sustainability

MDPI

Article

Foreign Direct Investment and Carbon Emission Efficiency: The Role of Direct and Indirect Channels

Qizhen Wang and Qian Zhang *

Business School, Nanjing Xiaozhuang University, Nanjing 210017, China
* Correspondence: zhangqian@njxzc.edu.cn

Abstract: A large number of foreign direct investment inflows not only promote China's economic development but also bring environmental pollution problems., Improving carbon emission efficiency and cutting carbon emissions while maintaining China's attractiveness to foreign investment has become a topic of concern in China. Firstly, this paper measures the carbon emission efficiency of different provinces in China with the super efficiency DEA model and studies the temporal and spatial characteristics of carbon emission efficiency. Secondly, the impact of FDI on carbon emission efficiency is investigated. FDI negatively affects carbon emissions but positively affects carbon emission efficiency. In addition, the interaction term of FDI and each channel negatively affects carbon emission efficiency, indicating that each channel has a negative impact on the relationship between FDI and carbon emission efficiency. Thirdly, the results of the sub-sample analysis show that the impact of FDI on carbon emission efficiency has the feature of regional heterogeneity. Based on the results, policy implications regarding the improvement of carbon emission efficiency are proposed.

Keywords: FDI; technological innovation; carbon emission efficiency; carbon emission

check for updates

Citation: Wang, Q.; Zhang, Q. Foreign Direct Investment and Carbon Emission Efficiency: The Role of Direct and Indirect Channels. *Sustainability* **2022**, *14*, 13484. https://doi.org/10.3390/su142013484

Academic Editor: Jonathan Oti

Received: 15 September 2022
Accepted: 14 October 2022
Published: 19 October 2022

1. Introduction

Carbon emission efficiency (CEE) refers to less energy consumption and less industrial carbon emissions but higher economic growth. As far as China's current development stage is concerned, excessive emission reduction will inevitably come when economic growth is extensive. Therefore, improving CEE is regarded as an effective way to attain sustainable development. With the in-depth implementation of China's reform and opening to the world policy, a large number of foreign direct investments have been attracted in mainland China. The inflow of foreign investment has promoted economic development and technological innovation in China. Meanwhile, the inflow of foreign investment has increased China's energy consumption and carbon emission (CE). The effect of FDI on carbon emission efficiency is divided into three parts: the effect of scales, the effect of structures, and the effect of technology spillovers. When the scale effect is greater than the sum of the structure effect and the technology spillover effect, the inflow of FDI is unfavorable for improving CEE and will increase CE. When the scale effect is smaller than the sum of the structure effect and the technology spillover effect, FDI inflow will increase CEE and reduce CE.

FDI directly affects regional carbon emission efficiency because the government often sacrifices the environment to introduce foreign investment to achieve rapid economic growth in the initial phase of the economy. The characteristics of rapid economic development are high economic growth along with a large amount of energy consumption and a lot of CEs, which harm the CEE. With the rapid growth of the economy, the public awareness in China on the need to protect the environment has grown exponentially and they are making greater demands for a better environmental quality. The region concentrates on the introduction of environmentally friendly FDI enterprises. Through the demonstration effect, technology spillover effect, and market competition effect, it advances environmental protection technology in the host country and increases carbon emission efficiency. The inflow of FDI affects the intensity of environmental regulation of the host country. At the beginning of economic development, the host country weakens its environmental protection to develop the economy, coupled with low environmental protection consciousness and little environmental protection technology, which leads to the adoption of low environmental regulation, attracting a large number of FDI enterprises with high carbon emissions. These FDI enterprises compete with enterprises with low-carbon technologies, leading low-carbon environment-friendly enterprises to give up R&D investment in environmental protection technology. This finally results in lowering the intensity of environmental regulation. In the period of rapid economic growth, the deterioration of the environment and the awakening of environmental protection consciousness make local governments improve the intensity of environmental regulation, which forces FDI enterprises to carry out technology innovation to compensate for environmental regulation costs, leading to the improvement of the ecological environment.

FDI indirectly affects regional carbon emission efficiency through different channels. Technological innovation is one of the important channels. FDI has brought advanced environmental protection technology and pollution control experience. Through the effect of demonstrations and the effect of competitions, it has encouraged enterprises in the host country to optimize production processes, improve environmental protection technology, and increase carbon emission efficiency. China has experienced fast economic growth and integration with the global economy. Some macroeconomic forces such as the increasing popularity of ESG investing and global economic policy uncertainty coinciding with China's economic development may affect China's CE and CEE. Meanwhile, central banks in the world put forward various monetary policies, which have a spillover effect on China's economy and environment. Deficits influence the strength of government spending multipliers and the aggregate credit risk of the banking sector, which then affect FDI, technological innovation, and the efficient utilization of energy sources. All these are vital channels through which FDI affects CEE.

The contribution of the study is as follows: first, unlike previous articles which applied carbon emission data in the specified region, we use provincial-level panel data to analyze CEE, which have been less used in the existing literature. Second, unlike existing studies focusing only on the relationship between CEE and the key variable, we pay attention to the relationship between CEE and the key variable as well as the channels through which the key variable affects CEE. In other words, this study investigates not only the direct effect of FDI but also the indirect effect of FDI through several channels. Third, this study conducts a sub-sample analysis—that is, it takes account of the regional heterogeneity in exploring the impact of FDI on CEE through several channels, which enriches the existing studies.

2. Literature Review

2.1. Measurement of CEE

There is no clear definition of CEE in the existing research, and the measurement of CEE is tightly correlated with its definition. CEE, initially defined as carbon productivity, is the proportion of carbon dioxide emissions generated relative to economic activities in GDP [1]. The ratio of CO_2 emissions to GDP, an index to measure CEE, is used as a vital standard for assessing a country's energy saving and CE reduction [2]. Some research takes energy intensity as CEE. CE intensity refers to the carbon emission per unit of energy consumption, reflecting the contribution of developing countries to energy saving, emission reduction, and climate change [3,4]. It can be seen that whether GDP is used as the basis or energy consumption is used as the basis to define carbon emission efficiency, they are both related to CO_2 emissions. The definition also includes the measurement of CEE, and the measurement is based on a single index. It is easy to understand CEE when CEE is calculated based on a single index. However, social and economic production activities are a complex system, and a single index based on a certain variable such as gross product or energy consumption cannot fully measure carbon emission efficiency. Since there are many indicators that can be used to construct the single index, the diversification of measurement indicators is prone to controversy [5]. Hence, the measurement of CEE should comprehensively consider energy consumption, economic development, carbon emission, and other factors [6] so that the assessment can be comprehensive and reasonable [7].

Much research has measured CEE with the multiple index evaluation method [8]. The common multiple index method for efficiency evaluation mainly includes data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The DEA method provides a new idea for multi-input and multi-output efficiency evaluation. This method was first proposed by Farrel [9] and was improved by Charnes et al. [10]. Ramanathan [11] used the DEA method to calculate global CEE and empirically studied the impact of energy consumption on CEE. Ren et al. [12] adopted a radial chance-constrained data envelopment analysis (DEA) model and a non-radial chance-constrained DEA model to calculate energy and carbon emission efficiency; the former was used to estimate the overall efficiency, and the latter was used to evaluate the pure CEE. Chu et al. [13] used a super efficiency SBM-DEA model to investigate municipal solid waste (MSW) treatment carbon emission efficiency. They found that the MSW treatment carbon emission efficiency had the feature of regional imbalance: except in Shanghai and Jiangsu, the carbon emission efficiency value in all provinces was less than 1; the national average efficiency had a fluctuating downward trend, but the average efficiency in the western region had an upward trend.

The DEA method has incomparable advantages compared with the frontier analysis method. However, the DEA method has to consider some random factors. Another parametric method, stochastic frontier analysis (SFA), considers random factors. Herrala and Goel [14] employed a stochastic cost frontier analysis model to calculate global carbon dioxide efficiency. They found that the level of efficiency had the feature of global imbalance. The highest efficiency values were in Africa and Europe, while the lowest were in China. The largest efficiency gains were in central and eastern Europe. As the two largest emitters, the US and China improved carbon dioxide efficiency, though their ranking deteriorated. Zhang et al. [15] used a stochastic frontier analysis model to measure total-factor CEE index (TCEI). They found that the TCEI values of four urban agglomerations were continuously on the rise. The TCEI value was highest in the Pearl River Delta area, whereas the value of TCEI was lowest in the Chengdu-Chongqing area. The results had great importance to achieve low-carbon development in the four urban agglomerations.

2.2. FDI and Technological Innovation

FDI affects the technological innovation level through technology spillovers. The research on FDI technology spillover can be traced back to the early 1960s. Macdougall [16] adopted static partial equilibrium analysis, incorporating a knowledge spillover index into the foreign direct investment effect, and studied the impact of FDI on labor productivity in the host country. They found that FDI and its knowledge spillover were positively correlated, which indicated that the effect of FDI technology spillover existed. There are two types of FDI technology spillover: one is the vertical spillover among industries, and the other is the horizontal spillover within the industry. The former refers to the forward and backward correlation between foreign enterprises and local enterprises in the same value chain. Forward (backward) technology spillovers are generated through a forward (backward) correlation effect [17,18]. The latter refers to the technology spillover caused by the association between domestic enterprises and foreign enterprises within an industry, and the influencing mechanisms include the demonstration–imitation effect, the competition effect, and the labor spillover effect [19].

Most research has found that FDI positively affects technological innovation. Smith et al. [20] on Russia, Das et al. [21] on African countries, and Yang et al. [22] on China all found that FDI positively affected regional innovation capacity. Sultana et al. [23] established a model to study the global FDI network and found that it had obvious central-periphery characteristics. The more technologically advanced a country was, the more it was in the center of the FDI network, which showed that whether a country could be in the center of the FDI network was related to the country's technological level. Liu et al. [24] found that advanced technology and environmental protection measures brought by multinational companies encouraged local enterprises to adopt green technologies, thus improving the environmental quality in the host country. This proved the pollution halo effect. Andrijauskiene and Dumiuvien [25], Ghebrihiwet [26] and Melane-Lavado, and Álvarez-Herranz [27] found that there was a positive relationship between FDI and technological innovation.

