

Article

The Energy-Saving Effect of E-Commerce Development—A Quasi-Natural Experiment in China

Mengyao Liu, Yan Hou and Hongli Jiang *

School of Finance and Economics, Jiangsu University, Zhenjiang 212013, China;
3190806010@stmail.ujs.edu.cn (M.L.); jsdxhy@stmail.ujs.edu.cn (Y.H.)

* Correspondence: 1000004098@ujs.edu.cn

Abstract: This study provides a viable path to save energy by means of e-commerce development. Taking the national e-commerce demonstration cities (NEDC) pilots policy implemented in China as a quasi-natural experiment, based on the city panel data from 2006 to 2019, this study applies the multi-period difference-in-difference (DID) method to evaluate the effect of NEDC on energy saving in pilot cities. The empirical results suggest that the NEDC policy obviously contributes to energy conservation. The treated cities reduced energy consumption by 14.2% as a result of the implementation of NEDC, relative to the untreated cities. The conclusions remain valid after conducting robustness tests such as placebo test, instrumental variables regression, propensity score matching-difference-in-difference (PSM-DID), and synthetic difference-in-difference (SDID). The NEDC achieves energy-saving effects through technological innovation, industrial restructuring, and economic agglomeration. Furthermore, the heterogeneity analysis indicates that, in cities with high levels of human capital, well-developed information infrastructure, non-resource-based cities, and favorable business environments, the impact of NEDC on energy saving is more significant. Analysis of spatial effects shows that the implementation of NEDC has negative externalities, increasing energy consumption in the surrounding area. In the context of the digital economy, this paper presents new insights on the relationship between e-commerce and energy consumption and provides policy direction for countries looking for energy-saving solutions.

Keywords: national e-commerce demonstration cities (NEDC) policy; energy saving; low-energy transformation; difference-in-difference (DID) model



Citation: Liu, M.; Hou, Y.; Jiang, H. The Energy-Saving Effect of E-Commerce Development—A Quasi-Natural Experiment in China. *Energies* **2023**, *16*, 4718. <https://doi.org/10.3390/en16124718>

Academic Editor: Dimitrios Katsaprakakis

Received: 8 April 2023
Revised: 12 June 2023
Accepted: 12 June 2023
Published: 14 June 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The industrial era, which has driven economic development, has also brought new crises to human civilization. With the continuous advancement of industrialization and modernization, global energy consumption has grown rapidly. The rapid growth of the population and large-scale industrial production have also led to a swift increase in energy demand. The rigid demand for energy and the finite nature of energy resources have led to a pronounced contradiction between energy supply and demand. In recent years, the global energy crisis has been exacerbated by issues such as the COVID-19 epidemic and political instability [1]. In addition, greenhouse gases and pollution generated by the combustion of fossil fuels are significant factors contributing to climate change, prompting countries to strengthen their management of energy consumption [2]. The “BP World Energy Statistics Report” (2022) indicates that global primary energy consumption was 595.15 EJ in 2021, a 40.11% increase compared to 2000. Of this total, China’s primary energy consumption accounts for 26.5% of the global share, ranking first in the world in 2021. China’s economy has experienced flourishing growth since reform and opening up [3]. However, in the early stages of development, China’s economic growth model was characterized by high energy consumption and low efficiency [4], and the extensive economic model severely hindered the sustainable development of the socio-economy [5]. Therefore, it is imperative

for China's economy to transition towards a high-quality development path, with energy saving as a key priority [6].

Since the "11th Five-Year Plan" proposed energy saving and emission reducing targets, China has continuously strengthened the implementation of energy conservation measures and issued a series of related policies. In 2021, the National Development and Reform Commission issued the "Scheme for Improving Energy Consumption Intensity and Total Control Dual-Control System", followed by the "14th Five-Year Plan for Modern Energy System" in 2022. In order to maintain economic growth while saving energy, China is vigorously promoting low-energy and green transformation within its economic growth model. The National E-commerce Demonstration Cities (NEDC) pilots program aims to save energy and drive the green economy growth. In September 2009, China officially authorized the creation of the first NEDC pilot in Shenzhen, aiming to popularize e-commerce within three years. In 2011, 2014, and 2017, China approved the construction of 23, 30, and 17 cities as e-commerce demonstration cities, respectively.

