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Impact of Policy Intensity on Carbon Emission Reductions: Based on the Perspective of China's Low-Carbon Policy

Haonan Chen [1,*], Xiaoning Cui [2,*], Yu Shi [3], Zhi Li [1] and Yali Liu [1]

[1] School of Economics, Capital University of Economics and Business, Beijing 100070, China; lizhi@cueb.edu.cn (Z.L.); 12021030002@cueb.edu.cn (Y.L.)
[2] School of International Business, Beijing Foreign Studies University, Beijing 100070, China
[3] School of Architecture and Art Design, Hebei University of Technology, Tianjin 300401, China; shiyu20001102@163.com
* Correspondence: chn@cueb.edu.cn (H.C.); cuixiaoning@bfsu.edu.cn (X.C.)

Abstract: Economic development often results in significant greenhouse gas emissions, contributing to global climate change, which demands immediate attention. Despite implementing various low-carbon policies to promote sustainable economic and environmental progress, current evaluations reveal limitations and deficiencies. Therefore, this study utilizes a dataset detailing policy intensity at a prefecture-level city in China to investigate the impacts of these policies on carbon emission reduction from 2007 to 2022 in 334 prefecture-level cities, employing a fixed-effects model. Additionally, it assesses the policies' efficacy. The findings indicate a significant negative correlation between China's low-carbon policies and carbon emissions, supported robustly by multiple tests. Specifically, a one-unit increase in China's policy intensity correlates with a 0.53-unit reduction in carbon emissions. Furthermore, the heterogeneity analysis shows that variations in urban agglomerations, environmental resource endowments, pollution levels, and low-carbon policy intensities influence the effectiveness of these policies in reducing carbon emissions. This analysis underscores that policy intensity achieves emission reductions through technological innovation, industrial transformation, welfare crowding out, and pollution transfer, with varying impacts across different environmental contexts, pollution levels, and policy intensities. Based on this analysis, we recommend several policies: formulating low-carbon strategies tailored to local conditions, enhancing regional low-carbon policies, establishing cross-regional coordination mechanisms, and so on. These recommendations not only offer valuable policy insights for China but also serve as useful references for the green and sustainable development of other developing countries.

Keywords: low-carbon policy intensity; carbon reduction; welfare crowding out; pollution shelters; urban economy

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1. Introduction

Over the past three decades, amidst the increasing frequency of climate extremes and worsening global warming, the governmental focus has increasingly turned towards concurrently advancing the economy and the ecosystem, heightening the urgency for carbon reduction efforts [1–3]. In response to these unsustainable trends, policymakers are actively pursuing pathways to achieve a low-carbon society, and in some cases, aiming for a zero-carbon society [4,5]. Urban economies contribute approximately 80% to the GDP and emit about 70% of carbon emissions, and so cities are recognized as pivotal arenas for carbon mitigation strategies and sustainable development initiatives [6,7]. As the world's largest developing nation and a significant carbon emitter, China is proactively exploring and implementing low-carbon policies to combat climate change [8–10]. However, substantial heterogeneity persists among Chinese cities regarding policy frameworks, scale, and economic development, emphasizing the need for further research to elucidate carbon mitigation dynamics at the municipal level [11,12].

In pursuit of its carbon reduction and sustainable development objectives, China introduced over 7200 low-carbon policy initiatives and climate change measures from 2007 to 2022 [13,14]. In 2007, the State Council of China launched the National Program for Responding to Climate Change, marking the beginning of China's comprehensive policy approach to addressing climate change [15]. In the realm of Chinese climate policy, a pivotal initiative emerged in 2009 with the inception of the first national program for climate change response by a developing nation. This foundational document laid the groundwork for subsequent provincial-level low-carbon pilots aimed at tailoring development pathways to local contexts [16]. Building upon this framework, the State Council furthered these efforts in 2010 through the issuance of the Notice on the Pilot Work of Low-Carbon Provinces, Regions, and Cities [17]. This notice formally introduced the concept of low-carbon development at the urban level, cementing it as the trajectory for future urban endeavors [18]. The year 2013 marked a significant milestone with the launch of seven pilot cities for carbon emissions trading, demonstrating China's commitment to involving enterprises in pursuing low-carbon development [19]. Additionally, on 17 June 2013, China inaugurated its first National Low Carbon Day, dedicated to promoting low-carbon development principles and advancing efforts to reduce greenhouse gas emissions in urban areas [20]. Subsequently, in 2015, China submitted its autonomous contributions to the United Nations, outlining its efforts to combat climate change [21]. This submission laid the groundwork for China's pursuit of objectives outlined by the United Nations Framework Convention on Climate Change (UNFCCC) [22]. China set a dual-carbon objective in 2021, aiming for carbon peaking by 2030 and carbon neutrality by 2060, underscoring its proactive stance toward achieving these goals across its cities. That same year, China achieved a governance milestone by incorporating carbon neutrality into both the 14th Five-Year Plan and the government's work report for the National People's Congress. Moreover, in 2021, China established a national carbon emissions trading market, positioning itself as the world's largest market in terms of greenhouse gas emissions [23]. However, at the regional level, particularly within local jurisdictions, the strength of low-carbon policies often exceeds that at the national level [24,25]. Local low-carbon policies demonstrate greater specificity and adaptability compared to national ones. Therefore, there is a critical need to quantify this phenomenon through the concept of policy intensity. This study aims to develop a policy indicator framework employing machine learning techniques [26]. This framework aims to assess the index of policy intensity at the prefectural municipal level in China from 2007 to 2022. Furthermore, it seeks to analyze the impact of policy intensity on carbon emissions.

The purpose of this paper is to examine how policy intensity influences reductions in carbon emissions. Building on this premise, the contributions of this study are two points. First, its approach to variable measurement is methodologically rigorous and robust. Departing from traditional practices reliant on proxy variables, this study extends the methodological foundation by employing machine learning methodologies [26]. This enables the development of a comprehensive indicator system designed to evaluate the intensity of low-carbon policies. Such an approach enhances the authenticity and scientific rigor of measuring policy intensity at the municipal level, distinguishing it from previous studies. Second, in the realm of selecting variables for carbon emission reduction, this study adopts a refined methodology inspired by the latest study [2]. By employing the continuous dynamic distribution method of the improved kernel density function, it overcomes the limitations associated with traditional techniques. This study applies their continuous dynamic distribution method using the improved kernel density function to analyze carbon emission reduction data across China's prefecture-level cities. This approach circumvents the constraints of traditional methods, which often rely on province-level panel data with limited sample sizes. Additionally, this study expands the scope of research on low-carbon policies and carbon emission reduction. While the existing literature has identified scientific and technological innovation and industrial transformation paths as mechanisms through which low-carbon policies affect carbon emission reduction [27–29], few studies have explored mechanisms from the perspectives of welfare crowding out and pollution transfer.

By incorporating these perspectives into the research framework, this study broadens the understanding of the relationship between policy intensity and carbon emission reduction. Consequently, it facilitates the analysis of the carbon emission reduction effects attributed to the intensity of low-carbon cities. Moreover, it provides a scientific basis for national and local governments to formulate urban low-carbon development plans and supportive policies within the context of the "dual-carbon" strategy. Additionally, this study presents a reference model for the low-carbon sustainable development pathways of other developing nations based on China's experiences in low-carbon road development.

