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How Does Urbanization Affect Carbon Emission Performance? Evidence from 282 Cities in China

Zhibo Zhao [1], Jiamin Ren [2,*] and Zheng Liu [1]

[1] School of Finance, Qilu University of Technology (Shandong Academy of Sciences), Jinan 250100, China; zhibozhao0728@163.com (Z.Z.); economicsliuzheng@126.com (Z.L.)
[2] College of Geography and Environment, Shandong Normal University, Jinan 250358, China
* Correspondence: renjm0928@163.com

Abstract: Improving carbon emission performance (CEP) is the key to realizing the goal of "carbon peaking and carbon neutrality" for China. Using a panel dataset of 282 cities at prefecture level and above in China from 2003 to 2017, this study employs the Global Malmquist–Luenberger (GML) index to measure CEP. Moreover, this study investigates the effect and transmission mechanisms of urbanization on CEP based on the extended STIRPAT model. The results show a significant positive "U-shaped" relationship between urbanization and CEP. When urbanization exceeds the inflection point, urbanization is conducive to improve CEP in Chinese cities. The mechanism analysis illustrates that human capital has a positive impact on CEP, while technological innovation inhibits it. The findings of this study can provide a scientific basis for local governments to formulate different strategies to improve China's high-quality development through human capital accumulation and low cost and scale of low-carbon technologies.

Keywords: urbanization; carbon emission performance; extended STIRPAT model; cities

Citation: Zhao, Z.; Ren, J.; Liu, Z. How Does Urbanization Affect Carbon Emission Performance? Evidence from 282 Cities in China. *Sustainability* **2023**, *15*, 15498. https://doi.org/10.3390/su152115498

Academic Editor: Wen-Hsien Tsai

Received: 1 October 2023
Revised: 22 October 2023
Accepted: 30 October 2023
Published: 31 October 2023

1. Introduction

From 6 to 20 November 2022, the United Nations launched the 27th Conference of the Parties to the United Nations Framework Convention on Climate Change (COP27), reiterating the goal to "pursue further efforts to limit the temperature increase to 1.5 °C" [1]. Greenhouse gases (GHGs), especially carbon emissions, are believed to be the main influencing factors of the global increase in mean temperature [2]. According to the *Review of World Energy 2020*, global carbon emissions increased by 40% from 2000 to 2019, reaching a historical record high of 34.46 billion tons [3]. In this context, many countries have committed to achieving net zero emissions and facilitating measures to achieve "low carbon" development [4,5].

China, the largest carbon emitter globally, is in charge of reducing carbon emissions [6]. In 2020, President Xi proposed China's carbon peak and carbon neutral goals (hereinafter referred to as the "dual carbon" goals) at the 75th Session of the United Nations General Assembly; the "dual carbon" goals have been successively written into the 2021 Government Work Report and the 14th Five-Year Plan. To achieve this goal, China must not only reduce carbon emissions but more significantly, increase the carbon emission performance (CEP).

CEP has drawn much attention from academics and policymakers, making a definition of its connotation. Wang et al. [7] pointed out that CEP is the result of the changes of the relationship between input and output factors in socioeconomic development. Xu et al. [8] proposed the improvement in CEP to be the environmentally sensitive productivity growth, considering carbon emissions as an undesirable output. Miao et al. [9] put forward that CEP depends on the influence of both carbon emissions and economic output factors. Zeng et al. [10] pointed out that it is an important breakthrough point to achieve a win-win situation between economic development and environmental protection. In this paper, CEP is defined as a term that reflects the comprehensive performance of regional units in various dimensions involved in the transformation within a certain time range. As an important indicator for cities to pursue low carbon development, there are two types of ways to measure CEP. Firstly, some scholars use a single index method to assess CEP. The CEP involved in these studies is expressed via the ratio of carbon emissions to a specific variable [11,12]. The benefit of this approach is that it is simple and requires a small amount of data. It can be applied in situations wherein data acquisition is difficult. However, Xiao et al. [13] pointed out that a single factor would ignore the substitution of factors, making it difficult to accurately estimate CEP. Thus, many scholars have proposed measuring CEP from the perspective of total factors [14,15]. Its core lies in putting the input–output theory into a theoretical framework and using multiple factors, such as capital, labor, energy, etc., to construct evaluation systems. Based on the broader connotation and deeper requirements of urban low-carbon development, this study uses the total factor productivity of carbon emissions to highlight the effective control and restriction of carbon emissions, expressed as a proxy variable of CEP.

With CEP drawing significant attention, there have been many in-depth analyses of studies investigating its influencing factors, such as the economic basis [16], industrial structures [17], energy consumption [18], urbanization [19], environmental regulation [20], government policies [21], and internet infrastructure [22]. Cities are regions where human economic and social activities are concentrated and distributed [23]. They account for about 2% of the global area but comprise about 70% of GDP, consume more than 60% of energy, and produce 75% of global carbon emissions [24]. Urbanization is the engine and driving force of socioeconomics, as well as an inevitable trend, playing an even more important role in achieving sustainable development goals (SDGs) and realizing responses to climate change [25]. Thus, urbanization plays an important role in CEP; existing studies have mainly focused on the impact of urbanization on CEP.

Many scholars have studied the relationship between urbanization and CEP, and these studies can be broadly divided into two categories. On the one hand, scholars have tried to figure out the relationship between urbanization and CEP. In general, unsustainable population growth would increase carbon emissions [26]; however, studies have indicated that there is no standardized relationship between urbanization and CEP, such as positive [27], negative [28], insignificant [29], inverted U-shaped [30], nonlinear [31], etc. On the other hand, researchers have focused on how urbanization affects CEP. In the process of urbanization, cities gradually show a tendency to concentrate population, industry, capital, etc. Thus, the effect of urbanization on CEP is very complex. Li et al. [32] argued that new urbanization stimulates green technological innovation and facilitates the development of industrial agglomeration, thus achieving a reduction in carbon emission intensity. Liu et al. [33] analyzed the effect of urbanization on CEP from population, industrial, spatial, and economic perspectives. Jiang et al. [34] argued that there is a self-regulating balance mechanism between urbanization and carbon emissions as well as carbon emissions and economic growth. Moreover, researchers have also explored the effect of different urbanization stages on CEP. Wang et al. [35] pointed out that semi-urbanization not only facilitates emission reduction in a particular region but also significantly reduces carbon emissions in surrounding regions. Moreover, the regional heterogeneity of the impacts has also been confirmed [36,37]. In addition, scholars have also analyzed these impacts from the perspective of land use, population migration, and public transport [38,39].

Although existing studies have examined the relationship between urbanization and CEP [40,41], their research still has the following gaps: Firstly, the relationship between urbanization and CEP in Chinese cities has not been examined clearly. Furthermore, 85% of carbon emissions in China are contributed by cities; thus, the influencing mechanisms between them need to be discussed more deeply. Secondly, the quantitative impacts of urbanization on CEP have not reached the same conclusions, especially in Chinese cities. Exploring the specific quantitative relationship between them will help the Chinese government formulate specific emission reduction measures. In addition, our research can also explore how to achieve a win-win situation for urbanization and carbon emission reduction under the background of "dual carbon".

Motivated by this aim, this study investigates the following questions: (1) How has CEP changed since 2003 in Chinese cities? What are the characteristics of spatial and temporal heterogeneity? (2) What is the impact mechanism of urbanization on CEP? More specifically, what are the transmission channels by which urbanization affects CEP? (3) What are the differences in the impacts of urbanization on CEP among Chinese cities? To answer these questions, we first explicate the theoretical mechanism between urbanization and CEP and then explore transmission channels between them. Secondly, we use the data of Chinese cities from 2003 to 2017 and the Global Malmquist–Luenberger (GML) index to measure the CEP of 282 cities and conduct an analysis from the perspective of temporal and spatial heterogeneity. Finally, we provide new evidence illustrating the effect of urbanization on CEP using a panel dataset covering 282 Chinese cities, which enriches the EKC theory empirically.

The rest of this paper is organized as follows: Section 2 introduces the influencing mechanism and proposes two theoretical hypotheses. Section 3 describes the methodology and data. The empirical research of this study is presented in Section 4. The final section summarizes the conclusions and proposed policy recommendations.

2. Research Hypothesis

2.1. Direct Path for Urbanization to Influence CEP

The impact of urbanization on CEP is different and depends on the combined effects of the various mechanisms. There are several theories that can help us to figure out this problem.

Firstly, Northam [42] proposed the theory of the three stages of urbanization. At the beginning of urbanization, city sizes are small, the ratio of the non-farming population in cities is relatively low, and the primary industry accounts for a large proportion of the regional economy. In the medium-term, more and more rural people immigrate to urban areas; meanwhile, urban industrialization levels gradually improve, and the urban economy thrives. In the last stage, the rate of migration of rural populations to urban areas flattens, and the development goal of cities changes from quantity to quality, which improves the efficiency of social development [43]. At different stages of urbanization, economic activities represent different characteristics; the high consumption of energy and carbon emissions in the medium-term cannot be ignored.

