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Environmental Protection Tax and Energy Efficiency: Evidence from Chinese City-Level Data

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Abstract: The aggravated global warming and energy crisis have greatly challenged the healthy and sustainable development of society worldwide. Improving energy efficiency is one of the vital ways to overcome the dilemma. Existing studies explore the impact of environmental regulation on energy efficiency; however, the potential impact of the environmental protection tax (EPT) on urban energy efficiency has received little attention. Using the panel dataset of 278 Chinese cities from 2011 to 2019, the unified efficiency index (UEI) based on a total non-radial directional distance function (TNDDF) is first used to calculate urban energy efficiency. A difference-in-differences (DIDs) model is conducted to explore the impact of the EPT policy on the urban UEI and its potential mechanisms. The findings indicate that: (1) The average UEI in cities experienced an uptrend and a downtrend during 2011–2019. The overall UEI levels were low, especially in Jiaxiaguan, Tianshui, and Huyang cities. (2) The EPT policy significantly increases energy efficiency for the heavily polluting cities by approximately 5.21% more than that of the non-heavily polluting cities. (3) Heterogeneity analysis shows that EPT has a better effect on improving UEI in higher-level economic and non-resource-based cities. (4) Mechanism analysis implies that EPT boosts the urban UEI by stimulating urban green technology innovation, upgrading the industrial structure, and introducing foreign direct investment. This study offers empirical evidence and implications for policymakers using EPT to achieve higher urban energy efficiency and sustainable targets.

Keywords: environmental protection tax; urban energy efficiency; green technology innovation; industrial structure; foreign direct investment

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1. Introduction

With the highest economic growth rate and remarkable achievements, China's economy has grown significantly since the reform and opening up [1]. However, as one of the largest developing countries, China's rapid economic expansion depends on considerable environmental pollution and energy consumption, which has hugely aggravated global warming and led to poor living conditions and poor social health [2]. The environmental pollution and energy crisis have already become the main bottlenecks for the green and health development of China. Accordingly, exploring low-energy consumption production methods and improving energy efficiency to curb continued climate change is one of China's most urgent concerns [3].

The Environmental Protection Tax (EPT) policy introduced in December 2016 is a breakthrough in the construction of environmental governance for the Chinese government to balance environmental conservation and economic growth. As an effective fiscal tool, it is the first tax in China that aims at environmental protection and contains mandatory and market-incentive measures [3]. Under the EPT policy, enterprises are subject to taxes for discharging four significant pollutants: air pollutants, water pollutants, solid waste, and noise. Due to the short implementation period of EPT policy in China, the literature focusing on EPT effects is not extensive [4]. Related studies proposed two main views. First, EPT policy has an impact on industrial economy performance. For example, Cheng et al. [2] found that the EPT policy can enhance the green investments of heavily polluting firms. Long et al. [3] found that the financial performance of heavily polluting companies drops after implementing EPT in a short time. Second, other studies pointed out that China's EPT can directly influence the effects of emissions reduction [5–7]. For example, Han and Li [5] found that the EPT policy in China can reduce the annual $PM_{2.5}$ concentrations in 31 provinces. Li et al. [8] demonstrated that the imposition of the EPT dramatically lowered sulfur dioxide (SO_2), nitrogen oxide (NO_x), and dust emissions. However, whether EPT policy can effectively promote cities' energy efficiency has not been addressed.

The core objective of this study is to explore how EPT policy affects urban energy efficiency. We chose Chinese cities as a setting to explore this research question for three reasons. First, urbanization has accelerated significantly in the last few decades [9]. Cities in China account for more than 70% of the GDP and have contributed to remarkable achievements in high-speed economic development. However, the price of economic prosperity is considerable environmental pollution and energy consumption. Therefore, exploring appropriate environmental policies to boost energy efficiency at the city level has become imperative. Second, the promulgation of the EPT policy is an exogenous shock that could provide an experimental scene for testing the "Porter effect" of environmental regulation and a valuable opportunity to identify how the green tax system affects urban energy efficiency. Third, our results offer valuable insights into the effectiveness of the EPT policy in China, which also provides empirical evidence from emerging markets for expanding the "Porter effect" theory's scope.

Using the total TNDDF to calculate China's urban unified efficiency index (UEI) from 2011 to 2019, we conduct the first study that quantifies the impacts of the EPT policy on urban energy efficiency. In addition, we further explore the mechanisms of influence and heterogeneous effects. This study advances the existing field of literature in three ways. First, it is a valuable addition to the literature on the sustainable impacts of EPT policy. Existing studies have examined the EPT policy's economic and air pollution effects, but the impact of the EPT policy on energy efficiency remains unknown [2,5,8]. This study, for the first time, examines whether EPT policy has affected urban energy efficiency and identifies a green tax policy as another important measure for boosting energy efficiency. Thus, the empirical evidence enriches the literature on environmental governance. Second, we chose the TNDDF method to calculate the energy efficiency of 278 Chinese cities from 2011 to 2019. Compared with other methods, the TNDDF method is more in line with the production expectation of maximizing desirable output while minimizing undesirable output [10]. The measurement helps to scientifically reveal the updated trends and problems of energy efficiency in Chinese cities. Third, we applied a difference-in-differences (DIDs) model to avoid biased estimation and provide policymakers with a better evaluation of the EPT policy's net impact. In addition, we also provide insights into the mechanisms by which the EPT policy influences the urban UEI and its heterogeneity, which deepens our understanding of the influence process of EPT policy and offers implications for policymakers in formulating and implementing EPT policy to better achieve sustainable development targets.

The following is an arrangement of the article's content. The literature review is discussed in Section 2. The institutional background and research hypothesis are introduced in Section 3. The research design is presented in Section 4. Empirical findings and robustness tests are presented in Sections 5 and 6. In Section 7, conclusions and policy implications are discussed.

2. Literature Review

This research is closely linked to two bodies of literature. The first focuses on measuring energy efficiency, while the second primarily considers how environmental policy and energy efficiency are related.

2.1. Measurement of Energy Efficiency

The data envelopment analysis (DEA) method has the advantage of considering multiple inputs and multiple output elements simultaneously. Meanwhile, the DEA method does not require the prior specification of functional forms. Considering the advantages, an increasing number of studies use the DEA method to calculate energy efficiency [11–13]. Traditional DEA techniques generally use the Shepard distance function (SDF), which sets the same increased number of all output elements [14]. However, the increase in desirable output accompanied by a decrease in non-desirable output is more in accordance with the expectation. To solve the limitations of the SDF, the directional distance function (DDF) was developed by Chambers et al. [15]. The DDF can simultaneously enlarge desirable output and contract undesirable output, which aligns more with our expectations. Chung et al. [16] are the first to employ this method to evaluate the productivity efficiency of the pulp and paper sector in Switzerland. Considering the environmental factor, Färe et al. [17] created an environmental DDF and used it to evaluate coal-fired plants' environmental efficiency in the United States. However, this method has limitations because it assumes that undesirable output contraction and desirable output expansion are strictly proportionate [18,19]. Notably, if there is slack, the calculation will be overestimated [19]. Additionally, if there is only one input factor, such as energy input, DDF is unable to handle the scenario [20]. To tackle these constraints, the non-radial directional distance function (NDDF) is created and adds slack considerations [21,22]. The NDDF was first defined and used by Zhou et al. [23], who evaluated power plants' energy and CO_2 emission performance across 126 countries, changing the assumption that the desirable and undesirable output must be contracted and expanded proportionately. Afterward, the NDDF method is frequently employed to evaluate the efficiency of various research objectives, particularly research on Chinese fossil fuel power plants [24,25]. A meta-frontier NDDF method was created by Yao et al. [26] and was used to calculate regional energy efficiency. Similarly, Li and Lin [27] also used the NDDF method to measure energy efficiency from a regional perspective. Using a micro-level dataset, TNDDF was first used by Zhang et al. [10] to quantify the energy efficiency of China's mining enterprises. The measurement of energy efficiency at the city level has, however, received little research attention.

Overall, extensive studies have measured energy efficiency from regional, provincial, industry, and enterprise perspectives. Studies on measurement or topics related to city energy efficiency are limited. Compared to other methods, the TNDDF method for calculating energy efficiency is consistent with the production expectation of maximizing desirable output while minimizing unwanted output [10]. However, existing studies have mainly applied this method to the energy efficiency measurement of power plants and various industries. To the best of our knowledge, it has not been used in any of the previous studies to calculate urban energy efficiency. Therefore, this paper calculates 278 prefecture-level cities by the TNDDF method, which is significant for future studies on energy efficiency at the city level.

2.2. Environmental Policy and Energy Efficiency

The impact of environmental-related policies on energy efficiency is controversial in academic circles. The neoclassical economic theory holds that environmental policy, as regulatory pressure, implies an additional burden on an organization and leads to a shift in the use of resources from traditional "production" to "pollution control" [28]. The increasing production costs and pollution control costs weaken organizations' productivity and competitiveness, hindering energy efficiency. Economists represented by Porter raised opposing views. The Porter hypothesis, which was formulated by Porter and van der Linde [29], holds that reasonable environmental regulations can mitigate the negative costs and lead to enhanced energy efficiency by promoting technological innovation and internal resource reallocation.

To achieve higher energy efficiency, many types of policies have been implemented around the world, such as state administrative orders, energy-related laws, environmental-related laws, financial subsidies, and awards [6,7,30]. Empirical studies on the links between various environmental policies and energy efficiency or productivity efficiency have sparked a lot of discussion, especially the effects of the command-and-control regulation (CCR) policy and the market-based environmental regulation (MER) policy. For instance, Metcalf [31] found that a carbon tax policy as a revenue and distributional-neutral approach can reduce U.S. greenhouse gas emissions. In the Indian cement industry, Mandal [32] discovered that environmental regulation strengthened energy efficiency. Similar conclusions also hold in European countries. Martin et al. [33] explored the impact of the carbon tax based on the UK Census of Production dataset. They argued that implementing the carbon tax reduced energy intensity by 18.1%, while carbon tax electricity consumption fell by 22.6%. Subsequently, Rivers and Schaufele [34] confirmed that the carbon tax leads to a decline in short-run gasoline demand in the Canadian province of British Columbia. Sen and Vollebergh [35] discovered that a one-euro energy tax reduced carbon emissions from the use of fossil fuels by 0.73% over the long term, using a cross-sectional dataset of OECD countries. Fu et al. [36] analyzed the emission reduction path of a high-tiered carbon tax. Chen et al. [37] found that the environmental policy mix can promote carbon emission reduction based on data from private cars. Thus, carbon or energy-related taxes are regarded as an effective MER tool for reducing carbon emissions worldwide.

