs on CEP was tested based on Equation (5) estimation results. Considering the possible variability in the mechanism of action between CICPs, GI, and CEP as fiscal pressure increases, a two-stage regression function was developed using a moderated mediation model. This method can not only determine the moderating effect of the direct effect more precisely, but it also provides significance tests for the moderating effect of the mediating mechanism (Hansen,2000). Taking the Moderated-mediation model as an example, the specification is

$$GI_{it} = \theta_0 + \theta_1 CI_{it} \times Post_{it} + \theta_2 FP_{it} + \theta_3 CI_{it} \times Post_{it} \times FP_{it} + \theta_4 X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{10}$$

$$CEP_{it} = \eta_0 + \eta_1 CI_{it} \times Post_{it} + \eta_2 GI_{it} + \eta_3 FP_{it} + \eta_4 CI_{it} \times Post_{it} \times FP_{it} + \eta_5 X_{it} + u_i + \lambda_t + \varepsilon_{it} \tag{11}$$

where FP_{it} denotes financial pressure, and θ_3 and η_4 are the moderating effect coefficients to be estimated.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics and Correlations

The descriptive statistics and correlations between the main variables are shown in Table 3. Among the 540 samples from 2002 to 2019, the mean CEP was -0.0660, with a standard deviation of 2.153, minimum value of -10.02, median of 0.181, and maximum of 6.871. These indicate that there are large differences in carbon reduction performance and that there are significant differences in CEP across regions. Before testing the impact of CICPs on CEP, this study examined the extent of correlation between various variables to inspect possible multicollinearity in the parameter estimation. Table 4 shows that the model's correlations among the variables were not high, and the VIF was less than 8. Therefore, there was no severe multicollinearity among the variables to conduct ordinary least squares regression directly.

Insert Table 3 about here

Insert Table 4 about here

4.2. Hypotheses Tests

In Table 5, the results of the quasi-DID model in the year-province fixed effects are reported. Models (1) – (4) report the impact of CICPs on GI and models (5) – (8) examine the effects of CICPs and GI on CEP. In Models 1 and 5, only the control variables are included. In Models 2 and 3, the independent variable (CICPs) and the moderating variable (FP) are included, respectively. Following Model 4, the interaction between CICPs and FP is included. In Models 6, 7 and 8, the independent variable (CICPs), mediating variable (GI), moderating variable (FP), and interaction between the CICPs and FP are added, respectively.

Insert Table 5 about here

4.2.1 Effect of the CICPs

Hypothesis 1 states that the implementation of CICPs has the potential to decrease CEP. Model 6 shows a negative and statistically significant relationship between CICPs (B=-0.383; p<0.001) and CEP. This result was also confirmed in the other models. After removing the possible confounding factors, implementing CICPs decreased CEP by approximately 0.383%. These results contradict the previous findings that environmental regulations drive carbon emissions performance (Shi et al., 2022; Gu et al., 2022). This result confirmed hypothesis 1, and showed that CICPs are negatively related to CEP, verifying the existence of the green paradox in the implementation of CICPs.

4.2.2 Mediation effect of government intervention

Hypothesis 2 states that government intervention (GI), as an underlying mechanism, mediates the effects of CICPs on CEP. Referring to Baron and Kenny (1986), this study used the causal steps approach to test the mediating role of GI, and the results are shown in Table 5. First, this study estimated the impact of CICPs on CEP. As shown in Model 6, CICP was negatively correlated with GI (B= -0.383; p<0.001). Second, this study regressed mediator-existing GI. As shown in Model 2, CICPs have a significantly positive effect on GI (B=0.335, p<0.001). Third, this study added the mediator to the primary model as an additional variable in Model 7 and found that GI significantly and negatively influenced CEP (B=-0.131 and p<0.001 in Model 3). This study also found that when GI was added, the magnitude of the impact of CICPs on CEP (B=-0.346, p<0.001) was decreased. This finding validates hypothesis 2. Overall, these findings indicate that the CICP does not affect CEP directly but through the intervening mechanism of government intervention. This result is consistent with this study's expectation that environmental policies are ineffective or even counterproductive due to local governments' excessive intervention aiming to quickly reach carbon reduction assessment targets.

The possible reasons are discussed as follows. First, the fiscal decentralization and political promotion systems allow local governments to allocate resources to intervene in economic development to meet carbon emission reduction targets with discretionary implementation. Meanwhile, the carbon emission reduction-oriented CICPs have increased the diversity of local government tasks, requiring local governments to balance economic development and environmental protection. Therefore, local governments must implement additional policy interventions to balance economic development and carbon emissions. Moreover, carbon emission reduction is a significant political achievement that can reduce local bureaucrats' political costs and risks, inducing local bureaucrats to disregard the actual development stage, distort factor markets, and alienate corporate behavior, leading to lower carbon emission performance. When local governments intervene in corporate behavior to reduce carbon emissions through financial subsidies, firms have a powerful incentive to make short-term profits. This incentive drives firms to use government environmental subsidies for capacity investment areas unrelated to emission reduction. In addition, local governments' coercive means of closing and restricting enterprise production undermine the means and methods of reducing emissions for enterprises and go against the laws of economic development. In other words, the mystery of the "green paradox" lies in the local government behavior, and therefore the distortion of local government behavior leads to the creation of the "green paradox".

4.2.3 Moderated-mediation effects of financial pressure

According to hypothesis 3, Financial Pressure (FP) had an indirect effect in the first (CICP→GI) and second stages (GI→CEP), and acted as a moderated mediator in both phases (Hayes, 2015). Table 5 (Model 3) shows that the interaction term for CICPs and FP had a significantly positive effect on GI (B=0.638, SE=10.39. p<.001). The simple slope plot (Figure 4a) shows that the impact of CICPs on GI is significant and negative under low FP, but positively significant and stronger under high FP. Table 5 (Model 6) shows that the interaction term for GI and FP has a significantly negative effect on CEP (B=-0.037, SE=-1.81, p<.001). Figure 4b shows that the negative impact of GI on CEP is more powerful and significant under high FP than under low FP. These results show that FP significantly increases the role of GI in the relationship between CICPs and CEP. In other words, with an increase in FP, both the driving effect of CICPs on GI and the inhibiting effect of GI on CEP were strengthened. Thus, hypothesis 3 is verified. The results are consistent with the studies of Chen and Chang (2020) and Zhao et al. (2023). This implies that the FP generated by the asymmetry of vertical financial and administrative power affects the behavior of local governments, leading to the distortion and alienation of implementation of CICPs, and causing the reverse results of environmental policy implementation.