Secondly, Panayotou [44] put forward the Environmental Kuznets Curve (EKC) hypothesis. This theory assumes there is an inverted U-shaped relationship between economic growth and environmental pollution. Economic growth initially increases environmental pollution discharge, but after a certain level, it negatively affects discharge. The next is the theory of ecological modernization. It claims that if we want to realize a win-win situation between economic development and environmental protection, we must leverage ecological advantages to enhance modern development [45]. With the gradual transition of urban economies from low stages to middle and high stages, ecological problems will present a state of continuous deterioration and improvement [46]. Then, from the perspective of urban environmental transformation theory, we know that in the early stage of urban development, there is not only greater consumption of pollution-intensive products but also an increased demand from people for a high-quality environment. Therefore, the impact on environmental quality is uncertain [47]. Finally, the compact city theory points out that in the process of urban development, increased urban density inevitably leads to concentrated urban public infrastructure, enterprises, and populations, which is conducive to generating scale and agglomeration economies, thus improving environmental quality [48].

It can be seen from the above analysis that there is not a simple linear relationship between urbanization and CEP. At different stages of urbanization, the impact of urbanization on CEP showed a "negative" to "positive" trend. Therefore, the first hypothesis is put forward as follows:

Hypothesis 1. *Urbanization has a U-shaped nonlinear effect on CEP.*

2.2. Indirect Path for Urbanization to Influence CEP

Based on a literature review and existing research, we argued that the U-shaped effect of urbanization on CEP may emerge from two channels: human capital accumulation and technological innovation.

(1) Human capital accumulation. With the development of urbanization, human capital accumulation constantly improves in urban areas, which contributes to improving urban environmental quality [49–51]. Although urbanization promotes carbon emission increase, human capital accumulation may weaken this increase [52,53]. Human capital and material capital are core production factors that promote economic growth. Compared with material capital, human capital plays a greater role in promoting economic growth [54–56]. In addition, human capital has a spillover effect on economic growth and promotes high-quality economic growth by improving total factor productivity [57]. In the process of economic growth, human capital can offset the diminishing marginal returns brought about via material capital and the negative effects of carbon emissions and breakthrough energy constraints, thereby achieving a win-win situation between economic growth and energy conservation, as well as emission reduction [58]. From the perspective of trade openness, it has a positive effect on promoting carbon emission performance, and improving the quantity and quality of human capital can consequently enhance this positive effect [59]. Moreover, improving population quality also forms a mutual learning effect among people, thus leveraging the externality of human capital. When the human capital accumulation of a city is relatively high, regional leading industries favor high-tech and innovative industries. The mode of production will restrict the increase in carbon emissions, thus promoting the improvement in CEP.

In conclusion, the transformation process of urban population structures would improve population quantity, and an increase in education opportunities would transform the pressure of huge populations into high-quality human capital, thus contributing to low-carbon development in China. Therefore, human capital accumulation has a positive effect on CEP. We can further propose the following hypothesis:

Hypothesis 2. *Human capital accumulation can inhibit the increase in carbon emissions and promote the improvement in CEP.*

(2) Technological innovation. Schumpeter pointed out that innovation is a way to combine production factors and production conditions in a production system [60,61]. In particular, new product manufacturing, new market openings, new production methods, new sources of material supply, and new organizational forms are the five basic forms of innovation [62]. The evolution of urban population structures provides a platform for technological innovation, and a low-carbon development model with the characteristics of low energy consumption, low pollution, and low emissions needs to be guided via the theory of technological innovation.

From the perspective of low-carbon development, technological innovation can be divided into low-carbon technological innovation and non-low-carbon technological innovation. Both of them can boost economic growth, but low-carbon technological innovation is the best way to restrict carbon emissions. In order to achieve the goals of peak carbon emissions and carbon neutrality, we must rely on low-carbon technological innovation [63]. In order to break the path dependence of enterprises' technological progress, the government should adopt a series of measures to encourage enterprises to engage in cleaner production and voluntarily reduce carbon emissions. Although the government has issued different environmental regulation policies to force enterprises to carry out technological innovation which restricts carbon emissions, enterprises have different responses to environmental regulation policies. The carbon emission trading market encourages technology and traditional production departments to choose clean production. The tendency to produce clean technology depends on the different contributions of output elasticity from clean and traditional departments to the output of terminal production and intermediate products. By adjusting the price of carbon emission trading, enterprises can control clean technology research and development processes [64]. Moreover, the cumulative effect of environmental policy and R&D efficiency influences the direction of environmental technology progress, and the effect of combined environmental regulation policies is better than a single-policy intervention. Under the constraints of combined environmental regulation policies, the production of urban economic sectors will gradually tend to adopt cleaner production technologies to suppress carbon emissions, thus promoting the improvement in CEP [65]. Therefore, in the process of technological innovation, environmental policies should be adjusted promptly based on policy implementation to ensure the effectiveness of policy implementation reaches its optimal level.

In summary, the evolution of urbanization provides a platform for technological innovation. Technological innovation can optimize the energy utilization efficiency of enterprises, increase the proportion of renewable energy, make up for the single-energy structure in China, and, thus, promote the low-carbon development of cities. Technological innovation can not only realize the decarbonization of enterprises' terminal production but also reduce energy consumption in the production chain, reduce the energy consumption cost of products, and, finally, control the carbon emissions of enterprises. Moreover, the products produced via this clean production mode are low-carbon throughout their life cycle, even after being used in the market, which contributes to the low-carbon development of Chinese cities. Thus, technological innovation has a positive effect on CEP. Hypothesis 3 is proposed as follows:

Hypothesis 3. *Cleaner production modes based on technological innovation are an effective way to restrict the increase in carbon emissions and promote the improvement in CEP.*

To test these hypotheses above, we employed the GML index to evaluate CEP at the city level firstly, and then, the extended STIRPAT model was used to examine the impact of urbanization on CEP and identify potential transmission channels of urbanization on CEP.

3. Materials and Methods

3.1. CEP Measurement Method

3.1.1. Global Malmquist–Luenberger Index

Assume that there are n decision-making units (DMUs, $n = 1, 2, \ldots, N$) over T time periods ($t = 1, 2, \ldots, T$). We denote the input vector by $x = (x_1{}^t, x_2{}^t, \ldots, x_N{}^t)$, $x \in R_+{}^N$; the desirable output vector by $y = (y_1{}^t, y_2{}^t, \ldots, y_N{}^t)$, $y \in R_+{}^M$; and the undesirable output vector by $b = (b_1{}^t, b_2{}^t, \ldots, b_N{}^t)$, $x \in R_+{}^I$. The production technology (T) can be expressed as follows:

$$T = \{(x, y, b) : x \; can \; produce(y, b)\} \tag{1}$$

T can transform the input vector to desirable and undesirable outputs. Färe et al. [66] pointed out that if the output satisfies the assumption of strong disposability, the undesirable output is equal to the disposable desirable output. Therefore, we assume that the undesirable outputs are as weakly disposed as (a). In addition, T must satisfy the null-jointness assumption, as shown in (b).

(a) if $(x, y, b) \in T$ and $0 \leq \theta \leq 1$, then $(x, \theta_y, \theta_b) \in T$.
(b) if $(x, y, b) \in T$ and $b = 0$, then $y = 0$.

The weak disposability assumption (a) implies that the reduction in undesirable outputs is not free but is a proportional reduction in desirable outputs. The null-jointness assumption (b) implies that the undesirable outputs are unavoidable during the production process [67]. Based on the above assumptions, Chung et al. [68] proposed a new directional distance function (DDF) to deal with the production process containing undesirable outputs by using the Malmquist–Luenberger (ML) index, as shown in Equation (2), where g = (y, $-b$) is the direction vector.

$$\vec{D}_0(x, y, b; g) = sup\{\theta : (y, b) + \theta_g \in T\} \tag{2}$$

Then, DDF can be solved via the following linear programming (LP) problem:

$$\begin{gathered}\vec{D}_0^{G}\left(x_0^t, y_0^t, b_0^t; y_0^t, -b_0^t\right) = max\theta \\ s.t.\begin{cases}\sum_{n=1}^{N} Z_n^t y_{nm}^t \geq (1+\theta) y_{0m}^t, m = 1, \ldots, M \\ \sum_{n=1}^{N} Z_n^t b_{ni}^t = (1-\theta) b_{0i}^t, i = 1, \ldots, I \\ \sum_{n=1}^{N} Z_n^t x_{nk}^t \leq (1-\theta) x_{0k}^s, k = 1, \ldots, K \\ Z_n^s \geq 0, n = 1, \ldots, N\end{cases}\end{gathered} \tag{3}$$

The ML index can obtain a more realistic productivity change; however, there are still some limitations which renders the ML index biased, including infeasibility in linear programming and the inability to facilitate multi-period comparisons. Additionally, radial and angular approaches struggle to overcome the bias introduced by the relaxation variables [69]. These deficiencies can be overcome via the GML index based on the global production possibility set (PPS), which envelopes all the contemporaneous PPS. Hence, DDF can be solved via the following LP, as shown in Equation (4):

$$\begin{gathered}\vec{D}_0^{G}\left(x_0^s, y_0^s, b_0^s; y_0^s, -b_0^s\right) = max\beta \\ s.t.\begin{cases}\sum_{n=1}^{N}\sum_{t=1}^{T} Z_n^t y_{nm}^t \geq (1+\beta) y_{0m}^s, m = 1, \ldots, M \\ \sum_{n=1}^{N}\sum_{t=1}^{T} Z_n^t b_{ni}^t = (1-\beta) b_{0i}^s, i = 1, \ldots, I \\ \sum_{n=1}^{N}\sum_{t=1}^{T} Z_n^t x_{nk}^t \leq (1-\beta) x_{0k}^s, k = 1, \ldots, K \\ Z_n^s \geq 0, n = 1, \ldots, N\end{cases}\end{gathered} \tag{4}$$

Then, the GML model is defined as follows:

$$\begin{gathered}GML_t^{t+1} = \frac{1+\vec{D}_0^{G}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_0^{G}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} = \frac{1+\vec{D}_0^{t}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \times \\ \left[\frac{\left(1+\vec{D}_0^{G}\left(x^t, y^t, b^t; y^t, -b^t\right)\right) / \left(1+\vec{D}_0^{t}\left(x^t, y^t, b^t; y^t, -b^t\right)\right)}{\left(1+\vec{D}_0^{G}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right) / \left(\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right)}\right] = EC_t^{t+1} \times TC_t^{t+1}\end{gathered} \tag{5}$$

where ${GML_t}^{t+1}$, indicating that productivity enables more economic outputs and fewer carbon emissions, suggests CEP has been improved. EC is the technical efficiency change index, which measures the catch-up effect of a sub-sector toward the contemporaneous frontier, and ${EC_t}^{t+1}$ means that the sub-sector is approaching the contemporaneous frontier over two periods. TC is the index that can judge the real existence of technological progress based on whether the distance between the frontier surface of two adjacent periods and the common frontier surface decreases, and ${TC_t}^{t+1}$ corresponds to technical progress.