The increase in carbon emissions resulting from economic growth has triggered global warming, underscoring the critical need to balance economic prosperity with environmental preservation for sustainable development [30,31]. Research highlights that reducing carbon emissions is essential for fostering sustainability [32–34]. There are two primary approaches to achieve this: leveraging scientific, technological, and innovative advancements to enhance energy efficiency and drive industrial transformation [35,36], and implementing regulatory measures to limit carbon emissions [37]. Among these methods, the effectiveness of low-carbon policies warrants thorough investigation. At the city level, such policies play a crucial role in achieving the Sustainable Development Goals [38]. Accordingly, extensive academic discourse has emerged on the efficacy of stringent policies in reducing carbon emissions at urban levels [39,40], thereby advancing the SDGs. Most research in this area focuses on developed countries, leaving a significant gap in studies of developing nations [41]. While some scholars have examined the objectives, developmental contexts, and assessment methodologies of low-carbon policies [42,43], little attention has been paid to investigating the impact of carbon intensity on emission reduction in low-carbon cities. This gap may stem from challenges in accurately measuring city-level carbon dioxide emissions, which hinders the creation of comprehensive datasets. This study addresses this gap by employing an enhanced continuous stochastic kernel density function method, building on a dynamic distribution approach, to quantify China's carbon emissions at the prefecture-level city scale from 2007 to 2022 [44]. Unlike conventional methods like vegetation carbon sequestration and urban satellite data, this approach mitigates subjective biases in sample partitioning, ensuring consistent traversal outcomes and transfer probabilities in the calculation results. Furthermore, it directly assesses the inherent nature of carbon emissions, thereby reducing the impacts of extraneous factors.

In the realm of urban low-carbon policies, scholarly attention predominantly focuses on elucidating the determinants of carbon emissions, outlining mechanistic pathways, and devising evaluation frameworks [45,46]. Significant contributions include the establishment of evaluative metrics by scholars, which serve as benchmarks for assessing the effectiveness of low-carbon policy initiatives. Liu et al. (2022) employed spatial Markov chains, nonparametric kernel density estimation, and spatial variability function models to analyze the spatial and temporal evolution of carbon emission intensity [47]. Zhou et al. (2021) utilized a double-difference approach to evaluate the effectiveness of low-carbon policy pilots [48]. Guo and Yu (2024) applied geographically weighted regression methods and exploratory spatial data analysis to measure the carbon emission rates in resource-based cities, all of which provide valuable references [49]. However, there is a scarcity of studies exploring the depth of low-carbon policies, primarily due to the absence of comprehensive databases detailing policy intensity. Consequently, some researchers resort to using binary variables to represent policy intensity, employing the double-difference (DID) methodology for analysis. However, this approach often fails to accurately capture the magnitude of regional policy intensities and frequently encounters challenges related to meeting the common trend assumption. Building on the foundation laid, this study assesses policy intensity through an indicator system crafted using machine learning techniques. This methodology addresses endogeneity issues and provides a more authentic and scientifically rigorous approach, thereby offering novel data and empirical insights into the investigation of policy intensity.

In urban centers, two primary strategies for carbon reduction emerge: one involves an active mechanism focused on scientific and technological innovation and industrial transformation, while the other adopts a passive approach that includes welfare displacement and pollution transference. The former strategy sees cities pioneering new energy sources and improving energy efficiency through scientific breakthroughs and industrial restructuring to foster industrial transformation, particularly toward cleaner energy sources [27,50]. Specifically, a heightened policy intensity leads to increased costs for enterprises with significant energy consumption and pollution within urban areas, making their survival and growth challenging. Consequently, these enterprises opt to engage in scientific and technological innovations aimed at improving energy efficiency, reducing energy consumption, and mitigating pollution, thereby adhering to principles of low-carbon development. According to Porter's hypothesis, appropriate environmental regulation will spur technological innovation, and so it can be inferred that environmental regulations stimulate innovation and progress. Specifically, appropriate environmental regulations can offset the "environmental compliance costs" borne by enterprises, enhance their competitiveness, and facilitate their transition toward low-carbon practices aimed at reducing carbon emissions. Moreover, low-carbon policies are positioned to optimize capital allocation and drive industries toward cleaner production methods. In the implementation of low-carbon policies, local governments often leverage their regional resource endowments and maximize their strengths in alignment with directives from higher tiers of government. For example, within the agricultural sector, considerations extend beyond ecological development to encompass low-carbon agricultural practices. Similarly, within the industrial sector, key energy-intensive industries, such as iron smelting, coal, chemicals, and electric power, must pursue energy-saving technological advancements and adopt low-energy-consumption equipment to achieve low-carbon development through equipment upgrades and technological innovations. Additionally, in the service sector, integrating low-carbon principles into modern service industries, such as finance, food and beverage, tourism, and transportation, is crucial.

The second strategy involves cities enacting stringent low-carbon policies aimed at internalizing the negative externalities of environmental pollution, thereby transforming them into endogenous costs. This approach aims to reduce firm welfare and restrain firm performance. According to the pollution refuge hypothesis, companies in polluting-intensive industries tend to be based in countries or regions with relatively low environmental standards, where firms typically operate to maximize profit. Consequently, such stringent policies incentivize pollution-intensive firms to adopt pollution-shifting strategies [51], ultimately leading to decreased firm welfare. Specifically, when a firm operates in a region with stringent regulations and high environmental standards, it faces higher environmental regulation costs, such as pollution taxes, compared to firms in less regulated areas. To maximize profitability, these firms may choose to relocate their operations to cities with more favorable regulatory environments to avoid the constraints imposed by environmental regulations. This relocation trend occurs spatially, with firms showing a tendency to move operations to areas with looser regulations, even if it results in increased pollution levels in the new location. This phenomenon supports the "pollution refuge hypothesis", which suggests that firms seek refuge from strict regulations by moving to less regulated areas, thereby undermining the effectiveness of environmental governance. Moreover, the relocation of pollution by firms increases transfer costs, further impacting their original welfare.

Based on this premise, the study proposes the following research hypotheses:

Hypothesis 1. *A greater intensity of low-carbon policies leads to a more significant reduction in carbon emissions.*

Hypothesis 2. *Intensified low-carbon policies achieve reductions in carbon emissions through technological innovation, industrial transformation, welfare crowding-out, and pollution transfer effects.*

2. Selection of Variables, Data Sources, and Modeling by Materials and Methods

2.1. Selection of Variables

First, the primary dependent variable in this study is urban carbon emissions (CO_2), measured using the enhanced continuous dynamic distribution method, which characterizes carbon emission reduction as described below.