Some scholars also found that FDI negatively influences technological innovation in the host countries and sometimes even has no influence. Lew et al. [28] found that FDI had no effect on the technological innovation of the host country. Marco et al. [29] found that FDI was disadvantageous to host country innovation due to the crowding out effect. Thus, it was not conducive to improving the technological innovation level of enterprises in the host country. Kim and Choi [30] used panel data of South Korean manufacturing enterprises and found that foreign-invested enterprises negatively affected the technological capabilities of South Korean enterprises. Falk [31] used firm-level data to study FDI and the technological innovation of local firms. They found that FDI positively affected innovation activities when there was no significant differentiation in labor productivity between local firms and foreign-owned firms. In terms of local firms, the resource of innovation ability was from their own intrinsic but the physical presence of foreign firms in the same industry.

Mohamad and Bani [32] attempted to explore the impact of FDI inflows and absorptive capacity on technological innovation. When only one individual was concerned, FDI and absorptive capacity had a negative and even insignificant effect on technological innovation. When considering their interaction, they found that the interactive item positively and significantly affected technological innovation. Filippetti et al. [33] and Negash et al. [34] both found the role of absorptive capacity in the technology spillovers of FDI. Adikari and Liu [35] employed the Autoregressive Distributed Lag (ARDL) cointegration procedure to explore the relationship between innovation and inward FDI in Sri Lanka using data from 1990 to 2019. The results showed that inward FDI was negatively related to innovation, whereas education expenditure (EDU) and research and development expenditure (RDE) were positively related to innovation. All the coefficients were statistically significant in the long term. This indicated that inward FDI inflows were conducive to technological innovation, and the government should shape the future of FDI in order to improve innovation ability.

2.3. Production and Carbon Emissions

The link between production and environmental pollution has been abundantly studied. Grossman and Krueger [36] employed sulfur dioxide data to investigate the relationship between economic growth and sulfur dioxide. They emphasized that in the early stage of economic growth, haze pollution would increase with economic growth. With the development of the economy, structural adjustment and technological progress would gradually offset this negative impact, so environmental quality could be improved.

In terms of carbon emissions, Ersin [37] investigated the nonlinear relationship between GDP and CO_2 emissions. The results showed an overall positive effect of economic growth rates on emission growth rate in Regime 1. In Regime 2, economic growth rates also had a positive effect on emissions, but the effect was lower than that in Regime 1. The threshold effect was not a direct function of economic growth and was instead a function of the emission growth rate itself. Magazzino et al. [38] employed an advanced methodology in machine learning to explore the causal relationship among solar and wind energy production; coal consumption; economic growth; and CO_2 emissions in China, India, and the US. They found a bi-directional relationship between GDP growth, coal consumption, and CO_2 emissions. In particular, the change in GDP growth led to an increase in coal demand and generated energy, which caused CO_2 emissions.

Aslam et al. [39] found that population density, industry, and trade increased China's CO_2 emission, while per capita GDP decreased CO_2 emissions in the long term. A bi-directional relationship between CO_2 emission and industrialization and a uni-directional relationship between population density and trade openness structure existed. They found that there was an inverted U-shaped relationship between economic growth level and CO_2 emissions. Different from Aslam et al. [39], Bildirici and Ersin [40] evaluated the relationship among CO_2 emissions, economic development, and petrol prices. They found that the relationship between economic development and environmental variables was far from an inverted U-shape. Instead, the relationship showed a J- or an S-shaped curve which depended on the regime that the economy was under. When analyzing two regimes together, they found that the shape of the relation was close to a U-shape. When economic growth was accelerated in two regimes, the J and S curves showed that CO_2 emissions accelerated by following a sigmoidal S curve, and the acceleration rates differed drastically at various magnitudes of economic growth.

Rafiq et al. [41] found that CO_2 emissions and income were of great significance in driving renewable energy consumption in China. In the short term, there was a causal link between renewable energy and income, and the link was bi-directional. They found that the feedback hypothesis between renewable energy consumption and CO_2 emissions held, and a bi-directional relationship between economic growth and CO_2 emissions existed. Zhang et al. [42] provided evidence supporting the inverted U-shaped EKC hypothesis. Trade openness had a significant and negative effect on emissions, whereas real GDP and energy had a significant and positive effect on emissions. The short-term causalities test indicated feedback of a hypothetical linkage of real GDP and trade as well as unidirectional linkages between energy and emissions and between trade and energy.

Some scholars used the Tapio decoupling model to study the decoupling status of provincial CEs from an economic perspective. Gao et al. [43] found that most provinces had a weak decoupling and the emissions–economy decoupling primarily depended on the decoupling of economy–energy–consumption, and energy de-carbonization contributed less. Jiang et al. [44] found that China's carbon emissions were mainly from the industrial sector; the industrial sector, the construction sector, other sectors, and the trade sector had a weak decoupling; the agriculture sector had an expansive negative decoupling; and the transport sector had an expansive coupling. Wang and Jiang [45] also found that China's CEs and economic contributions were largely from the industry sector. They found that the decoupling elasticity had a decreasing trend: it had an expansive negative decoupling during 2002–2005 and it had a weak decoupling during 2000–2002 and during 2005–2014. From the cumulative effect, they found that the construction sector made the largest contributions to promoting the decoupling effect, followed by the construction sector, the agriculture sector, the trade sector, other sectors, and the transport sector, while the industry sector had the smallest contributions.

2.4. FDI and Carbon Emissions

Scholars have carried out a large number of studies on FDI and carbon emissions, and there are mainly two hypotheses. The first is the "pollution paradise" hypothesis, which holds that in the process of economic globalization, developed countries transfer polluting industries to developing countries, which promotes economic development in the developing countries as well as intensifying the use of fossil energy, generating a lot of carbon dioxide [46–48]. Cil [49] employed the Fourier approximation for variables in order to explore whether FDI could affect environmental pollution. The results showed that FDI positively affected CO_2 emissions, though the effect was weak. This indicated that the pollution haven hypothesis (PHH) was valid for Turkey. Therefore, FDI with new and clean technology should be introduced to increase energy efficiency and reduce environmental pollution. Malik et al. [50] found that both economic growth and FDI affected carbon emissions in both the long and the short term. The causality analysis not only supported the above results but also provided a feedback effect between economic growth and carbon emission. They implied that the government should take the measures of carbon pricing and energy diversification to improve environmental quality when the flow of FDI is decreasing.

The other hypothesis is the "pollution halo" hypothesis, which holds that in the process of international capital cross-regional flow, FDI can be good to upgrade industrial structures and optimize energy structures through green technology spillovers and resource optimization allocation in the host country, restricting the production of carbon dioxide. Ahmad et al. [51] investigated the impact of FDI on CO_2 emissions with provincial-level data. They found that FDI was, on the whole, conducive to environmental sustainability, verifying the existence of the "pollution halo" hypothesis. At the provincial level, the impact had the feature of heterogeneity. FDI positively affected CO_2 emissions in seven provinces but had a negative impact on CO_2 emissions in fifteen provinces. This showed that both the "pollution halo" hypothesis and the "pollution paradise" hypothesis were valid. Liu et al. [24] found that the advanced environmental protection technology and environmental pollution control system of developed countries would spill over to the host country when they made foreign investment, which could increase the environmental quality level of the host country to varying degrees.

In addition to these two hypotheses, some scholars have found that FDI has an unstable influence on CEs or no effects. Gao et al. [52] used data covering the period 1973–2019 to investigate terrorism, FDI, and CO_2 emissions in ten fragile economies. They found that an asymmetric relationship did exist between each of these three variables. Positive changes in FDI positively affected CO_2 emissions, while negative changes in FDI significantly affected CO_2 emissions in most economies. Chen and Yang [53] used the STIRPAT extended model to study FDI and China's CEs and found that FDI had no obvious effect on carbon emissions. Al-Mulali and Tang [54] studied the impact of FDI on the environment using data from the Gulf Cooperation Council countries and found that FDI inflow had no influence on the environment in the short term.

Why do studies on FDI and CEs draw diametrically opposite conclusions? One reason lies in the heterogeneity of the research samples. For example, if the sample is a region with strict environmental regulation and a developed economy, FDI will reduce the CE intensity. If the sample is a region with relatively loose environmental regulations and a developing economy, FDI will increase the carbon emission intensity [55]. Another reason is the influencing mechanism of FDI on carbon emissions. The influence of FDI on carbon emissions has three mechanisms: the effect of scales, the effect of structures, and the effect of technology spillovers. When the scale effect is greater than the sum of the structure effect and the technology spillover effect, carbon emissions will increase. When the scale effect is smaller than the sum of the structure effect and the technology spillover effect, carbon emissions will reduce. When regions ignore ecological protection and have less environmental constraints, they will attract foreign direct investment from developed countries at a low cost. Foreign enterprises will make use of local production resources and expand the production scale, which increases energy consumption and CEs. The inflow of FDI promotes the upgrading of the industrial structures in the host country, brings advanced technology and advanced production management, and increases the technological spillover to the enterprises in the host country. Therefore, whether FDI can increase or reduce carbon emissions depends on the size of the three effects.

In summary, scholars have conducted informative research on CEE which provides a theoretical foundation for this study. The recent literature relevant to this topic is provided in chronological order in Table 1. According to the existing studies, there is still room for improvements. First, limited attention is given to the impact of FDI on CEE, and we consider whether there is a linear relationship between these two. Second, thus far, few studies have considered the channels affecting CEE. More specifically, the possible channels of technological innovation, total assets of listed companies in the environmental protection industry, the size of the Fed's assets, fiscal expenditure, and global economic policy uncertainty have been neglected by most prior research. Third, an analysis using sub-samples from different regions in China is insufficient, and the relationship between variables needs to be further investigated. Therefore, this study examines the relationship between FDI and CEE considering the role of direct and indirect channels. We further conduct a sub-sample analysis from the eastern, central, and western regions.