The new economic model represented by e-commerce has been the driving force of China's green and sustainable economic development [7] and a significant symbol of China's low-energy economic transformation [8]. According to the "China E-commerce Report," China's e-commerce transaction volume reached CNY 9.6 trillion in the first quarter of 2022. As an innovative commercial activity, e-commerce plays an integral part in the transformation of the economic model and has far-reaching impacts on society and the economy [9]. While enhancing China's economic vitality, e-commerce has inevitably had a substantial impact on energy consumption.

Previous studies regarding the effect of e-commerce on energy have been limited and their conclusions are inconsistent. Although some scholars agree that e-commerce can increase energy consumption, their views on the sources of increased energy consumption vary. Williams [10] suggested that the energy consumption of B2C e-commerce in Japan is higher than that of traditional retail due to additional packaging. Based on a structured literature review, Palsson et al. [11] argued that packaging and transportation in e-commerce channels increase energy consumption. Dost and Maier [12] applied the empirical dynamic model to the relationship between e-commerce and energy, concluding that the increase in energy consumption due to e-commerce is mainly in the residential and commercial sectors, rather than the transportation sector. However, some studies show that e-commerce can reduce energy consumption. Weber et al. [13] concluded that the energy use of e-commerce is lower compared to traditional retail. The dematerialization mode innovation of e-commerce on the consumption and logistics sides also improves energy utilization efficiency and saves energy of goods [14]. Other scholars have a neutral view that the influence of e-commerce on energy consumption has both advantages and disadvantages [15].

Since the implementation of the NEDC policy, most of the related literature has focused on using the multi-period difference-in-difference (DID) method to assess the effect of NEDC policy implementation on green development, pollution, and greenhouse gas emissions. Cao et al. [16] believed that the green total factor productivity in NEDC pilot cities has increased by an average of 1.24%, with a greater effect seen in China's central and western cities and resource-based cities. Zhang et al. [17] argued that the NEDC has reduced pollution in pilot cities by an average of 17.5%. Wang et al. [18] suggested that NEDC policy has led to varying degrees of reduction in the consumption of chemical fertilizers, nitrogen fertilizers, pesticides, and crop film in urban areas. Wang et al. [9] concluded that NEDC has significantly reduced carbon emissions, with optimized resource allocation, saved energy, and upgraded industrial structure as the main mechanisms. A natural problem is that of how NEDC policy influences energy consumption. Is the effect positive or negative? To our knowledge, there have been no studies assessing the effect of NEDC policy on energy consumption.

Theoretically, due to the progress of information technology, e-commerce accelerates the flow of information, benefiting enterprises in technological innovation, leading to increased production efficiency and reduced energy waste [19,20]. Additionally, e-

commerce integrates information technology into traditional industries, making them more information-driven and intelligent. Increasing the proportion of high value-added and high-tech industries, and accelerating industrial upgrading are effective measures to save energy [21]. Furthermore, NEDC preferential policies attract talent, capital, and enterprises to migrate to pilot cities, resulting in an agglomeration of economic spatial patterns. Economic agglomeration is beneficial for large-scale production, reducing energy waste caused by logistics transportation and production inefficiency [22]. Based on 2006–2019 panel data for prefecture-level cities in China, we investigate the energy-saving effect of NEDC policy using the multi-period DID model. Moreover, we analyze the mechanism of NEDC policy's influence on energy consumption using the intermediary effect model, and explore its heterogeneity using group regression. Further, we explore the spatial spillover effects to analyze the effect of the NEDC on energy saving in the surrounding areas.