As China's international economic status becomes more prominent and environmental issues become more urgent, the influence of environmental policy on carbon emissions, green production, or energy efficiency in the Chinese setting is a growing study area. For example, Si et al. [38] found that China's various energy-related policies have different impacts on regional energy consumption. Moreover, financial subsidies are more effective than other types of policies. Li et al. [39] discovered that MER policy increases environmental governance efficiency temporarily but that ongoing increases in this intensity will reduce efficiency. Energy intensity constraint policy (EICP) was found to be a hindrance to industry energy efficiency by Shao et al. [40], who used panel data from China's 36 industrial subsectors from 2001 to 2014. More recently, Han and Li [5] found that EPT policy in China can reduce the annual $PM_{2.5}$ concentrations in 31 provinces. Li et al. [8] provided empirical findings showing that pollution emissions from fossil fuel power plants in China dramatically decreased after the imposition of the EPT. Gao et al. [41] revealed that the low-carbon city pilot policy greatly improved urban energy efficiency using city-level data from 2006 to 2019. Accordingly, existing research has not found a common link between environmental policy and energy or environmental efficiency, and more empirical evidence from China is needed. Table 1 summarizes the most related literature.

In summary, existing research has not reached a common link between environmental policy and energy efficiency with various datasets, scopes, and methods; more empirical evidence from China is still needed. First, extensive existing research on energy efficiency is mainly conducted from provincial, regional, or industry perspectives, and there is still a lack of energy efficiency focus on prefectural-level cities. Provinces or regions cannot replace Chinese prefectural-level cities' unique operation mechanisms and characteristics. Thus, research exploring the measurement and determinant factors of energy efficiency from a city-level perspective is still needed. Second, existing studies mainly analyze the CCR or MER environmental policy effects and have not paid sufficient attention to the comprehensive environmental policy effects on energy efficiency, such as the EPT. EPT policy is a comprehensive environmental policy that considers both administrative order and economic incentives. Whether EPT policy can positively affect energy efficiency has not been holistically discussed before. To fill these gaps, this study initially calculates the urban UEI of 278 Chinese cities from 2011–2019 based on the NDDF method. Then, we explore the impact of the EPT policy on the urban UEI and the influencing mechanisms by using China's environmental tax reform in 2016 as a quasi-natural experiment. The findings give Chinese policymakers a theoretical basis for implementing comprehensive environmental regulation measures to achieve better urban energy efficiency.

Table 1. Summary of literature.

Author(s)	Sample	Period	Method	Result
Cheng et al. [2]	heavy-polluting firms	2015–2018	DID model	EPT policy promotes the green investments of heavy-polluting firms.
Long et al. [3]	heavily polluting industries	2015–2020	DID model	EPT policy significantly reduces the performance of heavy-polluting companies.
He et al. [42]	Listed companies	2014–2021	DID model	EPT policy significantly promotes heavy-polluting firms' ESG performance.
Han and Li [5]	31 provinces in China	2013–2018	Bayesian LASSO regression model	EPT policies improve air quality.
Li et al. [8]	30 provinces, 804 plants	July 2017 to December 2019	DID model	EPT policy significantly reduces emissions of pollutants (including sulfur dioxide (SO_2), nitrogen oxide (NO_x), and dust) from fossil fuel power plants.
Gao et al. [43]	107 cities	2015–2019	DID model	EPT policy accelerates the synergistic reduction of both pollution and carbon reduction.
Yang et al. [9]	281 cities	2005–2017	DID-model (Energy efficiency is measured by the ratio of the GDP of a city to the energy consumption of the city.	The construction of innovative cities boosts urban energy efficiency.
Li et al. [44]	271 cities	2004 to 2016	dynamic panel threshold model (undesirable SBM model)	Technical innovation has a positive effect on urban energy efficiency.
Liu et al. [45]	1370 observations at city level	2011 to 2018	dynamic panel data models (undesirable SBM model)	Digital finance can improve urban energy efficiency.
Gao et al. [41]	277 cities	2006 to 2019	DID model (undesirable SBM model)	Low-carbon city policies (LCCP) boost urban energy efficiency.

3. Background and Research Hypotheses

3.1. Institutional Background of EPT Policy in China

Environmental damage and excessive energy and resource consumption have gradually become the main bottlenecks for the healthy development of the economy. In 1982, China's State Council introduced the 'Provisional Measures on the Collection of Pollutant Discharge Fees.' [42]. The pollutant discharge fee collection standards experienced four modifications in 1998, 2003, 2007, and 2015, respectively. However, China's existing discharge fee approach has not achieved the desired effect. In contrast, a vicious circle of "pollution-treatment-re-pollution" appears in environmental governance. To this end, at the 18th and 19th National Congresses, the Chinese government emphasized the green development strategy, namely "vigorously promoting the construction of ecological civilization" [2]. To improve environmental governance and realize the green development strategy, a comprehensive policy that uses various means such as administration, economy, market, the rule of law, science and technology, and other measures is urgent. Thus, during the Third Plenary Session of the 18th Central Committee, the state endorsed the reform of transitioning pollutant discharge fees to environmental taxes in November 2013. Afterward, the Ministry of Finance, the Ministry of Environmental Protection, and the State Administration of Taxation jointly submitted an EPT policy draft. To this end, in December 2016, the Environmental Protection Tax Law of the People's Republic of China was passed. The EPT policy came into force officially on 1 January 2018 [43]. Table 2 shows the schedule of EPT formation, which was adopted from Cheng et al. [2].

The EPT policy contains the following main information: First, regions can determine their pollution collection standards. According to the EPT, the central government is responsible for building minimum standards for major pollutants, but the local governments can make the decision on adjusting the standards within ten times the minimum standards. Moreover, the governments of provinces have the right to choose major pollutants according to their local conditions and collection standards. Second, the revenues from the EPT are calculated as local government revenue. Third, the EPT policy has five chapters and

28 articles, further standardizing collection management procedures. The EPT is mainly levied on four primary pollutants: air, water, solid waste, and noise. There are a total of 117 major pollution factors on the levy scale. The implementation slogan of EPT is "who pollutes, who pays, who treats" and aims to effectively make up for the pollution by increasing enterprises' inner costs. The promulgation of the EPT policy has filled the pollution emission tax system gap and is a milestone in China's "greening tax system" process [2]. The prominent exogenous characteristics of EPT provide the opportunity to identify the EPT policy's effectiveness on urban energy efficiency.

Table 2. List of the detailed process of EPT policy in China.

Time	Relevant Events
2 May 1982	The State Council enacted the "Provisional Measures for the Collection of Pollutant Discharge Fees" on 1 July 1982.
15 August 1993	The State Planning Commission and the Ministry of Finance issued the "Notice on Collection of Sewage Discharge Fees."
2 January 2003	The State Council enacted the "Regulations on the Administration of Collection and Use of Pollutant Discharge Fees" on 1 July 2003.
1 September 2014	The "Notice on Adjusting the Collection Standards of Pollutant Discharge Fees and Other Relevant Issues" has been released.
9–12 November 2013	The Third Plenary Session of the 18th Central Committee decided to promote the reform of changing pollutant discharge fees to taxes.
13 November 2014	The "Environmental Protection Tax Law of the People's Republic of China" (draft) is submitted to the State Council.
10 June 2015	The Legislative Affairs Office of the State Council issued and published the "Environmental Protection Tax Law of the People's Republic of China" (Call for Opinions) and the explanations to the public.
5 August 2015	The Environmental Protection Tax Law was added to the legislative plan of the 12th National People's Congress Standing Committee.
29 August–3 September 2016	The 20th meeting of the 12th National People's Congress Standing Committee reviews the EPT policy draft for the first time.
25 December 2016	The EPT policy was passed.
1 January 2018	The EPT policy was formally implemented.

3.2. Research Hypothesis

3.2.1. Basic Hypothesis

The EPT policy may positively affect urban energy efficiency in the following three aspects: First, EPT policy directly increases the cost of enterprises in three ways: environmental tax costs, reducing pollution emissions costs, and penalty costs. The EPT policy set explicit environmental constraints, internalized the external cost of environmental pollution through the price mechanism, and imposed taxation on 117 major pollution factors. Under EPT policy, cities could forcibly shut down, transfer, or improve the energy efficiency of local polluting enterprises. Concerning the city's long-term sustainability and the sunk costs of the past production mode, the best choice for the city is the third one, promoting energy efficiency [41]. Second, the EPT policy has also incurred greater attention from central environmental protection and tax departments, particularly in cities with highly polluting industries. After the imposition of EPT policy, cities face higher political costs than before. To avoid being punished, cities will naturally transform or optimize their industries. Low-carbon industrial transformation will boost urban UEI. Third, the implementation of the EPT policy increased government revenue. In 2018, the Ministry of Finance of China reported that the country's EPT revenue was 15.1 billion yuan. However, revenue growth soared to 22.1 billion yuan in 2019 [2]. Thus, after the EPT policy, local governments have more monetary funds to improve cities' energy efficiency. For example, more subsidies can be used to develop environmental protection and energy-saving technologies, which are in turn beneficial for urban energy efficiency. Thereby, we propose the first hypothesis,

H1. *The implementation of EPT has a positive effect on urban energy efficiency.*

3.2.2. Mechanism Hypothesis

EPT policy may affect urban energy efficiency through three plausible channels: green technology innovation, industry structure upgrading, and FDI.

The green technology innovation effect. Strict environmental policies would stimulate companies to increase their green technology innovations to change their production mode, which can improve production efficiency and mitigate the adverse effects of treatment costs [29]. To avoid or reduce the taxation and political costs caused by the EPT policy, cities will significantly improve their green innovation capabilities to cope with environmental risks and alleviate cost pressures. On the one hand, green technology innovation can promote urban energy efficiency through directed technological change (DTC). For example, carbon storage technology, air quality management technology, and water pollution control technology can significantly reduce a city's undesirable carbon emissions, thus improving a city's energy efficiency [46]. Green innovations in heat-scavenging and end-of-pipe treatment technologies (such as waste disposal and reuse technology) can significantly lower energy consumption and reduce pollutant output [47]. On the other hand, green technology advancements can stimulate and shift production from heavy-polluted industries to environmentally sound ones, which can greatly boost the city's energy efficiency [48]. Thereby, we propose the following hypothesis:

H2: *EPT improves urban energy efficiency through green technology innovation.*

Industry structure upgrading effect. After the imposition of the EPT policy, cities are expected to reallocate their production resources to reduce pollutants. The input resources for the low-carbon, green, and clean industries will increase. In contrast, the input resources for "three high" initiatives, such as high pollution, high energy consumption, and high emission intensity, will significantly decrease. After a period, EPT will gradually gather urban resources in technology-intensive emerging industries, while resources will progressively withdraw from traditional pollution-intensive industries [49]. Thus, the EPT policy leads to an upgrade of the city's industrial structure. Moreover, the cities' industrial spatial structure will also be optimized with the "structural dividend," which can further contribute to energy efficiency. Additionally, the economies of scale that industrial agglomeration brings also reduce energy consumption and carbon emissions [41] and thus promote energy efficiency. Thus, we hypothesize that,

H3. *EPT improves urban energy efficiency by upgrading the industrial structure.*

FDI effect. EPT policy may affect urban UEI through the FDI effect. On the one hand, the polluting FDI that entered the host city market will gradually withdraw due to the constraints of the EPT. For example, cities' high-pollution and high-emission FDI face much higher tax costs than before, largely decreasing the return on total asset profit. As a result, those kinds of FDI have to be suspended or withdrawn. In contrast, the increase in high-quality FDI that entered the city will be accompanied by advanced technology knowledge and some sustainable green concepts for the host cities, which will enhance the technology innovation capability and green awareness of cities, thus promoting urban energy efficiency. In addition, foreign capital lowers the financial pressures of cities and generates green technology spillovers, which further help to improve cities' energy efficiency [41]. Thereby, we proposed the following hypothesis:

H4. *EPT improves urban energy efficiency through foreign direct investment.*

The research framework based on the hypothesis is shown in Figure 1.