Table 1. Summary of recent studies relevant to four topics.

Author(s)	Countries	Sample Period	Methodology	Estimation Results
Topic 1: Measurement of CEE				
[4]	/	/	Ratio of energy to GDP	/
[3]	/	/	Ratio of energy to GDP	/
[7]	World	1980–2001	Data envelopment analysis (DEA)	/
[2]	/	/	Ratio of CO_2 emissions to GDP	/
[14]	170 countries	1997–2007	A stochastic cost frontier analysis model	/
[15]	China	2006–2016	A stochastic frontier analysis model	/
[12]	China	2017	A radial chance-constrained data envelopment analysis (DEA) model	/
[13]	China	2010–2019	A super efficiency SBM-DEA model	/
Topic 2: FDI and technological innovation				
[31]	Central and East European countries	2006	Panel regression	Unstable
[29]	Europe and Central Asia (ECA) region	1995–2010	Panel regression	Negative
[28]	China	2009–2011	Panel regression	Unstable
[20]	Russia	1997–2011	A knowledge production function	Positive
[22]	China	2001–2011	A stochastic frontier analysis method	Positive
[26]	South Africa	2005, 2008, 2012	Probit regression	Positive
[30]	South Korea	2006–2013	Panel regression	Negative
[25]	EU	2013–2016	Statistical Significance Test	Positive
[21]	Sub-Saharan African countries (SSA) countries and emerging economies	1999–2020	A stochastic production frontier method	Positive
[23]	World	2009–2016	Two-stage least squares (2SLS) and generalized method of moments (GMM)	Positive
[27]	Spain	2009–2016	Panel regression	Positive
[35]	Sri Lanka	1990–2019	ARDL Approach	Negative
Topic 3: Production and carbon emissions				
[41]	6 emerging economies	1996–2016	ARDL model	Inverted U-shaped curve
[37]	13 developed countries	1970–2011	Panel-STAR model	Nonlinear relationship
[42]	10 newly industrialized countries	1971–2013	Panel VECM Granger causality	Inverted U-shaped curve
[40]	the USA and the UK	1871–2016	MS-VAR-MLP model	J- or S-shaped curve
[44]	China	2000–2014	Tapio decoupling model	Weak decoupling, expansive negative decoupling
[45]	China	2002–2014	Tapio decoupling model	Weak decoupling, expansive negative decoupling
[38]	China, India, and the US	1983–2017	ML D2C model	Bi-directional relationship
[39]	China	1962–2018	ARDL approach	Bi-directional relationship
[43]	China	2001–2016	Tapio decoupling model	Weak decoupling
Topic 4: FDI and carbon emissions				
[46]	54 countries	1990–2011	OLS method	Positive
[24]	China	2002–2015	Panel regression	Negative
[47]	Pakistan	1980–2014	Simultaneous equation model	Positive
[48]	Pakistan	1971–2014	ARDL approach	Positive
[50]	Pakistan	1971–2014	ARDL and nonlinear ARDL approaches	Positive
[51]	China	1998–2016	Panel regression	Unstable
[49]	Turkey	1970–2020	Fourier cointegration tests	Positive
[52]	10 fragile economies	1973–2019	ARDL and NARDL approaches	Unstable

3. Methods and Materials

3.1. Super Efficiency DEA Method

When calculating efficiency values based on the traditional DEA method, we can obtain two kinds of efficiency values: one is less than 1, and the other is equal to 1. The former indicates that the efficiency value is invalid, whereas the latter shows that the efficiency value is valid. The traditional DEA method cannot compare and analyze the effective decision-making units (DMUs) because all efficiency values are 1. In fact, differences among these effective DMUs exist. Anderson and Petersen [56] proposed a super efficiency DEA model, and this method could solve this problem. The formula is as follows:

$$\begin{cases} \min(\theta) - \varepsilon\left(\sum\limits_{i=1}^{m} s_i^- - \sum\limits_{r=1}^{s} s_r^+\right) \\ s.t. \sum\limits_{j=1}^{n} x_{ij}\lambda_j + s_r^- = \theta x_{ij_0} \\ \sum\limits_{j=1}^{n} y_{ij}\lambda_j - s_r^+ = y_{ij_0} \\ \lambda_j, s_r^-, s_r^+ \geq 0, i = 1, 2, \ldots, m \\ j = 1, 2, \ldots, j_0 - 1, j_0 + 1, \ldots, n \end{cases} \tag{1}$$

The above formula is the super efficiency model, which evaluates j_0 decision-making unit DMU_0. It removes the evaluated unit DMU_0 from the reference set and obtains its own value by referring to the frontiers of other DMU units. This makes up for the shortcoming of the traditional DEA model that cannot further conduct an analysis and sorting when the efficiency value is 1. The multi-input multi-output evaluation system has n decision-making units, including m input indicators and s output indicators; x_{ij} is the i-th input of the j-th decision-making unit; y_{ij} is the i-th output of the j-th decision-making unit; θ is the super efficiency value of the decision-making unit j_0; ε represents the non-Archimedean infinitesimal; and s^- and s^+ are slack variables.

3.2. Data Resources

The data are from the 2005–2020 China Statistical Yearbook, the 2005–2020 China Science and Technology Statistical Yearbook, the 2005–2020 China Statistical Yearbook on Environment, the China Economic Network Statistical Database, World Bank, the United Nations Conference on Trade and Development Database, China's Carbon Emissions Database, and the Wind Database. The US Federal Reserve's assets and economic policy uncertainty can be found respectively at https://fred.stlouisfed.org/series/WALCL (accessed on 1 January 2020) and https://www.policyuncertainty.com/ (accessed on 1 January 2020). Tibet, Macao, Hong Kong, and Taiwan are not included due to incomplete data.

(1) Carbon emission efficiency

In this study, the super efficiency DEA model was used to estimate CEE. Based on the previous research literature and considering the characteristics of this study, the input variables selected were capital (X_1), labor (X_2), and energy consumption (X_3), and the output variables were GDP (Y_1) and CO_2 (Y_2). The input and output variables are presented in Table 2.

Table 2. Regional carbon emission efficiency index system.

	Index Category	Index Form	Data Sources
Input index	Capital (X_1)	Capital stock	China Statistical Yearbook, 2005–2020
	Labor (X_2)	Employees	China Statistical Yearbook, 2005–2020
	Energy consumption (X_3)	Total energy consumption	China Statistical Yearbook on Environment, 2005–2020
Output index	GDP (Y_1)	Regional GDP	China Statistical Yearbook, 2005–2020
	CO_2 (Y_2)	Carbon dioxide emissions	China Statistical Yearbook on Environment, 2005–2020

In Table 1, capital—i.e., the stock of fixed capital—is the weighted sum of the previous investment flows measured at constant prices. Total current capital is the total capital of the previous period minus depreciation plus the current capital, which can be expressed as $K_{jt} = K_{jt-1}(1 - \delta_{jt}) + I_{jt}$. K_{jt} is the capital stock of province j in period t, K_{jt-1} is the capital stock of province j in period $t-1$, δ_{jt} represents the depreciation rate of province j in year t, and I_{jt} represents the investment in province j in year t by the prices of the current year. The base year is 2004. Labor input is the employed persons in each province and energy consumption is total energy consumption of each province. The GDP was calculated based on the GDP deflator of 2004 and CO_2 is the carbon dioxide emissions of each province.

The values of CEE are shown in Table 3. In order to save space, we selected the efficiency values in several years. It can be seen that the value of CEE in the eastern region was relatively high. Among the 11 provinces and cities, the average value of CEE exceeded 1, except for Liaoning, Zhejiang, and Fujian. The largest average efficiency was in Beijing, and the smallest was in Liaoning Province. The CEE in the central region ranked second, with the maximum of 1.086 in Shanxi Province and the minimum of 0.983 in Jilin Province. The CEE in the western region was the lowest. Among the 10 provinces and cities, the CEE value of 7 was lower than the national average. The maximum value was 1.009 in Inner Mongolia, followed by 1.049 in Ningxia. Shaanxi Province and Qinghai Province ranked third with 0.996. From 2004 to 2019, the efficiency value displayed a parabola shape, which began to rise from 2004, reaching the maximum of 1.005 in 2013, and then dropped to 0.999 in 2019.

Figure 1 shows the average value of CEE at the national and regional levels. China's CEE has an increasing trend and there is a phenomenon of regional imbalance. The national average value of CEE has increased since 2004, reaching a peak in 2015, and decreased afterwards. The eastern region had the highest value of CEE while the western region had the lowest value of CEE before 2012 (including 2012). Since 2013, the central region exceeded the eastern region in CEE value, ranking first among the three regions. The western region had the lowest value of CEE during the sample period. The average value of CEE in the eastern region was higher than the national average value of CEE before 2016, and the average value of CEE was higher in the central region than the national average value of CEE for most years. The average value of CEE was lower in the western region than the national average value of CEE during the sample period.