The marginal contributions of this paper are shown below. First, by using China as a case study, this paper discusses the issue of energy conservation from the viewpoint of e-commerce growth, offering empirical evidence from an emerging economy. Our findings reveal that the NEDC policy has remarkable energy-saving benefits. Second, we investigate the mechanisms by which the NEDC policy impacts energy consumption. The results demonstrate that the NEDC policy fosters technological innovation, upgrades the industrial structure, and encourages economic agglomeration, ultimately leading to a reduction in energy consumption. Third, we explore the heterogeneity of impact of the NEDC policy on energy consumption. Our study shows that the energy-saving effect of the policy is more significant in areas with higher levels of human capital, well-developed information infrastructure, and favorable business environments. Finally, utilizing a spatial econometric model, we explore the spatial spillover effects of the NEDC policy on energy consumption. We discover that, while the NEDC policy curtails local energy consumption, it inadvertently increases energy consumption in surrounding regions. This study not only enriches the comprehension of the economic consequences of NEDC policy and the driving factors behind energy conservation, but also offers valuable insights for the design of energy-saving policies.

The remaining structure of this paper is shown below. Section 2 presents the policy background and theoretical frame. Section 3 shows the method and data. Section 4 analyzes benchmark regression results, robustness tests, influence mechanisms, heterogeneity, and spatial spillover effect. Section 5 concludes and makes policy suggestions.

2. Policy Background and Theoretical Frame

2.1. Policy Background

To accelerate the e-commerce development, China released its first e-commerce plan, the “E-commerce Development Eleventh Five-Year Plan”, in June 2007. To further facilitate the sustainable expansion of e-commerce, and fully unleash its potential in optimizing resource allocation, saving energy, and developing green economy, China's National Development and Reform Commission formally allowed Shenzhen to establish the first NEDC pilot in 2009. In November 2011, 22 cities were approved as the first batch of national e-commerce demonstration cities. The second batch of 30 cities were approved to build national e-commerce demonstration cities in 2014, with renewed emphasis on accelerating the transition to a green economy and saving energy. China added 17 cities as the third batch of NEDC pilots in 2017. The distribution of cities in each batch is shown in Figure 1. In total, 70 cities nationwide have been approved as NEDC pilots. The construction of NEDC has promoted the prosperous growth of urban e-commerce, increased the share of the tertiary sector, and optimized the industrial structure. Simultaneously, it has contributed to reducing material resource and energy consumption and fostering a green economy.

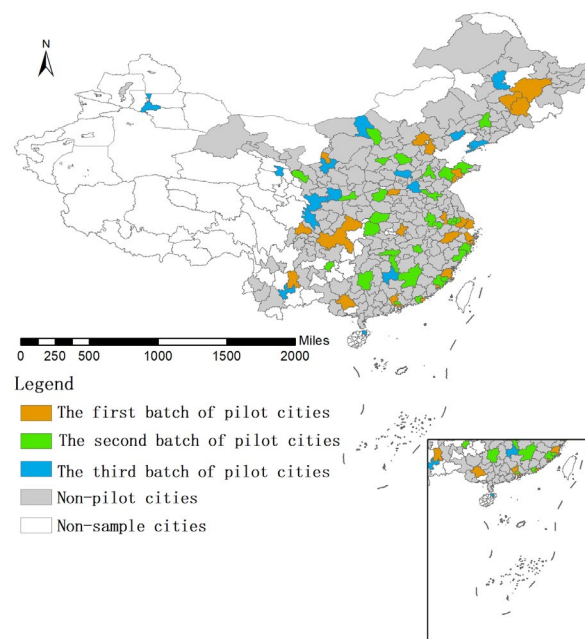


Figure 1. NEDC pilot cities distribution map.