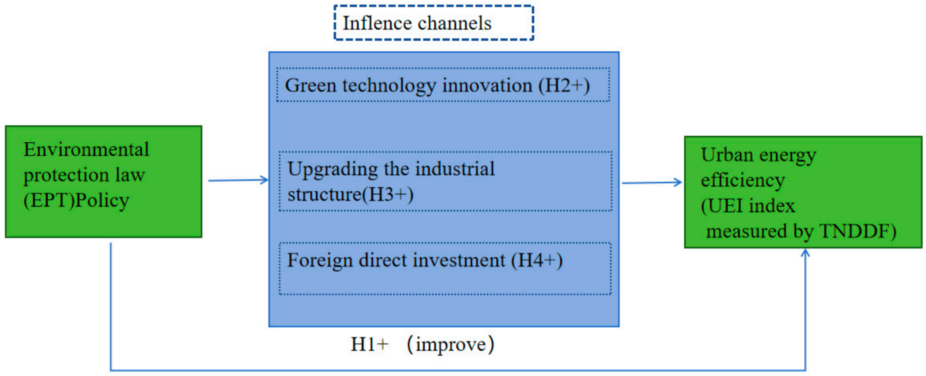

Figure 1. Conceptual framework of the research.

4. Methodology and Data Source

4.1. Measurement of Energy Efficiency

The measurement of urban energy efficiency has, however, received little research attention. As far as we could find, Yang et al. [9] use the ratio of energy consumption to GDP to calculate urban energy efficiency. Following Li et al. [45], Liu et al. [8] and Gao et al. [50] measured China's urban green energy efficiency by the same undesirable slacks-based model (SBM), and they adopted pollutants as the undesirable output. Thus, compared with the single ratio, the TNDDF considers more comprehensive factors and can reflect the reality of the energy-economic system. Compared with the undesirable SBM model, the TNDDF model can more reliably measure urban energy efficiency and is relatively more flexible. Meanwhile, it also considered the substitution effect of energy and other input elements that can simultaneously maximize expected output and minimize unexpected emissions [10]. In addition, we consider CO_2 rather than SO_2, industrial snoot, and industrial wastewater as undesirable outputs because we are not only focused on heavily polluted cities or regions. Thus, this study uses the urban unified efficiency index (UEI) by the TNDDF method. Specifically, each prefectural-level city is supposed to be a production decision-making unit (DMU). Following Färe et al. [17], each city generates desirable output Q and undesirable output C using input K, L, and E elements. Then, each city's DEA technique is denoted as follows:

$$T = \{(K, L, E, Q, C) : (K, L, E) \text{ can produce } (Q, C)\} \quad (1)$$

The following production possibility set can also be used to create the multi-output production technology:

$$P(K, L, E) = \{(Q, C) : (K, L, E, Q, C) \in T\} \quad (2)$$

Three assumptions are commonly made based on the set above:

I. Inputs and undesirable outputs are highly disposable. That is, if $(Q, C) \in P(K, L, E)$ and then $(Q', C) \in P(K, L, E)$;
II. A weakly disposable set is satisfied by the joint production set of desirable and undesirable outputs. Namely if $(Q, C) \in P(K, L, E)$ and $0 \leqslant \theta \leqslant 1$, $(\theta Q, \theta C) \in P(K, L, E)$;
III. Desirable output has no intersection with undesirable output. Then if $(Q, C) \in P(K, L, E)$ and $C = 0$, $Q = 0$;

To be more specific, it is assumed that there are $n = 1, \ldots, N$ decision-making units. Regarding the fact that returns to scale are unchanged, we formulated the production technology as follows:

$$T = \left\{ \begin{array}{c} (K, L, E, Q, C) \colon \sum_{n=1}^{N} z_n K_n \leqslant K, \sum_{n=1}^{N} z_n L_n \leqslant L, \sum_{n=1}^{N} z_n E_n \leqslant E, \sum_{n=1}^{N} z_n Q_n \geqslant Q, \\ \sum_{n=1}^{N} z_n C_n = C \end{array} \right\} \tag{3}$$

where $z_n \geqslant 0$, n = 1,2, 3, . . ., N.

Next, based on Zhou et al. [23], the TNDDF is used for measuring the energy efficiency of each DMU and can be formulated as follows:

$$\vec{D}(K, L, E, Q, C; G) = \sup\left\{ W^T B : \left(Q + \beta_Q g_Q, C - \beta_c g_C\right) \in P(K - \beta_K g_K, L - \beta_L g_L, E - \beta_E g_E) \right\} \tag{4}$$

where $W = (w_K, w_L, w_E, w_Q, w_C)^T$ represents the normalized weight matrix and indicates the relative weights of each element. The proportion that can be increased or decreased for each element is reflected by the vector of the scaling factor $B = (\mathrm{b}_K, b_L, b_E, b_Q, b_C) \geqslant 0$. We use $G = (-\mathrm{g}_K, -g_L, -g_E, g_Q, -g_C)^T$ as the directional vector. The explanations for the NDDF expressed by Equation (4) indicate: Once the production method is chosen, the producer anticipates increasing the desirable output based on the direction g_Q. Meanwhile, the producer will reduce capital investment, labor investment, energy consumption, and undesirable output based on the direction of $-\mathrm{g}_K, -g_L, -g_E, -g_C$ [10].

Considering the substitution effect between the energy input element and the other two input elements [51]. The TNDDF can be created as follows:

$$\vec{D}_T(K, L, E, Q, C; G) = \max . w_K \beta_K + w_L \beta_L + w_E \beta_E + w_Q \beta_Q + w_C \beta_C$$

$$s.t. \begin{cases} \sum_{n=1}^{N} z_n K_n \leqslant K, \sum_{n=1}^{N} z_n L_n \leqslant L, \sum_{n=1}^{N} z_n E_n \leqslant E - \beta_E g_E, \\ \sum_{n=1}^{N} z_n Q_n \geqslant Q + \beta_Q g_Q, \sum_{n=1}^{N} z_n C_n = C - \beta_C g_C \\ z_n \geqslant 0, n = 1, 2, 3, \cdots, N \text{ and } \beta_K, \beta_L, \beta_E, \beta_Q, \beta_C \geqslant 0 \end{cases} \tag{5}$$

When $\vec{D}_T(K, L, E, Q, C; G)$ = 0, the DMU of each city operates at the frontier of best practice in the direction $G = (-\mathrm{g}_K, -g_L, -g_E, g_Q, -g_C)$. Using the most commonly used weighting approach by Liu et al. [51] and Zhang et al. [10], equal importance is given to inputs, desirable output, and undesirable output in the TNDDF. Thus, $W^T = (\frac{1}{9}, \frac{1}{9}, \frac{1}{9}, \frac{1}{3}, \frac{1}{3})$ is chosen as the weight matrix. The aforementioned weight matrix is entered into Equation (5). Assuming that $B^* = (\mathrm{b}_K^*, \mathrm{b}_L^*, \mathrm{b}_E^*, \mathrm{b}_Q^*, \mathrm{b}_C^*)$ is the optimal solution, the following Equation (6) can be used to estimate each city's *UEI* under the TNDDF:

$$\begin{aligned} UEI_n &= \frac{1}{4} \left[\begin{array}{c} \frac{Q_n / K_n}{\left(Q_n + \beta_{nQ}^* Q_n\right) / \left(K_n - \beta_{nK}^* K_n\right)} + \frac{Q_n / L_n}{\left(Q_n + \beta_{nQ}^* Q_n\right) / \left(L_n - \beta_{nL}^* L_n\right)} \\ + \frac{Q_n / E_n}{\left(Q_n + \beta_{nQ}^* Q_n\right) / \left(E_n - \beta_{nE}^* E_n\right)} + \frac{Q_n / C_n}{\left(Q_n + \beta_{nQ}^* Q_n\right) / \left(C_n - \beta_{nC}^* C_n\right)} \end{array} \right] \\ &= \frac{1}{4} \left[\frac{\left(1 - \beta_{nK}^*\right) + \left(1 - \beta_{nL}^*\right) + \left(1 - \beta_{nE}^*\right) + \left(1 - \beta_{nC}^*\right)}{1 + \beta_{nQ}^*} \right] \\ &= \frac{1 - \frac{1}{4}\left(\beta_{nK}^* + \beta_{nL}^* + \beta_{nB}^* + \beta_{nC}^*\right)}{1 + \beta_{nQ}^*}, n = 1, 2, 3, \cdots, N. \end{aligned} \tag{6}$$

The *UEI* in Equation (6) ranges from 0 to 1, and the greater the value, the higher the efficiency level the city has. If the *UEI* equals the maximum value of 1, the city is at the production frontier.

4.2. DID Model for Exploring the Effects of the EPT

The DID model is popular for evaluating the effectiveness of environmental policies [40,41,52]. The DID approach treats the policy as an exogenous shock and can scientifically identify the net impact of a policy by effectively alleviating the endogeneity problem. Thus, following Shao et al. [40], this study uses the DID research design proposed by Bertrand and Mullainathan [53] to examine whether EPT policy impacts urban energy efficiency. Meanwhile, given that the data on urban energy efficiency is truncated and the value ranges from 0 to 1, we apply a Tobit regression model as follows:

$$UEI_{it} = \beta_0 + \beta_1 treat + \beta_2 time + \beta_3 time \times treat + \lambda X + \gamma_{\mathrm{t}} + \mu_i + \varepsilon_{\mathrm{it}} \tag{7}$$

where i appointed as the city, t stands for the year. UEI_{it} is the explained variable, urban energy efficiency. *time* is used as a time dummy variable that equals 1 after the EPT is introduced (after 2016) and 0 before the EPT is introduced. *treat* represents the treatment variable. The heavily polluting cities that are strongly affected by the imposition of EPT are set as the treatment group (value = 1), and the remaining sample cities are set as the control group (value = 0). (The EPT policy in China aims to internalize the social cost of environmental pollution by imposing taxes on enterprises' air, water, solid waste, and noise pollutants. Thus, implementing the EPT policy strongly influences pollution controls and constraints for producers with heavy pollution. Accordingly, we divide the sample cities into heavily polluting and low-polluting groups. Heavily polluting cities are defined as those whose industrial wastewater discharge, industrial SO_2 emissions, and industrial smoke and dust are all higher than the average values before the EPT was promulgated. Notably, highly polluting cities are significantly influenced by EPT. Thus, we treat heavily polluting cities as a treatment group. The remaining cities are low-polluting cities, which are set as the control group. As a result, 1909 observations belong to the control group, whereas 593 observations belong to the treatment group). The effect of the EPT on the city's energy efficiency is measured by the coefficient β_3 in Equation (7). X are control variables. γ_t controls the time-fixed effect, which includes any unquantified year-specific factors such as business cycles and macroeconomic influences. μ_i controls the city fixed effect, which considers any enduring variations between cities, such as geographic features. $\varepsilon_{\mathrm{it}}$ represents a random error term. Based on previous studies on the determinants of energy efficiency, the following control variables are included:

(1) Environmental regulation (*lnregulation*). Existing evidence certifies that environmental regulations have an impact on energy efficiency [50,54]. Thus, environmental regulation is expected to affect urban energy efficiency. Following the method of Zhou et al. [55], the environmental regulation index of a city is used to measure environmental regulation. Meanwhile, the improved entropy method is used to put different weights on different indicators to construct the comprehensive index. The indicators included in the comprehensive index contain industrial wastewater emissions, industrial smoke (dust) emissions, and industrial sulfur dioxide emissions. Considering emission intensity and environmental regulation intensity usually have a negative correlation, we take the inverse of the weighted index to represent *lnregulation*.