Assuming that the distribution of the variable x at time t can be represented using the terms $f_t(x)$ denoted by the distribution, $f_t(x)$ conforms to a normal distribution, and if this distribution obeys a one-medium stochastic process, the distribution at period $t+\tau(\tau>0)$ can then be represented by Equation (1):

$$f_{t+\tau}(z)=\int_0^\infty g_\tau(z|x)f_{t+\tau}(x)dx \tag{1}$$

where $g_\tau(z|x)$ is the conditional probability density function of z with respect to x. Assuming that $g_\tau(z,x)$ is the joint distribution density function, then we have

$$g_\tau(z|x)=\frac{g_\tau(z,x)}{g_\tau(x)} \tag{2}$$

To estimate the joint distribution density, it must be calculated using the following equation:

$$g_\tau(z,x)=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5(\frac{x-x_i}{h_x})^2}\frac{1}{h_z\sqrt{2\pi}}e^{-0.5(\frac{z-z_i}{h_z})^2} \tag{3}$$

Among them, h_x and h_z denote the moments of variables x and z, respectively, which can be computed utilizing Silveman's Rule of Thumb:

$$h=\left(\frac{4}{3n}\right)^{1/5}\sigma \tag{4}$$

At this juncture, we can derive the marginal distribution of x as follows:

$$\begin{aligned}g_\tau(x)&=\textstyle\int_{-\infty}^{\infty}g_\tau(z,x)dz\\&=\tfrac{1}{n}\textstyle\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5(\frac{x-x_1}{h_x})^2}\int_{-\infty}^{\infty}\frac{1}{h_z\sqrt{2\pi}}e^{-0.5(\frac{z-z_1}{h_z})^2}dz\end{aligned} \tag{5}$$

This, in turn, facilitates the determination of the long-run distribution employing the following formula $f_\infty(z)$:

$$f_\infty(z)=\int_0^\infty g_\tau(z|x)f_\infty(x)dx \tag{6}$$

When the transfer probability matrix remains constant, this long-term distribution tends towards a steady state devoid of further change, effectively capturing the evolutionary trajectory of the variable. Given the focus of this paper solely on the transfer probability of each city, a more accurate representation of this transfer probability is achieved by utilizing the net transfer probability to construct the transfer probability map, computed as follows:

$$p(x)=\int_x^\infty g_\tau(z|x)dx-\int_0^x g_\tau(z|x)dx \tag{7}$$

In terms of carbon emissions, a positive value indicates an inclination towards increased emissions in the city, while a negative value suggests a tendency towards reduction.

This study categorizes urban carbon emissions into two primary components: direct energy consumption, which includes coal, natural gas, and gasoline, and indirect energy consumption, such as electricity and heat. Carbon emissions from direct consumption can be calculated using conversion factors outlined by the Intergovernmental Panel on Climate Change (IPCC2006). It is worth mentioning that the conversion factor is always being updated, but in order to unify the measurement criteria and facilitate the calculation, we used the conversion factor of 2006 as the conversion factor for each year. Electricity consumption poses significant computational challenges, and this study adopts the methodology proposed to address this complexity. The methodology assumes a single emission factor per region and utilizes baseline emission factors for both regional grids and city-specific electricity consumption to estimate carbon emissions attributable to electricity use in each city [52].

Urban transportation primarily relies on gasoline, and this study follows the approach outlined in [53]. They establish a proportional relationship between energy consumption intensity and carbon emission intensity across different transportation modes. This study uses transportation sector energy consumption data to estimate transportation-related carbon emissions per unit.

Regarding thermal energy dynamics in cities, this study considers the heat supply from thermal power plants and boilers utilizing historical centralized heat supply data. Given that the boiler thermal efficiency typically ranges from 65% to 78%, this research adopts an average value of 70% to calculate thermal efficiency. Additionally, this study incorporates low-level heat generation from raw coal, approximately 20,908 kJ/kg. Based on these factors, this study derives a standard coal coefficient of 0.7143 kg standard coal/kg to quantify energy consumption. Using IPCC2006 data, this study calculates the amount of raw coal consumed for thermal energy, applying a carbon emission factor of 2.53 kg CO_2/kg per kg of raw coal to determine thermal energy-related carbon emissions.

Second, the main independent variable is identified. Building on the research, this study adopts the intensity of low-carbon policies as its central independent variable [26]. It utilizes a "policy target–policy instrument" model, quantifying intensity through the multiplication of policy targets, instruments, and their respective levels. This approach addresses challenges associated with selecting a singular policy instrument for analysis and mitigates concerns about the endogeneity inherent in constructing a policy indicator system. Moreover, this indicator incorporates phrase-oriented natural language processing algorithms and text-based cue learning techniques, reducing human subjectivity and enhancing the reproducibility of experimental outcomes. Importantly, this methodological approach embodies a significant degree of scientific innovation.

Specifically, we constructed a list of low-carbon policies based on the PKULaw.com (https://pkulaw.com/, accessed on 1 July 2024) policy database. The policy texts were then generated according to the policy titles, focusing on articles related to "dual carbon", "low carbon", "green technology", "emission reduction", "energy conservation", and "capacity utilization". The extracted policy texts were subsequently screened; irrelevant text files were manually excluded, and the remaining texts were refined using the "policy objectives–policy tools" model. This process resulted in the generation of 38 seed words. Word2vec was then employed to extract detailed expressions, yielding 90 synonyms with the highest similarity. A low-carbon policy dictionary was constructed, categorizing policies into three main classes based on the frequency of central phrases: policy level (e.g., carbon emission reduction and energy conservation), policy tools (e.g., capacity utilization and green technology), and policy objectives (e.g., carbon emission reduction). The intensity of low-carbon policies was quantified according to these classifications using the following formula:

$$PI_{r,a,t} = L_{r,a,t,l} \times O_{r,a,t,o} \times I_{r,a,t,i} \tag{8}$$

where $PI_{r,a,t}$ denotes the intensity of low-carbon policies for policy a in region r during year t; $L_{r,a,t,l}$ represents the intensity of the policy level in region r during year t; $O_{r,a,t,o}$ indicates the intensity of policy objective o in region r during year t; and $I_{r,a,t,i}$ signifies the strength of the policy instrument in region r during year t. A supervised prompt learning model was then trained on the policy texts to predict the intensity of policy objectives and tools. Given the varying industries and economic conditions across cities in China, classifying carbon policy intensities is challenging. Therefore, this study employs manual labeling for further subdivision. For instance, policy objectives that are more specific to sectors, regions, and those mentioned repeatedly will receive higher scores. Due to differing evaluation systems for policy levels, policy instruments, and policy objectives, a four-level scoring system and normalized assignment are used in this study.

Subsequently, machine learning and prediction were carried out. Based on the manual labeling described, a fixed architecture of the language model (LM) was constructed and trained using a fine-tuning paradigm through natural language processing (NLP) to adapt the model for downstream tasks. The text task model $P(y|x;\theta)$ was employed to measure performance θ. First, a dataset was designed with the prompt function $promptx' = f_{prompt}(x)$, mapping the input text x to output text z. The pre-trained language model was then used to classify the output z, obtaining the highest score $\hat{z}$ as given by Equation (9). Finally, the output label y with the highest score was predicted.

$$\hat{z} = searchP\left(f_{fill}(x', z); \theta\right) \tag{9}$$

ERNIE 3.0, a large-scale knowledge-enhancement pre-trained model demonstrating strong performance, was employed to execute the classification task concerning policy objectives and intensity using machine learning techniques. Additionally, the augmentation strategy known as TrustAI was utilized to address data divergence and ensure accurate predictions.