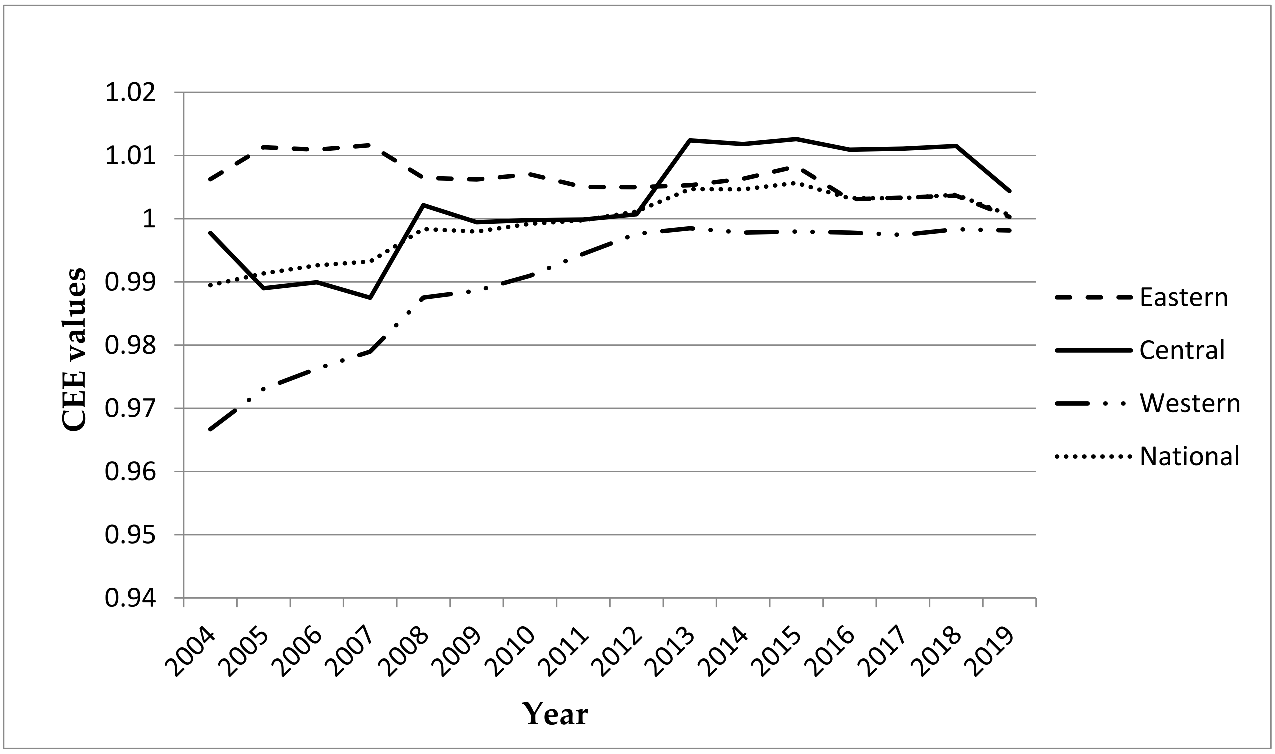

Figure 1. Average CEE values, 2004–2019.

Table 3. CEE values in selected years.

Region	Province and City	2004	2007	2010	2013	2016	2019	Mean
Eastern	Beijing	0.966	1.012	1.021	1.037	1.049	1.044	1.026
	Tianjin	1.030	1.054	1.031	1.032	0.992	0.957	1.021
	Hebei	1.028	1.011	1.001	1.000	0.989	0.978	1.001
	Liaoning	0.996	0.985	0.986	0.990	0.971	0.977	0.984
	Shanghai	1.000	1.004	0.998	0.997	1.000	1.001	1.001
	Jiangsu	1.014	1.003	1.004	1.003	1.007	1.001	1.005
	Zhejiang	0.995	1.003	1.001	0.996	0.994	0.994	0.998
	Fujian	1.007	0.993	0.993	0.995	0.992	1.000	0.994
	Shandong	1.027	1.043	1.017	1.000	1.003	0.992	1.014
	Guangdong	1.008	1.030	1.020	1.013	1.010	1.005	1.017
	Hainan	0.996	0.993	1.005	0.995	1.027	1.054	1.009
Central	Shanxi	1.063	0.982	1.059	1.143	1.141	1.127	1.086
	Jilin	0.968	0.986	0.979	0.983	0.991	0.969	0.983
	Heilongjiang	1.019	0.993	0.991	0.989	0.979	0.960	0.989
	Anhui	0.987	0.987	0.994	1.002	1.005	1.012	0.997
	Jiangxi	0.977	0.982	0.994	0.998	0.995	0.995	0.990
	Henan	0.992	0.997	0.992	0.986	0.978	0.984	0.989
	Hubei	0.987	0.982	0.990	0.994	0.990	0.994	0.988
	Hunan	0.990	0.992	0.999	1.004	1.007	0.995	0.998
Western	Inner Mongolia	0.990	1.017	1.018	1.007	1.017	0.997	1.009
	Guangxi	0.979	0.989	0.979	0.983	0.978	0.970	0.982
	Chongqing	0.963	0.949	0.973	0.982	0.993	0.998	0.975
	Sichuan	0.983	0.979	0.988	0.996	0.992	0.997	0.989
	Guizhou	0.944	0.958	0.985	1.000	1.000	0.990	0.984
	Yunnan	0.965	0.962	0.960	0.968	0.960	0.975	0.965
	Shaanxi	0.944	0.983	1.005	1.010	1.009	1.008	0.996
	Gansu	0.958	0.979	0.983	0.992	0.971	0.973	0.978
	Qinghai	0.971	0.966	0.996	1.000	1.003	0.993	0.996
	Ningxia	0.996	1.034	1.041	1.061	1.082	1.105	1.049
	Xinjiang	0.941	0.953	0.972	0.985	0.970	0.973	0.966
National mean		0.989	0.993	0.999	1.005	1.003	1.001	0.999

(2) Other variables

The main explanatory variable is FDI (*fdi*), which was measured as the total amount of foreign direct investment and takes a logarithmic form. Technological innovation (*rd*) is the R&D expenditure of each province over the years. China experienced fast economic growth during the sample period, which coincided with the increasing integration of global capital markets, the increasing popularity of ESG investing, and energy policy discussions regarding the transition from fossil fuels to cleaner sources of energy. Environmental, social, and governance (ESG) investing pays attention to the social responsibility of investment, which creates direct and indirect incentives for the development of technologies that improve the efficiency of energy sources [57]. Therefore, ESG (*fund*) is a vital variable affecting CEE. Considering the reality of China and the continuity of data, we used the total assets of listed companies in the environmental protection industry to measure ESG in China.

During the sample period, central banks around the world put forth various rounds of quantitative easing [58]. Quantitative easing policies by the central banks of developed economies, in particular the US Federal Reserve (Fed), are important because they distort the equilibrium values of asset prices, tail risks, exchange rates, and FDI [58,59]. As shown by Cortes et al. [58], spillovers from the Fed's QE policies can be particularly detrimental for emerging market economies (such as China). Therefore, we used the size of the Fed's assets (*mp*) as one of variables affecting CEE.

Deficits affect the strength of government spending multipliers and the aggregate credit risk of the banking sector [60], which will affect the levels of FDI and capital investments and then affect technological development and the efficient utilization of energy sources. Hence, deficits are an important variable affecting CEE. Fiscal expenditure (*fine*) is used to measure deficits, which is the proportion of fiscal expenditure in GDP of each province. Global economic policy uncertainty (*epu*), as proposed by Baker et al. [61], is a vital variable affecting FDI [62,63] and can ultimately affect CEE. The degree of openness (*open*) refers to the proportion of the total import and export volumes in the current GDP. Industrial structure (*industry*) is the ratio of the output value of the secondary industry to the total output value.

3.3. Econometric Models

The inflow of FDI into the host country has made the economy scale up. However, it has also increased energy consumption and pollution emissions in the host country. At the same time, the technology level of FDI enterprises is generally better than that of the enterprises of the host country. Its inflow leads to technology spillover in the host country enterprises, which improves industrial technology and increases CEE in the host country. Therefore, FDI will not only directly affect CEE but also indirectly affect CEE through other channels. In order to better test the relationship between FDI and CEE and study the role of direct and indirect channels, the following model was established:

$$co_{it} = \alpha_0 + \alpha_1 fdi_{it} + \alpha_2 X_t + \alpha_3 open_{it} + \alpha_4 industry_{it} + \varepsilon_{it} \tag{2}$$

where i represents the province; t represents the year; $\alpha_i (i = 0, 1, \ldots, 4)$ is the regression coefficient; ε_{it} is the residual term; *co* refers to CEE; *fdi* is foreign direct investment; *open* and *industry* are the control variables, namely the degree of openness and industrial structure, respectively; and X_t is one of variables affecting *co*, which both directly and indirectly affects *co* through interactions with FDI. The variables are technological innovation (*rd*), total assets of listed companies in the environmental protection industry (*fund*), the size of the Fed's assets (*mp*), fiscal expenditure (*fine*), and global economic policy uncertainty (*epu*). The new model is as follows:

$$co_{it} = \beta_0 + \beta_1 fdi_{it} + \beta_2 X_t + \beta_3 X_t * fdi_{it} + \beta_4 open_{it} + \beta_5 industry_{it} + \mu_{it} \tag{3}$$

where X_t has a linear effect on *co*. Furthermore, it has a moderating effect on the relationship between FDI and *co*.

Before conducting an empirical analysis, we first checked whether there is serious multicollinearity. If the data are highly correlated, it will lead to distorted regression results and inaccurate estimated results. In order to save space, we have listed the correlation analysis results of one set of panel data in Table 4. The maximum correlation coefficient between *open* and *fdi* was 0.451, and the minimum correlation coefficient between *fine* and *fdi* was −0.566. Therefore, there was no serious multicollinearity problem, and panel regression could be performed.

Table 4. Results of the correlation analysis.

Variable	*co*	*fdi*	*open*	*industry*	*fine*
co	1.000				
fdi	0.159	1.000			
open	0.146	0.451	1.000		
industry	0.012	0.129	−0.101	1.000	
fine	0.012	−0.566	−0.168	−0.274	1.000

Table 5 shows the results of the descriptive statistical analysis. There were 464 observed values. Except for the variable *open*, the mean of all other variables was greater than the standard error. The mean value of the variable *open* was 0.053, and the standard error was 0.076. The mean value was smaller than the standard error, which indicates that this group was a little dispersed. Since the sample size was larger than 30, the regression result was not affected. The table shows the maximum and minimum values of each variable. The highest maximum value was obtained for the variable *rd*, but the smallest maximum value was obtained for the variable *open*. The highest minimum value was that of the variable *mp*, but the smallest minimum value was that of the variable *fdi*. The largest difference between the maximum value and the minimum value was obtained for the variable *rd*, where the difference was 8.386; the smallest difference between the two was obtained for the variable *co*, where the difference was 0.207.