(2) Economic development level (*lnGDP*). Existing evidence has demonstrated that the level of regional economic development can influence the mode of production and energy consumption in regions [55,56]. Thus, the per capita GDP is expected to affect a city's energy efficiency. The logarithm of 1 plus the per capita GDP of each city is used in this paper.

(3) Foreign direct investment (*lnFDI*). There is an ongoing debate on whether FDI has environmental effects on the host countries, on which there are mainly two views. The "pollution haven hypothesis" holds that FDI can amplify carbon emissions and energy consumption burdens directly in the host country, which leads to a decrease in energy efficiency [46,57]. However, based on the "pollution halo effect", Antweiler et al. [58] found that the introduction of FDI can increase the inflow of technological innovation

knowledge and increase the technological spillover effect. Therefore, the FDI of a city is expected to have an influence on the city's energy efficiency. In this study, we measure the variable by using the logarithm of 1 plus the total foreign direct investment of each city.

(4) Export (*Inexport*). Export behavior is often closely related to city business activities [59]. Through the export trade, a city can gain advanced technology and business experience to promote its energy efficiency, which may have a significant influence on the city's energy efficiency. *Lnexport* is calculated by the logarithm of 1 plus the total exports in a city.

(5) Industrial structure (*lntertind*). Existing literature has shown that rationalizing and upgrading industrial structures can boost energy efficiency [46]. Thus, it is expected that a city's industrial structure may affect urban energy efficiency. To measure the industrial structure of a city, we used the ratio of the tertiary industry to the city's GDP.

(6) Freight (*lnfreight*). The production intensity of a city can be represented by its road freight, which could have an impact on the consumption of energy and pollutant emissions of cities, thereby influencing energy efficiency. We use the logarithm of 1 plus the road freight to measure the variable.

4.3. Data Description

Our study includes a sample of 278 Chinese prefecture-level cities from 2011–2019. The data used in the models are from the National Bureau of Statistics of China (NBSC), China Statistical Yearbook (CSY), China City Statistical Yearbook (CCSY), China Statistical Yearbook for Regional Economic (CSYRE), China Energy Statistical Yearbook (CESY), China Statistical Yearbook on Environment (CSYE), China Urban Construction Statistical Yearbook (CUCSY), and the State Intellectual Property Office of the People's Republic of China (SIPO). Given the absence of data for Taiwan, Hong Kong, Macao, and Tibet, cities in those areas are excluded from the sample. Moreover, we delete cities that lacked essential data either before or after implementing the environmental protection tax policy. Ultimately, the data cover 278 prefectural-level cities and 2502 observations in total from 2011 to 2019, after a series of filter matches.

4.3.1. Data for Urban Energy Efficiency Measurement

The unified efficiency index (UEI) measures urban energy efficiency. The calculation of UEI by the TNDDF method introduced in Section 4.1. In this study, capital (K), labor (L), and energy (E) are the three input indicators. We set GDP (Q) as a desirable output indicator, while CO_2 (C) is chosen as an undesirable output indicator. The five elements in TNDDF reflect energy efficiency that maximizes economic output while minimizing environmental impact. Data resources are processed as follows:

(1) Capital (K). To calculate the capital input indicator, we use the city's actual capital stock, which is calculated by the "perpetual inventory approach". The data are from the CCSY and the NBSC.

(2) Labor (L). The total labor of each city is used to measure the labor input indicator. The total number of employees in the unit plus all private and independent employees is used to calculate labor input. Data are collected from the CCSY.

(3) Energy (E). The total energy consumption of a city is used to measure the energy input indicator. The energy consumption unit is expressed in tons of coal equivalent (tcc). We compensated for the missing energy data in some cities following Yu et al. [56]. The data resources are from CSY, CCSY, and CESY.

(4) Desirable output (Q). We convert the desirable output to constant 2011 prices using each city's GDP as the desirable output indicator. The data on the GDP of each city are from CCSY.

(5) Undesirable output (C). We use each city's total CO_2 emissions to measure undesirable output indicators. The primary sources of city CO_2 emissions are direct energy use, for instance, coal gas and liquefied petroleum gas. Secondary sources of city CO_2

emissions are indirect energy use of electricity and thermal. To calculate the CO_2 emissions from direct energy use, we use the conversion coefficients provided by the IPCC [10,60]. The following is the calculation formula:

$$C = \sum_{ij} C_{\mathrm{ij}} = E_{ij} \times CAL_j \times CC_{\mathrm{j}} \times O_{\mathrm{j}} \times \frac{44}{12} \tag{8}$$

In Equation (8), i stands for city, j represents energy type. *CAL* is the net calorific value. CC means the carbon content. O refers to the rate of carbon oxidation. The rate at which carbon is converted to carbon dioxide is 44/12. In addition, following Glaeser and Kahn [61], we also consider the indirect CO_2 from electricity and thermal energy consumption in this study. Table 3 shows the descriptive statistics of the five input and output indicators used to calculate the urban *UEI*. As we could see in Table 3, the standard deviation values of the input indicators K, L, and E and the output factors Q and C are large, indicating that input and output factors between different cities are quite different, especially the capital investment, the GDP, and the total CO_2 emissions indicators.

Table 3. Descriptive statistics for input–output indicators.

Ch	Sample Size	Mean	Standard Deviation	Minimum	Maximum
K (10^8 RMB)	2502	1853.783	1942.934	35.62	24,844.25
L (10^4 persons)	2502	122.986	173.345	8.508	1729.071
E (10^4 tce)	2502	184.868	338.482	3.63	4067.33
Q (10^8 RMB)	2502	2518.183	3626.195	222.42	65,858.27
C (10^4 tons)	2502	1132.108	1632.306	15.58	14,812.43

4.3.2. Data for the DID Model

Control variables and mechanism variables are obtained from the CSY, CCSY, CUCSY, SIPO, and CSYE databases. Table 4 describes the measurement units, data source, and sample size of all variables in the DID model. The mean of UEI is 0.305, showing that the overall urban energy efficiency in China is relatively low. Furthermore, the mean of treatment is 0.237, showing that 23.7% of the samples are heavily polluted cities, while the mean of time is 0.333, indicating that the sample after the EPT policy represents 33.3% of the total samples. Additionally, the standard deviation value of *lnregulation*, *lnFDI*, *lnexport*, *lnfreight*, and *lnpatent* is high, indicating there is a large gap in environmental regulation, FDI, export, and freight between different cities.

Table 4. Descriptive statistics of econometric model variables.

Variable	Sample Size	Unit	Data Source	Mean	Standard Deviation	Minimum	Maximum
UEI	2502	—	CCSY; CSY NBSC; CESY	0.305	0.134	0.108	1
treat	2502	—	—	0.237	0.426	0	1
time	2502	—	—	0.333	0.471	0	1
lnregulation	2502	—	CCSY; CSYE	3.216	1.018	0.851	8.204
lnGDPper	2502	RMB/person	CCSY NBSC	10.697	0.57	9.091	12.503
lnFDI	2502	10^4 dollars	CCSY	9.974	1.695	4.511	14.212
lnexport	2502	10^4 RMB	CCSY; CSYRE	6.78	1.101	0.693	7.816
lntertind	2502	—	CCSY NBSC	0.348	0.089	0.052	1.644
lnfreight	2476	10^4 tons	CCSY CUCSY	9.015	1.063	0	13.225
lnpatent	2502	—	SIPO	4.343	1.723	0	10.182

5. Results and Discussion

5.1. Overall Analysis of the Energy Efficiency in Chinese Cities

To track the dynamic changes in UEI levels in 278 prefectural-level cities from 2011–2019, we use a topographic map to display the distribution of urban UEI values. The K-Means clustering method is the most common clustering technique that aims to reduce the average squared distance between points in the same cluster. Following Shi et al. [62], we use K-Means clustering method and SPSS software 26.0 to classify the energy efficiency of 278 cities. As shown in Figure 2, the sample cities are grouped into low, medium-low, medium-high, and high levels. Cities that were not included in the research sample on the map are shown by the white area. The greater the value of the urban UEI, the darker the green of the marked cities will be. Here, we only list the results for 2011, 2015, 2017, and 2019 due to space limitations.