Thirdly, attention is directed towards the control variables. Given the multifaceted nature of factors influencing urban carbon emissions, this study draws insights from the relevant literature [54,55]. Variables such as per capita gross domestic product (GDP), industrial output value (IOV), green coverage area within urban built-up spaces (Green), foreign direct investment (FDI), and industrial soot and dust emissions (Smoke) are incorporated as control variables. Additionally, to address concerns regarding heteroskedasticity, this study employs the logarithmic transformation of each variable. Descriptive statistics for these variables are presented in Table 1.

Table 1. Descriptive statistics of the independent variable, dependent variable and control variables.

Variables	**Mean**	**S.D.**	**Min.**	**Max.**	**P_{50}**	**N**
CO_2	29.47	25.16	0.48	230.77	22.41	2993
Intensity	3.93	0.86	0.69	5.28	4.030	2993
Gdpr	10.58	0.63	8.19	12.28	10.56	2993
Ser	47.12	12.22	9.74	90.97	47.04	2993
Green	3.71	0.24	0.86	5.96	3.75	2993
Smoke	9.67	1.14	3.58	15.46	9.75	2993
Fdi	0.02	0.01	0.00	0.20	0.01	2993

2.2. Data Sources

The primary data sources for the core dependent variable (CO_2) in this study include the China Statistical Yearbook, China Urban Construction Statistical Yearbook, China Regional Statistical Yearbook, and China Urban Statistical Yearbook. Meanwhile, the core independent variable (Intensity) is sourced from an open dataset provided by Nature (https://www.nature.com/articles/s41597-024-03033-5#Abs1, accessed on 1 July 2024). The control variables are extracted from authoritative references such as the China Statistical Yearbook, the China Environmental Yearbook, and the China Urban Statistical Yearbook. In the end, we obtained data from 2007 to 2022 for 334 prefecture-level cities, but due to data availability, we deleted the samples with missing data.

2.3. Modeling by Materials and Methods

2.3.1. Benchmark Regression Model

The principal objective of this study is to examine the impact of policy intensity on carbon emissions and quantify the reduction in carbon emissions per unit of intensity. Consequently, the paper formulates the regression model as follows:

$$Co_{2it} = \alpha_1 + \alpha_2 intensity_{it} + \alpha_3 X_{it} + \delta_t + \eta_i + \varepsilon_{it} \quad (10)$$

where CO_{2it} denotes carbon emissions, a_i represents the coefficient, $intensity_{it}$ signifies the carbon emission intensity, δ_t denotes the time fixed effect, η_i represents the city fixed effect, and ε_{it} indicates the random perturbation term.

2.3.2. Robustness Test of the Model

We used three methods to perform the robustness test. The first methodological consideration addressed is the omitted variable test. This study acknowledges the potential for coefficient instability when additional control variables are introduced, a phenomenon known as selective bias, as per the principle of coefficient stability. Given the potential influence of regional population activities on carbon emissions, we introduce the logarithm of the regional year-end population number (denoted as "Human") as a control variable. Subsequently, we conduct the replacement variable test to address potential measurement biases within the sample, which could skew the results of the benchmark regression. In this examination, we choose to replace both the independent and dependent variables to strengthen the robustness of our analysis. Specifically, the annual mean of PM2.5 (PM2_5) is designated as the dependent variable for estimation. Considering the time lag effect, the independent variable is lagged by one period (denoted as "L_lntensity") before estimation. Lastly, we consider the aspect of policy transferability. Given China's characteristic of top-down incremental reforms, a meticulous examination of the top-level design and policy transmissibility concerning low-carbon policies becomes imperative. To this end, we aggregate indicators at both the national and provincial levels to evaluate the impact of China's policy intensity on carbon emissions.

Based on the above analysis, we can set up the following robustness test model:

$$Co_{2it} = \alpha_1 + \alpha_2 intensity_{it} + \alpha_3 X_{it} + Human_{it} + \delta_t + \eta_i + \varepsilon_{it} \quad (11)$$

$$PM_{2\_5it} = \alpha_1 + \alpha_2 intensity_{it} + \alpha_3 X_{it} + +\delta_t + \eta_i + \varepsilon_{it} \quad (12)$$

$$Co_{2it} = \alpha_1 + \alpha_2 L\_intensity_{it} + \alpha_3 X_{it} + Human_{it} + \delta_t + \eta_i + \varepsilon_{it} \quad (13)$$

2.3.3. Instrumental Variable Test

Instrumental variable tests are crucial when the explanatory variables in the model exhibit correlations with the random error term, potentially leading to biased estimates and endogeneity issues. Recognizing this concern, to precisely discern the effects of low-carbon development stemming from policy intensity, an instrumental variable estimation is employed in this study. Drawing from established research methodologies, this paper uses the frequency of climate extremes (referred to as "Climate") documented in international climate reports sourced from the website of the China Meteorological Administration as an instrumental variable. Climate extremes are intricately linked to the introduction of climate policies, and the intensity of low-carbon policies stems from the inception and frequent modifications of these policies. Furthermore, climate extremes represent infrequent, objective climate phenomena less susceptible to carbon emission influences. Hence, this instrumental variable satisfies the prerequisites of homogeneity and relevance. Nevertheless, it is imperative to acknowledge that extreme climate events operate at a macro-level, making it unfeasible to control for temporal and regional effects if directly utilized as an instrumental variable. Consequently, this study employs the Batik instrumental variable method to refine the utilization of this instrumental variable. Regions characterized by lower levels of policy intensity are more susceptible to climate policy regulations when confronted with extreme climate events. This study employs the product of the mean value of regional climate change per year ("Score") to represent the magnitude of impact, with the number of extreme climate occurrences ("Climate") serving as the external shock (designated as "Score_Climate") used as the instrumental variable.

2.3.4. Mechanistic Tests

Drawing on the theoretical analysis in the preceding section, it is evident that the intensity of low-carbon policies contributes to reducing carbon emissions through proactive and reactive avenues. However, empirical explorations of the mechanisms underlying these pathways remain limited. Thus, this study adopts a stepwise regression approach to investigate the roles of scientific and technological innovation, industrial transformation, welfare crowding out, and pollution transfer in shaping the relationship between policy intensity and carbon emissions.

The first mechanism under consideration is the scientific and technological innovation mechanism. As the intensity of low-carbon policies increases, enterprises with high energy consumption and pollution face higher operational costs in urban settings, making survival and growth challenging. Consequently, these enterprises are incentivized to undertake scientific and technological innovation initiatives to enhance energy utilization efficiency, reduce energy consumption, and curb pollution levels. These strategic shifts align with the overarching goal of promoting low-carbon development. Drawing upon Porter's hypothesis, environmental regulations can spur innovation by reducing the "environmental compliance cost" burden on enterprises, thereby enhancing business competitiveness and accelerating the transition to low-carbon practices, leading to reduced carbon emissions. To quantify the capacity for scientific and technological innovation, this study employs the logarithm of regional R&D income, denoted as "Tec".