3.1.2. Variable Selection

According to the method described above, we constructed an evaluation system as well as the selection of input variables and output variables, as described below.

In this study, labor, capital stock, and energy are selected as the inputs. (1) Labor force: we use the sum of the number of employees in urban areas as well as employees in private enterprises and self-employed individuals in urban areas at year-end as the labor input index [70]. (2) Capital input: this indicator is expressed via the total fixed assets investment by Song et al. [71]. (3) Energy input: due to the lack of city-level energy consumption data, drawing on the research of Xu et al. [72], the electricity consumption of the whole city is used to measure energy input. We divided the output variables into desirable output and undesirable output. (1) Desirable output: GDP is selected as the economic output [73]. (2) Undesirable output: Carbon emissions are used as undesirable outputs in this study. We followed the method of Chen et al. [74] to calculate carbon emissions at city level.

The GDP deflator was used to convert total fixed assets investment and GDP to comparable prices in 2003, eliminating the impact of price changes.

3.2. Extended STIRPAT Model

3.2.1. Model Construction

Ehrlich and Holdren proposed the IPAT model, which illustrates that environmental impact (I) is associated with population (P), affluence (A), and technology (T) [75]. In this model, they are independent of each other. Assuming that all other factors remain constant, the effect can only be analyzed by changing one of them. In order to overcome this limitation, Dietz and Rosa improved the STIRPAT model [76]. After taking logarithms on both sides, the formal formula can be written as follows:

$$\ln I_{it} = a_{it} + blnP_{it} + clnA_{it} + dlnT_{it} + ln\varepsilon_{it} \tag{6}$$

This study develops the following model to examine the role of urbanization in CEP. The specific model setting is given in Equation (7):

$$lnGML_{it} = \alpha_0 + \alpha_1 lnurb_{it} + \alpha_2 lnurb_{it}^2 + \alpha_3 lnpgdp_{it} + \alpha_4 lnpgdp_{it}^2 + \alpha_5 lnti_{it} + \alpha_6 lnhc_{it} + \alpha_7 lnX_{it} + \eta_{it} \tag{7}$$

where i and t represent some province and year, respectively; GML denotes the environmental impact; population structure (urb) and human capital (hc) refer to population; per capita GDP (pgdp) and technological innovation (ti) are used to represent affluence and technology, respectively; urb^2 and pgdp^2 are the squares of pgdp and urb, respectively; X denotes some control variables that correlate to CEP; and αi (i = 0, 1, 2,. . ., 7) is a coefficient that needs to be estimated. The error term is denoted by η.

3.2.2. Variable Selection

Explanatory Variables

Urbanization level (urb): This variable is measured via the proportion of urban residents in each city [77]. It can fully reflect the evolution of China's urban population structure under the background of new urbanization. In line with our proposed theoretical hypothesis, urb may contribute to explaining CEP; there is a "U"-shaped nonlinear relationship between urbanization and CEP. In other words, we can expect that the evolution of urbanization will promote long-term improvement in CEP.

Core Control Variables

Since CEP is influenced by many factors, to be precise and reliable for the study, we also selected three core control variables as follows:

Economic development (pgdp): Economic development is considered a key factor in affecting carbon emissions based on the EKC hypothesis; here, economic development is also chosen as a key variable. This variable is measured via GDP per capita. According to the EKC hypothesis [78], we also put the quadratic term of GDP per capita into the regression model.

Human capital (hc): In this paper, we used the proportion of university students in the total population to measure human capital [79]. The impact of hc on carbon emission is positive.

Technological innovation (ti): Scholars have used the number of granted patents as a measure of technological innovation. However, it is important to note that there is a time lag in the publication of patents granted; thus, we used the number of patent applications per 10,000 persons to measure this variable.

Other Control Variables

Environmental regulation (er): ers are regarded as effective ways to reduce carbon emissions, but previous studies on the relationship between er and carbon emission have not reached a consensus [80]. Among them, pollution reduction and control expenditure, sewage fees, and environmental subsidies are usually used to measure er [81]. Since the abovementioned data at the city level could not be obtained, we used the ratio of wastewater centrally treated in sewage work to measure er.

Public transportation (pub): Nowadays, public transport is considered an important means of green transport and is being promoted by the local government. The development of public transport in cities can facilitate multiple ways of reducing greenhouse gas emissions from passenger mobility [82]. Therefore, the influence of pub on carbon emission is negative. The total annual volume of passengers transported via buses and trolley buses is chosen to reflect pub.

Energy consumption structure (ei): The proportion of industrial electricity consumption was selected here for several reasons. Firstly, coal consumption acts as a kind of high-emission and high-polluting energy source, which is also the major determinant of carbon emissions in China. However, data on energy consumption at the city level are not available. Secondly, according to a study by Li and Lin [83], electricity consumption is recorded via Watt–hour meters and, thus, is much more accurate, given that energy consumption in China is widely believed to be underestimated. Finally, with the expansion of the scale, energy consumption in industry has increased rapidly, leading to substantial carbon emissions. This indicator has also been used by Yuan et al. [84].

Industrial structure (ind): Upgrading industrial structures is a valid measure to curb the continuous increase in carbon emissions, which changes the patterns in high-energy-consuming industries through the rational allocation of production factors and technological innovation [85]. The industrial structure is measured via the ratio of the added value of the secondary industry to GDP.

Openness (fdi): This variable is measured via the proportion of foreign direct investment in GDP. There are two hypotheses—the pollution haven and halo effect hypotheses—regarding the relationship between fdi and carbon emissions [86]. The former argues that fdi may promote carbon emission growth with minimum environmental standards in developing countries. The latter proposes that fdi can bring low-carbon technologies to poor nations, thus leading to a cleaner environment. Therefore, the impact of fdi on carbon emissions is uncertain.

3.3. Data Sources

Due to the relatively serious data missing in city samples, this study investigated the impact of urbanization on CEP based on panel data from 282 prefecture-level cities in China from 2003 to 2017. Owing to the lack of energy statics, it is difficult to obtain carbon emission data at the city level directly. Chen et al. [74] put forward a particle swarm optimization–back propagation (PSO-BP) algorithm to unify the scale of DMSP/OLS and NPP satellite imagery and estimate the carbon emission in 2735 Chinese counties during 1997–2017. Thus, we obtained the county-level carbon emissions in China during 2003 to 2017 from Carbon Emission Accounts & Datasets (www.ceads.net.cn) (accessed on 28 April 2023). Then, we transformed the county-level data into city-level data. The original socioeconomic data came from the "*China City Statistical Yearbook (2004–2018)*", "*China Urban Construction Statistical Yearbook (2004–2018)*", and Chinese Research Data Services Platform (www.cnrds.com) (accessed on 12 May 2023). Some missing data were supplemented by the linear interpolation method. Descriptive statistics of each variable are shown in Table 1.

Table 1. Descriptive statistics of each variable.

Variable Type	Variable	Obs.	Mean	Std.Dev.	Min	Max
Dependent variable	lnCEP	3948	0.0408	0.251	−2.033	1.585
Independent variable	lnurb	3632	−0.322	0.506	−3.051	0
Mechanism variable	lnhc	3486	1.065	1.015	−4.077	5.569
	lnrd	3942	2.027	1.477	−2.791	6.194
Control variable	lnpgdp	3898	10.50	0.759	2.791	15.68
	lnind	3935	3.872	0.281	2.086	4.511
	lnfdi	3467	0.355	1.472	−8.739	7.306
	lnei	3864	−0.469	0.384	−5.261	0
	lnpub	3637	8.902	1.419	1.792	13.15
	lner	3583	4.197	0.519	−1.833	4.605

4. Results

4.1. Spatiotemporal Pattern of CEP in Chinese Cities

4.1.1. Temporal Heterogeneity Characteristics

To preliminarily show the temporal evolution characteristics of GML, EC, and TC, Figure 1 presents the average value of 282 cities in Chinese cities from 2003 to 2017. It can be seen that the GML index shows an obvious change in phase, which can be divided into two stages. Firstly, the GML index showed an overall increasing trend from 2003 to 2016, with a value higher than 1, indicating that the GML index in China gradually improved. From 2016 to 2017, the GML index of carbon emissions showed a decline, as shown in Figure 1. In terms of EC and TC, neither was in a stage of fluctuation but showed different changes in trends. During the study period, EC was in an overall fluctuant downward trend, with the variation range deviating from 1, while TC significantly increased from 2003 to 2017, with an overall increase of 189%. Accordingly, we can confirm that the reason for the continuous increase in the GML index is the significant growth in TC, while the change in EC restricts the increase in the GML index. The growth in the GML index and decomposition was due to the sustainable strategies and low-carbon policies in China [87]. Under this economic growth model, cities actively improved their CEP to reduce carbon emissions. However, the decline in the GML index from 2016 to 2017 also suggests that local governments in China should pay more attention to the task of carbon reduction while developing the economy, and they cannot ignore the problem of carbon emissions.