Table 5. Descriptive statistical analysis.

Variable	Obs	Mean	Std.Dev.	Min	Max
co	464	0.999	0.029	0.941	1.148
fdi	464	3.662	1.517	−0.778	6.793
open	464	0.053	0.076	0.002	0.442
industry	464	0.426	0.119	0.161	2.126
fine	464	0.199	0.101	0.071	0.846
rd	464	13.831	1.797	8.863	17.249
fund	464	13.829	0.794	12.361	14.877
mp	464	14.633	0.675	13.560	15.316
epu	464	4.793	0.394	4.137	5.546

4. Results

4.1. Statistical Test Results

Statistical tests are employed to navigate the behavior of data for the selection of apt estimation solution. For this, cross sectional dependence tests, as well as unit root test is conducted.

4.1.1. Cross-Sectional Dependence Test Results

We conduct the cross-sectional dependence test and the results are given in Table 6. Except Panel A, the test results for Panel B, Panel C, Panel D and Panel E indicate that there are not significant cross-sectional dependence. For Pesaran's test of Panel A, cross sectional dependence exists at a significant level of 10%. Hence, we think that there is no cross-section correlation in panel data, and it is unnecessary to use panel-corrected standard errors.

Table 6. Cross-sectional dependence test results.

Panel	Method	Value	*p*-Value
Panel A	Pesaran's test	−1.738	0.0821
	Friedman's test	9.858	0.9994
Panel B	Pesaran's test	−0.493	0.6223
	Friedman's test	14.413	0.984
Panel C	Pesaran's test	−1.286	0.1985
	Friedman's test	11.248	0.9979
Panel D	Pesaran's test	−1.107	0.2682
	Friedman's test	12.931	0.9932
Panel E	Pesaran's test	0.923	0.3561
	Friedman's test	30.685	0.3313

4.1.2. Panel Unit Root Test Results

There are a variety of methods for testing panel unit root, and the development process is mainly divided into two stages. The first generation of tests was put forward earlier. The main assumption is that cross-sections are independent, including two types: unit root tests under the same root hypothesis and unit root tests under different root assumptions. The former type includes the LLC test, Breitung test, and Hadri test, and the latter type includes the IPS test, Fisher ADF test, and Fisher PP test. The second-generation test assumes that there is a spatial effect of cross-section correlation, considering cross-section heterogeneity and cross-section dependence, such as the CADF test designed by Pesaran in 2007.

According to Ahmad et al. [51], the first-generation panel data unit root test has the disadvantage that it ignores cross-sectional dependence, while the second-generation test involves cross-sectional dependency. Taking into consideration the results in Table 6, we investigated each variable with the Maddala–Wu test in this study. The results are given in Table 7. The Maddala–Wu test results show that each variable series is stationary. Thus, econometric analyses can be conducted with the data.

Table 7. Panel unit root test results.

Variable	Method	Statistic	*p*-Value
fdi	Maddala–Wu test	166.5032	0.0000
rd	Maddala–Wu test	155.9507	0.0000
fund	Maddala–Wu test	88.4507	0.0061
mp	Maddala–Wu test	88.8581	0.0057
fine	Magdala–Wu test	97.0817	0.0010
epu	Maddala–Wu test	151.2951	0.0000
open	Maddala–Wu test	105.1414	0.0002
industry	Maddala–Wu test	104.8853	0.0002

4.2. Analysis of the Impact of FDI on CEE

The impact of FDI on CEE is analyzed first in the paper. When processing the panel data, we had to decide whether to use the fixed effect model or the random effect model. The null hypothesis that "unobservable random variables are not related to all explanatory variables" was to be tested. If the null hypothesis was proven, the random effect model would be used for the test; if the null hypothesis was not proven, the fixed effect model would be used for the test. The Hausman test is generally used as the test method. In this study, we found that the panel data were significant at the statistical level of 1%, so the random effect model was rejected, and the fixed effect model was used.

Table 8 reports the fixed effect regression results. FDI positively affects CEE. If FDI increases by 1%, CEE will increase by 0.002%. The inflow of foreign investment will spread foreign advanced environmental protection technologies, standards, and concepts to the host country. The host country's enterprises will reduce their carbon emissions and increase their CEE through the imitation effect and demonstration effect. The introduction of foreign environmental protection ideas is of great significance to the improvement of the CEE of the host country. Environmental protection is not only related to human health but is also very important to the long-term development of society. The dissemination of environmental protection ideas makes the host country become aware of the role of the environment, pay attention to the improvement of environmental protection technology, and improve the intensity of environmental regulation.

Table 8. Impact of FDI on CEE.

Variable			***co***		
fdi	0.002 *	0.001	0.001	0.004 ***	0.003 *
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
rd	0.002 ***				
	(0.001)				
fund		0.005 ***			
		(0.001)			
mp			0.007 ***		
			(0.001)		
fine				0.040 ***	
				(0.012)	
epu					0.007 ***
					(0.002)
open	0.113 ***	0.116 ***	0.117 ***	0.082 **	0.112 ***
	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)
industry	−0.011	−0.008	−0.007	−0.009	−0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
_cons	0.954 ***	0.913 ***	0.891 ***	0.974 ***	0.951 ***
	(0.010)	(0.016)	(0.019)	(0.007)	(0.011)
R^2	0.024	0.027	0.028	0.030	0.030

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively; the data in parentheses are standard errors.

Technological innovation has a positive impact on CEE. Technological innovation itself is a process of improving the technology level, which will bring technology spillover effects to enterprises, reduce CEs, and increase CEE. Since China's entry to the WTO [64], China has been the recipient of FDI inflows, but it has also engaged in large-scale investments in foreign countries. China's fast economic growth is integrated with the global economy. The macroeconomic variables *fund*, *mp*, *fine*, and *epu* positively affect CEE. Fiscal expenditure positively affects CEE. Since the implementation of reform and opening up to outside policy, local governments have focused on the development of the economy in China, and there has also been a phenomenon of sacrificing the environment for achieving development. The consequences of ignoring environmental protection, such as river pollution, ecological environment destruction, and human health threats, have made local governments gradually realize the importance of environmental protection and change from an extensive development mode that sacrifices the environment to an intensive development mode that pays attention to environmental protection. Local governments have increased financial expenditure on environmental protection, thus reducing CEs and increasing CEE.

Among the control variables, *open*, which is measured by the ratio of international trade to GDP, positively affects CEE. The larger the value is, the greater the degree of openness will be. When a country is open enough, the country is in line with the world. This means that the country can acquire advanced environmental protection technologies from developed countries, which is conducive to China's energy conservation and carbon emission efficiency. The variable *open* negatively affects R&D expenditure. A plausible reason is that most of China's foreign trade products win by volume, and the technology content is generally low, which cannot produce a strong technology spillover to domestic R&D. Industrial structure, measured by the ratio of secondary industry output to the total output, negatively and insignificantly affects CEE. This is because the secondary industry consumes a large amount of energy in the production process and generates large CEs, which is not good for the improvement of CEE.

4.3. Analysis of the Impact of FDI on CEE through Several Channels

Table 9 reports the impact of FDI on CEE through several channels. There are five channels, namely technological innovation, total assets of listed companies in the environmental protection industry, size of the Fed's assets, fiscal expenditure, and global economic policy uncertainty. It is evident that these channels are not conducive to the impact of FDI on CEE. Except for *fdi*fine*, the other interaction terms have a significant effect on the relationship of FDI and CEE. This indicates that each channel has a substitution effect on FDI. Taking technological innovation for example, some FDIs flowing into China engage in OEM production in China; produce, process, and assemble products in China; and finally export the products to foreign countries. In the production process, foreign technical production standards and environmental protection standards also flow into the local enterprises, resulting in technology spillover and improving the CEE in the host country. However, these technologies are not core technologies, which is not conducive to improving the technology level of local enterprises. What is more, this will encourage local enterprises to be idle in their ways and they cannot thus conduct technological innovation.

Table 9. Impact of FDI on CEE through several channels.

Variable			***co***		
fdi	0.032 ***	0.055 ***	0.066 ***	0.006 ***	0.036 ***
	(0.004)	(0.009)	(0.011)	(0.002)	(0.006)
rd	0.011 ***				
	(0.001)				
fund		0.019 ***			
		(0.002)			
mp			0.022 ***		
			(0.003)		
fine				0.051 ***	
				(0.017)	
epu					0.032 ***
					(0.005)
*fdi*rd*	−0.002 ***				
	(0.0003)				
*fdi*fund*		−0.003 ***			
		(0.0006)			
*fdi*mp*			−0.004 ***		
			(0.0007)		
*fdi*fine*				−0.006	
				(0.007)	
*fdi*epu*					−0.007 ***
					(0.001)
open	0.009	0.023	0.033	0.086 ***	0.035
	(0.038)	(0.038)	(0.037)	(0.037)	(0.038)
industry	−0.009	−0.007	−0.007	−0.010	−0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
_cons	0.845 ***	0.733 ***	0.672 ***	0.969 ***	0.834 ***
	(0.010)	(0.033)	(0.042)	(0.009)	(0.024)
R^2	0.016	0.030	0.033	0.031	0.032

Note: *** indicate significance levels at 1%; the data in parentheses are standard errors.

4.4. Robustness Test

In order to test whether there is a consistent and stable explanation between the new regression results and the above regression results when some parameters are changed, a robustness test was conducted. There are generally three methods for robustness testing:

the variable replacement method, the method replacement method, and the sample size changing method. In this study, the sample size changing method was adopted. Since a financial crisis occurred in 2008 and had a vital impact on the global economy and investment, the sample data may be inconsistent before and after 2008. We therefore used sample data from 2009 to 2019 to conduct the analysis, and the results are shown in Table 10. The variables *fdi*, *rd*, *fund*, *mp*, *fine*, and *epu* have positive impacts on CEE. All interaction items negatively affect CEE. Therefore, the regression results are robust.