The second mechanism under scrutiny pertains to industrial transformation. Low-carbon policies play a crucial role in optimizing capital allocation and facilitating the transition of industries toward cleaner production methods. In implementing low-carbon policies, local governments often leverage their regional resources and strengths in alignment with higher-level directives. For example, in the agricultural sector, considerations extend beyond ecological development to encompass low-carbon agricultural practices. Within the industrial sector, critical energy-intensive industries, such as iron smelting, coal, chemicals, and electric power, are required to adopt energy-saving technological innovations and upgrade to low-energy-consuming equipment. These measures are pivotal for fostering low-carbon development through enhanced technological capabilities. Similarly, the service sector, encompassing industries like finance, food and beverage, tourism, and transportation, must integrate low-carbon concepts to align with contemporary environmental imperatives. To quantify the transformation and upgrading of industries (Ind), this study utilizes the index of advanced industrial institutions, defined as the ratio of tertiary industry output to total industrial output.

Lastly, welfare crowding-out and pollution transfer mechanisms are observed. Rigorous low-carbon policies transform environmental pollution externalities into internal costs, thereby diminishing firm welfare and impeding performance. Firms, driven by profit maximization, may resort to pollution-shifting decisions under such stringent policies, leading to reduced welfare. Specifically, firms operating in regions with stricter environmental regulations face higher environmental compliance costs, such as pollution taxes. To optimize profits, these firms may relocate to cities with less stringent regulations, resulting in increased pollution levels at the new locations. This relocation trend confirms the "pollution refuge hypothesis", undermining environmental governance efficiency. Moreover, pollution transfer escalates relocation costs for enterprises, further squeezing their original welfare. To quantify the output of heavily polluting industries within a region, data from the Ministry of Ecology and Environment's Guidelines for Environmental Information Disclosure of Listed Companies are utilized. These guidelines classify heavy polluting industries, including thermal power, iron and steel, cement, electrolytic aluminum, coal, metallurgy, chemicals, petrochemicals, building materials, papermaking, brewing, pharmaceuticals, fermentation, textiles, tanneries, and mining. The study aggregates output values from these industries using industry-specific coding sourced from publications like the China Statistical Yearbook, the China Industrial Economic Statistics Yearbook, and the China Environmental Statistics Yearbook. Consequently, the logarithm of the absolute change in the output value of these industries serves as a key variable characterizing the welfare crowding-out effect (denoted as "Wel"). Furthermore, enterprise transfers are categorized based on the alignment between registered offices and headquarters of listed enterprises. The aggregation of transferred enterprises within each region quantifies the welfare crowding-out effect. Similarly, we aggregate the number of firm transfers at the regional level, denoted as "Trans".

3. Empirical Analysis

3.1. Benchmark Regression Results

In this study, Equation (8) is utilized to formulate the benchmark regression model, with detailed results presented in Table 2 below. Notably, whether area-fixed effects or year-fixed effects are employed, a statistically significant negative relationship ($p < 0.01$) is observed between policy intensity (Intensity) and carbon emissions. This suggests that a higher policy intensity is associated with reduced carbon emissions. This finding is consistent with prior research by the latest studies [5,56,57]. Of particular interest in this paper is the coefficient measuring the relationship between policy intensity and carbon emissions. Our analysis indicates that a one-unit change in the intensity of low-carbon policies corresponds to a 0.53% decrease in carbon emissions. This observed effect is attributed to the utilization of an improved continuum dynamic distribution methodology for measuring urban carbon emissions, which enhances the accuracy of regional carbon emission assessments and thereby provides initial validation for Hypothesis 1. In economics, we should pay more attention to the significance of coefficients, and there is no comparison between the magnitude of coefficients. Therefore, it is normal for some control variables to be of high significance, but small in size.

Table 2. Benchmark regression results for the none-fixed effect, area-fixed effect, year-fixed effect, and double-fixed effect.

Variables	None-Fixed	Area-Fixed	Year-Fixed	Double-Fixed
Intensity	−0.002 ***	−0.019 ***	−0.004 ***	−0.005 ***
	(−8.27)	(−6.32)	(−7.45)	(−3.87)
Gdpr	0.029 ***	0.046 ***	0.016 ***	0.050 ***
	(5.61)	(2.78)	(3.17)	(3.03)
Ser	0.000 ***	0.001 ***	0.000	0.001 ***
	(4.37)	(4.79)	(0.12)	(3.74)
Green	−0.002 **	−0.002	−0.002 **	−0.000
	(−2.42)	(−0.47)	(−2.34)	(−0.01)
Fdi	0.063 ***	0.244 ***	0.034 **	0.202 ***
	(3.81)	(4.56)	(2.33)	(3.75)
SO_2	0.027 ***	0.406 ***	0.013 ***	0.384 ***
	(3.61)	(3.09)	(3.07)	(2.79)
Constant	−0.353 ***	−5.586 ***	−0.014	−5.268 ***
	(−3.38)	(−2.85)	(−0.25)	(−3.07)
City	No	Yes	No	YES
Year	No	No	Yes	YES
Obs	2993	2993	2993	2993
R_2	0.987	0.469	0.990	0.458

Note: Robust t-statistics are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$.

3.2. Robustness Tests

This research used three methods for robustness testing. As shown in columns (1)–(3) of Table 3, whether adding control variables, replacing core variables, or lagging variables, there was no substantial change in the magnitude and significance of the coefficients ($p < 0.01$). The robustness of our findings is evident, further validating Hypothesis 1.

Table 3. Results of robustness tests and instrumental variable tests.

Variables	(1) Add Control Variables	(2) PM2_5	(3) CO_2	(4) Intensity (First Stage)	(5) CO_2 (Second Stage)
Intensity	−0.002 ***	−0.070 ***			−0.038 ***
	(−2.70)	(−3.87)			(−2.97)
L_Intensity			−0.004 ***		
			(−2.93)		
Score_Climate				0.028 ***	
				(3.89)	
Human	0.055 ***				
	(4.93)				
Gdpr	0.057 ***	0.658 ***	0.049 ***	0.113 ***	0.026 ***
	(4.09)	(3.10)	(2.83)	(2.96)	(3.18)
Ser	0.001 ***	0.014 ***	0.001 ***	0.021 ***	0.001 ***
	(−8.02)	(11.86)	(11.31)	(9.39)	(2.78)
Green	−0.008 **	−0.000	−0.002	−0.043	−0.003
	(−2.03)	(−0.01)	(−0.53)	(0.50)	(−1.08)
Fdi	0.094 ***	2.708 ***	0.232 ***	0.462	0.067
	(2.66)	(3.80)	(4.17)	(0.44)	(1.34)
SO_2	0.274 ***	5.478 ***	0.392 ***	0.953 ***	0.018 ***
	(2.99)	(3.27)	(2.89)	(3.19)	(2.94)
Constant	−4.191 ***	−75.044 ***	−5.357 ***	−9.79 ***	0.213
	(−2.69)	(−3.58)	(−2.60)	(−2.77)	(0.92)
City	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
Obs	2993	2993	2730	2993	2993
R_2	0.706	0.476	0.449	0.426	0.693

Note: Robust t-statistics are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$.