One possible reason why FP exacerbates the "green paradox" effect is that, on the one hand, FP pushes local governments to seek all kinds of revenues (He et al., 2022) and local governments can obtain financial subsidies to relieve fiscal pressure by entering into list of environmental protection model cities. Meanwhile, accomplishing carbon emission reduction targets under government intervention avoids the deduction of incentive funds. On the other hand, FP also affects CEP by influencing local government revenues and expenditures, weakens investment in low-carbon green innovation, and limits CEP improvement. Simultaneously, FP causes local governments to adopt discriminatory regulations, weakens regulations on enterprises that provide large amounts of tax revenues, strengthens carbon constraints on other enterprises and even enterprises in non-high-carbon industries, and results in failure to correctly implement the central government's environmental policies (Tu et al., 2019; Xu et al., 2022). Song et al. (2023) also show that high fiscal pressure on local governments not only directly adversely affects the implementation of environmental policies but also indirectly affects the transmission channel exacerbating the policy implementation gap. Therefore, under FP, local governments tends to use GI to distort implementation of CICPs, resulting in a decrease in CEP, and the "green paradox" effect becomes more apparent.

Insert Figure 4a about here

Insert Figure 4b about here

4.3 Robustness Test

4.3.1 Parallel Trend Test

The quasi-DID model identifies the causal effect of CICPs on CEP by comparing the differences between groups unaffected by the policy and those affected by the policy. However, the DID estimation strategy is potentially controversial, because the differences between the treated and control groups were caused by other factors before 2010. This study introduces the dummy variable Treat × Post for a parallel trend test, whose coefficients can be used to assess whether the growth of the dependent variable is consistent between the treated group and the control group before the implementation of the policy. Figure 5 shows the estimates of CEP along with the 95% confidence interval. The results clearly show that the estimated coefficients fluctuate around the zero value and are insignificant before the implementation of the CICPs (i.e., before 2010), suggesting that the impact of CICPs either has the wrong sign or is not statistically significant. It can be inferred that the CEP followed a similar time in both the treated and control groups before the implementation of CICPs in 2010, satisfying the requirements of the parallel trend assumption. Meanwhile, Table 7 of the econometric test results shows that the CICPs initially had a negative statistically significant effect in 2010. This indicates that the impact of the CICP on CEP is not immediate and takes some time to take effect. The above parallel trend test shows that the quasi-DID estimator works well and remains unbiased in this case, and this study can attribute the difference to the effect of the implementation of CICPs.

Insert Figure 5 about here

4.3.2 Concurrent Exclusion Policy

Other parallel carbon reduction policies influence the implementation of CICPs. Therefore, this study excluded significant carbon reduction policies after 2010, such as the carbon emissions trading (CET) scheme of 2011. Specifically, this study add CET dummy variables and the cross-term of the time trend into the basic model to control for the impact of other relevant carbon reduction policies on CEP. Model (1) in Table 6 provides the regression results. Compared with the baseline results, the dummy variables Period×Treated of CICPs and time trends are still significantly negative. However, the CET dummy variables and time trends are not significant. This result indicates that other carbon reduction policies did not interfere with the main conclusions.

4.3.3. Setting the Strength Quasi-DID Model

According to the 12^{th} and 13^{th} FYP, the Chinese central government sets different regional carbon emission reduction targets, which mean different intensities of CICPs. Therefore, this study used the intensity quasi-DID method to reassign the value of the policy dummy variables. According to the emission control targets in the 12^{th} and 13^{th} FYPs, the importance of policy dummy variables was assigned a range of values, including 9.5%, 19%, and 18%, respectively. As shown in Column (2) of Table 6, the model Period×Treated coefficients are significantly negative at the 1% level. Hence, CICPs restricted CEP, and this conclusion was reliable and robust.

4.3.4. Different Settings for Control Variables

The effect of CICPs on CEP is inevitably confounded by the control variables, resulting in the overestimation or underestimation of the estimation results. Therefore, this study further adds the interaction term between the control variables and time trend to investigate the potential impact of the time-varying effects of control variables on the estimation results. Suppose that the coefficient of the policy dummy variable is not significant after adding the interaction term between the control variables and the time trend; in that case, it indicates that the hindering effect of CICPs is not present and the conclusions of this study are not robust. Suppose that the coefficients of the policy dummy variables are significant, but the coefficients are reduced after adding the interaction term between the control variables and the time trend; in that case, it indicates the relative robustness of the estimation results of this study. As shown in the estimation results in Column (3) of Table 6, CICPs' coefficient is significantly negative, and the degree of the coefficient is reduced compared to the baseline regression. The results show that the restricted effect of CICP is still present and significant, indicating that the estimation conclusion of this study is relatively robust.

Insert Table 6 about here

Insert Table 7 about here

4.4 Further Analysis

4.4.1 Dynamic effect of the CICPs

The above study examines the average effect of CICPs on CEP from 2002 to 2019 but needs to reveal the dynamic impact of CICPs. Estimating the dynamic effect is important for evaluating the actual effect of the CICPs because it can capture the yearly effect of the CICP and determine whether the average influence is lagged.