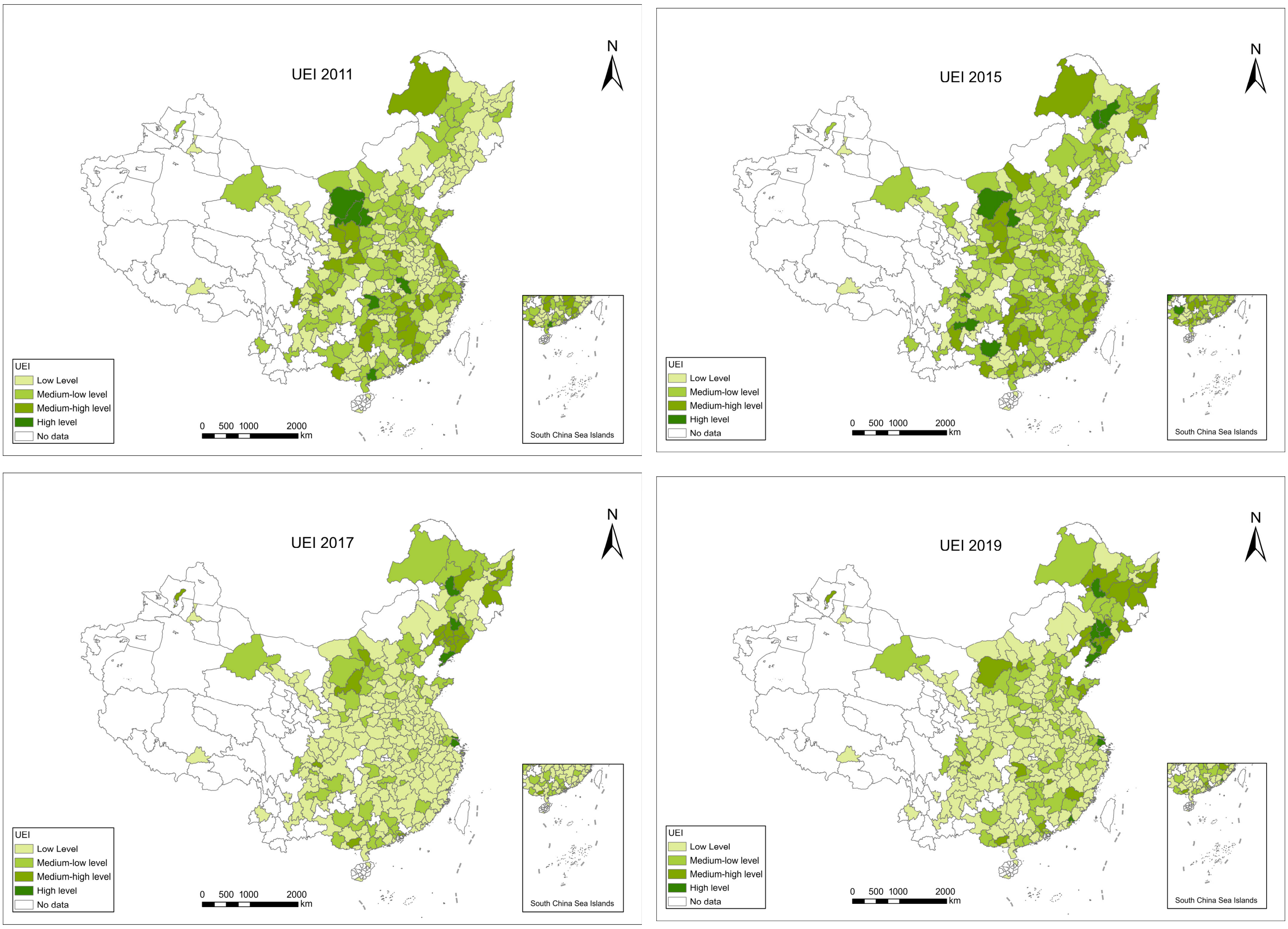

Figure 2. Trends in UEI distribution in Chinese cities.

As shown by Figure 2, an increase in the number of green cities from 2011 to 2015 is presented. However, the overall urban UEI of 2017 has decreased compared to 2015, and the color is even lighter than that of 2011. The map of 2019 is slightly greener than the map of 2017. The average UEI in cities experienced an upward and downward trend from 2011 to 2019. The average urban UEI is 0.305, which is much lower than the theoretically ideal value of 1. Thus, the overall urban UEI values are generally low, and urban UEI has a lot of room for improvement. This is probably because, in the last decade, China has been in the process of transferring from an expansive economic growth model to one that emphasizes sustainable growth [40].

When it comes to the state-quo of UEI in cities, up to the year 2019, 173 cities had a low UEI, 71 cities had a medium-low UEI, and only 26 cities and 8 cities had a medium-high UEI and a high UEI, respectively. In the UEI map of 2019, it can be seen that the darkest area appears in the city of Shanghai, in the cities of Anshan, Dalian, Shenyang, Fushun, and Tieling from Liaoning Province, in the city of Daqing from Heilongjiang Province, and in the city of Chaoshan from Guangdong Province. This is probably due to the fact that the cities with high UEI levels are located in China's northern and eastern areas, where technology and economics are more developed [63]. Cities in these areas have a large number of state-owned and high-tech industries, and they are more actively responding to environmental policies; thus, energy efficiency has improved rapidly. The UEI in cities with low values is mainly from the central and western regions, located in Fujian Province, Anhui Province, Hubei Province, Hunan Province, Henan Province, Sichuan Province, and Chongqing. The extremely low UEI values are in the cities of Jiaxiaguan, Tianshui, Lanzhou, and Baiyin from Gansu Province; city of Sanya from Hainan Province; the city of Huyang from Anhui Province; the cities of Jingzhou and Huangshi from Hubei province; and the city of Kunming from Yunnan Province. Although those cities have resource conditions, their economic level is relatively low, and the environmental policy thereby may not help. Thereby, economic development and industrial structure upgrading should be emphasized first in cities with low levels of energy efficiency.

5.2. Analysis of the Effect of the EPT Policy on Urban Energy Efficiency

The DID study design needs to meet the preconditions. Before the EPT policy shock, the UEI of the treatment and control groups selected for this study was required to show the same trend of change. As shown in Figure 3, before the year 2017, the UEI of the control group selected in this study did show exactly the same change trends compared to the treatment group. Thus, it is assumed that the treatment and control groups meet the preconditions of natural experiments. Moreover, it can also be seen that the overall average urban UEI of the control group has always been higher than that of the treatment group before 2017. However, after the EPT was introduced in 2017, the treatment group's average UEI dramatically increased and even surpassed the control group's average UEI. This is preliminary evidence that the EPT policy can probably boost heavily polluting cities' UEI. To further confirm the findings, a more rigorous test is required.

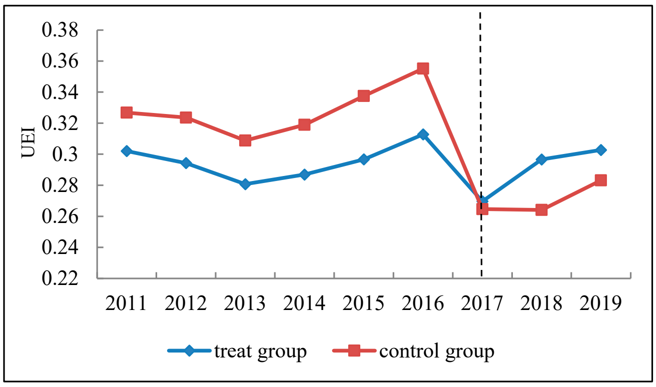

Figure 3. Trends in the UEI of the treatment and control groups.

The estimation results of Equation (7). are presented in Table 5. Column (1) reports the regression results after controlling city-fixed and year-fixed effects; the influencing coefficient of $time \times treat$ is 0.0519 and significant at the 1% level. Column (2) displays the results after controlling for the variables included. The influencing coefficient of $time \times treat$ is significant at the 1% level with a value of 0.0521. The regression results are basically unchanged. This implies that the EPT policy introduced in 2016 did significantly improve urban energy efficiency. In general, the introduction of the EPT policy led to an increase in energy efficiency for the heavily polluting cities by approximately 5.21% more than that of the cities in the control group. Thus, Hypothesis 1 is supported. Our results are similar to those of Li, and Masui, and Niu et al. [64]. They provide evidence that environmental tax shocks can influence China's energy structure and reduce carbon emissions. However, our results differ from those of Pan et al. [64], who found that strict environmental laws trigger US firms' transfer of carbon emissions and energy use rather than improve energy efficiency. The inconsistent conclusions are probably caused by different legal environments and global value chains within different countries. Therefore, the EPT policy could provide management implications for Chinese cities for boosting energy efficiency.

Table 5. Results of the benchmark regression.

Variable	Tobit	
	(1)	**(2)**
time × *treat*	0.0519 ***	0.0521 ***
	(0.00871)	(0.00876)
treat	0.182 ***	0.0375
	(0.0413)	(0.0601)
time	−0.0454 ***	−0.139 ***
	(0.00769)	(0.0214)
lnRegulation		0.00319
		(0.00517)
lnGDPper		0.160 ***
		(0.0382)
ln FDI		−0.00273
		(0.0191)
ln export		−0.00429 *
		(0.00239)
Intertind		0.0792 **
		(0.0329)
Infreight		−0.0100 ***
		(0.00264)
Constant	0.237 ***	−1.268 ***
	(0.0296)	(0.361)
Year fixed effect	yes	yes
City fixed effect	yes	yes
Observations	2502	2476

The asterisk ***, ** and * represent level of significance at 1%, 5% and 10% respectively, and similarly hereafter.

Column (2) of Table 5 also reports the estimated results of the control variables. In the regression model, the estimated coefficient of *InGDP* is significantly positive, demonstrating that an increase in GDP per capita can raise urban UEI. Our finding is consistent with previous studies [65,66]. It is further certified that economic development has a spillover technology effect of reducing emissions and saving energy consumption for cities, thereby improving urban energy efficiency. When it comes to the *Inexport* variable, the coefficient is negative and significant at the 10% level, suggesting that exports hinder the growth of the urban UEI. This phenomenon is directly related to global production relocation and the carbon transfer effect. As a large exporting powerhouse, China exports large numbers of products that need to consume substantial energy resources and emit CO_2 [67]. Thus, export trade in Chinese cities has aggravated local enterprises' pollution-intensive and energy-consuming production activities. The coefficients of the industrial structure and road freight variables are both significantly positive, indicating that optimized industrial and city road freight also play important roles in promoting the city's UEI.

5.3. Dynamic Effect of the EPT

The baseline model results report the average impact of EPT policy on urban energy efficiency; however, they do not account for variations in the effects over time. Exploring a policy's dynamic effects is necessary, which is vital for proposing a sustainable development policy. Thus, we develop the following Equation (9) in the manner of Jacobson et al. [68] to capture the dynamic impact of EPT on urban energy efficiency:

$$UEI_{it} = \alpha_0 + \sum_{t=2011}^{2019} \alpha_t time \times treat \times year^t + \alpha_1 treat + \alpha_2 time + \lambda X + \gamma_t + \mu_i + \varepsilon_{it} \quad (9)$$

where $year^t$ stands for a dummy variable. $year^t$ equals to 1 in year t, otherwise 0. The coefficient α_t represents the EPT's dynamic impact on urban energy efficiency from 2011 to 2019. Other variables in Equation (9) have the same definitions as in Equation (7).

Table 6 reports the estimated results of Equation (9). The estimated coefficient α_t for the 2011 to 2016 period are all statistically insignificant. It illustrates that UEI in cities in the treatment group had no difference from cities in the control group before the EPT policy was implemented. Additionally, we notice that the estimated influence coefficients were significantly positive in 2018 and remained significant in 2019. The EPT policy was proposed at the end of 2016 and has been formally enforced since 2018. Thus, our findings imply that the EPT's positive effects on urban energy efficiency occurred as soon as the policy was formally set in place.

Table 6. Dynamic effect of the ETs on the UEI of prefecture city.

Variables	Coefficient	Variables	Coefficient
$time \times treat \times year^{2011}$	0.0572	*lnregulation*	0.00470
	(0.0608)		(0.00515)
$time \times treat \times year^{2012}$	0.0527	*lnGDPper*	0.150 ***
	(0.0606)		(0.0381)
$time \times treat \times year^{2013}$	0.0533	*lnFDI*	−0.00917
	(0.0605)		(0.0189)
$time \times treat \times year^{2014}$	0.0497	*lnexport*	−0.00402 *
	(0.0604)		(0.00238)
$time \times treat \times year^{2015}$	0.0440	*lntertind*	0.0669 **
	(0.0601)		(0.0328)
$time \times treat \times year^{2016}$	0.0409	Constant	−1.197 ***
	(0.0603)		(0.354)
$time \times treat \times year^{2017}$	0.0896	Year-fixed effect	yes
	(0.0600)	City-fixed effect	yes
$time \times treat \times year^{2018}$	0.117 *	Observations	2502
	(0.0602)		
$time \times treat \times year^{2019}$	0.103 *		
	(0.0600)		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6. Robustness Test

Figure 3 shows that after the promulgation of the EPT policy, the treatment group's increase in urban energy efficiency is more obvious. However, the parallel trend assumption of the DID method still has to be confirmed. It is an assumption that if there is no EPT policy, the UEI in the treatment group is expected to change in the same way as in the control group before or after the implementation of the EPT policy. However, the EPT has already been introduced, and there are also other factors during the research sample period that may affect the results. Hence, robustness tests are necessary to verify our results further.