2.2. Theoretical Frame

E-commerce, a combination of digital techniques and commercial model innovation, is significantly impacted by the construction of the policy pilot of NEDC. This leads to the increasing use of e-commerce and encourages businesses to adopt more advanced digital technologies. E-commerce introduces digital technology into the manufacturing industry chain and supply chain, facilitating the upgrade of manufacturing industry [9]. The use of emerging technology reduces information gathering costs and promotes efficient matching between supply and demand sides [23]. Furthermore, the matching of supply and demand optimizes the efficiency and level of factor allocation for enterprises, effectively reducing resource waste. Additionally, the construction of NEDC policy increases supply information transparency, resulting in more efficient division of labor and cooperation while presenting economic agglomeration in the spatial form of the economy. The economies of scale brought about by industrial agglomeration make a significant contribution to improving the overall output efficiency of the region, reducing backward production capacity. Driven by NEDC policy, e-commerce becomes an essential factor in transforming economic growth and achieving economic growth that is less dependent on resource use and environmental damage. Based on the emerging business model, NEDC policy facilitates reasonable configuration of resources and saves energy through the sustainable transformation of the traditional supply chain.

H1. NEDC policy has a significant effect on energy saving.

The rapid progress of the internet presents opportunities for e-commerce to flourish. The increased level of internet development not only improves technological innovation and energy efficiency but also promotes definite improvements in productivity across industries [19]. The increased level of internet development further enhances the role of technological innovation in saving energy. From the perspective of enterprises, the development of e-commerce enables knowledge and technology to circulate at a lower cost, which reduces the cost for enterprises to acquire innovation factors and cultivate their innovation capabilities. On the other hand, e-commerce allows efficient matching of supply and demand information. The supply side receives information from the demand side faster, and competition among enterprises intensifies, driving them to accelerate technological innovation. Technological innovation enables companies to develop clean energy to replace

traditional energy sources. Technological innovation is an effective measure to achieve energy saving [20]. As a result of technological innovation, the level of energy conservation and the efficiency of energy use in enterprises have increased, significantly achieving an energy-saving effect [24].

H2. NEDC policy is conducive to saving energy by technological innovation.

The development of NEDC policy leads to a significant increase in the economic share of the service sector and promotes the upgrading of the industrial structure. In particular, the introduction and application of e-commerce bring a series of information technology innovations. E-commerce integrates information technology into traditional industries, promoting the digitalization and intelligence of these industries. The introduction of digital technology accelerates the transition to higher value-added industries, ultimately leading to an upgrade of the industrial structure [25]. To a certain extent, the features of the industrial structure determine the layout of energy consumption [16]. The upgrade of industrial structure has led to a lower share of energy-intensive industries, resulting in less energy consumption. Industrial structure optimization is an efficient measure to reduce energy consumption [26].

H3. NEDC policy is conducive to saving energy by industrial restructuring.

NEDC pilot cities formulate various preferential policies to encourage e-commerce transactions. These preferential policies attract human resources and capital to the pilot cities, exhibiting aggregation in spatial patterns. Furthermore, the integrated planning of urban e-commerce infrastructure development is one of the main tasks of NEDC policy. A wide coverage information network and modern logistics and storage facilities build a platform for the flourishing growth of e-commerce while attracting enterprises to migrate to the pilot cities. Economic agglomeration has a spillover effect, and resources, technology, talent and other factors are fully shared and spread [22]. The agglomeration of a large number of enterprises allows the technology and knowledge of energy saving and energy efficiency improvement to be disseminated, thus promoting energy saving. The economic agglomeration effect plays an irreplaceable role in saving energy [22]. A high degree of economic agglomeration tends to result in high energy use efficiency and sustainable environmental conditions [27].

H4. NEDC policy is conducive to saving energy by economic agglomeration.

In this paper, a system theoretical framework is constructed, as shown in Figure 2.