Table 7 reports the results of examining the dynamic impact of the CICPs on regional CEP. The significance and signs of the control variables are consistent with those shown in Table 5. Dynamic analysis suggests that the temporal effect of CICPs on CEP is negative in all years, and the overall trend of the relationship is inverted N-shaped, indicating that the negative impact of CICPs on CEP goes from weak to strong and then weak. The temporal effect of the CICPs, which started in 2009, was insignificant, and the policies' effect became significant in 2010. Since the implementation of a new policy usually needs to experience a refined or revised process with a short-term lag, the negative impact of the CICPs came into effect and appeared one year after the policy implementation. However, the evident effect lasted only for that year. The CICPs started to play a significant inhibitory role in 2011 but became insignificant in 2012. Due to increasing long-term carbon constraints, local governments probe the Chinese central government's determination to reduce carbon emissions by weakening carbon emission regulations from an opportunistic perspective. However, a significantly negative effect (caused by the policy) reappeared from 2012 onwards. These results are consistent with the introduction of the new environmental law, which demonstrated the determination to reduce carbon emissions at the time of the actual policy. Under conditions of increased carbon emission constraints, local industrial enterprises are forced to adjust the structure of production factors to maintain or increase their output levels, exacerbating factor allocation distortions. In addition, this study find that the restriction of the CICPs goes from weak to strong and then weakens over 2012-2019. In the initial stages of implementation of CICPs, the local government energetically carries out emission reduction activities to achieve reduction goals. However, as the carbon emission reduction target was achieved, the binding force gradually decreased. According to statistics, by 2015, China's carbon emission intensity decreased by 20% compared with 2010, with 20% reduction targets being accomplished ahead of schedule. Therefore, the inhibitory effect of CICPs was weakened in 2015. The Chinese central government has relied primarily on administrative measures rather than market mechanisms to reduce carbon emissions. Mandatory administration helps to temporarily curb the growth of carbon emissions but negatively affects sustainable development.

4.4.2 Heterogeneity effect of the CICP

The above analysis suggests that the CICPs can significantly restrict regional CEP. However, China’s vastness endows numerous remarkable differences among regions, such as economic development stage and scale. The average treatment effect may mask the differences between regions. Therefore, it is necessary to provide further evidence on whether the restricted impact of the CICPs is heterogeneous among different regions.

Different treatment effects in the economic development stage: As the industrial structure evolves with economic development, the proportion of tertiary industries is an indicator of the stage of economic growth. From the economic development stage perspective, regions with tertiary industries as leading industries are more responsive to the impact of the CICPs through market mechanism adjustment. However, regions with a large share of secondary industries can only adjust their industrial structures slowly under the constraints of carbon emission targets. Therefore, the impact of the CICPs on CEP is heterogeneous in terms of the economic development stages, and the CICPs have a stronger restrictive effect on CEP in regions where the tertiary industry is the dominant industry. Based on the above analysis, this study further verifies the effects of the CICPs in regions with different dominant industries. This study categorizes the sample provinces into two subsamples based on the share of secondary and tertiary industries. Columns (1) and (2) in Table 8 show that the estimated coefficients are negative but insignificant in regions where the secondary industry is dominant. By contrast, the estimated coefficients are significantly negative in areas dominated by tertiary industries. The results means that it is more significant for the restrictive impact of CICPs on CEP in the subsample in which the tertiary industry is the dominant industry. A possible reason is that the secondary industry usually has a higher demand for energy sources, such as coal, mainly in the industrial sector. Because China still has an extensive economic growth pattern and relatively backward technology, the total carbon emissions of the secondary industry are higher. The tertiary industry's energy consumption and carbon emissions were both relatively low. Compared to regions where the secondary industry is the dominant industry, regions where the tertiary industry is the dominant industry have a lighter task of carbon emission reduction, less need for industrial restructuring, and less mandatory government intervention. Therefore, the CICPs will have less impact on the CEP for regions with better foundations for carbon emission reduction. In contrast, the CEP of regions dominated by the secondary industry with heavy carbon emission reduction tasks is more susceptible to the impact of CICPs.

Different treatment effects on the scale of economic development: The provinces in the eastern region have a relatively higher level of economic development, a more reasonable industrial structure, and a foundation for low-carbon green development transformation. In comparison, the central and western regions have relatively lower levels of economic development and industrial systems to be optimized. Therefore, regional heterogeneity exists in the impact of CICPs on CEP, and the restrictive effect of CICPs on CEP in the central and western regions is stronger than that in the eastern regions. This study categorized the sample into two subsamples of the eastern and central-western regions for heterogeneity testing. Columns (3) and (4) in Table 8 present the regression results for the eastern and central-western subsamples, respectively. As shown in Table 8, the estimated coefficients for the eastern subsample are negative but insignificant. The estimated coefficients of the central-western subsample are significantly negative and higher in absolute value than the former. The results indicate that the CICPs significantly reduce the CEP in the central and western regions but not in the eastern regions. The reason may be that the eastern region have a higher level of economic development than the central and western regions and do not need to over-adjust the distorted production factor structure to maintain or increase economic output when facing the carbon emission constraint target. Besides, the economic agglomeration effect in the eastern region will improve the efficiency of resource allocation and utilization, which does not require excessive government intervention and can balance economic development and carbon emission reduction. Finally, the higher level of green technological progress in the eastern region can rely on technological innovation and industrial restructuring to rapidly reduce total carbon emissions and weaken excessive government intervention. Therefore, the negative impact of the CICPs on CEP was stronger in the central and western regions.

Insert Table 8 about here

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5. CONCLUSIONS AND POLICY IMPLICATIONS

China's CICPs are designed to foster green and low-carbon development. However, in a bid to meet carbon emission control targets, some local governments have indiscriminately limited electricity consumption and mandated the shutdown of high-carbon-emitting enterprises (Jiang, 2022). Such abrupt approaches can breach economic principles, skew resource allocation, and trigger unforeseen repercussions. Hence, it's pivotal to have a strategic top-down design that instructs local governments and businesses on energy conservation, emission reduction, and the prevention of policy-induced green paradoxes (Huang et al., 2022).

Impact Analysis: Using the quasi-DID method with a panel dataset spanning China's 30 provinces from 2002 to 2019, this study assessed the effect of CICPs on regional CEP. The results revealed that CICPs negatively influenced CEP, suggesting suboptimal policy outcomes. Consequently, this study advocates for the adoption of market-driven solutions over direct interference. The government should prioritize market demands, leverage market-driven resource allocation, and phase out high-carbon industries through competitive means.

Mediating Role of Government Intervention: This study explored the intermediary role of government intervention (GI) between CICPs and regional CEP. Excessive governmental interference emerged as a chief hindrance to the desired outcomes of CICPs. Misguided interventions can skew market dynamics, conflicting with economic principles and culminating in policy failures. To rectify this, refining the quality and scope of government interventions is essential. This involves clarifying governmental roles, setting clear boundaries between the state and market forces, and curbing over-interventions. A multifaceted evaluation mechanism for local officials, balancing economic growth and low-carbon environmental protection, could help mitigate the ramifications of excessive interference.