6.1. Placebo Test

A placebo test was conducted by assigning policy time dummy variables at random due to our concern that our results would be influenced by the omitted factors rather than by the implementation of the EPT. First of all, 180 cities were chosen at random as the treatment group. Then, the remaining cities served as the control group. By using random sampling, it is possible to ensure that the independent variable $time \times treat$ in the model does not affect the dependent variable UEI. Instead, any significant findings will imply that the regression results shown above are biased. Then, the above random assignment is repeated 500 times. The estimated coefficients and p-values for the above 500 random samples are shown in the distribution in Figure 4. It is clear that all of the distributions are roughly centered at 0, and the majority of p values are higher than 0.1. Consistent with expectations, the above-estimated p values of the coefficient are shown by the right side of the vertical dotted red line. The values are outliers. Thus, our findings are not caused by other omitted factors within a city or a time.

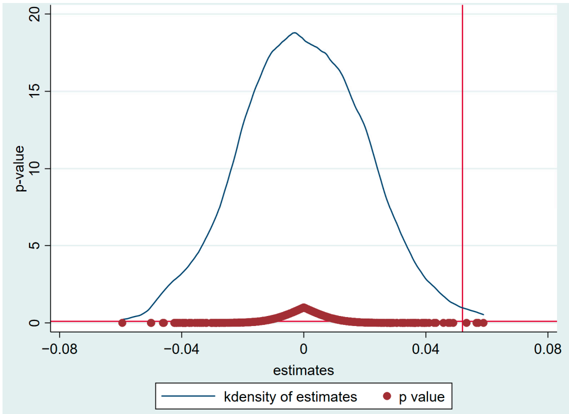

Figure 4. Results of the placebo test.

6.2. Excluding the Influence of Other Policies

The Notice on the Pilot Work of Low-carbon Provinces and Cities (LCCs), as a green program to address both energy poverty and climate change, was released by the National Development and Reform Commission (NDRC) in 2010. Since the implementation time of LCC policy partially overlaps with the research sample period of 2011–2019, it is possible that the effect of EPT on the energy efficiency of cities may be due to the LCC policy. To accurately and effectively quantify the impact of the EPT policy on the improvement in urban energy efficiency, we further control for the interference of the LCC policy on the results. Thus, in this section, we exclude all the low-carbon pilot cities between 2011 and 2019 from the original sample and conduct the regression model without the influence of the LCC policy on the results. Table 7 presents the regression results. As shown by the positive and significant coefficients in Columns (1) and (2) at the 1% level, our baseline findings are unaffected by the LCC policy. Therefore, the results are reliable.

Table 7. Results, excluding the effects of other policies.

Variable	**(1)**	**(2)**
time × *treat*	0.0404 ***	0.0422 ***
	(0.00920)	(0.00928)
treat	0.186 ***	0.0320
	(0.0413)	(0.0607)
time	−0.0374 ***	−0.141 ***
	(0.00827)	(0.0224)
LnRegulation		0.00346
		(0.00552)
LnGDPper		0.158 ***
		(0.0383)
In FDI		−0.00323
		(0.0191)
In export		−0.00551 **
		(0.00249)
Intertind		0.169 ***
		(0.0545)
Infreight		−0.00833 ***
		(0.00268)
Constant	0.232 ***	−1.274 ***
	(0.0296)	(0.362)
Year-fixed effect	yes	yes
City-fixed effect	yes	yes
Observations	2178	2153

*** $p < 0.01$, ** $p < 0.05$.

6.3. Heterogeneity Analysis

Due to China's vast territory and unbalanced spatial development, we further explore the potential heterogeneity effects of city resource dependence and level of economic development on the results.

Cities differ greatly in their reliance on resources, which may lead to heterogeneous effects from EPT. We divided the sample into two groups: resource-based cities and non-resource-based cities, respectively. The estimated results of subsamples are shown in Columns (1) and (2) of Table 8. In Column (1), the coefficient of $time \times treat$ is 0.0821 and is significant. Comparatively, in Column (2), the coefficient of $time \times treat$ is insignificant. In other words, only in non-resource-based cities does the EPT policy considerably increase energy efficiency. This is probably because the dominant industries in resource-based cities are related to natural resources, such as mineral exploitation and fossil fuel processing. The prosperity of the natural resource industry directs cities' capital and labor flow from manufacturing to mining [40]. Thus, heavy resource dependence leads to a monolithic industrial structure and resource-intensive economic growth patterns in resource-based cities. Meanwhile, the introduction of FDI into resource-based cities is also more likely to flow into resource-intensive industries, further contributing to a vast quantity of CO_2 emissions. In such situations, the EPT policy cannot play the role of promoting urban energy efficiency through reasonable industrial upgrading and FDI mechanisms. Thus, the findings indicate non-resource cities in China exhibit the resource gospel effect.

Table 8. Heterogeneity analysis results.

Variables	(1)	(2)	(3)	(4)
	Non-resource-based cities	Resource-based cities	High economic level	Low economic level
time × *treat*	0.0821 ***	0.00170	0.0401 ***	−0.000101
	(0.0104)	(0.0150)	(0.0128)	(0.0152)
treat	−0.104	0.272 **	−0.254	−0.262 *
	(0.135)	(0.129)	(0.322)	(0.138)
time	−0.209 ***	0.100 **	0.0329	−0.0894 ***
	(0.0226)	(0.0500)	(0.106)	(0.0316)
LnRegulation	−0.00362	0.00953	−0.00654	0.0106 *
	(0.00594)	(0.00936)	(0.00989)	(0.00616)
lnGDPper	0.276 ***	−0.277 ***	−0.0753	−0.0343
	(0.0395)	(0.0922)	(0.213)	(0.0588)
lnFDI	−0.0295	0.110**	0.135	0.0347 *
	(0.0192)	(0.0527)	(0.107)	(0.0202)
lnexport	−0.000291	−0.00620 *	−0.00372	−0.00210
	(0.00329)	(0.00347)	(0.00459)	(0.00261)
lntertind	0.0377	0.135 *	0.143 *	0.0731 **
	(0.0354)	(0.0698)	(0.0790)	(0.0335)
lnfreight	−0.0145 ***	−0.00434	−0.00929 **	−0.0115 ***
	(0.00423)	(0.00354)	(0.00451)	(0.00316)
Constant	−2.037 ***	1.981 **	0.000858	0.437
	(0.351)	(0.941)	(2.069)	(0.522)
Year-fixed effect	yes	yes	yes	yes
City-fixed effect	yes	yes	yes	yes
Observations	1514	962	910	1566

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Moreover, the impact of EPT on urban energy efficiency may vary depending on the economic level of the city. We divided the cities into two subsamples: high-income cities (the value of urban per capita GDP is higher than the average) and low-income cities (the value of urban per capita GDP is lower than the average). In Column (3) of Table 8, the estimated coefficient of $time \times treat$ is 0.0401 in the high economic level subsample, which is positive at the 1% significant level. Comparatively, the estimated results of the subsample of low economic development are shown in Column (4), and the coefficient of $time \times treat$ is insignificant. This indicates that EPT positively impacts urban energy efficiency only in high-income cities. This is because lower-income cities face greater financial constraints than higher-income cities. As a result, investment in green technology innovation is reduced, which prevents cities from benefiting from the spillover effect to increase energy efficiency.

6.4. Mechanism Analysis

In this section, we further explore how EPT boosts urban energy efficiency by testing three potential influencing mechanisms: the green innovation technology channel, the industry structure channel, and the FDI channel. To test the possible mechanisms, Equation (10) was used for estimation.

$$UEI_{it} = \beta_0 + \beta_1 treat + \beta_2 time + \beta_3 time \times treat + \beta_4 time \times treat \times M + \lambda X + \gamma_t + \mu_i + \varepsilon_{it} \quad (10)$$

where $time \times treat \times M$ denotes mechanism variables, which contain variables $time \times treat \times Inpatent$, $time \times treat \times Intertind$ and $time \times treat \times InFDI$, respectively. We took the logarithm of 1 plus the number of green patent applications as a measurement of the city's green technology innovation (We first collected the total number of green patent applications from the State Intellectual Property Office of China (SIPO) website. We research the applications according to the IPC classification numbers provided by the World Intellectual Property Organization (WIPO). Then match enterprises in each prefecture-level city with the number of green patents). Other variables in the Equation (10) have the same definitions in the Equation (7).

Table 9 reports the mechanism results. In Column (1), we could see that the coefficient of the interaction terms $time \times treat \times Inpatent$ is 0.0236 and is positive at the 1% significance level, indicating that EPT policy has a "Porter effect" in Chinese cities. EPT policy boosts urban UEI through low-carbon green technology, thereby significantly increasing the city's energy efficiency. Thus, research Hypothesis 2 is supported. In Column (2), we could see that the coefficient of the interaction terms $time \times treat \times Intertind$ is significant at the 1% level with a value of 0.817, suggesting that EPT significantly helps promote optimization of industrial structures in the city. Under the EPT policy, high-pollution and energy-consumption industries are curbed by high tax charges and penalties on pollutants. Meanwhile, high-tech and green service industries are encouraged by the EPT policy, which further helps to optimize industrial structure and thus promotes UEI in a city. Thereby, Hypothesis 3 is verified. Column (3) presents the FDI effect. The estimated coefficient of the interaction terms $time \times treat \times InFDI$ is significantly positive and equal to 0.0296. The evidence suggests that the EPT policy can encourage green foreign investment, through which advanced technology and green concepts are brought to cities, thus promoting the city's energy efficiency. In summary, the mechanism hypotheses are all confirmed, suggesting that EPT policy mainly enhances cities' energy efficiency through three channels: stimulating green technological innovation, upgrading industrial structure, and FDI.

Table 9. Mechanism analysis results.