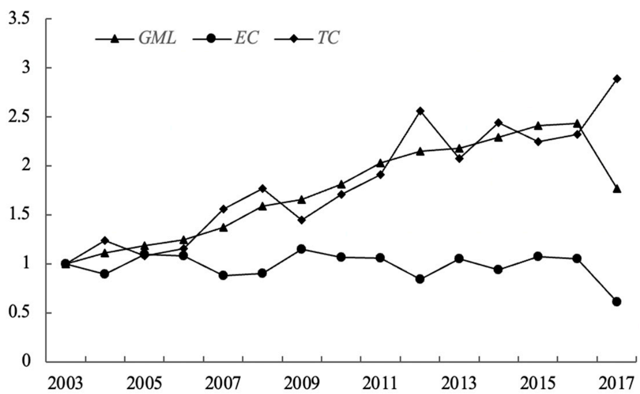

Figure 1. The GML index and its decomposition change in China from 2003 to 2017.

4.1.2. Spatial Heterogeneity Characteristics

To analyze the spatial heterogeneity characteristics of CEP, EC, and TC, we classified the average value of CEP, EC, and TC into four groups using the Natural Breaks method in ArcGIS 10.5 (Figure 2).

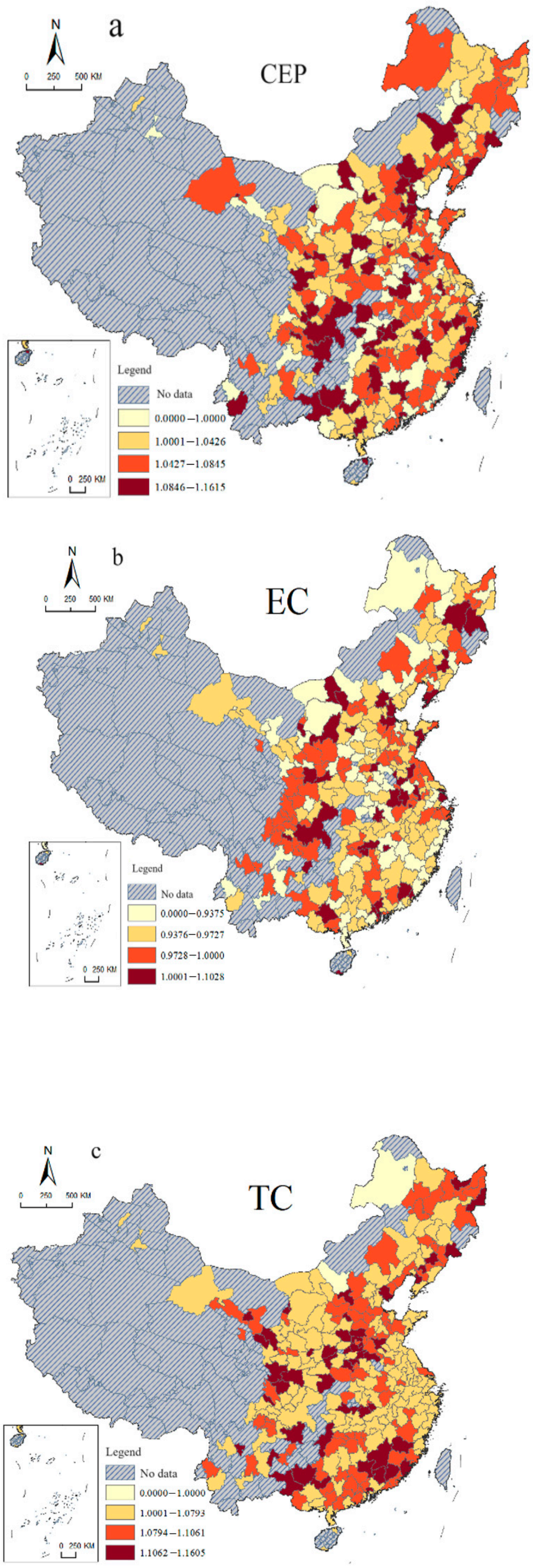

Figure 2. Spatial variation in CEP (**a**), EC (**b**), and TC (**c**) (2003–2017). Note: This map is based on the standard map No. GS(2020)4630, which can be downloaded from the Standard Map Service website of the Ministry of Natural Resources. The base map has not been modified.

As can be seen in Figure 2a, low-carbon development in China has good prospects; the CEP value in most cities is higher than 1, accounting for 83.69%. They are mainly distributed in developed cities and provincial capital cities with good development prospects, such as Beijing, Tianjin, Xiamen, Nanchang, and Nanjing. Only 45 cities had an average value of less than 1, such as Huai'an, Bazhong, and Jingdezhen, which are located in inland areas and are less-developed western regions in China. In comparison, in China, the EC index is higher than 1 in only 14.18% of cities, such as Beijing, Hefei, and Harbin (Figure 2b). Most cities have a higher TC index value, and only two cities, Hulunbuir and Ulanqab, have a value below 1 (Figure 2c). From the perspective of spatial distribution, there are few cities with the highest TC index in China, accounting for only 16.67% of the total cities. There is still significant space for improvement in China's technological progress in carbon emission reduction.

Green and low-carbon technological innovation is important for promoting high-quality development and achieving the "double carbon" goals, but there are still challenges for green and low-carbon technology innovation in Chinese cities, such as weak independent innovation abilities, large investment demands, and the need for financing channels to be expanded. To this end, we should strengthen scientific research and innovation leadership, promote technology transformation, save enterprises' energy transformation costs through upgrading green and low-carbon technologies, and improve energy efficiency [88].

4.2. The Influence of Urbanization on CEP

4.2.1. Empirical Results

To avoid endogeneity caused via dependent and explanatory variables, a GMM system was applied to estimate the model, and the highest third-order lag term was used as an instrumental variable. In addition, the validity of the instrumental variable was tested in this study. Through the empirical finding that the K-P F statistic is far greater than 10, the problem of weak instrumental variables was eliminated. Moreover, the overestimated test of instrumental variables was also carried out in this study, and we found that instrumental variables satisfied the homogeneity hypothesis. The results are shown in Table 2.

Table 2. Regression results of urbanization on CEP.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
lnurb	0.377 *	0.368	0.422 *	0.481 *	0.488 *	0.621 **
	(0.222)	(0.238)	(0.239)	(0.249)	(0.249)	(0.304)
lnurb_2	0.295 *	0.300 *	0.337 *	0.378 **	0.382 **	0.493 **
	(0.153)	(0.172)	(0.172)	(0.179)	(0.179)	(0.228)
lnpgdp	0.308 ***	0.392 **	0.433 **	0.391 **	0.329 *	0.368
	(0.043)	(0.194)	(0.195)	(0.191)	(0.194)	(0.235)
lnpgdp2	−0.015 ***	−0.018 **	−0.021 **	−0.019 **	−0.016 *	−0.019 *
	(0.002)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
lnrd	−0.023 ***	−0.020 ***	−0.022 ***	−0.021 ***	−0.020 ***	−0.020 ***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
lnhc	0.021 ***	0.019 **	0.016 **	0.019 **	0.020 **	0.018 **
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
lner		−0.022 *	−0.025 **	−0.027 **	−0.026 **	−0.031 **
		(0.012)	(0.012)	(0.012)	(0.012)	(0.016)
lnpub			0.010 ***	0.011 ***	0.012 ***	0.015 ***
			(0.004)	(0.004)	(0.004)	(0.005)
lnei				0.037 **	0.030 **	0.027
				(0.015)	(0.015)	(0.017)
lnind					0.028	0.029
					(0.026)	(0.028)
lnfdi						0.006
						(0.004)
_cons	−1.513 ***	−1.881 *	−2.123 **	−1.841 *	−1.612	−1.781
	(0.194)	(1.008)	(1.015)	(0.996)	(1.002)	(1.224)
K−P F statistic	50.154	40.358	41.633	40.623	40.235	35.830
N	2109	1993	1985	1955	1954	1756

Note: *, **, and *** indicate passing the significance inspection at the levels of 10%, 5%, and 1%, respectively. The values in brackets are robust standard errors.

As can be seen from Table 2, the primary term and secondary term of urb in Model (1) basically pass the significance test of 10%, denoting that there is an obvious "U-shaped" relationship between urbanization and CEP. With the improvement in the urb level, the influence of urbanization on CEP would improve. Additionally, pgdp is significantly positive at a 1% level. However, the secondary term of pgdp is significantly negative at the level of 1%, which is not consistent with the traditional EKC hypothesis. This conclusion is consistent with the research of Shao et al. [89], which shows that China has not realized the decoupling effect of carbon emission and economic growth, and the task of low-carbon development in each city is very difficult.