Moderated Mediating Effects: This study uncovered the effects introduced by fiscal pressures (FP) using a moderated mediation model. Findings suggest that fiscal pressures amplify the mediating role of government intervention on CICP's impact on CEP. Local governments, under fiscal constraints, intensified interventions to secure environmental subsidies and sidestep fiscal penalties, thereby affecting local financial dynamics and misguiding low-carbon technology investments. To alleviate this, restructuring the fiscal dynamics between China's central and local governments is proposed. Streamlining local fiscal incentives could guide regional governments in selecting efficient policy tools to meet carbon reduction objectives.

Dynamic and Heterogeneous Outcomes: The temporal effects of CICPs on CEP trace an inverted N-shaped trajectory, with more pronounced adverse impacts in economically challenged regions. To address this, long-term carbon reduction strategies, instead of short-term targets, are recommended. A tailored approach considering regional industrial structures, economic maturity, and technological capabilities, especially in secondary industry-dominated and economically lagging areas, is essential.

This research holds both theoretical and pragmatic significance. While earlier studies posited that environmental regulations curb carbon emissions (Shi et al., 2022; Gu et al., 2022), China's CEP has not remarkably improved with stringent CICPs, pointing to a green paradox. This paper not only confirms this paradox in the context of CICPs but also pinpoints excessive local government intervention as its primary cause. This analysis not only aids China's pursuit of carbon peak and carbon neutrality goals but also furnishes other developing nations with insights on climate change and greenhouse gas reduction.

Furthermore, this paper pioneers an investigation into the origins of the green paradox, offering policy insights. It is the first study that examined the impact of China’s CICPs on CEP as well as original research that combined government intervention and green paradox theories.

Yet, it has limitations: the study's macroscopic provincial-level scope precludes intricate, micro-level analysis, and the singular focus on government interventions might overlook the nuances of individual firm differences. Future inquiries should dissect the CICP's impacts using firm-level data, providing a detailed exploration of factors influencing company-specific disparities and further enlightening the green paradox conundrum.

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Figures

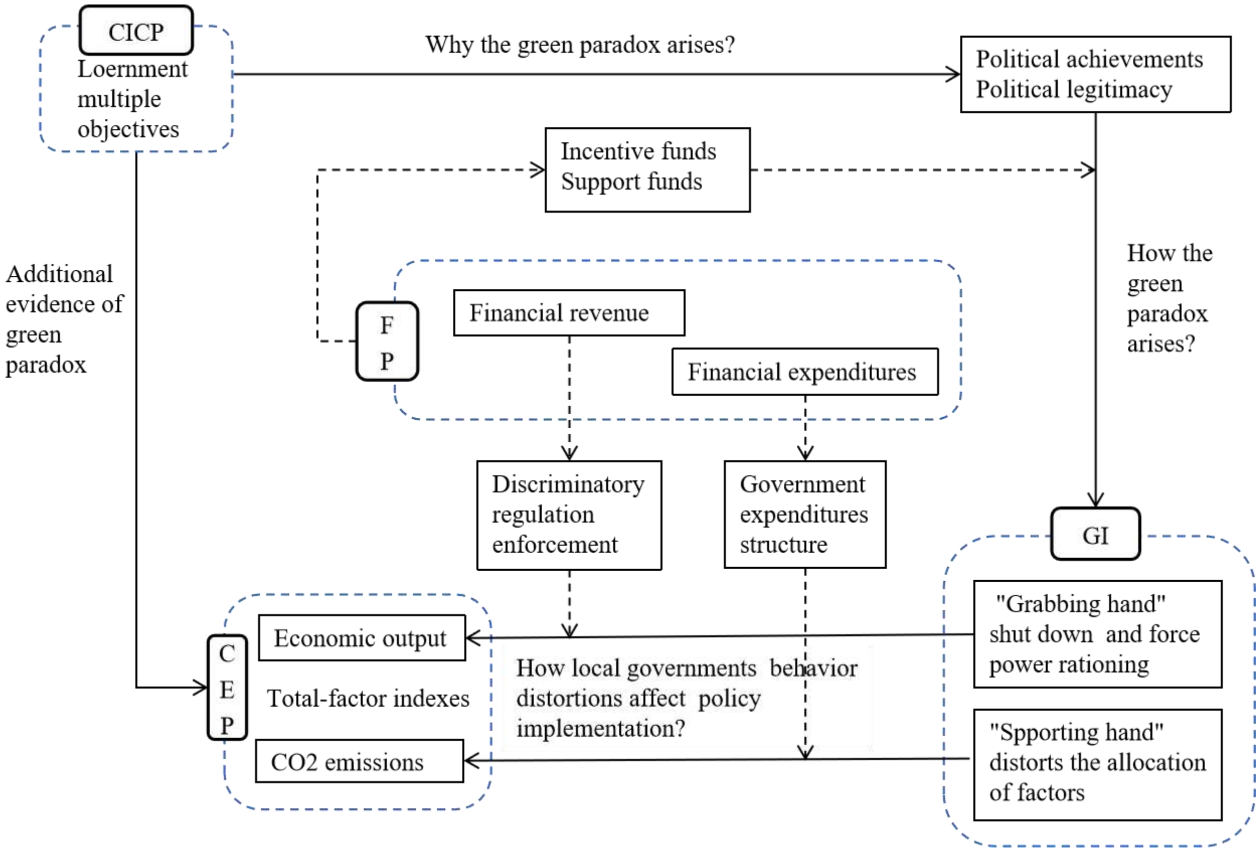

Figure 1. Conceptual model.