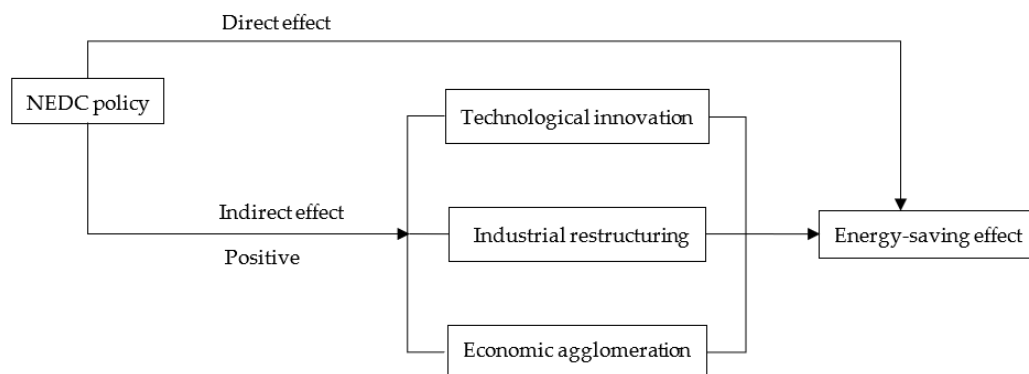


Figure 2. Theoretical framework chart.

3. Methodology and Data

3.1. Model Construction

3.1.1. Baseline Regression Model

The DID approach treats new policy as a natural experiment exogenous to the economic system, thus avoiding endogeneity problems. The NEDC pilot policy creates differences not only before and after the implementation of the policy in the same pilot region, but also between the pilot and non-pilot regions at the same point in time. The basic idea of the DID method is to perform a first difference to derive the amount of change before and after the policy implementation in the experimental and control groups, followed by a second difference between the changes in the two groups to eliminate the incremental change over time. The net effect of policy implementation is obtained after the two differences. The DID method is now widely used in policy evaluation [28,29]. The approval of the initial NEDC pilots in 2011 constructed a quasi-natural experiment between pilot and non-pilot cities in China. This was followed by two additional batches of NEDC pilot cities in 2014 and 2017, resulting in two more shocks. Due to the staggered timing of these shocks, this paper employs a multi-period DID model to study the impact of NEDC policy on energy consumption, as represented by Equation (1).

$$EC_{it} = \beta_0 + \beta_1 Treat_i \times Time_t + \gamma Control_{it} + \delta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i and t represent city and year. EC_{it} represents the logarithm of the energy consumption in the city i in the year t . $Treat_i \times Time_t$ is the explanatory variable. $Control$ is a series of control variables that affect energy consumption, including population density (PD), foreign direct investment (FDI), research and development ($R\&D$) investment intensity (RD), gross domestic product per capita ($PGDP$), environmental regulation (ER), and urbanization rate (UR). δ_i is a city fixed effect and λ_t is a time fixed effect. ε_{it} denotes the error term.

3.1.2. Intermediary Effect Model

Following the impact mechanisms discussed above, the implementation of NEDC policy affects energy saving through technological innovation, industrial restructuring and economic agglomeration. Drawing on Baron and Kenny [30], we build the intermediary effect model to verify Hypotheses 2–4, as shown in Equations (2) and (3).

$$MV_{it} = \alpha_0 + \alpha_2 Treat_i \times Time_t + \gamma Control_{it} + \delta_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$EC_{it} = \beta_0 + \beta_1 Treat_i \times Time_t + \beta_2 MV_{it} + \gamma Control_{it} + \delta_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where MV_{it} is the mediating variable, which represents the technological innovation (TI), industrial structure (IS), and economic agglomeration (EA), respectively.

3.2. Variables

3.2.1. Explained Variable

The explanatory variable is energy consumption (EC). Referring to Xue et al. [31], the variable of energy consumption is expressed as the logarithm of the total regional energy consumption.