Table 10. Results of robustness test.

Variable			***co***		
fdi	0.040 ***	0.069 ***	0.099 ***	0.004 ***	0.028 ***
	(0.011)	(0.019)	(0.030)	(0.002)	(0.011)
rd	0.015 ***				
	(0.004)				
fund		0.018 ***			
		(0.005)			
mp			0.028 ***		
			(0.007)		
fine				0.019 ***	
				(0.017)	
epu					0.014 *
					(0.008)
*fdi*rd*	−0.002 ***				
	(0.0008)				
*fdi*fund*		−0.004 ***			
		(0.001)			
*fdi*mp*			−0.006 ***		
			(0.002)		
*fdi*fine*				−0.0004	
				(0.006)	
*fdi*epu*					−0.004 **
					(0.002)
open	0.039	0.046	0.056	0.086 *	0.065 *
	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)
industry	−0.002	−0.002	−0.003	−0.004	−0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
_cons	0.781 ***	0.720 ***	0.560 ***	0.980 ***	0.906 ***
	(0.053)	(0.072)	(0.116)	(0.009)	(0.043)
R^2	0.009	0.008	0.009	0.049	0.065

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively; the data in parentheses are standard errors.

4.5. Sub-Sample Regression

In the process of the research, we found that some regions have more developed economies, more foreign investment, and a higher quality of foreign investment, which improves the local technology level, increases the proportion of environmentally friendly enterprises, and ultimately improves CEE and reduces environmental pollution. In other regions, the economic development is relatively backward. In order to develop the economy, they do not hesitate to sacrifice the ecological environment. Among the introduced foreign enterprises, there are a large number of non-environment-friendly enterprises which reduce CEE and increase regional environmental pollution. Therefore, the level of regional economic development has different effects on the introduction of FDI and CEE. China's regional economic development has always been characterized by the developed economy in the eastern region and the backward economy in the central and western regions. In this section, according to the geographical location of different regions in China, the total sample data are divided into the data of the eastern region and the data of the central and western regions for regression.

In order to investigate the characteristics of the data in the different regions, we conducted a homogeneity test, and the results are given in Table 11. The principle of testing the homogeneity of two regions lies in whether the variables of the two datasets obey the same distribution. Usually, we judge the same distribution of two datasets based on normal or approximate normal distribution. Since we did not know the distribution of the data set, we used a non-parametric test, the Kolmogorov–Smirnov test, to test the homogeneity of the two regions. For each variable, the *p*-value was less than 0.05, meaning that the data of the two regions are highly heterogeneous.

Table 11. Results of homogeneity test.

Variable	D-Value	*p*-Value	Variable	D-Value	*p*-Value
dea	0.468	0.000	*mp*	0.346	0.000
fdi	0.572	0.000	*epu*	0.271	0.000
open	0.825	0.000	*rd*fdi*	0.534	0.000
industry	0.211	0.000	*fund*fdi*	0.512	0.000
fine	0.460	0.000	*mp*fdi*	0.525	0.000
rd	0.405	0.000	*fine*fdi*	0.148	0.000
fund	0.378	0.000	*epu*fdi*	0.495	0.000

The results of the sub-sample regression are given in Table 12. In the eastern region, FDI affects CEE in three channels, and *fund*, *mp*, *fine*, and *epu* have positive effects on CEE. All interaction terms negatively affect CEE, though some of these terms have an insignificant effect on CEE. In the central and western regions, FDI, *rd*, *fund*, *mp*, *fine*, and *epu* positively affect CEE, and all interaction terms negatively affect CEE. The reason for these great differences between the two regions is because there is great heterogeneity between them. The eastern region has attracted a large number of FDIs with high technology, which has improved the level of technological innovation, CEE, and the ecological environment in the eastern region. The central and western regions may be areas where a large number of non-environmentally friendly FDI enterprises are transferred. The effect of foreign enterprises on CEE is not greater than that in the eastern region. The substitution effect of several channels on FDI in the eastern region is greater than that in the central and western regions. This indicates that the absorption capacity in the eastern region is greater than that in the central and western regions, and the eastern region can increase its technology level through the technology spillover effects from FDI enterprises.

4.6. Discussion

Large numbers of studies focus on the relationship between FDI and CEs. There are two famous hypotheses: the pollution heaven hypothesis [48] and the pollution halo hypothesis [24]. The former holds that the inflow of FDI can increase CEs, while the latter has the opposite results. Unlike existing studies only focusing on the two hypotheses, we studied the relationship between FDI and CEE considering the role of direct and indirect channels.

There are a few studies that have paid attention to the channels affecting CEE. In this study, we considered five channels, namely technological innovation, total assets of listed companies in the environmental protection industry, the size of the Fed's assets, fiscal expenditure, and global economic policy uncertainty. He et al. [65] investigated the relationship between technological innovation and CEE and found that both market segmentation and market potential were important channels in affecting CEE. Pan et al. [66] found that environmental policy not only affected CEE but also improved CEE through the reduction in energy intensity and adjustment of the industrial structure.

Table 12. Results of sub-sample regression.

Variable	*co*									
	Eastern Region					**Central and Western Regions**				
fdi	0.004	0.062 ***	0.058 **	−0.001	0.047 ***	0.021 ***	0.036 ***	0.042 **	0.006 **	0.024 ***
	(0.011)	(0.020)	(0.025)	(0.004)	(0.013)	(0.007)	(0.013)	(0.016)	(0.003)	(0.009)
rd	−0.002					0.011 ***				
	(0.004)					(0.001)				
fund		0.019 ***					0.015 ***			
		(0.007)					(0.002)			
mp			0.017 *					0.018 ***		
			(0.008)					(0.003)		
fine				0.094 *					0.052 ***	
				(0.049)					(0.019)	
epu					0.041 ***					0.026 ***
					(0.014)					(0.006)
*fdi*rd*	−0.0001					−0.001 ***				
	(0.0007)					(0.0005)				
*fdi*fund*		−0.004 ***					−0.002 ***			
		(0.001)					(0.0009)			
*fdi*mp*			−0.004 **					−0.002 **		
			(0.002)					(0.001)		
*fdi*fine*				−0.018					−0.007	
				(0.016)					(0.008)	
*fdi*epu*					−0.010 ***					−0.004 **
					(0.002)					(0.002)
open	0.053	−0.022	0.002	0.026	−0.023	0.141	0.148	0.132	0.255	0.247
	(0.041)	(0.042)	(0.041)	(0.035)	(0.039)	(0.194)	(0.197)	(0.196)	(0.204)	(0.198)
industry	0.001	0.003	0.001	−0.001	0.006	−0.074 ***	−0.069 ***	−0.065 **	−0.099 ***	−0.088 ***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.024)	(0.026)	(0.025)	(0.025)	(0.025)
_cons	1.021 ***	0.744 ***	0.766 ***	1.007 ***	0.814 ***	0.879 ***	0.802 ***	0.749 ***	1.004 ***	0.896 ***
	(0.051)	(0.094)	(0.118)	(0.020)	(0.061)	(0.025)	(0.041)	(0.052)	(0.013)	(0.030)
R^2	0.003	0.024	0.009	0.005	0.032	0.186	0.13	0.128	0.124	0.032

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively; the data in parentheses are standard errors.

In this study, we used the super efficiency DEA method to obtain the values of 30 provinces and cities in China. It can be seen from Figure 1 that China's CEE has the feature of regional imbalance. A plausible explanation is that uneven economic growth in the different regions has led to the inequality in energy consumption, which affects CEs and CEE [67]. On the whole, the national and regional values have an increasing trend. Fang et al. [8] also found a regional imbalance of CEE, but they found that there was a decreasing trend in different regions. We found that the western region had the lowest value during the sample period, the average value of CEE in the eastern region was higher than the national average value of CEE before 2016, and the average value of CEE in the central region was higher than the national average value of CEE for most years. However, Fang et al. [8] found that the western region had the lowest value during the sample period and only the values in the western region were higher than the national average value of CEE.

We found that the average value of CEE in the eastern region was relatively high. This is similar to Yan et al. [68], who found that the eastern region had a relatively high efficiency and had a positive spillover effect on the neighboring provinces. What is more, they found that some of the wealthy provinces in the eastern region had higher CEE. This is consistent with the results in our study. Similar to Cheng et al. [69], we found that CEE has significant spatial heterogeneity and temporal heterogeneity, and eastern China had the highest CEE value, followed by central China, and western China had the lowest. The differences between this study and these two previous studies are that Yan et al. [68] and Cheng et al. [69] adopted the undesirable-SBM (slacks-based measure) model and a non-radial directional distance function, respectively, using different sample data.

We found that technological innovation has a positive impact on CEE, which is consistent with Rizwana et al. [70] and Fang et al. [8]. Rizwana et al. [70] found that technological innovation could reduce the cost of energy consumption and improve the environmental quality of Belt and Road economies. According to Fang et al. [8], R&D investment had a green growth effect, which led green technology progress in the innovation system, and green technology is conducive to improving CEE. They found that there were two ways for technological innovation to have a green growth effect on CEE. One way was wide R&D investment in low-carbon production technologies, bringing green growth effects to environmental quality. The other way was the existence of an energy rebound effect, which may offset the green effect of technological innovation. When the green growth effect brought by technology investment is greater than its energy rebound effect, R&D investment positively affects CEE. When the green growth effect brought by technology investment is lower than its energy rebound effect, R&D investment negatively affects CEE.

We found that five channels are not only directly but also indirectly related to CEE. Except for fdi*fine, the other interaction terms had a negative effect on the relationship of FDI and CEE. We took technological innovation as an example and found that there are technology spillover effects with the inflow of foreign technical production standards and environmental protection standards. Since most technologies are not core technologies, it is not conducive to improving the technology level and CEE. The results are similar to those of Liu and Hao [6]. Liu and Hao [6] found that technological innovation had direct and indirect effects on CEE. On the one hand, the level of science and technology innovation had a positive effect on CEE, and the energy efficiency increased when technology continued to be innovated. On the other hand, the level of science and technology innovation had a negative effect on the CEE of neighboring provinces and cities. The reason was that the technological progress in one region would make the scale of energy exploration, exploitation, and production in neighboring regions expand, leading to an increase in energy consumption and thus negatively affecting CEE. Liu and Hao [6] used a spatial lag model analysis, which was different from our study.