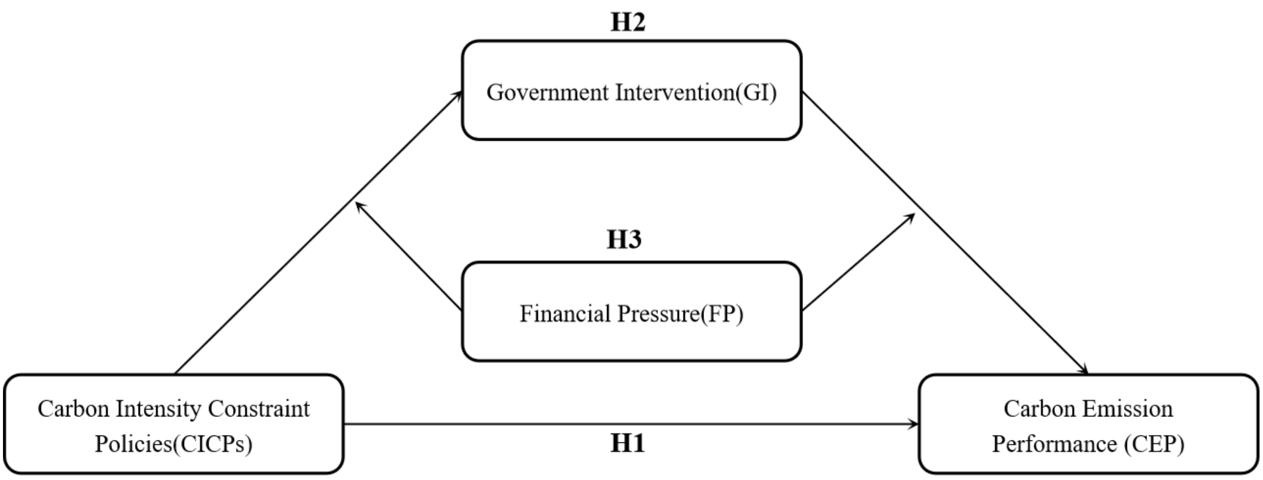

Figure 2. The moderated-mediation model of carbon intensity constraint policies.

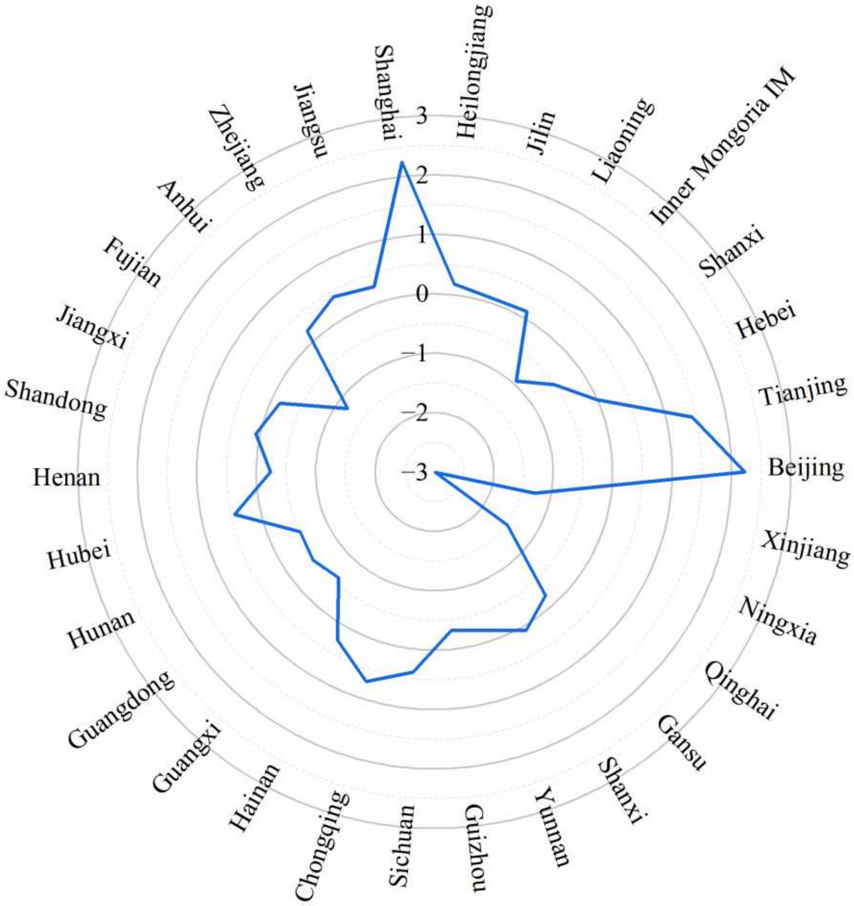

Figure 3. Means of carbon emission performance.