3.2.2. Explanatory Variable

This study views NEDC construction as a quasi-natural experiment. The explanatory variable is the multiplicative term $Treat_i \times Time_t$ of the policy dummy variable $Treat_i$ and the time dummy variable $Time_t$. $Treat_i$ is equal to 1 if the city is an e-commerce demonstration city; otherwise, it equals 0. $Time_t$ equals 1 for every year after the city as an e-commerce demonstration city; otherwise, it equals 0.

3.2.3. Control Variables

Drawing on previous research [5,6,32,33], we chose the following control variables. Population density (*PD*) is defined as the population per square kilometer of land area. The migration of people to cities has led to a rapid expansion of urban resources, resulting in a massive increase in energy consumption. Foreign direct investment intensity (*FDI*) is measured by the ratio of regional FDI volume to regional GDP. FDI not only facilitates energy conservation, but also enhances environmental benefits [34]. R&D investment intensity (*RD*) is calculated by the percentage of regional internal expenditure on R&D to regional GDP. Government R&D subsidies can increase enterprises' R&D investment and improve their technological innovation [35]. The higher the level of R&D, the more advanced the technology, thus reducing energy consumption [36]. Gross domestic product per capita (*PGDP*) is measured as the ratio of regional GDP to the number of people in the region. Economic growth is the crucial factor driving the growth of energy consumption. Environmental regulation (*ER*) is calculated using the relative levels of the weighted average urban emissions intensity of each type of pollution. Command-based and market-oriented environmental regulation have a positive effect on energy- and environment-related technological progress [37], which contributes significantly to energy conservation. Urbanization rate (*UR*) is defined by the percentage of the city's resident population to total population. Urbanization is a consequence of social and economic structural transition and is closely linked to energy consumption [38].

3.2.4. Mediating Variables

The mediating variables are technological innovation (*TI*), industrial structure (*IS*), and economic agglomeration (*EA*). Technological innovation (*TI*) is represented by the quantity of patents issued during the year [39]. Industrial structure (*IS*) is measured in terms of the proportion of the tertiary sector to the secondary sector [6]. Economic agglomeration (*EA*) is characterized as the percentage of urban non-agricultural output to the area of that city [40].

3.3. Data Sources

This paper constructs a panel data set of 283 prefecture-level cities in China for the period 2006–2019. Compared to existing studies using data as late as 2016, this paper extends the time period of the study to 2019, thus allowing the phased impact of NEDC construction on energy saving to be studied over a longer time frame. The data are mainly obtained from the “China City Statistical Yearbook”, the statistical bureaus of each prefecture-level city, CSMAR Database, and government work reports of each prefecture-level city. Table 1 demonstrates the results of the descriptive statistics. Overall, Guangdong Province and Henan Province have higher population densities, with Zhanjiang City and Zhengzhou City at the top. Tongchuan and Zigong have the highest foreign direct investment. Southern cities have a higher intensity of R&D investment than northern cities. The GDP per capita in Huzhou City, Guangdong Province, in 2017 was the highest in recent years. Shanxi Province has an overall high level of environmental regulation, and Shenzhen has the highest urbanization rate.

Table 1. Descriptive statistics.

	Variables	Obs.	Mean	SD.	Min	Max
Explained variable	<i>EC</i>	3962	4.402	1.270	0.089	8.311
Explanatory variable	$Treat_i \times Time_t$	3962	0.108	0.310	0.000	1.000
Control variables	<i>PD</i>	3962	3.781	2.777	0.144	20.093
	<i>FDI</i>	3962	0.022	0.055	0.000	1.282
	<i>RD</i>	3962	0.238	0.392	0.001	8.293
	<i>PGDP</i>	3962	4.293	3.231	0.277	38.241
	<i>ER</i>	3962	1.003	1.252	0.008	32.865
	<i>UR</i>	3962	0.517	0.161	0.153	1.000