Variable	(1)	(2)	(3)
$time \times treat \times Inpatent$	0.0236 ***		
	(0.00472)		
$time \times treat \times Intertind$		0.817 ***	
		(0.126)	
$time \times treat \times InFDI$			0.0296 ***
			(0.00458)
$time \times treat$	−0.0975 ***	−0.281 ***	−0.282 ***
	(0.0306)	(0.0520)	(0.0524)
treat	0.0744	0.0371	0.0348
	(0.0593)	(0.0596)	(0.0596)
time	−0.0968 ***	−0.139 ***	−0.141 ***
	(0.0219)	(0.0212)	(0.0212)
lnpatent	−0.0319 ***		
	(0.00427)		
lnregulation	0.00279	0.00321	0.00391
	(0.00509)	(0.00513)	(0.00513)
lnGDPper	0.183 ***	0.159 ***	0.160 ***
	(0.0377)	(0.0379)	(0.0379)
lnFDI	−0.00847	−0.00254	−0.00269
	(0.0188)	(0.0189)	(0.0189)

Table 9. *Cont.*

Variable	(1)	(2)	(3)
lnexport	−0.00413 *	−0.00380	−0.00400 *
	(0.00235)	(0.00237)	(0.00237)
lntertind	0.0711 **	0.0720 **	0.0883 ***
	(0.0325)	(0.0326)	(0.0327)
lnfreight	−0.00944 ***	−0.00993 ***	−0.0109 ***
	(0.00260)	(0.00261)	(0.00262)
Constant	−1.364 ***	−1.269 ***	−1.273 ***
	(0.355)	(0.358)	(0.358)
Year-fixed effect	yes	yes	yes
City-fixed effect	yes	yes	yes
Observations	2476	2476	2476

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7. Conclusions and Policy Implications

Based on a sample of 278 prefectural-level cities in China from 2011 to 2019, the effectiveness of EPT policy on urban energy efficiency has been explored in this study. Our important conclusions are as follows:

Firstly, the average UEI in cities experienced an upward and downward trend during 2011–2019. However, the overall levels were still low. There is a great deal of room for improvement in the urban UEI, especially in the cities of Jiaxiaguan, Tianshui, Lanzhou, Baiyin, Sanya, Huyang, Jingzhou, Huangshi, and Kunming. (2) The implementation of the EPT policy significantly promotes heavily polluting cities' urban UEI. Overall, the cities in the heavily polluting cities increased their energy efficiency by approximately 5.21% more than the cities in the control group. (3) Moreover, EPT policy mainly enhances cities' energy efficiency through three channels: stimulating green technological innovation, upgrading industrial structures, and FDI. (4) The positive effects of EPT policy exist mainly in non-resource-based cities and high-income cities. Our results remain consistent after robustness tests. The findings of this study have the following implications and action plans for the development of EPT policy in China and other emerging countries that face the double pressure of the coexistence of environmental protection and energy slackness.

Firstly, our empirical evidence shows that the EPT policy is an effective measure for improving urban energy efficiency, especially in heavily polluting cities; thus, the local governments, environmental protection departments, and taxation departments should join together to support and insist on enforcing the EPT policy in the long run. Although environmental protection tax is more mandatory than sewage charges, to ensure a smooth transition from tax to charge, the current EPT is relatively conservative in terms of both taxable objects and tax rates, which may result in a relatively limited effect and barriers to the promotion of energy efficiency in cities. Therefore, it is necessary to improve the implementation of EPT further. The specific action plan could be: (1) the tax rate of EPT should be set scientifically according to the damage cost of pollution; (2) the tax incentives of environmental protection tax for technological innovation and green production should be expanded to realize the economic effect of technological innovation; and (3) the effective cooperation between local government, environmental protection departments, and tax departments should be strengthened. The collection and management of EPT should be enhanced to ensure that the EPT can effectively restrain sewage disposal behaviour and eliminate the highly polluting and energy-consuming production model so as to promote urban energy efficiency. (4) The tax revenue from the EPT should be used effectively for the purpose of protecting the environment rather than obtaining fiscal revenue. Therefore, the revenue from EPT should be used to combat pollution and energy savings or compensate for damages caused by pollution, especially the environmental inequity caused by pollution discharge between regions, which can be considered to be coordinated and solved by EPT.

Secondly, our results indicate that the EPT policy mainly enhances cities' energy efficiency through three channels; thereby, the local government could go beyond its policy and focus on relevant supporting measures, including emphasizing cities' innovation capabilities, speeding industrial structure upgrading, and attracting green FDI. For example, the detailed action plans in the future process of promoting urban energy efficiency could be: (1) the establishment of a special technology transformation fund by the Ministry of Ecology and Environment in conjunction with the Ministry of Industry and Information Technology can support and guide industrial enterprises lacking innovative capacity in upgrading their processes and carrying out green technological transformation to accelerate the realization of cleaner production-type technological progress by traditional industrial enterprises. (2) Preferential environmental protection taxation and government green innovation subsidies can be given to local enterprises and high-end technical personnel to boost green technology innovation in cities. (3) Market mechanisms such as taxation and trading to combat pollution should be further explored. Specifically, the scope of EPT policy can be further expanded, for example, by exploring the imposition of a carbon tax; the incentives provided by market-oriented policies to enterprises for technological innovation can be strengthened, which could adjust the industrial structure and FDI to meet the needs of the cities or regions in terms of economic and social development to promote urban energy efficiency.

Lastly, our findings also indicate that the effect of EPT policy on energy efficiency enhancement is better in developed and non-resource-based cities; the policy arrangement could work better if it is tailored to the characteristics of the city. For example, local governments in developed and non-resource-based cities can appropriately raise the tax rate and improve the taxation collection methods based on the actual local cities' conditions. For resource-based and lower economic-level cities, local governments should strengthen the coordination between EPT and other policies and take multiple measures to encourage the restructuring of the urban energy consumption pattern.

Considering some limitations of our work, future research directions could proceed with the following approaches: First, this study only considers EPT at the level of whether the policy is introduced or not and has not considered the specific content of the tax. In light of this, it will be interesting to further research whether the environmental tax price or rate has an impact on cities' UEI. For example, Shanxi Province in China is a typical coal-energy region, ranked first in China. However, the environmental tax rate in Shanxi Province is very low. Thus, whether the tax rate influences its energy efficiency is quite interesting. Second, China's double-carbon targets have become a hot topic globally; future research can be carried out on how the green tax reform relates to the targets. For example, it would be possible to consider reforming the environmental protection tax targets for individual consumption to achieve carbon peaking and carbon neutrality more quickly.

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Abbreviations

UEI	Unified Efficiency Index
TNDDF	Total-factor Non-radial Directional Distance Function
DID	Difference-In-Difference
EPT	Environmental Protection Tax law
CER	Command-and-control Environmental Regulation
MER	Market-based Environmental Regulation
CSY	China Statistical Yearbook
CCSY	China City Statistical Yearbook
NBSC	The National Bureau of Statistics of China
CESY	China Energy Statistical Yearbook
CSYRE	China Statistical Yearbook for Regional Economic
CSYE	China Statistical Yearbook on Environment,
CUCSY	China Urban Construction Statistical Yearbook
SIPO	The State Intellectual Property Office of the People's Republic of China

References

1. Wang, M.; Feng, C. The Win-Win Ability of Environmental Protection and Economic Development during China's Transition. *Technol. Forecast. Soc. Change* **2021**, *166*, 120617. [CrossRef]
2. Cheng, B.; Qiu, B.; Chan, K.C.; Zhang, H. Does a Green Tax Impact a Heavy-Polluting Firm's Green Investments? *Appl. Econ.* **2022**, *54*, 189–205. [CrossRef]
3. Long, F.; Lin, F.; Ge, C. Impact of China's Environmental Protection Tax on Corporate Performance: Empirical Data from Heavily Polluting Industries. *Environ. Impact Assess. Rev.* **2022**, *97*, 106892. [CrossRef]
4. Wang, Y.; Yu, L. Can the Current Environmental Tax Rate Promote Green Technology Innovation?—Evidence from China's Resource-Based Industries. *J. Clean. Prod.* **2021**, *278*, 123443. [CrossRef]
5. Han, F.; Li, J. Assessing Impacts and Determinants of China's Environmental Protection Tax on Improving Air Quality at Provincial Level Based on Bayesian Statistics. *J. Environ. Manag.* **2020**, *271*, 111017. [CrossRef]
6. Lu, J. Can Environmental Protection Tax Aggravate Illegal Pollution Discharge of Heavy Polluting Enterprises? *Environ. Sci. Pollut. Res.* **2022**, *29*, 33796–33808. [CrossRef] [PubMed]
7. Niu, T.; Yao, X.; Shao, S.; Li, D.; Wang, W. Environmental Tax Shocks and Carbon Emissions: An Estimated DSGE Model. *Struct. Change Econ. Dyn.* **2018**, *47*, 9–17. [CrossRef]
8. Li, P.; Lin, Z.; Du, H.; Feng, T.; Zuo, J. Do Environmental Taxes Reduce Air Pollution? Evidence from Fossil-Fuel Power Plants in China. *J. Environ. Manag.* **2021**, *295*, 113112. [CrossRef]
9. Yang, J.; Xiong, G.; Shi, D. Innovation and Sustainable: Can Innovative City Improve Energy Efficiency? *Sustain. Cities Soc.* **2022**, *80*, 103761. [CrossRef]
10. Zhang, Y.; Li, X.; Jiang, F.; Song, Y.; Xu, M. Industrial Policy, Energy and Environment Efficiency: Evidence from Chinese Firm-Level Data. *J. Environ. Manag.* **2020**, *260*, 110123. [CrossRef]
11. Wang, J.-M.; Shi, Y.-F.; Zhang, J. Energy Efficiency and Influencing Factors Analysis on Beijing Industrial Sectors. *J. Clean. Prod.* **2017**, *167*, 653–664. [CrossRef]
12. Wu, H.; Hao, Y.; Ren, S.; Yang, X.; Xie, G. Does Internet Development Improve Green Total Factor Energy Efficiency? Evidence from China. *Energy Policy* **2021**, *153*, 112247. [CrossRef]
13. Zhang, Y.; Song, Y. Environmental Regulations, Energy and Environment Efficiency of China's Metal Industries: A Provincial Panel Data Analysis. *J. Clean. Prod.* **2021**, *280*, 124437. [CrossRef]
14. Shephard, R.W. *Theory of Cost and Production Functions*; Princeton University Press: Princeton, NJ, USA, 1970.
15. Chambers, R.G.; Chung, Y.; Färe, R. Benefit and Distance Functions. *J. Econ. Theory* **1996**, *70*, 407–419. [CrossRef]
16. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and Undesirable Outputs: A Directional Distance Function Approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [CrossRef]
17. Färe, R.; Grosskopf, S.; Pasurka, C.A. Environmental Production Functions and Environmental Directional Distance Functions. *Energy* **2007**, *32*, 1055–1066. [CrossRef]
18. Zhang, N.; Choi, Y. A Note on the Evolution of Directional Distance Function and Its Development in Energy and Environmental Studies 1997–2013. *Renew. Sustain. Energy Rev.* **2014**, *33*, 50–59. [CrossRef]
19. Fukuyama, H.; Weber, W.L. A Directional Slacks-Based Measure of Technical Inefficiency. *Socio Econ. Plan. Sci.* **2009**, *43*, 274–287. [CrossRef]
20. Sueyoshi, T.; Goto, M. DEA Approach for Unified Efficiency Measurement: Assessment of Japanese Fossil Fuel Power Generation. *Energy Econ.* **2011**, *33*, 292–303. [CrossRef]
21. Barros, C.P.; Managi, S.; Matousek, R. The Technical Efficiency of the Japanese Banks: Non-Radial Directional Performance Measurement with Undesirable Output. *Omega* **2012**, *40*, 1–8. [CrossRef]