3.3. Instrumental Variable Tests

The instrumental variables are displayed in columns (4) and (5) of Table 3. The first-stage regression analysis reveals a significant positive correlation between the instrumental variables and the intensity of urban low-carbon policies ($p < 0.01$). Subsequently, the second-stage regression results indicate a significant negative correlation between the intensity of low-carbon policies and the impact of carbon emissions ($p < 0.01$), consistent with the findings of the baseline regression analysis, thereby confirming result robustness [58]. In summary, H1 is further substantiated.

4. Further Analysis

4.1. Analysis of the Mechanism of Action

4.1.1. Science, Technology, and Innovation Mechanisms

The findings presented in Table 4, specifically columns (1) and (2), underscore the role of policy intensity in driving low-carbon development through STI, consistent with recent research [59,60]. Based on the above research, H2 has been partially verified.

Table 4. Results of the mechanism of action tests.

Variables	(1) Tec	(2) CO_2 (Tec)	(3) Ind	(4) CO_2 (Ind)	(5) Wel	(6) CO_2 (Wel)	(7) Trans	(8) CO_2 (Trans)
Tec		−0.025 ***						
		(−3.29)						
Ind				−0.238 ***				
				(−3.12)				
Wel						−0.025 ***		
						(−3.39)		
Trans								−0.032 ***
								(−3.81)
Intensity	0.051 ***	−0.003 **	0.202 ***	−0.001 *	−0.096 **	−0.005 ***	0.079 ***	−0.001
	(3.80)	(−2.23)	(−3.57)	(−1.89)	(−2.09)	(−3.48)	(−5.55)	(−0.77)
Gdpr	0.096 ***	0.014 ***	0.068 ***	0.003 ***	0.058 **	0.043 ***	0.112 ***	0.014 ***
	(3.36)	(6.51)	(2.76)	(7.77)	(2.46)	(23.78)	(4.26)	(7.66)
Ser	0.008 ***	0.001 ***	0.009 ***	0.001 ***	0.007 ***	0.001 ***	0.008 ***	0.001 ***
	(7.23)	(5.95)	(7.32)	(51.27)	(6.46)	(9.99)	(7.34)	(7.47)
Green	−0.013	−0.008 **	−0.025	−0.005 ***	−0.027	−0.004	−0.001	−0.011 ***
	(−0.21)	(−2.51)	(−0.42)	(−5.70)	(−0.47)	(−1.04)	(−0.01)	(−3.24)
Fdi	0.441	0.147 ***	0.058	0.048 ***	0.575	0.207 ***	0.090	0.068
	(0.63)	(2.95)	(0.09)	(6.25)	(0.83)	(3.76)	(0.13)	(1.50)
SO_2	0.880 ***	0.344 ***	0.640 ***	0.008 ***	0.938 ***	0.390 ***	0.781 ***	0.315 ***
	(5.41)	(3.10)	(3.52)	(3.23)	(5.79)	(3.21)	(4.74)	(3.52)
Constant	−7.481 ***	−4.594 ***	−4.433 *	−0.098 ***	−8.383 ***	−5.383 ***	−5.900 ***	−4.125 ***
	(−3.46)	(−2.61)	(−1.82)	(−2.95)	(−3.91)	(−2.95)	(−2.69)	(−3.35)
City	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Obs	2993	2993	2991	2991	2856	2856	2988	2988
R_2	0.038	0.574	0.037	0.984	0.035	0.466	0.044	0.621

Note: Robust t-statistics are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.1.2. Mechanisms for Industrial Transformation

The results of the industrial transformation mechanism test are detailed in Table 4 below. An analysis of columns (3) and (4) in Table 4 indicates that stringent low-carbon policies drive sustainable development through scientific and technological innovation, facilitating improvements in industrial processes and reductions in carbon emissions. These findings corroborate other studies [27,61]. Based on the above research, H2 has been partially verified.

4.1.3. Welfare Crowding-Out and Pollution Transfer Mechanisms

Based on the data presented in columns (5) and (6) of Table 4, it is evident that the intensity of low-carbon policies reduces regional welfare and carbon emissions, primarily due to decreased output in heavy-polluting industries. Likewise, an examination of columns (7) and (8) reveals a significant increase in firms' likelihood to relocate operations due to intensified low-carbon policies, resulting in reduced carbon emissions—a finding consistent with empirical evidence. Therefore, H2 is substantiated. Based on the above research, H2 has been fully verified.

4.2. Heterogeneity Analysis

In light of the foregoing analysis, it can be inferred that the intensity of low-carbon policies significantly inhibits carbon emissions in urban settings. However, the magnitude of this effect may vary across distinct urban agglomerations due to differences in natural resource endowments, pollution levels, and the varying intensity of policy implementation. This study addresses these variations from four perspectives, urban agglomeration, regional natural resource endowment, pollution severity, and the intensity of low-carbon policy implementation, thereby facilitating an exploration of the heterogeneous effects of policy intensity on carbon emissions.

4.2.1. Heterogeneity of Urban Agglomerations

The phenomenon of agglomeration among cities leads to the formation of city clusters, promoting the free flow of factors within these clusters and generating a synergistic effect where the whole exceeds the sum of its parts. Consequently, variations in sample attributes are expected across different city clusters. China's vast geographic expanse further amplifies these differences, as factors influencing city clusters, alongside their spatial and temporal contexts, exhibit significant disparities. These divergences contribute to varying effects on the intensity of low-carbon policies and subsequent reductions in carbon emissions. In this study, we categorize the sample into eleven distinct city clusters: Beijing–Tianjin–Hebei (Jjj), the Yangtze River Delta (Csj), the Pearl River Delta (Zsj), Guangdong–Hong Kong–Macao Bay Area (Yg), the West Coast of the Taiwan Straits (Hx), the Shandong Peninsula (Sd), Chengdu–Chongqing (Cy), the Central Yangtze River Delta (Cj), the Central Plains (Zy), the Guanzhong Plain (Gz), and Central–South Liaoning (Lzn). The heterogeneity test results for these city clusters are presented in Table 5 below. The empirical analysis indicates that policy intensity and carbon emissions exhibit negative and statistically significant relationships across these eleven city clusters, albeit with varying levels of significance. Specifically, the Beijing–Tianjin–Hebei city cluster (Jjj), Yangtze River Delta city cluster (Csj), Pearl River Delta city cluster (Zsj), Guangdong–Hong Kong–Macao Greater Bay Area city cluster (Yg), Shandong Peninsula city cluster (Sd), and Central Plains city cluster (Zy) demonstrate highly significant results ($p < 0.01$). Situated primarily in eastern and central regions, these clusters highlight the notable intensities and impacts of their low-carbon policies, which have effectively curbed highly polluting and energy-consuming industries. This has facilitated the rapid transformation of industrial structures, thereby fostering a reduction in carbon emissions. In contrast, the West Coast city cluster (Hx), Chengdu–Chongqing city cluster (Cy), and the city cluster in the middle reaches of the Yangtze River (Cj) show relatively less significance ($p < 0.05$), while the city clusters of Guanzhong Plain (Gz) and Central–South Liaoning (Lzn) exhibit slightly higher significance levels ($p < 0.1$). Most of these urban agglomerations are located in central and northeastern China. This geographical distribution suggests that these regions experience slower scientific and technological development, a relatively limited capital scale, slower marketization, and less effective spatial layout and industrial integration. Consequently, the impact of regional green and low-carbon development is comparatively weaker than that observed in the eastern region. This finding aligns with previous studies on urban agglomerations and low-carbon development [55,62].