The regression equation shown in Models (2)–(6) is gradually increases the control variables based on Model (1) and then explores the impact of urbanization on CEP. The regression results of Models (1)–(6) show that urbanization significantly promotes the increase in CEP, and the relationship between urbanization and CEP presents a "U"-shaped nonlinear relationship. When urbanization exceeds the inflection point, urbanization is conducive to improve CEP in Chinese cities. Along with urbanization, the impacts of urbanization on CEP will be still in line with the law. Therefore, the government should grasp the urbanization process, effectively deal with the increase in carbon emissions, and avoid more problems such as diseases in big cities caused by rapid urbanization. Moreover, the secondary term of pgdp also has an inverted "U"-shaped relationship with CEP, and human capital and technological innovation significantly promote and inhibit CEP, respectively.

4.2.2. Robustness Test

In this part, we examine the impact of urbanization on CEP through a robustness test. Specifically, we use the instrumental variable method, replace the explained variable, and no longer take the logarithm of the explained variable to test robustness. In other words, the robustness of the conclusion can be verified from the following three aspects. The regression is further estimated based on the GMM system, and the highest third-order lag term is used as an instrumental variable. We tested the validity of the instrumental variables, and the test showed that the K-P F statistic was far greater than 10, thus determining that there was no weak instrumental variable problem in the study. Firstly, the logarithmic processing of the data can make the data more consistent with normal distribution characteristics, thus reducing the sensitivity of the regression coefficient to outliers. Therefore, in column (1) of Table 3, this study does not perform logarithmic processing for the regression of CEP. Secondly, CEP is measured via the GML index in the baseline regression, while in column (2) of Table 4, the dependent variable is measured via the ML index and processed via logarithm. Thirdly, similar to robustness test (1), in robustness test (3), we no longer perform logarithmic processing on CEP and instead perform regression calculations. The results of the above robustness tests did not change the impact of urbanization on CEP. Therefore, the abovementioned regression results have strong robustness.

Table 3. Robustness test results of the impact of urbanization on CEP.

	(1)	**(2)**	**(3)**
lnurb	0.573 *	1.395 ***	1.250 ***
	(0.348)	(0.324)	(0.444)
lnurb_2	0.458 *	1.070 ***	0.955 ***
	(0.261)	(0.249)	(0.335)
lnpgdp	0.370	0.881 **	0.652 *
	(0.274)	(0.395)	(0.374)
lnpgdp2	−0.018	−0.043 **	−0.032 *
	(0.013)	(0.019)	(0.017)
lnrd	−0.021 ***	−0.025 ***	−0.012

Table 3. *Cont.*

	(1)	(2)	(3)
	(0.007)	(0.008)	(0.025)
lnhc	0.017 *	0.021 *	−0.009
	(0.010)	(0.012)	(0.052)
lner	−0.032 *	−0.049 **	−0.040 *
	(0.018)	(0.020)	(0.024)
lnpub	0.015 ***	0.021 ***	0.036
	(0.005)	(0.006)	(0.024)
lnei	0.025	0.041 **	0.029
	(0.021)	(0.020)	(0.032)
lnind	0.029	0.028	0.076
	(0.037)	(0.033)	(0.080)
lnfdi	0.004	0.010 *	0.009 **
	(0.005)	(0.005)	(0.005)
_cons	−0.799	−4.410 **	−2.564
	(1.414)	(2.032)	(1.675)
K−P F statistic	35.830	35.830	35.830
N	1756	1756	1756

Note: *, **, and *** indicate passing the significance inspection at the levels of 10%, 5%, and 1%, respectively. The values in brackets are robust standard errors.

Table 4. Test results of human capital accumulation mechanism.

	Explained Variable (Human Capital)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
lnurb	0.442 ***	0.215 ***	0.156 ***	0.153 ***	0.151 ***	0.150 ***	0.144 ***
	(0.031)	(0.051)	(0.036)	(0.034)	(0.034)	(0.034)	(0.039)
lnpgdp		0.256 ***	0.307 ***	0.258 ***	0.258 ***	0.258 ***	0.254 ***
		(0.052)	(0.041)	(0.039)	(0.039)	(0.039)	(0.042)
lner			−0.003	−0.003	−0.007	−0.007	0.004
			(0.021)	(0.019)	(0.019)	(0.019)	(0.022)
lnpub				0.084 **	0.077 **	0.078 **	0.087 ***
				(0.034)	(0.034)	(0.034)	(0.033)
lnei					−0.092 *	−0.094 *	−0.083
					(0.054)	(0.055)	(0.060)
lnind						0.024	0.037
						(0.088)	(0.091)
lnfdi							0.026 ***
							(0.008)
_cons	1.184 ***	−1.552 ***	−2.049 ***	−2.295 ***	−2.254 ***	−2.356 ***	−2.469 ***
	(0.008)	(0.549)	(0.410)	(0.449)	(0.454)	(0.584)	(0.643)
N	3182	3148	2869	2651	2607	2606	2363

Note: *, **, and *** indicate passing the significance inspection at the levels of 10%, 5%, and 1%, respectively. The values in brackets are robust standard errors.

4.3. The Influence of Human Capital on CEP

4.3.1. Empirical Results

The abovementioned theoretical analysis suggests that human capital plays a mediating role between urbanization and CEP. The Hausman test results show that the null hypothesis was rejected; thus, this paper adopts the panel fixed-effect mode to empirically test whether urbanization indirectly affects CEP through human capital, and the results are shown in Table 4.

It can be seen from Model (1) in Table 4 that only ur is used for human capital regression. The coefficient of ur is 0.442, which is significant at a 1% level. In Models (2) to (7), control variables are gradually added based on Model (1), and more control variables are incorporated. The regression results show that a city with higher urbanization has a higher human capital level, and the two have a significant positive correlation at the level of 1%. The increase in ur means that rural people migrate to cities, and the increase in human capital accumulation contributes to sustainable economic growth, alleviates damage to the ecological environment caused via economic growth, and, thus, plays a role in improving CEP. Moreover, China is a country with a large population migrating from the underdeveloped regions to the developed coastal regions. At the same time, a high-quality labor force is helpful for enterprises to choose cleaner production modes. Therefore, human capital accumulation can encourage enterprises to choose cleaner production modes, thus reducing carbon emissions and promoting the improvement in CEP.

4.3.2. Robustness Test

In the relationship between urbanization and human capital, urbanization is an endogenous variable, and its endogeneity mainly comes from reverse causality. For example, the improvement in human capital means the sound economic development of cities, which promotes the migration of more people from rural areas to cities, thus promoting the improvement in urbanization. This endogeneity problem is solved by using instrumental variables. Table 5 shows the robustness test results of the GMM system, with the highest third-order lag as the instrumental variable of this study.

Table 5. Robustness test results of human capital mechanism.

	Explained Variable (Human Capital)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
lnurb	1.142 ***	0.256 *	0.306 **	0.511 ***	0.508 ***	0.512 ***	0.614 ***
	(0.103)	(0.148)	(0.147)	(0.148)	(0.149)	(0.149)	(0.175)
lnpgdp		0.498 ***	0.453 ***	0.113 **	0.159 ***	0.210 ***	0.153 ***
		(0.064)	(0.044)	(0.050)	(0.051)	(0.053)	(0.058)
lner			0.068	0.010	−0.007	−0.030	−0.017
			(0.060)	(0.066)	(0.065)	(0.068)	(0.084)
lnpub				0.274 ***	0.268 ***	0.254 ***	0.241 ***
				(0.017)	(0.017)	(0.017)	(0.019)
lnei					−0.314 ***	−0.194 ***	−0.178 ***
					(0.053)	(0.058)	(0.065)
lnind						−0.400 ***	−0.492 ***
						(0.096)	(0.107)
lnfdi							0.063 ***
							(0.014)
_cons	1.337 ***	−4.095 ***	−3.891 ***	−2.466 ***	−2.969 ***	−1.680 **	−0.628
	(0.026)	(0.705)	(0.546)	(0.548)	(0.566)	(0.667)	(0.769)
K−P F statistic	157.591	153.043	117.731	116.317	116.669	117.352	85.965
N	2136	2109	1993	1985	1955	1954	1756

Note: *, **, and *** indicate passing the significance inspection at the levels of 10%, 5%, and 1%, respectively. The values in brackets are robust standard errors.

By calculating the K-P F statistic, we find that its value is far greater than 10, indicating that the instrumental variables in this study are valid, and there is no weak instrumental variable problem. Moreover, through the overidentification test, we found that the instrumental variables used in this study satisfied the exogeneity hypothesis. Model (1) of Table 6 only includes core explanatory variables and does not add any control variables for regression. Control variables are gradually added to Models (2) to (7) in Table 6 for systematic GMM regression. Through an analysis of the results, we find that the improvement in urbanization significantly promotes the improvement in human capital. Therefore, we find that the larger urbanization is, the higher the level of urban human capital is, and its promoting effect is significant and stable.

Table 6. Test results of technological innovation mechanism.