4. Empirical Results

First, this paper uses the DID model constructed above to test whether there is an energy-saving effect of the NEDC policy, that is, to verify whether Hypothesis 1 is valid. A parallel trend test is used to examine whether the pilot areas and non-pilot areas have the same development trend before the policy occurs, which means that the DID method is applicable. To confirm the robustness of the baseline regression results, the paper uses five methods: placebo test, PSM-DID, instrumental variables approach, excluding other policies, replacing explanatory variables, and SDID. To explore the Hypotheses 2–4 inferred from the theory, we use an intermediary effect model to verify three mechanisms of technological innovation, industrial restructuring and economic agglomeration. Further, this paper regresses the sample groups to investigate whether the effect of NEDC policy has different degrees of effect due to different urban characteristics. To deepen the study, this paper chooses a spatial econometric model to investigate whether there is a spillover effect of the implementation of NEDC policy on the surrounding areas, and, if there is a spillover effect, whether it is positive or negative. The research framework of this paper is shown in Figure 3.

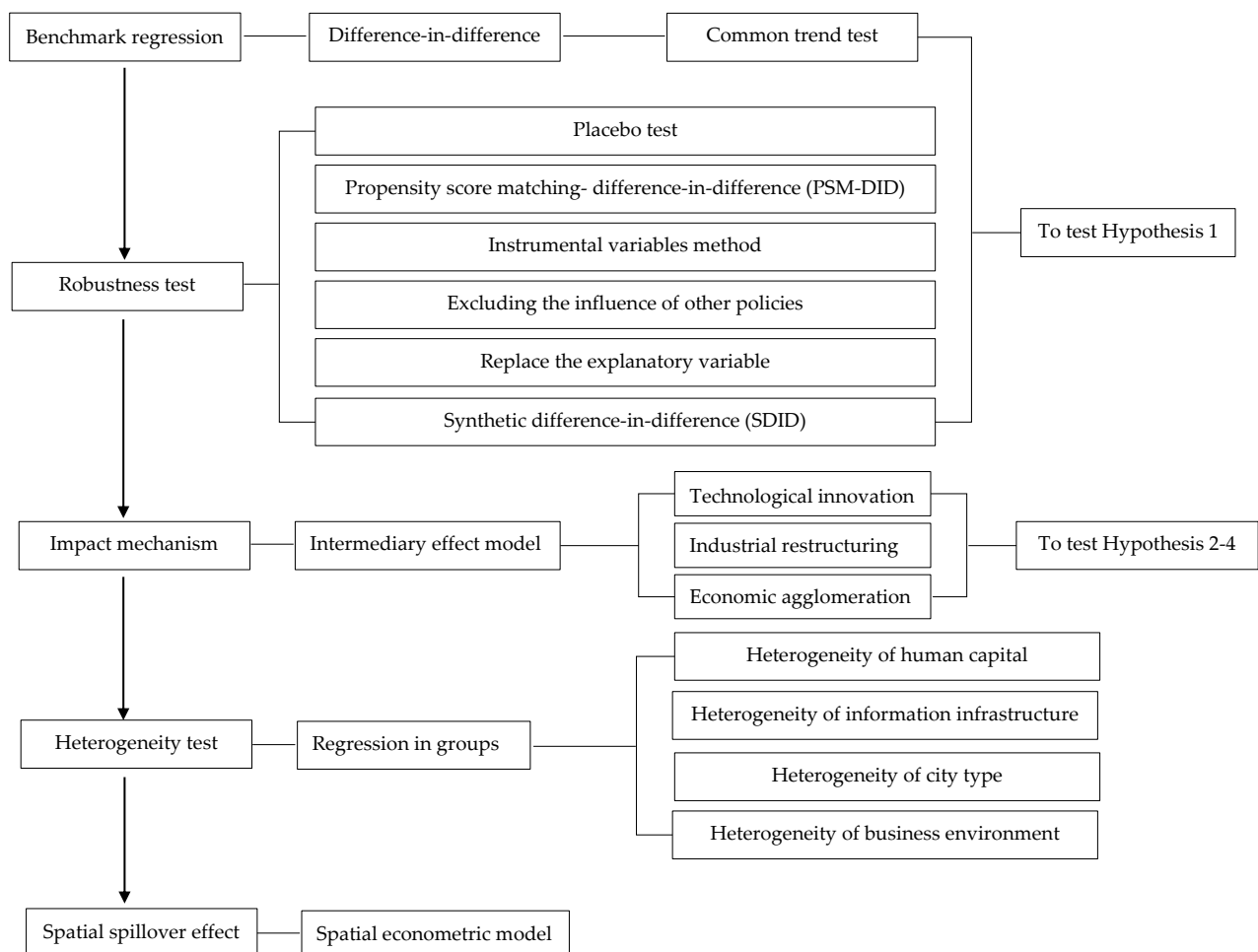


Figure 3. Empirical research process diagram.

4.1. Benchmark Regression Results

The regression results of Equation (1) are shown in Table 2. Columns (1) and (2) contain city fixed effects and time fixed effects, while column (2) adds six control variables to column (1). Regression coefficients $Treat_i \times Time_t$ are significantly negative at the 1% level regardless of whether or not control variables are contained, indicating that the construction of NEDC policy achieves significant energy-saving effects in the pilot cities.

Specifically, from column (2), the regression coefficient is -0.142 , showing that the NEDC policy achieves energy-saving effects in the pilot cities of 14.2% on average. Therefore, hypothesis 1 is confirmed.

Table 2. Benchmark regression estimation results.

Variables	(1)	(2)
	EC	EC
$Treat_i \times Time_t$	-0.169^{***} (0.027)	-0.142^{***} (0.028)
PD		-0.001 (0.005)
FDI		-0.232 (0.506)
RD		0.005 (0.014)
PGDP		-0.008 (0.007)
ER		0.003 (0.007)
UR		1.697^{***} (0.238)