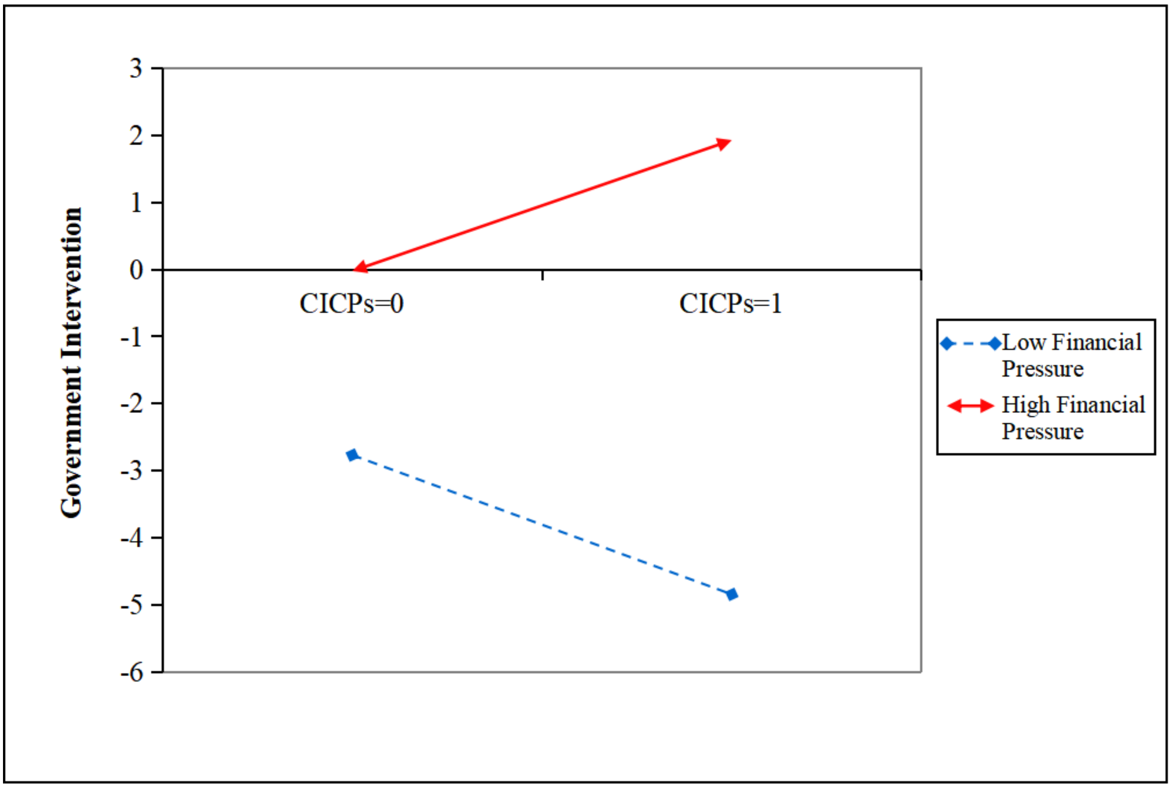

Figure 4a. The moderation effects of financial pressure (FP) on the relationship between carbon intensity constraint policy (CICP) and government intervention (GI)

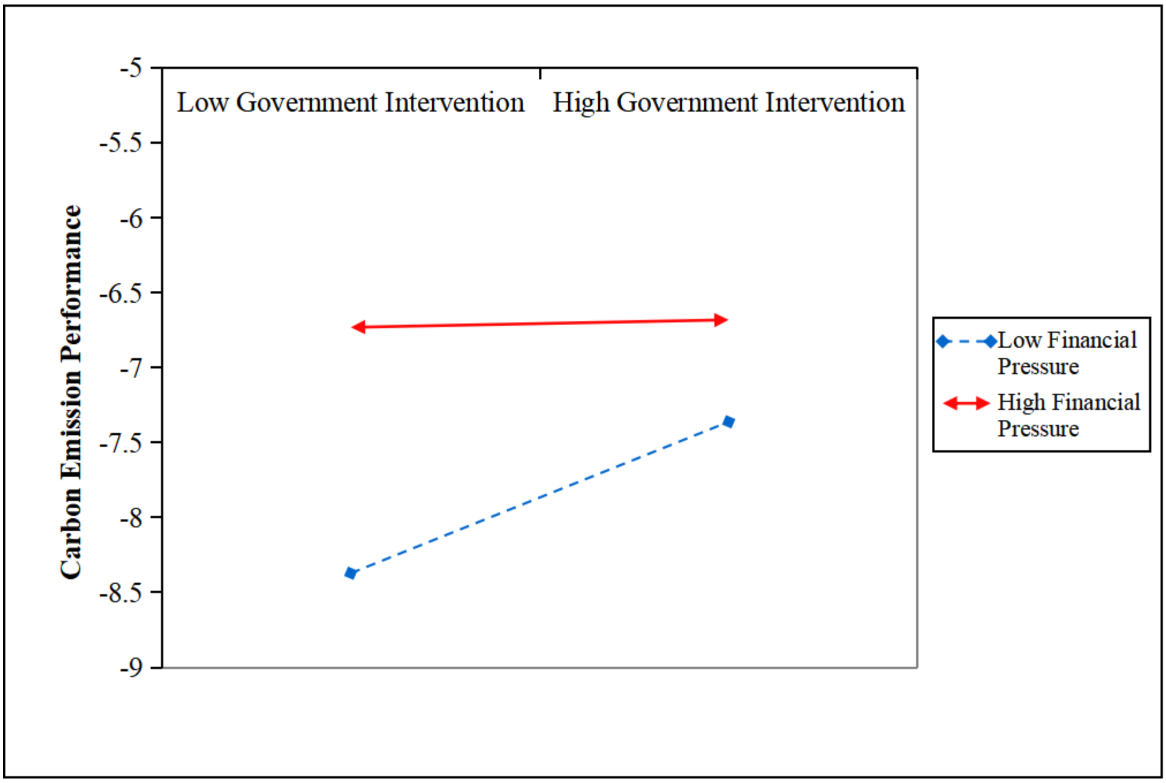

Figure 4b. The moderation effects of financial pressure (FP) on the relationship between government intervention (GI)) and carbon emission performance (CEP)