	Explained Variable (Technological Innovation)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
lnurb	0.565 ***	0.217 ***	0.077 *	0.067	0.166 ***	0.154 ***
	(0.054)	(0.050)	(0.045)	(0.044)	(0.046)	(0.048)
lner		1.074 ***	0.887 ***	0.880 ***	0.844 ***	0.885 ***
		(0.071)	(0.067)	(0.068)	(0.067)	(0.068)
lnpub			0.622 ***	0.626 ***	0.593 ***	0.619 ***
			(0.070)	(0.071)	(0.068)	(0.076)
lnei				−0.286 **	−0.184	−0.231
				(0.126)	(0.112)	(0.147)
lnind					−1.440 ***	−1.537 ***
					(0.214)	(0.233)
lnfdi						−0.038 **
						(0.017)
_cons	2.203 ***	−2.293 ***	−7.072 ***	−7.219 ***	−1.107	−1.090
	(0.018)	(0.299)	(0.585)	(0.604)	(1.115)	(1.270)
N	3632	3284	3049	2996	2991	2679

Note: *, **, and *** indicate passing the significance inspection at the levels of 10%, 5%, and 1%, respectively. The values in brackets are robust standard errors.

4.4. The Influence of Technological Innovation on CEP

4.4.1. Empirical Results

Similarly, according to the Hausman test, the fixed-effect model was selected in this section. Table 6 shows the test results of the technological innovation mechanism.

Model (1) of Table 6 independently investigated the relationship between the core explanatory variables—urbanization and technological innovation—without adding any control variables. The results show that the regression coefficient of urbanization was 0.565, which was significant at a 1% level, indicating that the higher urbanization is, the higher the level of technological innovation is. Models (2) to (6) in Table 6 are the regression results of gradually increasing control variables. We can see that except for Model (4), urbanization can significantly promote the improvement in technological innovation. Therefore, the authors believe that urbanization promotes the level of technological innovation. “Demand-induced innovation theory” holds that market demand stimulates the improvement in technological innovation levels. When urbanization gradually improves, urban development gradually matures, and the competition faced by enterprises gradually increases.

In order to face the pressure of competition, enterprises carry out product innovation and increase their market share through innovation. Moreover, China has been advocating low-carbon development across various industries, issuing effective and reasonable environmental regulation policies. In this case, enterprises must control carbon emissions through technological innovation if they want to achieve long-term vitality. For example, since China’s energy consumption has been dominated by fossil fuels and energy efficiency is low, it will vigorously develop low-carbon technologies, such as carbon capture and sequestration, to curb the increase in carbon emissions.

4.4.2. Robustness Test

This study also tests the robustness of the mediating effect of technological innovation on CEP. Table 7 shows the robustness test results of the GMM system, with the highest third-order lag as the instrumental variable of this study. In addition, we also tested the problem of the overidentification of instrumental variables and the problem of weak instrumental variables. We found that the instrumental variables in this study are valid and satisfy the exogeneity hypothesis. Column (1) of Table 7 includes only core explanatory variables and does not add any control variables for regression. Control variables are gradually added to columns (2) to (6) of Table 7 for systematic GMM regression. Through an analysis of the results, we find that the improvement in urbanization significantly promoted the improvement in technological innovation. Therefore, this chapter concludes that the larger urbanization is, the higher the level of urban technological innovation is, and its promoting effect is significant and stable.

Table 7. Robustness test results of technological innovation mechanism.

	Explained Variable (Technological Innovation)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
lnurb	3.932 ***	3.229 ***	2.721 ***	2.704 ***	2.776 ***	2.906 ***
	(0.315)	(0.324)	(0.291)	(0.291)	(0.322)	(0.385)
lner		1.109 ***	0.865 ***	0.872 ***	0.852 ***	0.900 ***
		(0.161)	(0.139)	(0.140)	(0.139)	(0.100)
lnpub			0.298 ***	0.301 ***	0.293 ***	0.221 ***
			(0.025)	(0.026)	(0.027)	(0.031)
lnei				0.048	0.282 ***	0.294 ***
				(0.081)	(0.097)	(0.111)
lnind					−0.731 ***	−1.107 ***
					(0.200)	(0.253)
lnfdi						0.065 **
						(0.030)
_cons	3.235 ***	−1.663 **	−3.424 ***	−3.451 ***	−0.331	1.668
	(0.084)	(0.711)	(0.598)	(0.608)	(1.182)	(1.310)
K−P F statistic	158.311	121.640	121.587	121.808	116.902	86.215
N	2437	2286	2273	2236	2231	1992

Note: **, and *** indicate passing the significance inspection at the levels of 5%, and 1%, respectively. The values in brackets are robust standard errors.

5. Conclusions

In the context of global climate change, low-carbon development has increasingly attracted the attention of various countries and gradually become an inevitable choice to solve the increasingly serious environmental and energy problems. Under the background of new urbanization, exploring the relationship, as well as the mechanisms, between the evolution of urbanization and CEP can provide a decision-making basis for the government to formulate precise carbon emission reduction policies. However, the relationship between urbanization and CEP in Chinese cities has not been examined clearly, and the quantitative impacts of urbanization on CEP have not reached the same conclusions. Filling these gaps, this study distinguishes the theoretical mechanisms between urbanization and CEP and explores transmission channels between them. Accordingly, we used the panel data of 282 Chinese prefecture-level cities from 2003 to 2017 as samples and the GML index to measure and analyze the law of change in CEP; then, we selected the GMM system and the fixed-effect model to systematically examine the relationship between the evolution of China's urbanization and CEP in Chinese cities. The conclusions are as follows:

(1) From the time trend, from 2003 to 2016, the GML index showed a rising state, but from 2016 to 2017, the GML index showed a decline. From the perspective of regional heterogeneity, developed cities and cities with development potential had a higher GML index, such as Beijing, Tianjin, and Xiamen. Moreover, the urban technical efficiency change index is an obstacle to the improvement in the GML index, and technological progress is the driving force supporting the improvement in the GML index. These results are consistent with those of Zhao et al. [50].

(2) Under the premise of considering the endogeneity of urbanization, there is a significant "U-shaped" nonlinear relationship between urbanization and the GML index, indicating that urbanization has an impact on CEP in Chinese cities. The relationship presents a channel of action that is first inhibited and then promoted. Furthermore, it reveals that China's urban economic development and carbon emissions have not yet been decoupled, and further efforts are needed. This indicates that the role of

urbanization in promoting CEP may be an effective way to decouple carbon emissions from economic development [90].

(3) By investigating the channels of human capital in urban areas, after controlling for endogeneity, the regression results found that human capital is an effective channel by which urbanization can promote the improvement in CEP, and the higher the level of urbanization is, the higher the level of human capital is, thereby effectively promoting the improvement in CEP. As a result, it is of vital importance to pursue human capital accumulation to encourage the development of urbanization, with the aim of further improving CEP [53].

(4) Through the channel test of urban technological innovation, we found that although the evolution of urbanization has promoted the development of technological innovation, technological innovation has inhibited the improvement in CEP in Chinese cities. Therefore, the technological innovation level has not yet been transformed into a driving force that promotes the improvement in CEP in China, and cleaner production methods need to be further developed. Therefore, the low cost and scale of green and low-carbon technologies are more conducive to their role in improving CEP [12].

There are additional opportunities to extend our research in the future. First, the time scale of the research should be further expanded, and more detailed data analysis will lead to more guiding conclusions and development suggestions. Second, the key areas of Chinese cities should receive special attention to explore the relationship between low-carbon urban development and carbon emissions in special regions.

Author Contributions: Conceptualization, data curation, methodology, formal analysis, and writing—original draft preparation, Z.Z.; project administration, supervision, writing—review and editing, and funding acquisition, J.R.; data curation and formal analysis, Z.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Shandong Provincial Natural Science Foundation (ZR2022QD129), the Humanities and Social Science Research Innovation Team Building Project of Qilu University of Technology (Shandong Academy of Sciences) (11230103), the Shandong Provincial Education Department, China (2022RW028, 2022RW064), the and Science and Technology Innovation Project of Shandong Academy of Agricultural Sciences (CXGC2023F07).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Sharm el-Sheikh Implementation Plan. Available online: https://unfccc.int/documents/624444 (accessed on 23 September 2023).
2. Ménard, I.; Thiffault, E.; Boulanger, Y.; Boucher, J. Multi-model approach to integrate climate change impact on carbon sequestration potential of afforestation scenarios in Quebec, Canada. *Ecol. Model.* **2022**, *473*, 110144. [CrossRef]
3. Zhou, D.; Huang, Q.; Chong, Z. Analysis on the effect and mechanism of land misallocation on carbon emissions efficiency: Evidence from China. *Land Use Policy* **2022**, *121*, 106336. [CrossRef]
4. Dudley, H.; Jordan, A.; Lorenzoni, I. Advising national climate policy makers: A longitudinal analysis of the UK Climate Change Committee. *Glob. Environ. Chang.* **2022**, *76*, 102589. [CrossRef]
5. Zhang, Y.; Xu, Y.; Kong, H.; Zhou, G. Spatial-Temporal Evolution of Coupling Coordination between Green Transformation and the Quality of Economic Development. *Sustainability* **2022**, *14*, 16267. [CrossRef]
6. Chen, M.; Zhao, S.; Wang, J. The Impact of the Digital Economy on Regional Carbon Emissions: Evidence from China. *Sustainability* **2023**, *15*, 14863. [CrossRef]
7. Wang, S.; Wang, Z.; Fang, C. Evolutionary characteristics and driving factors of carbon emission performance at the city level in China. *Sci. Sin. Terrae* **2022**, *65*, 1292–1307. (In Chinese) [CrossRef]
8. Xu, L.; Fan, M.; Yang, L.; Shao, S. Heterogeneous green innovations and carbon emission performance: Evidence at China's city level. *Energy Econ.* **2021**, *99*, 105269. [CrossRef]