5. Conclusions

This study used the super efficiency DEA model to calculate the CEE values of 30 provinces and cities in China and investigated the impact of FDI on CEE. The results show that the value of CEE has the characteristics of regional heterogeneity and FDI positively affects CEE.

Firstly, the highest efficiency value was in the eastern region, the second-best efficiency value was in the central region, and the lowest efficiency value was in the western region. The value of CEE shows an upward trend and there is a feature of regional heterogeneity. Secondly, the paper investigated the direct impact of FDI on CEE and the indirect impact of FDI on CEE through five channels. A plausible explanation is that advanced environmental protection technologies, standards, and concepts are transferred to the host country when multinational enterprises invest in this region. Enterprises in the host country imitate the advanced technology and standards and conduct technological innovation, leading to a decrease in carbon emissions and increase in CEE. There are five channels involved in this process, namely technological innovation, total assets of listed companies in the environmental protection industry, size of the Fed’s assets, fiscal expenditure, and global economic policy uncertainty. Each channel positively affects CEE, but their interaction terms with FDI negatively affect CEE. This indicates that each channel does not contribute to the impact of FDI on CEE and has a substitution effect on FDI. Finally, we divided the total sample into an eastern region sample and a central and western regions sample according to the geographical positions in China. The results show that both the direct and indirect impacts of FDI on CEE have the characteristic of regional heterogeneity. The eastern region attracted a large number of FDIs with high technology and the central and western regions attracted a large number of non-environmentally friendly FDI enterprises, leading to regional heterogeneity in the relationship between FDI and CEE.

It can be seen from the empirical results that FDI inflow is beneficial to improve the CEE of the host country, indicating that the scale effect of FDI entering the Chinese market is smaller than the sum of the structure effect and the technology spillover effect. Therefore, foreign investors should be encouraged to enter the Chinese market; bring clean and efficient low-carbon production technology; and push domestic enterprises to use green, low-carbon, and clean energy. Domestic enterprises carry out technological innovation through the demonstration effect and competition effect, thus improving the level of green technology in China. On the other hand, we can increase the proportion of low-carbon industries in the total industry and eliminate the backward production capacity to promote the rationalization and advancement of industrial structures through the inflow of FDI.

The inflow of foreign investments in the central and western regions has a strong tendency to transfer pollution. This kind of investment promotes the economic development of the central and western regions but brings serious environmental pollution problems. Therefore, the central and western regions should take measures to attract the investment of environmentally friendly foreign enterprises. We can raise the environmental regulation standards and attract more foreign investment by preferential policies based on the established environmental protection standards. On the other hand, the central and western regions should vigorously develop the economy, improve the attractiveness of talents, and achieve a spiral of economic and human capital so as to improve the absorption capacity of the region. The improvement of the absorptive capacity will help the central and western regions to obtain more FDI technology spillovers, which will be converted into their own technological innovation ability and ultimately improve CEE and reduce CEs.

According to the empirical results, FDI not only directly affects the regional CEE but also affects the CEE through technological innovation. Therefore, the technological innovation of the host country is of great significance in absorbing FDI technology spillovers and promoting the improvement of carbon emission efficiency. It is suggested that enterprises invest in product innovation and process innovation and improve their own technological level by imitating the technology of FDI enterprises. With the improvement of environmental protection standards and the awakening of environmental awareness, enterprises should also invest in R&D of environmental protection technology to enhance their competitiveness in the market. Since some new energy technologies such as solar and wind power need more investment, it is recommended that multiple enterprises jointly carry out technology research and development so as to achieve the simultaneous development of environmental protection and production.

Author Contributions: Conceptualization, Q.W. and Q.Z.; methodology, Q.W.; software, Q.W.; validation, Q.Z.; formal analysis, Q.Z.; investigation, Q.Z.; resources, Q.Z.; data curation, Q.Z.; writing—original draft preparation, Q.W.; writing—review and editing, Q.W.; visualization, Q.W.; supervision, Q.Z.; project administration, Q.W.; funding acquisition, Q.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

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. Kaya, Y.; Yokobori, K. *Environment, Energy, and Economy: Strategies for Sustainability*; United Nations University Press: Tokyo, Japan, 1997.
2. Sun, J.W. The decrease of CO_2 emission intensity is decarbonization at national and global levels. *Energy Policy* **2005**, *33*, 975–978. [CrossRef]
3. Mielnik, O.; Goldemberg, J. Communication the evolution of the "carbonization index" in developing countries. *Energy Policy* **1999**, *27*, 307–308. [CrossRef]
4. Ang, B.W. Is the energy intensity a less useful indicator than the carbon factor in the study of climate change? *Energy Policy* **1999**, *27*, 943–946. [CrossRef]

5. Zhou, P.; Ang, B.W.; Han, J.Y. Total factor carbon emission performance: A malmquist index analysis. *Energy Econ.* **2010**, *32*, 194–201. [CrossRef]
6. Liu, Q.; Hao, J. Regional differences and influencing factors of carbon emission efficiency in the Yangtze River economic belt. *Sustainability* **2022**, *14*, 4814. [CrossRef]
7. Ramanathan, R. Combining indicators of energy consumption and CO_2 emissions: Across country comparison. *Int. J. Glob. Energy Issues* **2002**, *17*, 214–227. [CrossRef]
8. Fang, G.; Gao, Z.; Tian, L.; Fu, M. What drives urban carbon emission efficiency?—Spatial analysis based on nighttime light data. *Appl. Energy* **2022**, *312*, 118772. [CrossRef]
9. Farrell, M.J. The measurement of production efficiency. *J. R. Stat. Soc.* **1957**, *120*, 25–281.
10. Charnes, A.; Cooper, W.W. Programming with linear fractional functional. *Nav. Res. Logist. Q.* **1962**, *9*, 181–186. [CrossRef]
11. Ramanathan, R.A. Multi-factor efficiency perspective to the relationships among world GDP: Energy consumption and carbon dioxide emissions. *Technol. Forecast. Soc. Chang.* **2006**, *73*, 483–494. [CrossRef]
12. Ren, J.; Gao, B.; Zhang, J.; Chen, C. Measuring the energy and carbon emission efficiency of regional transportation systems in China: Chance-constrained DEA models. *Math. Probl. Eng.* **2020**, *2020*, 9740704. [CrossRef]
13. Chu, X.; Jin, Y.; Wang, X.; Song, X. The evolution of the spatial-temporal differences of municipal solid waste carbon emission efficiency in China. *Energies* **2022**, *15*, 3987. [CrossRef]
14. Herrala, R.; Goel, R.K. Global CO_2 efficiency: Country-wise estimates using a stochastic cost frontier. *Energy Policy* **2012**, *45*, 762–770. [CrossRef]
15. Zhang, F.; Jin, G.; Li, J.; Wang, C.; Xu, N. Study on dynamic total factor carbon emission efficiency in China's urban agglomerations. *Sustainability* **2020**, *12*, 2675. [CrossRef]
16. Macdougall, G.D.A. The benefits and costs of private investment from abroad: A theoretical approach. *Oxf. Bull. Econ. Stat.* **1960**, *22*, 189–211. [CrossRef]
17. Kugler, M. Spillovers from foreign direct investment: Within or between industries? *J. Dev. Econ.* **2006**, *80*, 444–477. [CrossRef]
18. Javorcik, B.S. Does foreign direct investment increase the productivity of domestic firms? in search of spill-overs through backward linkages. *Am. Econ. Rev.* **2004**, *94*, 605–627. [CrossRef]
19. Gorg, H.; Greenaway, D. Much ado about nothing? do domestic firms really benefit from foreign direct investment? *World Bank Res. Obs.* **2004**, *19*, 171–197. [CrossRef]
20. Smith, N.; Thomas, E. Regional conditions and innovation in Russia: The impact of foreign direct investment and absorptive capacity. *Reg. Stud.* **2017**, *51*, 1412–1428. [CrossRef]
21. Das, G.G.; Drine, I. Distance from the technology frontier: How could Africa catch-up via socio-institutional factors and human capital? *Technol. Forecast. Soc. Chang.* **2020**, *150*, 119755. [CrossRef]
22. Yang, Z.; Shao, S.; Yang, L.; Liu, J. Differentiated effects of diversified technological sources on energy-saving technological progress: Empirical evidence from China's industrial sectors. *Renew. Sustain. Energy Rev.* **2017**, *72*, 1379–1388. [CrossRef]
23. Sultana, N.; Turkina, E. Foreign direct investment, technological advancement, and absorptive capacity: A network analysis. *Int. Bus. Rev.* **2020**, *29*, 101668. [CrossRef]
24. Liu, Y.; Hao, Y.; Gao, Y. The environmental consequences of domestic and foreign investment: Evidence from China. *Energy Policy* **2017**, *108*, 271–280. [CrossRef]
25. Andrijauskiene, M.; Dumiuvien, D. Inward foreign direct investment and national innovative capacity. *Eng. Econ.* **2019**, *30*, 339–348. [CrossRef]
26. Ghebrihiwet, N. FDI technology spillovers in the mining industry: Lessons from South Africa's mining sector. *Resour. Policy* **2019**, *62*, 463–471. [CrossRef]
27. Melane-Lavado, A.; Álvarez-Herranz, A. Cooperation networks as a driver of sustainability-oriented innovation. *Sustainability* **2020**, *12*, 2820. [CrossRef]
28. Lew, Y.K.; Liu, Y. The contribution of inward FDI to Chinese regional innovation: The moderating effect of absorptive capacity on knowledge spillover. *Eur. J. Int. Manag.* **2016**, *10*, 284–313. [CrossRef]
29. Marco, L.C.K.; Steve, Y.F.; Zhang, Z.; Leung, V.K.K. Determinants of innovative activities: Evidence from Europe and central Asia region. *Singap. Econ. Rev.* **2015**, *60*, 1550004.
30. Kim, M.; Choi, M.J. R&D spillover effects on firms' export behavior: Evidence from South Korea. *Appl. Econ.* **2019**, *51*, 3066–3080.
31. Falk, M. The relationship between FDI through backward linkages and technological innovations of local firms: Evidence for emerging economies. *East. Eur. Econ.* **2015**, *53*, 424–438. [CrossRef]
32. Mohamad, A.; Bani, N.M. Foreign direct investment, absorptive capacity and technological innovation: Empirical evidence in developing economies. *Glob. Conf. Bus. Econ. Res.* **2017**, *8*, 14–15.
33. Filippetti, A.; Frenz, M.; Ietto-Gillies, G. The impact of internationalization on innovation at countries' level: The role of absorptive capacity. *Camb. J. Econ.* **2017**, *41*, 413–439. [CrossRef]
34. Negash, E.S.; Zhu, W.; Lu, Y.; Wang, Z. Does Chinese inward foreign direct investment improve the productivity of domestic firms? horizontal linkages and absorptive capacities: Firm-level evidence from Ethiopia. *Sustainability* **2020**, *12*, 3023. [CrossRef]
35. Adikari, A.P.; Liu, H.; Marasinghe, S. Inward foreign direct investment-induced technological innovation in Sri Lanka? Empirical evidence using ARDL approach. *Sustainability* **2021**, *13*, 7334. [CrossRef]