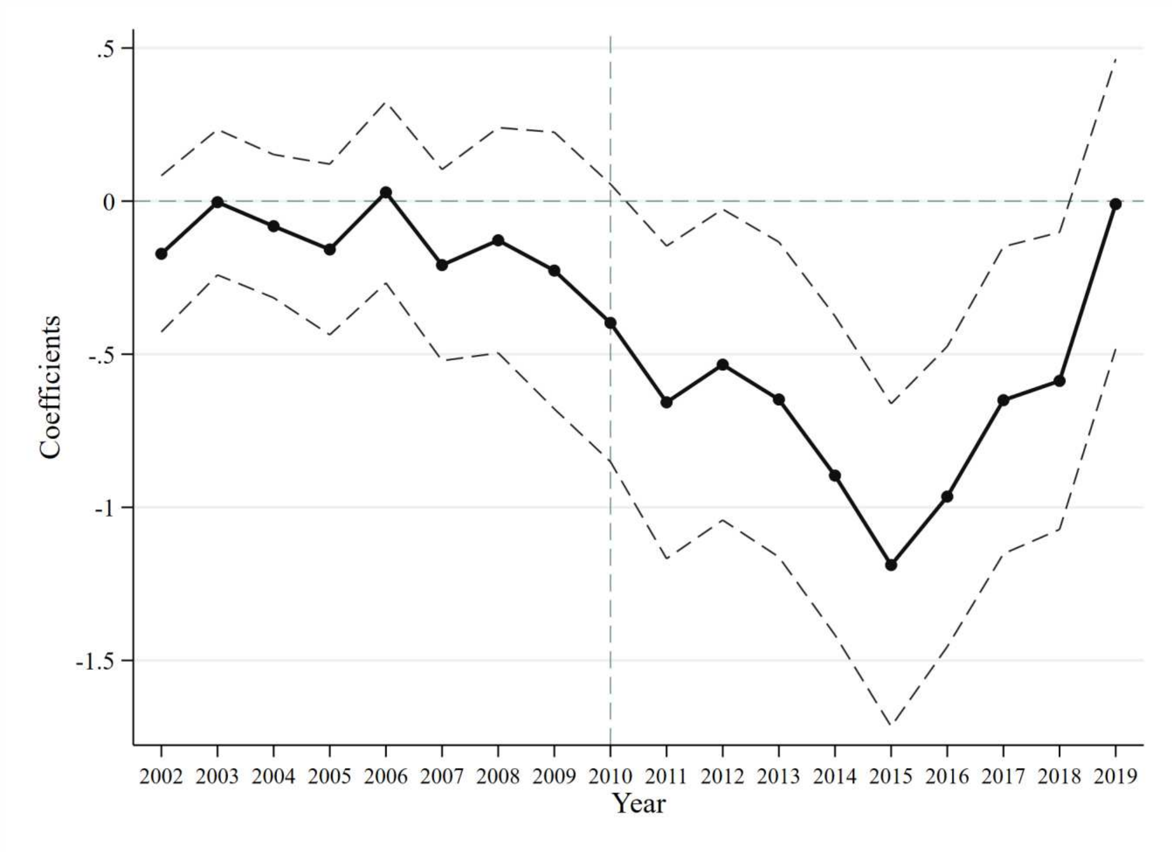

Figure 5. Parallel trends test of carbon intensity constraint policy

Tables

Table 1 Regions and targets covered by China's carbon intensity constraint policies in the 12th and 13th FYPs

Regions	Targets of decreased CO_2 emissions per unit of GDP in 12th FYP	Targets of decreased CO_2 emissions per unit of GDP in 13th FYP	Regions	Targets of decreased CO_2 emissions per unit of GDP in 12th FYP	Targets of decreased CO_2 emissions per unit of GDP in 13th FYP
Beijing	18%	20.5%	Hubei	17%	19.5%
Tianjing	19%	20.5%	Hunan	17%	18
Hebei	18%	20.5%	Guangdong	19.5%	20.5%
Shanxi	17%	18%	Guangxi	16%	17%
Inner Mongoria	16%	17%	Hainan	11%	12%
Liaoning	18%	18%	Chongqing	17%	19.5%
Jilin	17%	18%	Sichuan	17.5%	19.5%
Heilongjiang	16%	17%	Guizhou	16%	18%
Shanghai	19%	20.5%	Yunnan	16.5%	18%
Jiangsu	19%	20.5%	Shaanxi	17%	18%
Zhejiang	19%	20.5%	Gansu	16%	17%
Anhui	17%	18%	Qinghai	10%	12%
Fujian	17.5%	19.5%	Ningxia	16%	17%
Jiangxi	17%	19.5%	Xinjiang	11%	12%
Shandong	18%	20.5%	Tibet	10%	12%
Henan	17%	19.5%			

Table 2 Definition of variables

Variables	Definitions
Dependent Variables	
Carbon emission performance (CEP)	DEA Model in 4.2.1.
Input-output variable in DEA model.	
Desired output	GDP(Y): The GDP of the region in the current year converted into the real GDP at the constant price in 2007.
Undesirable input:	Carbon emissions (C): the prefecture-level carbon emissions data of the region.
Input factors	Capital stock (K): We use the perpetual inventory method, takes 2007 as the base period and 10.96% as the annual depreciation rate of each region to calculate. Labor (L): The average value of the number of employed persons at the end of the current year and the number of employed persons at the end of the last year. Energy consumption (E): the prefecture-level electricity consumption data of the region.
Independent Variables	
Carbon emission intensity (CI)	Carbon dioxide emissions per unit of GDP.
POST	Dummy variable of CICP: equal to 1 in the year when implementing the CICP and each subsequent year, and 0 otherwise.

Carbon intensity constraint policies (CICPs)	$CI_{it} \times Post_{it}$
Mediating Variable	
Government intervention (GI)	The ratio of environmental protection fiscal expenditure to GDP.
Moderating Variable	
Financial pressure (FP)	The per capita fiscal gap= (fiscal expenditure − fiscal revenue)/total population of the region at the end of the year.
Control Variables	
Foreign direct investment (FDI)	Foreign investment and the annual average exchange rate as a proportion of GDP.
Financial development scale (FDS)	The loans of financial institutions to GDP.
Industrial structure (IND)	The ratio of the value-added of the secondary industry to that of the tertiary industry.
Economic growth level (GDP)	The logarithm of real GDP per capita.
Labor per capital stock (KL)	The actual capital stock to the annual average labor force.

Table 3 Descriptive statistics of variables

Variable	Mean	p50	Max	Min	Sd	Skewness	Kurtosis	VIF
1.CEP	-0.0660	0.181	6.871	-10.02	2.153	-0.870	5.310	Mean = 3.51
2.CI	3.383	2.666	18.50	0.382	2.512	2.222	10.42	2.05
3.POST	0.500	0.500	1	0	0.500	0	1	2.39
4.FDI	13.21	13.45	17.90	6.030	2.438	-0.207	2.402	6.20
5.FDS	1.870	1.665	7.310	-0.480	1.241	1.182	4.856	2.57
6.IND	0.969	0.845	4.240	0.490	0.492	3.529	18.41	1.58
7.GDP	10.12	10.14	11.91	6.407	0.819	-0.672	4.113	2.25
8.KL	0.912	0.639	4.056	-0.720	0.749	1.750	6.104	2.91
9.GI	15.37	13.98	49.97	6.136	6.995	1.771	7.839	5.93
10.FP	1.246	1.193	5.745	0.0520	0.928	1.637	7.311	5.74

Table 4 Correlation coefficients and VIF among variables

Variable	1	2	3	4	5	6	7	8	9
1.CEP	1								
2.CI	-0.2855*	1							
3.POST	0.2201*	-0.3837*	1						
4.FDI	0.3274*	-0.5323*	0.1925*	1					
5.FDS	0.1696*	-0.3268*	0.6022*	0.3579*	1				
6.IND	0.2615*	-0.2660*	0.1743*	0.1538*	0.2705*	1			
7.GDP	0.0819*	-0.00450	0.2946*	0.4660*	0.2433*	-0.2514*	1		
8.KL	-0.1651*	0.3767*	-0.5763*	-0.4267*	-0.7217*	-0.1763*	-0.3299*		
9.GI	-0.1684*	0.1804*	0.2964*	-0.6670*	0.1785*	0.1255*	-0.3967*	-0.1470*	1
10.FP	-0.2608*	0.2960*	0.0242	-0.8199*	-0.1665*	-0.1845*	-0.4395*	0.1650*	0.7930*

Note: the value in parentheses is the robust standard deviation with "*** p<0.01, ** p<0.05, * p<0.1".