Table 5. Results of the heterogeneity test for city clusters.

Variables	(1) Jjj	(2) Csj	(3) Zsj	(4) Yg	(5) Hx	(6) Sd	(7) Cy	(8) Cj	(9) Zy	(10) Gz	(11) Lzn
Intensity	−0.002 ***	−0.007 ***	−0.004 ***	−0.004 ***	−0.003 **	−0.001 ***	−0.002 **	−0.001 **	−0.007 ***	−0.004 *	−0.001 *
	(−3.32)	(−2.60)	(−2.99)	(−3.92)	(−2.21)	(−3.12)	(−2.53)	(−2.31)	(−2.63)	(−1.74)	(−1.68)
Gdpr	0.037 ***	0.049 ***	0.014 **	0.025 ***	0.038 ***	0.018 **	0.019 ***	0.040 ***	0.026 ***	0.068 ***	0.033 ***
	(3.72)	(8.33)	(2.27)	(3.99)	(6.23)	(2.48)	(4.37)	(4.09)	(4.82)	(7.08)	(6.72)
Ser	0.000	0.002 ***	0.002 ***	0.000	0.002 ***	0.001	0.001 ***	0.002 ***	0.001 ***	0.002 ***	0.000
	(0.72)	(3.68)	(7.34)	(1.49)	(5.93)	(0.99)	(5.54)	(5.31)	(7.59)	(5.17)	(1.09)
Green	−0.014	−0.130 ***	−0.001	−0.037 **	−0.060 ***	−0.006	−0.077 ***	−0.004	−0.005	−0.004	−0.036 *
	(−0.56)	(−3.21)	(−0.31)	(−2.05)	(−4.56)	(−1.21)	(−3.67)	(−0.12)	(−0.38)	(−0.31)	(−1.89)
Fdi	0.643 ***	0.181	1.396 ***	3.493 ***	0.010	0.808 ***	0.420 ***	0.202 **	0.719 **	0.043	0.597 **
	(3.41)	(1.08)	(8.46)	(11.82)	(0.04)	(3.22)	(2.61)	(2.12)	(2.26)	(0.14)	(2.30)
SO_2	0.142 ***	0.492 ***	0.484 ***	0.116 ***	0.194 ***	0.350 ***	0.179 ***	0.199 ***	0.235 ***	0.317 ***	0.517 ***
	(4.88)	(3.72)	(3.42)	(4.93)	(3.43)	(5.54)	(4.62)	(3.55)	(8.66)	(5.61)	(7.01)
Constant	−1.931 ***	−6.156 ***	−6.107 ***	−1.651 ***	−2.347 ***	−4.517 ***	−1.862 ***	−2.649 ***	−3.011 ***	−4.508 ***	−6.761 ***
	(−5.86)	(−3.15)	(−4.13)	(−4.97)	(−3.05)	(−5.66)	(−3.50)	(−3.54)	(−8.31)	(−5.92)	(−6.84)
Obs	133	309	78	172	237	87	192	112	344	101	217
City	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R_2	0.462	0.534	0.850	0.822	0.288	0.526	0.271	0.467	0.477	0.543	0.328

Note: Robust t-statistics are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.2.2. Heterogeneity of Resource Endowments

Resource-based cities are defined as urban centers where the extraction and processing of natural resources, such as minerals and forests, constitute the primary industry. These cities serve as crucial strategic bases for China's energy resources, playing a pivotal role in the sustained and healthy development of the national economy. Facilitating the sustainable progress of resource-based cities stands as a significant strategy to expedite the transition towards an economically and environmentally sustainable trajectory. Given China's vast expanse, the heterogeneous nature of regional resource endowments can variably influence the implementation of low-carbon policies and carbon emissions. Consequently, guided by the National Sustainable Development Plan for Resource-Based Cities endorsed by the State Council, this study categorizes Chinese cities into growth, maturity, decline, and regeneration phases. The analysis presented in Table 6 reveals that regenerative regions exhibit marginal significance ($p < 0.1$). This underscores the substantial impacts of disparities in natural resource endowments on the intensity of low-carbon policies and carbon emissions. It emphasizes China's imperative, despite its reliance on resources, to swiftly transform towards achieving sustainable economic and environmental development goals, echoing findings in Song et al.'s (2020) study [63].

Table 6. Resource endowment heterogeneity test results.

Variables	(1) Grow	(2) Mature	(3) Rebore	(4) Decline
Intensity	−0.006 ***	−0.013 ***	−0.007 **	−0.000
	(−2.87)	(−2.87)	(−1.99)	(−0.04)
Gdpr	0.041 ***	0.039 ***	0.030 ***	0.084 ***
	(5.74)	(5.34)	(4.83)	(3.51)
Ser	0.001 ***	0.000	0.001 ***	0.000
	(4.36)	(1.26)	(3.64)	(0.04)
Green	−0.004	−0.047	−0.021	−0.034 **
	(−0.56)	(−1.34)	(−1.51)	(−2.48)
Fdi	0.019	0.859 ***	0.336 *	0.686
	(0.22)	(6.72)	(1.70)	(0.97)
SO_2	0.387 ***	0.236 ***	0.312 ***	0.180 ***
	(2.99)	(4.11)	(5.45)	(4.04)
Constant	−5.209 ***	−3.440 ***	−4.066 ***	−2.826 ***
	(−2.93)	(−3.65)	(−5.37)	(−4.90)
Obs	1179	167	233	130
City	YES	YES	YES	YES
Year	YES	YES	YES	YES
R_2	0.428	0.544	0.209	0.711

Note: Robust t-statistics are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.2.3. Heterogeneity in Pollution Levels and Low-Carbon Policy Intensity

Moreover, due to the heterogeneous impact of pollution levels, regional variations in policy intensity can affect carbon emissions. Therefore, this paper classifies the median carbon dioxide emissions as the pollution degree (Poll) and the median policy intensity as the policy intensity (Lcb). Table 7 illustrates the heterogeneity of pollution degrees and low-carbon policy intensities in the test results. It reveals that irrespective of whether pollution levels are low or high, the policy intensity consistently exerts a negative and significant effect on carbon emissions ($p < 0.01$). This indicates that the impact of policy intensity on pollution levels, specifically carbon emissions, is comprehensive and far-reaching, consistent with the study's conclusions. However, areas with a low policy intensity show no significant effects, with only cities exhibiting a high policy intensity demonstrating substantial reductions in carbon emissions, and so they do not need too strong low-carbon policies, while the cities with a high policy intensity are significant, which shows that the policy effect is significant, consistent with the findings [64,65].

Table 7. Results of the test for heterogeneity in pollution degree and heterogeneity in low-carbon policy intensity.