36. Grossman, G.M.; Krueger, A.B. Environmental Impacts of a North American Free Trade Agreement. Working Paper, 1991, 3914. Available online: http://s.dic.cool/S/HOEe7P8Q (accessed on 14 September 2022).
37. Ersin, Ö. The nonlinear relationship of environmental degradation and income for the 1870-2011 period in selected developed countries: The dynamic panel-STAR approach. *Procedia Econ. Financ.* **2016**, *38*, 318–339. [CrossRef]
38. Magazzino, C.; Mele, M.; Schneider, N. A machine learning approach on the relationship among solar and wind energy production, coal consumption, GDP, and CO_2 emissions. *Renew. Energy* **2021**, *167*, 99–115. [CrossRef]
39. Aslam, B.; Hu, J.; Shahab, S.; Ahmad, A.; Hassan, M. The nexus of industrialization, GDP per capita and CO_2 emission in China. *Environ. Technol. Innov.* **2021**, *23*, 101674. [CrossRef]
40. Bildirici, M.; Ersin, Ö. Markov-switching vector autoregressive neural networks and sensitivity analysis of environment, economic growth and petrol prices. *Environ. Sci. Pollut. Res.* **2018**, *25*, 31630–31655. [CrossRef]
41. Rafiq, S.; Salim, R.; Ruhul, A. Why do some emerging economies proactively accelerate the adoption of renewable energy? *Energy Econ.* **2012**, *34*, 1051–1057.
42. Zhang, S.; Liu, X.; Bae, J. Does trade openness affect CO_2 emissions: Evidence from ten newly industrialized countries? *Environ. Sci. Pollut. Res.* **2017**, *24*, 17616–17625. [CrossRef]
43. Gao, C.; Ge, H.; Lu, Y.; Wang, W.; Zhang, Y. Decoupling of provincial energy-related CO_2 emissions from economic growth in China and its convergence from 1995 to 2017. *J. Clean. Prod.* **2021**, *297*, 126627. [CrossRef]
44. Jiang, R.; Zhou, Y.; Li, R. Moving to a low-carbon economy in China: Decoupling and decomposition analysis of emission and economy from a sector perspective. *Sustainability* **2018**, *10*, 978. [CrossRef]
45. Wang, Q.; Jiang, R. Is China's economic growth decoupled from carbon emissions? *J. Clean. Prod.* **2019**, *225*, 1194–1208. [CrossRef]
46. Omri, A.; Nguyen, D.K.; Rault, C. Causal interactions between CO_2 emissions, FDI, and economic growth: Evidence from dynamic simultaneous-equation models. *Econ. Model.* **2014**, *42*, 382–389. [CrossRef]
47. Bakhsh, K.; Rose, S.; Ali, M.F.; Ahmad, N.; Shahbaz, M. Economic growth, CO_2 emissions, renewable waste and FDI relation in Pakistan: New evidences from 3SLS. *J. Environ. Manag.* **2017**, *196*, 627–632. [CrossRef]
48. Nadeem, A.M.; Ali, T.; Khan, M.T.I.; Guo, Z.Q. Relationship between inward FDI and environmental degradation for Pakistan: An exploration of pollution haven hypothesis through ARDL approach. *Environ. Sci. Pollut. Res.* **2020**, *27*, 15407–15425. [CrossRef]
49. Cil, N. Re-examination of pollution haven hypothesis for Turkey with Fourier approach. *Environ. Sci. Pollut. Res.* **2022**, *6*, 1–13. [CrossRef] [PubMed]
50. Malik, M.Y.; Latif, K.; Khan, Z.; Butt, H.D.; Nadeem, M.A. Symmetric and asymmetric impact of oil price, FDI and economic growth on carbon emission in Pakistan: Evidence from ARDL and non-linear ARDL approach. *Sci. Total Environ.* **2020**, *726*, 138421. [CrossRef]
51. Ahmad, M.; Jabeen, G.; Wu, Y. Heterogeneity of pollution haven/halo hypothesis and Environmental Kuznets Curve hypothesis across development levels of Chinese provinces. *J. Clean. Prod.* **2020**, *285*, 124898. [CrossRef]
52. Gao, X.; Li, X.; Chishti, M.Z.; Ullah, S.; Sohail, S. Decomposing the asymmetric effects of terrorism and FDI on carbon emission: Evidence from fragile economies. *Environ. Sci. Pollut. Res.* **2022**, *29*, 41125–41139. [CrossRef]
53. Chen, K.M.; Yang, S.F. Impact of outward foreign direct investment on domestic R&D activity: Evidence from Taiwan's multinational enterprises in low-wage countries. *Asian Econ. J.* **2013**, *27*, 17–38.
54. Al-Mulali, U.; Tang, C.F. Investigating the validity of pollution haven hypothesis in the gulf cooperation council (GCC) countries. *Energy Policy* **2013**, *60*, 813–819. [CrossRef]
55. Hao, Y.; Liu, Y.M. Has the development of FDI and foreign trade contributed to China's CO_2 emissions? An empirical study with provincial panel data. *Nat. Hazards* **2015**, *76*, 1079–1091. [CrossRef]
56. Andersen, P.; Petersen, N.C. A procedure for ranking efficient units in data envelopment analysis. *Manag. Sci.* **1993**, *39*, 1261–1264. [CrossRef]
57. Dantas, M. Are ESG Funds More Transparent? 2021. Available online: https://ssrn.com/abstract=3269939 (accessed on 10 March 2021).
58. Cortes, G.S.; Gao, G.P.; Silva, F.B.; Song, Z. Unconventional monetary policy and disaster risk: Evidence from the subprime and COVID–19 crises. *J. Int. Money Financ.* **2022**, *122*, 102543. [CrossRef] [PubMed]
59. Dedola, L.; Georgiadis, G.; Gräb, J.; Mehl, A. Does a big bazooka matter? Quantitative easing policies and exchange rates. *J. Monet. Econ.* **2020**, *117*, 489–506. [CrossRef]
60. Silva, F.B.G. Fiscal defcits, bank credit risk, and loan-loss provisions. *J. Financ. Quant. Anal.* **2021**, *56*, 1537–1589. [CrossRef]
61. Baker, S.R.; Bloom, N.; Davis, S.J. Measuring economic policy uncertainty. *Q. J. Econ.* **2016**, *131*, 1593–1636. [CrossRef]
62. Azzimonti, M. The politics of FDI expropriation. *Int. Econ. Rev.* **2018**, *59*, 479–510. [CrossRef]
63. Azzimonti, M. Does partisan conflict deter FDI inflows to the US? *J. Int. Econ.* **2019**, *120*, 162–178. [CrossRef]
64. Amiti, M.; Dai, M.; Feenstra, R.C.; Romalis, J. How Did China's WTO Entry Benefit Us Consumers? CEPR Discussion Paper No. DP12076. 2017. Available online: https://ssrn.com/abstract=2980856 (accessed on 5 June 2017).
65. He, A.; Xue, Q.; Zhao, R.; Wang, D. Renewable energy technological innovation, market forces, and carbon emission efficiency. *Sci. Total Environ.* **2021**, *796*, 148908. [CrossRef]
66. Pan, X.; Pan, X.; Li, C.; Song, J.; Zhang, J. Effects of China's environmental policy on carbon emission efficiency. *Int. J. Clim. Chang. Strateg. Manag.* **2019**, *11*, 326–340. [CrossRef]
67. Yao, X.; Yasmeen, R.; Padda, I.U.H.; Shah, W.U.H.; Kamal, M.A. Inequalities by energy sources: An assessment of environmental quality. *PLoS ONE.* **2020**, *15*, e0230503. [CrossRef]

68. Yan, D.; Lei, Y.; Li, L.; Song, W. Carbon emission efficiency and spatial clustering analyses in China's thermal power industry: Evidence from the provincial level. *J. Clean. Prod.* **2017**, *156*, 518–527. [CrossRef]
69. Cheng, Z.; Li, L.; Liu, J.; Zhang, H. Total-factor carbon emission efficiency of China's provincial industrial sector and its dynamic evolution. *Renew. Sustain. Energy Rev.* **2018**, *94*, 330–339. [CrossRef]
70. Rizwana, Y.; Cui, Z.; Wasi, U.H.S.; Muhammad, A.K.; Anwar, K. Exploring the role of biomass energy consumption, ecological footprint through FDI and technological innovation in B&R economies: A simultaneous equation approach. *Energy* **2022**, *244*, 122703.