Table 5 Results of quasi-DID regression analyses of government intervention (GI) and carbon emission performance (CEP)

	Government intervention (GI)				Carbon emissions performance (CEP)			
Variables	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
FDI	-1.211***	-1.131***	-0.865***	-0.505***	0.569***	0.482***	0.315**	0.393***
	(-7.64)	(-7.09)	(-5.89)	(-3.68)	(3.94)	(3.33)	(2.10)	(4.71)
FDS	0.803***	0.828***	0.820***	0.843***	-0.434**	-0.448***	-0.354**	0.151
	(4.28)	(4.41)	(4.81)	(5.47)	(-2.53)	(-2.63)	(-2.06)	(1.39)
IND	2.230***	2.212***	1.928***	2.315***	-0.375	-0.331	-0.140	0.897***
	(4.69)	(4.68)	(4.49)	(5.93)	(-0.87)	(-0.78)	(-0.32)	(4.08)
GDP	2.422***	1.862***	2.262***	1.737***	-0.770	-0.111	0.124	0.122
	(4.48)	(3.30)	(4.40)	(3.71)	(-1.56)	(-0.22)	(0.24)	(0.82)
KL	-2.247***	-2.262***	-1.798***	-1.694***	0.334	0.343	0.068	0.066
	(-8.26)	(-8.37)	(-7.22)	(-7.50)	(1.35)	(1.40)	(0.26)	(0.34)
Main effects								
CICP		0.335***	0.381***	-0.813***		-0.383***	-0.346***	-0.181**
		(3.10)	(3.89)	(-5.60)		(-3.91)	(-3.54)	(-2.58)
GI							-0.131***	0.084**
							(-3.22)	(2.36)
FP			3.053***	1.790***				1.194***
			(10.27)	(6.06)				(3.85)
Cross-level interaction								
CICP×FP				0.638***				
				(10.39)				
GI×FP								-0.037***
								(-4.41)
Constant	0.959	5.269	-1.895	-3.635	3.584	-1.746	-0.204	-9.356***
	(0.16)	(0.85)	(-0.34)	(-0.71)	(0.65)	(-0.31)	(-0.04)	(-4.15)
R-squared	0.930	0.931	0.944	0.954	0.380	0.400	0.416	0.304
Observations	540							
Province FE	YES							
Year FE	YES							

Note: the value in parentheses is the robust standard deviation with "*** p<0.01, ** p<0.05, * p<0.1".

Table 6 Results of the robustness test

	Carbon emission performance(CEP)		
Variable	Modle1	Modle2	Modle3
CICP(POST×CI)	-0.554***(-3.79)		-0.403***(-3.38)
POSTCET(POST×CET)	-0.619(-1.57)		
CICPERT(POST×CI×ERT)		-0.014**(-2.29)	
FDS	-0.437**(-2.57)	-0.440**(-2.55))	
FDS×POST			-0.167(-1.06)
IND	-0.135(-0.30)	-0.338(-0.79)	
IND×POST			-0.238(-0.92)

GDP	-0.101(-0.20)	-0.419(-0.82)	
GDP×POST			-0.052(-0.35)
KL	0.439*(1.74)	0.343(1.39)	
KL×POST			0.647(1.03)
FDI	0.536***(3.61)	0.538***(3.71)	
FDI×POST			0.208**(2.37)
Constant	-2.952(-0.53)	0.445(0.08)	1.572***(2.92)
R-squared	0.403	0.388	0.332
Observations		540	
Province FE		YES	

Note: the value in parentheses is the robust standard deviation with "*** p<0.01, ** p<0.05, * p<0.1".

Table 7 Results of the dynamic effect of the CICP on the CEP

Variable	Coefficient	Variable	Coefficient
POST×CI2002	-0.172(-1.32)	POST×CI2011	-0.657**(-2.53)
POST×CI2003	-0.004(-0.03)	POST×CI2012	-0.534**(-2.07)
POST×CI2004	-0.082(-0.69)	POST×CI2013	-0.648**(-2.48)
POST×CI2005	-0.158(-1.11)	POST×CI2014	-0.896***(-3.38)
POST×CI2006	0.029(0.19)	POST×CI2015	-1.188***(-4.43)
POST×CI2007	-0.209(-1.31)	POST×CI2016	-0.965***(-3.87)
POST×CI2008	-0.128(-0.68)	POST×CI2017	-0.650**(-2.55)
POST×CI2009	-0.227(-0.99)	POST×CI2018	-0.587**(-2.38)
POST×CI2010	-0.398*(-1.72)	POST×CI2019	-0.010(-0.04)
Constant	2.859***(3.87)	R-squared	0.404
Province fixed effect	YES	Time fixed effect	YES

Note: the value in parentheses is the robust standard deviation with "*** p<0.01, ** p<0.05, * p<0.1".

Table 8 Results of the heterogeneity test

	Carbon emission performance(CEP)			
Variable	Modle1	Modle2	Modle3	Modle4
CICP(POST×CI)	-0.173(-0.26)	-0.391***(-2.95)	-0.157(-0.46)	-0.286**(-2.53)
FDI	0.292(0.86)	0.535***(3.28)	0.287(0.73)	0.557***(3.50)
FDS	-0.008(-0.03)	-0.666***(-3.00)	-0.061(-0.22)	-0.716***(-3.16)
IND	-0.599(-0.97)	0.426(0.54)	-0.477(-0.72)	0.190(0.25)
GDP	0.894(0.79)	-0.286(-0.48)	2.126*(1.80)	-0.394(-0.66)
KL	0.292(0.60)	0.331(0.87)	1.122*(1.82)	0.114(0.35)
Constant	-12.351(-0.97)	-2.715(-0.44)	-25.450*(-1.92)	-1.777(-0.29)
Observations	270	270	215	325
R-squared	0.387	0.438	0.417	0.416
Province FE		YES		
Year FE		YES		

Note: the value in parentheses is the robust standard deviation with "*** p<0.01, ** p<0.05, * p<0.1".