9. Miao, X.; Feng, E.; Siu, Y.; Li, S.; Wong, C. Can China's carbon intensity constraint policies improve carbon emission performance? Evidence from regional carbon emissions. *Sci. Total Environ.* **2023**, *348*, 119268. [CrossRef]
10. Zeng, L.; Lu, H.; Liu, Y.; Zhou, Y.; Hu, H. Analysis of Regional Differences and Influencing Factors on China's Carbon Emission Efficiency in 2005–2015. *Energies* **2019**, *12*, 3081. [CrossRef]
11. Wang, Q.; Wang, S.; Jiang, X.T. Preventing a rebound in carbon intensity post-COVID-19—Lessons learned from the change in carbon intensity before and after the 2008 financial crisis. *Sustain. Prod. Consump.* **2021**, *27*, 1841–1856. [CrossRef]
12. Murshed, M.; Apergis, N.; Alam, M.S.; Khan, U.; Mahmud, S. The impacts of renewable energy, financial inclusivity, globalization, economic growth, and urbanization on carbon productivity: Evidence from net moderation and mediation effects of energy efficiency gains. *Renew. Energy* **2022**, *196*, 824–838. [CrossRef]
13. Xiao, Y.; Ma, D.; Zhang, F.; Zhao, N.; Wang, L.; Guo, Z.; Zhang, J.; An, B.; Xiao, Y. Spatiotemporal differentiation of carbon emission efficiency and influencing factors: From the perspective of 136 countries. *Sci. Total Environ.* **2023**, *879*, 163032. [CrossRef] [PubMed]
14. Ding, L.; Lei, L.; Zhao, X.; Călin, A.C. Modelling energy and carbon emission performance: A constrained performance index measure. *Energy* **2020**, *197*, 117274. [CrossRef]
15. Gao, S.; Sun, D.; Wang, S. Do development zones increase carbon emission performance of China's cities? *Sci. Total Environ.* **2023**, *863*, 160784. [CrossRef] [PubMed]
16. Zhang, W.; Liu, X.; Wang, D.; Zhou, J. Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy* **2022**, *165*, 112927. [CrossRef]
17. Yu, Y.; Qian, T.; Du, L. Carbon productivity growth, technological innovation, and technology gap change of coal-fired power plants in China. *Energy Policy* **2017**, *109*, 479–487. [CrossRef]
18. Zhang, X.; Tang, Y.; Han, H.; Chen, Z. Evolution Characteristics and Main Influencing Factors of Carbon Dioxide Emissions in Chinese Cities from 2005 to 2020. *Sustainability* **2023**, *15*, 14849. [CrossRef]
19. Wang, Q.; Li, L.; Li, R. The asymmetric impact of renewable and non-renewable energy on total factor carbon productivity in 114 countries: Do urbanization and income inequality matter? *Energy Strateg. Rev.* **2022**, *44*, 100942. [CrossRef]
20. Zhang, W.; Li, G.; Uddin, M.K.; Guo, S. Environmental regulation, Foreign investment behavior, and carbon emissions for 30 provinces in China. *J. Clean. Prod.* **2020**, *248*, 119208. [CrossRef]
21. Du, Z.; Wang, Y. Does energy-saving and emission reduction policy affects carbon reduction performance? A quasi-experimental evidence in China. *Appl. Energy* **2022**, *324*, 119758. [CrossRef]
22. Kou, J.; Xu, X. Does internet infrastructure improve or reduce carbon emission performance?—A dual perspective based on local government intervention and market segmentation. *J. Clean. Prod.* **2022**, *379*, 134789. [CrossRef]
23. Duan, X.; Li, X.; Tan, W.; Xiao, R. Decoupling relationship analysis between urbanization and carbon emissions in 33 African countries. *Heliyon* **2022**, *8*, e10423. [CrossRef] [PubMed]
24. Xu, Q.; Dong, Y.; Yang, R. Urbanization impact on carbon emissions in the Pearl River Delta region: Kuznets curve relationships. *J. Clean. Prod.* **2018**, *180*, 514–523. [CrossRef]
25. Xu, Z.; Peng, J.; Liu, Y.; Qiu, S.; Zhang, H.; Dong, J. Exploring the combined impact of ecosystem services and urbanization on SDGs realization. *Appl. Geogr.* **2023**, *153*, 102907. [CrossRef]
26. Rehman, E.; Rehman, S. Modeling the nexus between carbon emissions, urbanization, population growth, energy consumption, and economic development in Asia: Evidence from grey relational analysis. *Energy Rep.* **2022**, *8*, 5430–5442. [CrossRef]
27. Zimon, G.; Pattak, D.C.; Voumik, L.C.; Akter, S.; Kaya, F.; Walasek, R.; Kochański, K. The Impact of Fossil Fuels, Renewable Energy, and Nuclear Energy on South Korea's Environment Based on the STIRPAT Model: ARDL, FMOLS, and CCR Approaches. *Energies* **2023**, *16*, 6198. [CrossRef]
28. Bu, Y.; Wang, E.; Möst, D.; Lieberwirth, M. How population migration affects carbon emissions in China: Factual and counterfactual scenario analysis. *Technol. Forecast. Soc.* **2022**, *184*, 122023. [CrossRef]
29. Pattak, D.C.; Tahrim, F.; Salehi, M.; Voumik, L.C.; Akter, S.; Ridwan, M.; Sadowska, B.; Zimon, G. The Driving Factors of Italy's CO_2 Emissions Based on the STIRPAT Model: ARDL, FMOLS, DOLS, and CCR Approaches. *Energies* **2023**, *16*, 5845. [CrossRef]
30. Wang, W.Z.; Liu, L.C.; Liao, H.; Wei, Y. Impacts of urbanization on carbon emissions: An empirical analysis from OECD countries. *Energ. Policy* **2021**, *151*, 112171. [CrossRef]
31. Wang, Q.; Wang, L. The nonlinear effects of population aging, industrial structure, and urbanization on carbon emissions: A panel threshold regression analysis of 137 countries. *J. Clean. Prod.* **2021**, *287*, 125381. [CrossRef]
32. Li, X.; Zheng, Z.; Shi, D.; Han, X.; Zhao, M. New urbanization and carbon emissions intensity reduction: Mechanisms and spatial spillover effects. *Sci. Total Environ.* **2023**, *905*, 167172. [CrossRef]
33. Liu, B.; Tian, C.; Li, Y.; Song, H.; Ma, Z. Research on the effects of urbanization on carbon emissions efficiency of urban agglomerations in China. *J. Clean. Prod.* **2018**, *197*, 1374–1381. [CrossRef]
34. Jiang, J.; Zhu, S.; Wang, W. Carbon Emissions, Economic Growth, Urbanization, and Foreign Trade in China: Empirical Evidence from ARDL Models. *Sustainability* **2022**, *14*, 9396. [CrossRef]
35. Wang, X.; Zhou, D.; Telli, S. The impact of semi-urbanization on carbon emissions: A spatial econometric perspective. *Environ.Sci. Pollut. Res.* **2022**, *29*, 54718–54732. [CrossRef]
36. Feng, Y.; Yuan, H.; Liu, Y.; Zhao, S. Does new-type urbanization policy promote green energy efficiency? Evidence from a quasi-natural experiment in China. *Energy Econ.* **2023**, *124*, 106752. [CrossRef]