22. Färe, R.; Grosskopf, S. Directional Distance Functions and Slacks-Based Measures of Efficiency. *Eur. J. Oper. Res.* **2010**, *200*, 320–322. [CrossRef]
23. Zhou, P.; Ang, B.W.; Wang, H. Energy and CO_2 Emission Performance in Electricity Generation: A Non-Radial Directional Distance Function Approach. *Eur. J. Oper. Res.* **2012**, *221*, 625–635. [CrossRef]
24. Zhang, N.; Kong, F.; Choi, Y.; Zhou, P. The Effect of Size-Control Policy on Unified Energy and Carbon Efficiency for Chinese Fossil Fuel Power Plants. *Energy Policy* **2014**, *70*, 193–200. [CrossRef]
25. Zhang, N.; Choi, Y. Total-Factor Carbon Emission Performance of Fossil Fuel Power Plants in China: A Metafrontier Non-Radial Malmquist Index Analysis. *Energy Econ.* **2013**, *40*, 549–559. [CrossRef]
26. Yao, X.; Zhou, H.; Zhang, A.; Li, A. Regional Energy Efficiency, Carbon Emission Performance and Technology Gaps in China: A Meta-Frontier Non-Radial Directional Distance Function Analysis. *Energy Policy* **2015**, *84*, 142–154. [CrossRef]
27. Li, J.; Lin, B. Does Energy and CO_2 Emissions Performance of China Benefit from Regional Integration? *Energy Policy* **2017**, *101*, 366–378. [CrossRef] [PubMed]
28. Gray, W.B. The Cost of Regulation: OSHA, EPA and the Productivity Slowdown. *Am. Econ. Rev.* **1987**, *77*, 998–1006.
29. Porter, M.E.; van der Linde, C. Toward a New Conception of the Environment-Competitiveness Relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118. [CrossRef]
30. Leinert, S.; Daly, H.; Hyde, B.; Gallachóir, B.Ó. Co-Benefits? Not Always: Quantifying the Negative Effect of a CO_2-Reducing Car Taxation Policy on NO_x Emissions. *Energy Policy* **2013**, *63*, 1151–1159. [CrossRef]
31. Metcalf, G.E. Designing a Carbon Tax to Reduce U.S. Greenhouse Gas Emissions. *Rev. Environ. Econ. Policy* **2009**, *3*, 63–83. [CrossRef]
32. Mandal, S.K. Do Undesirable Output and Environmental Regulation Matter in Energy Efficiency Analysis? Evidence from Indian Cement Industry. *Energy Policy* **2010**, *38*, 6076–6083. [CrossRef]
33. Martin, R.; de Preux, L.B.; Wagner, U.J. The Impact of a Carbon Tax on Manufacturing: Evidence from Microdata. *J. Public Econ.* **2014**, *117*, 1–14. [CrossRef]
34. Rivers, N.; Schaufele, B. Salience of Carbon Taxes in the Gasoline Market. *J. Environ. Econ. Manag.* **2015**, *74*, 23–36. [CrossRef]
35. Sen, S.; Vollebergh, H. The Effectiveness of Taxing the Carbon Content of Energy Consumption. *J. Environ. Econ. Manag.* **2018**, *92*, 74–99. [CrossRef]
36. Fu, M.; Wu, W.; Tian, L.; Zhen, Z.; Ye, J. Analysis of Emission Reduction Mechanism of High-Tiered Carbon Tax under Green and Low Carbon Behavior. *Energies* **2023**, *16*, 7555. [CrossRef]
37. Chen, W.; Wu, X.; Xiao, Z. Impact of Environmental Policy Mix on Carbon Emission Reduction and Social Welfare: Scenario Simulation Based on Private Vehicle Trajectory Big Data. *Energies* **2023**, *16*, 5839. [CrossRef]
38. Si, S.; Lyu, M.; Lin Lawell, C.-Y.C.; Chen, S. The Effects of Energy-Related Policies on Energy Consumption in China. *Energy Econ.* **2018**, *76*, 202–227. [CrossRef]
39. Li, H.; Zhu, X.; Chen, J.; Jiang, F. Environmental Regulations, Environmental Governance Efficiency and the Green Transformation of China's Iron and Steel Enterprises. *Ecol. Econ.* **2019**, *165*, 106397. [CrossRef]
40. Shao, S.; Yang, Z.; Yang, L.; Ma, S. Can China's Energy Intensity Constraint Policy Promote Total Factor Energy Efficiency? Evidence from the Industrial Sector. *Energy J.* **2019**, *40*, 101–128. [CrossRef]
41. Gao, D.; Li, Y.; Li, G. Boosting the Green Total Factor Energy Efficiency in Urban China: Does Low-Carbon City Policy Matter? *Environ. Sci. Pollut. Res.* **2022**, *29*, 56341–56356. [CrossRef]
42. He, Y.; Zhao, X.; Zheng, H. How Does the Environmental Protection Tax Law Affect Firm ESG? Evidence from the Chinese Stock Markets. *Energy Econ.* **2023**, *127*, 107067. [CrossRef]
43. Gao, X.; Liu, N.; Hua, Y. Environmental Protection Tax Law on the Synergy of Pollution Reduction and Carbon Reduction in China: Evidence from a Panel Data of 107 Cities. *Sustain. Prod. Consum.* **2022**, *33*, 425–437. [CrossRef]
44. Li, G.; Gao, D.; Li, Y. Dynamic Environmental Regulation Threshold Effect of Technical Progress on Green Total Factor Energy Efficiency: Evidence from China. *Environ. Sci. Pollut. Res.* **2021**, *29*, 8804–8815. [CrossRef] [PubMed]
45. Liu, Y.; Xiong, R.; Lv, S.; Gao, D. The Impact of Digital Finance on Green Total Factor Energy Efficiency: Evidence at China's City Level. *Energies* **2022**, *15*, 5455. [CrossRef]
46. 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]
47. Xie, X.; Zhu, Q.; Wang, R. Turning Green Subsidies into Sustainability: How Green Process Innovation Improves Firms' Green Image. *Bus. Strategy Environ.* **2019**, *28*, 1416–1433. [CrossRef]
48. Du, K.; Li, P.; Yan, Z. Do Green Technology Innovations Contribute to Carbon Dioxide Emission Reduction? Empirical Evidence from Patent Data. *Technol. Forecast. Soc. Change* **2019**, *146*, 297–303. [CrossRef]
49. Xu, X.; Xu, X.; Chen, Q.; Che, Y. The Impact on Regional "Resource Curse" by Coal Resource Tax Reform in China—A Dynamic CGE Appraisal. *Resour. Policy* **2015**, *45*, 277–289. [CrossRef]
50. Gao, D.; Mo, X.; Xiong, R.; Huang, Z. Tax Policy and Total Factor Carbon Emission Efficiency: Evidence from China's VAT Reform. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9257. [CrossRef]
51. Liu, H.; Li, J.; Long, H.; Li, Z.; Le, C. Promoting Energy and Environmental Efficiency within a Positive Feedback Loop: Insights from Global Value Chain. *Energy Policy* **2018**, *121*, 175–184. [CrossRef]

52. Zhang, Y.; Song, Y.; Zou, H. Transformation of Pollution Control and Green Development: Evidence from China's Chemical Industry. *J. Environ. Manag.* **2020**, *275*, 111246. [CrossRef] [PubMed]
53. Bertrand, M.; Mullainathan, S. Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *Am. Econ. Rev.* **2004**, *94*, 991–1013. [CrossRef]
54. Zhao, X.; Mahendru, M.; Ma, X.; Rao, A.; Shang, Y. Impacts of Environmental Regulations on Green Economic Growth in China: New Guidelines Regarding Renewable Energy and Energy Efficiency. *Renew. Energy* **2022**, *187*, 728–742. [CrossRef]
55. Zhou, Q.; Zhang, X.; Shao, Q.; Wang, X. The Non-Linear Effect of Environmental Regulation on Haze Pollution: Empirical Evidence for 277 Chinese Cities during 2002–2010. *J. Environ. Manag.* **2019**, *248*, 109274. [CrossRef] [PubMed]
56. Ouyang, X.; Shao, Q.; Zhu, X.; He, Q.; Xiang, C.; Wei, G. Environmental Regulation, Economic Growth and Air Pollution: Panel Threshold Analysis for OECD Countries. *Sci. Total Environ.* **2019**, *657*, 234–241. [CrossRef] [PubMed]
57. Cole, M.A.; Elliott, R.J.R.; Okubo, T. Trade, Environmental Regulations and Industrial Mobility: An Industry-Level Study of Japan. *Ecol. Econ.* **2010**, *69*, 1995–2002. [CrossRef]
58. Antweiler, W.; Copeland, B.R.; Taylor, M.S. Is Free Trade Good for the Environment? *Am. Econ. Rev.* **2001**, *91*, 877–908. [CrossRef]
59. Ren, S.; Liu, D.; Li, B.; Wang, Y.; Chen, X. Does Emissions Trading Affect Labor Demand? Evidence from the Mining and Manufacturing Industries in China. *J. Environ. Manag.* **2020**, *254*, 109789. [CrossRef]
60. Mi, Z.; Meng, J.; Guan, D.; Shan, Y.; Song, M.; Wei, Y.-M.; Liu, Z.; Hubacek, K. Chinese CO2 Emission Flows Have Reversed since the Global Financial Crisis. *Nat. Commun.* **2017**, *8*, 1712. [CrossRef]
61. Glaeser, E.L.; Kahn, M.E. The Greenness of Cities: Carbon Dioxide Emissions and Urban Development. *J. Urban Econ.* **2010**, *67*, 404–418. [CrossRef]
62. Shi, F.; Liao, X.; Shen, L.; Meng, C.; Lai, Y. Exploring the Spatiotemporal Impacts of Urban Form on CO_2 Emissions: Evidence and Implications from 256 Chinese Cities. *Environ. Impact Assess. Rev.* **2022**, *96*, 106850. [CrossRef]
63. Wang, K.; Yu, S.; Zhang, W. China's Regional Energy and Environmental Efficiency: A DEA Window Analysis Based Dynamic Evaluation. *Math. Comput. Model.* **2013**, *58*, 1117–1127. [CrossRef]
64. Pan, L.; Han, W.; Li, Y.; Wu, H. Legitimacy or Efficiency? Carbon Emissions Transfers under the Pressure of Environmental Law Enforcement. *J. Clean. Prod.* **2022**, *365*, 132766. [CrossRef]
65. Wang, J.; Zhao, T. Regional Energy-Environmental Performance and Investment Strategy for China's Non-Ferrous Metals Industry: A Non-Radial DEA Based Analysis. *J. Clean. Prod.* **2017**, *163*, 187–201. [CrossRef]
66. Xiong, S.; Ma, X.; Ji, J. The Impact of Industrial Structure Efficiency on Provincial Industrial Energy Efficiency in China. *J. Clean. Prod.* **2019**, *215*, 952–962. [CrossRef]
67. ul Haq, I.; Zhu, S.; Shafiq, M. Empirical Investigation of Environmental Kuznets Curve for Carbon Emission in Morocco. *Ecol. Indic.* **2016**, *67*, 491–496. [CrossRef]
68. Jacobson, L.S.; LaLonde, R.J.; Sullivan, D.G. Earnings Losses of Displaced Workers. *Am. Econ. Rev.* **1993**, *83*, 685–709.