Variables	(1) Poll_Low	(2) Poll_High	(3) Lcb_Low	(4) Lcb_High
Intensity	−0.004 ***	−0.002 ***	−0.001	−0.006 ***
	(−2.74)	(−3.63)	(−0.43)	(−3.51)
Gdpr	0.050 ***	0.050 ***	0.037 ***	0.051 ***
	(2.68)	(2.87)	(3.20)	(3.81)
Ser	0.001 ***	0.001 ***	0.001 ***	0.001 ***
	(3.59)	(3.89)	(4.43)	(3.25)
Green	−0.001	−0.000	−0.006	−0.003
	(−0.10)	(−0.03)	(−1.10)	(−0.47)
Fdi	0.225 ***	0.167 **	0.446 ***	0.103 *
	(2.69)	(2.38)	(4.32)	(1.69)
SO_2	0.403 ***	0.374 ***	0.401 ***	0.389 ***
	(3.74)	(2.60)	(5.27)	(4.36)
Constant	−5.536 ***	−5.115 ***	−5.374 ***	−5.348 ***
	(−3.38)	(−3.58)	(−5.76)	(−5.33)
Obs	1146	1847	1132	1861
City	YES	YES	YES	YES
Year	YES	YES	YES	YES
R_2	0.442	0.467	0.433	0.445

Note: Robust t-statistics are shown in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5. Discussion and Conclusions

5.1. Discussion, Limitations, and Future Developments

5.1.1. Discussion

Policy intensity refers to the extent of implementation of sustainable development policies aimed at reducing carbon emissions. It serves as a pivotal strategy for fostering a mutually beneficial relationship between the economy and ecology, thereby promoting low-carbon sustainable development in urban areas. This study meticulously selected panel data spanning from 2007 to 2022, encompassing prefecture-level cities in China. Employing fixed-effects and mediated-effects models, we analyzed the directional impact of policy intensity on regional carbon emissions. Our methodology integrated empirical analyses to substantiate the causal pathway and test our research hypotheses.

Over the past three decades, as climate extremes have intensified and global warming worsened, policymakers are seeking ways to achieve a low-carbon society. The government has actively promulgated a series of policies on low-carbon and sustainable development to promote carbon emission reduction, but whether the intensity of these policies can promote carbon emission reduction is an open question. After a series of theoretical and empirical analyses, this study found that policy intensity significantly suppressed carbon emissions, which broadened the existing research perspective [34,66]. From the perspective of the mechanistic pathway, our study finds that there is an important influencing mechanism of technological innovation and industrial transformation between policy intensity and carbon emission reduction, which is consistent with the existing research [29,35,36], but the welfare crowding-out and pollution transfer effects are slightly different from those reported by relevant scholars [67]. In the heterogeneity analysis, we found that different urban agglomerations, environmental resource endowments, and pollution levels had different impact effects, which is in line with the current mainstream academic view [37,68].

5.1.2. The Limitations of This Research

Despite its contributions, this study has limitations. Quantifying the impact of low-carbon policies proves challenging due to the cross-effects of policy implementation in both the short and long term, regional cultural differences, and varying levels of public awareness. Moreover, the experimental data's accuracy may be compromised because the policy intensity data, sourced from the PKULaw.com Policy Database (https://pkulaw.com/, accessed on 1 July 2024), might exclude certain policies. This limitation could affect the precision of the data, though it does not substantially impact the overall regression results of the study. We used the conversion factors outlined in the 2006 Intergovernmental Panel on Climate Change report as a measure of carbon emissions for each year, but the conversion factors have been updated, which is also a shortcoming of this study, but it does not have much impact on the conclusions and we will further address these issues in future studies.

5.1.3. The Future Developments of This Research

Future research should continue to investigate the impacts of quantitative low-carbon policies on short-term and long-term cross-cutting effects, regional cultural differences, and public awareness. It will be essential to develop more refined methods for quantifying low-carbon policies and to construct research addressing these areas comprehensively. Additionally, integrating the Policy Modeling Consistency (PMC) model with our measurement approach could facilitate an analysis of policy consistency, highlighting the strengths and weaknesses of evaluated policies. This approach would provide insights into the significance and levels of various variables beyond a mere intensity measurement. Furthermore, applying existing research methods to other countries could enable comparisons of carbon emission intensity and responsibilities, potentially advocating for enhanced United Nations carbon reduction mandates and the Sustainable Development Goals.

5.2. Conclusions and Policy Recommendations

5.2.1. Conclusions

Our study yields two primary findings. First, the policy intensity demonstrates a substantial capacity to reduce carbon emissions across the sample of prefecture-level cities examined. This conclusion persisted following rigorous robustness tests, indicating that a unit increase in low-carbon intensity corresponds to a 0.53% decrease in carbon emissions. Second, the relationship between policy intensity and carbon emissions exhibits heterogeneous effects across different urban agglomerations, environmental resource endowments, pollution levels, and intensities of low-carbon policies. Specifically, significant reductions in carbon emissions were observed in urban agglomerations located in the eastern, central, and southern regions, with less pronounced effects noted in the western and northeastern areas. Moreover, regions categorized as growing, mature, and regenerative showed significant impacts, whereas declining regions did not display statistical significance. Additionally, irrespective of pollution levels, policy intensity consistently exerts a negative and significant influence on carbon emissions, with primary significance observed in higher-intensity regions compared to lower-intensity ones. Policy intensity achieves carbon emission reductions through both active and passive mechanisms, including innovation, industrial transformation, welfare crowding-out, and pollution transfer effects.

5.2.2. Policy Recommendations

Based on our analysis, this study proposes several policy recommendations.

First, it advocates for maintaining a focused approach to carbon peaking at the prefecture-level city level, rooted in principles of low-carbon development and adapted to local conditions. This involves implementing scientifically formulated carbon-neutral and carbon-peak strategies, optimizing energy policies, reducing fossil fuel consumption, promoting renewable energy sources, offering policy incentives for clean energy adoption, launching low-carbon flagship projects, and widely disseminating carbon-peak and carbon-neutral policies.

Second, there is a call to strengthen the intensity of low-carbon policies across China's diverse regions. Given regional disparities, governments should bolster environmental regulations, adopt a new development paradigm, and enhance environmental constraints to effectively address variations in carbon emission reductions. To address environmental challenges effectively, stringent measures are imperative. These include compelling heavily polluting enterprises to innovate and undergo industrial transformation, intensifying local pollution control supervision, and enhancing penalties.

Additionally, a multifaceted approach is necessary to achieve pollution and carbon reduction objectives. This involves bolstering territorial spatial planning, minimizing human encroachment on the environment, prioritizing the conservation of local ecological stability, fostering the greening of industries, and accelerating the growth of clean sectors. Facilitating the transfer and transformation of heavily polluting industries is crucial for reducing carbon emissions. Leveraging "big data +" methodologies for monitoring, fostering public environmental oversight and engagement, advancing environmental education, and augmenting human environmental literacy and ecological civilization awareness are pivotal steps.

Moreover, establishing a cross-regional negative list coordination mechanism is imperative to mitigate the potential ecological ramifications of relocating polluting industries. A comprehensive negative list for environmental access should be devised to regulate such relocations. Concurrently, implementing a collaborative prevention and integrated management strategy is essential. This strategy promotes harmonization of environmental regulations across regions to incentivize enterprises to proactively transform rather than simply relocate. The precise identification of industries positioned for future advantages, refinement of relocation–industry criteria, elevation of social welfare standards in each region, and mitigation of environmental pollution-induced harm are crucial objectives for minimizing ecological and environmental damage.

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