37. He, L.; Zhang, X.; Zhang, X. Urbanization with the pursuit of efficiency and ecology: Theory and evidence from China. *Environ. Impact Assess.* **2023**, *103*, 107274. [CrossRef]
38. Tang, M.; Hu, F. Land urbanization and urban CO_2 emissions: Empirical evidence from Chinese prefecture-level cities. *Heliyon* **2023**, *9*, e19834. [CrossRef]
39. Xiao, G.; Lu, Q.; Ni, A.; Zhang, C. Research on carbon emissions of public bikes based on the life cycle theory. *Transp. Lett.* **2023**, *15*, 278–295.
40. Chen, W.; Wang, G.; Xu, N.; Ji, M.; Zeng, J. Promoting or inhibiting? New-type urbanization and urban carbon emissions efficiency in China. *Cities* **2023**, *140*, 104429. [CrossRef]
41. He, M.; Xiao, W.; Fan, M.; Cui, L. Study on convergence trend and heterogeneity of carbon performance in China based on market and urbanization. *Clean. Environ. Syst.* **2023**, *8*, 100106. [CrossRef]
42. Northam, R.M. *Urban Geography*; John Wiley& Sons: New York, NY, USA, 1979.
43. Chen, C.; Qin, Y.; Gao, Y. Does new urbanization affect CO_2 emissions in China:A spatial econometric analysis. *Sustain. Cities Soc.* **2023**, *96*, 104687. [CrossRef]
44. Panayotou, T. *Empirical Tests and Policy Analysis of Environmental Degradation at Different Stages of Economic Development*; International Labor Office: Geneva, Switzerland, 1993.
45. Huber, J. Towards industrial ecology: Sustainable development as a concept of ecological modernization. *J. Environ. Pol. Plan.* **2000**, *2*, 269–285. [CrossRef]
46. Sadorsky, P. The effect of urbanization on CO_2 emissions in emerging economies. *Energy Econ.* **2014**, *41*, 147–153. [CrossRef]
47. McGranahan, G.; Jacobi, P.; Songsore, J.; Surjadi, C.; Kjellén, M. *The Citizens at Risk: From Urban Sanitation to Sustainable Cities*; International Journal of Sustainability in Higher Education; Routledge: Abingdon, UK, 2004; Volume 5.
48. Burton, E. The compact city: Just or just compact? A preliminary analysis. *Urban Stud.* **2000**, *37*, 1969–2006. [CrossRef]
49. Hao, L.; Umar, M.; Khan, Z.; Ali, W. Green growth and low carbon emission in G7 countries: How critical the network of environmental taxes, renewable energy and human capital is? *Sci. Total Environ.* **2021**, *752*, 141853. [CrossRef] [PubMed]
50. Zhao, Z.; Yuan, T.; Shi, X.; Zhao, L. Heterogeneity in the relationship between carbon emission performance and urbanization: Evidence from China. *Mitig. Adapt. Strateg. Glob. Chang.* **2020**, *25*, 1363–1380. [CrossRef]
51. Bano, S.; Zhao, Y.; Ahmad, A.; Wang, S.; Liu, Y. Identifying the impacts of human capital on carbon emissions in Pakistan. *J. Clean. Prod.* **2018**, *183*, 1082–1092. [CrossRef]
52. Zhao, Z.; Shi, X.; Cao, Y.; Hu, M. The impact of urban population spatial distribution on CO_2 emissions in China from the perspective of individual and interactive effects. *Environ. Sci. Pollut. Res.* **2023**, 1–14. [CrossRef]
53. Huang, C.; Zhang, X.; Liu, K. Effects of human capital structural evolution on carbon emissions intensity in China: A dual perspective of spatial heterogeneity and nonlinear linkages. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110258. [CrossRef]
54. Schultz, T.W. Investment in Human Capital. *Am. Econ. Rev.* **1961**, *51*, 1–17.
55. Becker, G.S. Investment in Human Capital: A Theoretical Analysis. *J. Political Econ.* **1962**, *70*, 9–49. [CrossRef]
56. Lucas, R.E. On the mechanics of economic development. *J. Monet. Econ.* **1988**, *22*, 3–42. [CrossRef]
57. Rauch, J.E. Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities. *J. Urban Econ.* **1993**, *34*, 380–400. [CrossRef]
58. Payab, A.H.; Kautish, P.; Sharma, R.; Siddiqui, A.; Mehta, A.; Siddiqul, M. Does human capital complement sustainable development goals? Evidence from leaga carbon emitter countries. *Util. Policy* **2023**, *81*, 101509. [CrossRef]
59. Li, Z. Threshold effects of foreign direct investment on China's carbon emissions. *Resour. Sci.* **2015**, *37*, 163–174. (In Chinese)
60. Schumpeter, J.A. *Business Cycles*; McGraw-Hill: New York, NY, USA, 1939.
61. Schumpeter, J.A. Capitalism, Socialism and Democracy. *Harv. Bus. Rev.* **1951**, *29*, 107.
62. Zhang, F.; Hou, T. Review on theories of technological innovation. *J. Northeast. Univ. Soc. Sci.* **2008**, *2*, 101–105. (In Chinese)
63. Hou, S.; Yu, K.; Fei, R. How does environmental regulation affect carbon productivity? The role of green technology progress and pollution transfer. *J. Environ. Manag.* **2023**, *345*, 118587. [CrossRef]
64. Wang, J. Carbon emissions trading system and biased clean technology effects. *Econ. Rev.* **2016**, *2*, 29–47. (In Chinese) [CrossRef]
65. Meng, X.; Wen, Z.; Qian, Y.; Yu, H. Evaluation of cleaner production technology integration for the Chinese herbal medicine industry using carbon flow analysis. *J. Clean. Prod.* **2017**, *163*, 49–57. [CrossRef]
66. Färe, R.; Grosskopf, S.; Lovell, C.A.; Pasurka, C. Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. *Rev. Econ. Stat.* **1989**, *71*, 90–98. [CrossRef]
67. Zhao, Z.; Shi, X.; Zhao, L.; Zhang, J. Extending production-theoretical decomposition analysis to environmentally sensitive growth: Case study of Belt and Road Initiative countries. *Technol. Forecast. Soc.* **2020**, *161*, 120289. [CrossRef]
68. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and Undesirable Outputs: A Directional Distance Function Approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [CrossRef]
69. Sun, Y.; Zhang, M.; Zhu, Y. Do Foreign Direct Investment Inflows in the Producer Service Sector Promote Green Total Factor Productivity? Evidence from China. *Sustainability* **2023**, *15*, 10904. [CrossRef]
70. Fan, M.; Shao, S.; Yang, L. Combining global Malmquist–Luenberger index and generalized method of moments to investigate industrial total factor CO_2 emission performance: A case of Shanghai (China). *Energy Policy* **2015**, *79*, 189–201. [CrossRef]
71. Song, M.; Zhao, X.; Shang, Y. The impact of low-carbon city construction on ecological efficiency: Empirical evidence from quasi-natural experiments. *Resour. Conserv. Recycl.* **2020**, *157*, 104777. [CrossRef]

72. Xu, Y.; Liu, S.; Wang, J. Impact of environmental regulation intensity on green innovation efficiency in the Yellow River Basin, China. *J. Clean. Prod.* **2022**, *373*, 133789. [CrossRef]
73. Chai, J.; Tian, L.; Jia, R. New energy demonstration city, spatial spillover and carbon emission efficiency: Evidence from China's quasi-natural experiment. *Energy Policy* **2023**, *173*, 113389. [CrossRef]
74. Chen, J.; Wang, B.; Huang, S.; Song, M. The influence of increased population density in China on air pollution. *Sci. Total Environ.* **2020**, *735*, 139456. [CrossRef] [PubMed]
75. Ehrlich, P.; Holdren, J. Impact of population growth. *Obstet. Gynecol. Surv.* **1971**, *26*, 769–771. [CrossRef]
76. Dietz, T.; Rosa, E.A. Effects of population and affluence on CO_2 emissions. *Proc. Natl. Acad. Sci. USA* **1997**, *94*, 175–179. [CrossRef] [PubMed]
77. Wu, L.; Sun, L.; Qi, P.; Ren, X.; Sun, X. Energy endowment, industrial structure upgrading, and CO_2 emissions in China: Revisiting resource curse in the context of carbon emissions. *Resour. Policy* **2021**, *74*, 102329. [CrossRef]
78. Grossman, G.; Kruerger, A. Economic growth and the environment. *Q. J. Econ.* **1995**, *110*, 353–377. [CrossRef]
79. Jia, R.; Fan, M.; Shao, S.; Yu, Y. Urbanization and haze-governance performance: Evidence from China's 248 cities. *J. Environ. Manag.* **2021**, *288*, 112436. [CrossRef] [PubMed]
80. Lu, W.; Wu, H.; Yang, S.; Tu, Y. Effect of environmental regulation policy synergy on carbon emissions in China under consideration of the mediating role of industrial structure. *J. Environ. Manag.* **2022**, *322*, 116053. [CrossRef] [PubMed]
81. Song, W.; Han, X. Heterogeneous two-sided effects of different types of environmental regulations on carbon productivity in China. *Sci. Total Environ.* **2022**, *841*, 156769. [CrossRef]
82. Wimbadi, R.W.; Djalante, R.; Mori, A. Urban experiments with public transport for low carbon mobility transitions in cities: A systematic literature review (1990–2020). *Sustain. Cities Soc.* **2021**, *72*, 103023. [CrossRef]
83. Li, J.; Lin, B. Green Economy Performance and Green Productivity Growth in China's Cities: Measures and Policy Implication. *Sustainability* **2016**, *8*, 947. [CrossRef]
84. Yuan, H.; Feng, Y.; Lee, C.C.; Cen, Y. How does manufacturing agglomeration affect green economic efficiency? *Energy Econ.* **2020**, *92*, 104944. [CrossRef]
85. Tian, X.; Bai, F.; Jia, J.; Liu, Y.; Shi, F. Realizing low-carbon development in a developing and industrializing region: Impacts of industrial structure change on CO_2 emissions in southwest China. *J. Environ. Manag.* **2019**, *233*, 728–738. [CrossRef]
86. Zhu, H.; Duan, L.; Guo, Y.; Yu, K. The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: Evidence from panel quantile regression. *Econ. Model.* **2016**, *58*, 237–248. [CrossRef]
87. Zheng, J.; Mi, Z.; Coffman, D.M.; Milcheva, S.; Shan, Y.; Guan, D.; Wang, S. Regional development and carbon emissions in China. *Energy Econ.* **2019**, *81*, 25–36. [CrossRef]
88. Yang, Y.; Wang, H.; Löschel, A.; Zhou, P. Energy transition toward carbon-neutrality in China: Pathways, implications and uncertainties. *Front. Eng. Manag.* **2022**, *9*, 358–372. [CrossRef]
89. Shao, S.; Li, X.; Cao, J. Urbanization promption and haze pollution governance in China. *Econ. Res. J.* **2019**, *54*, 148–165. (In Chinese)
90. Zeng, L.; Zhao, Y.; Wang, X. How to develop the new urbanization in mineral resources abundant regions in China? A VIKOR-based path matching model. *Resour. Policy* **2022**, *79*, 103095. [CrossRef]