Constant	4.420^{***} (0.007)	3.581^{***} (0.125)
Year-FE	YES	YES
City-FE	YES	YES
Obs.	3962	3962
R-squared	0.915	0.917

Note: robust standard errors in parentheses. *** represents the significance at 1% level.

4.2. Common Trend Test

A prerequisite for assuring that DID regression estimates are unbiased is that the experimental and control groups meet the assumption of parallel trends prior to the construction of the NEDC [41]. If the estimated coefficient is not significant before the NEDC policy occurs, then the parallel trend test is valid [42]. Referring to Beck et al. [43], we use the event study method to test the parallel trend hypothesis, as in Equation (4).

$$EC_{it} = \beta_0 + \sum_{j=2}^{11} \beta_j d_{i,n+t} + \gamma Control_{mit} + \delta_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where $d_{i,n+t}$ is a dummy variable that is equal to 1 when the NEDC policy is implemented before or after k year. γ is the regression coefficient of control variables.

As seen from Figure 4, it is clear that the explanatory variable is significantly different from the control groups before the policy implementation, which means that the prerequisite for using the DID model is satisfied.

4.3. Robustness Test

4.3.1. Placebo Test

It is possible that the differences in the experimental and control groups observed after policy application were caused by other policies or unobservable elements. To avoid biased results, we performed the placebo test. We randomly generated 70 false experimental groups and assigned a value of 1 to the dummy variable $Treat_i$ for the false experimental group and 0 to the dummy variable $Treat_i$ for the false control group. We repeated this random sampling 1000 times and performed regression using the baseline model. The placebo test results are presented in Figure 5, which indicates that the regression coefficients of $Treat_i \times Time_t$ based on the false pilot cities were clustered around 0 and different from

the true regression coefficient of -0.142 . As evidenced by the majority of p -values being larger than 0.1 , the regression coefficients for the randomly selected experimental groups were not significant at the 10% level. These results suggest that the energy-saving effect observed in the pilot cities in the baseline regression results is attributable to the NEDC policy and not due to other factors.

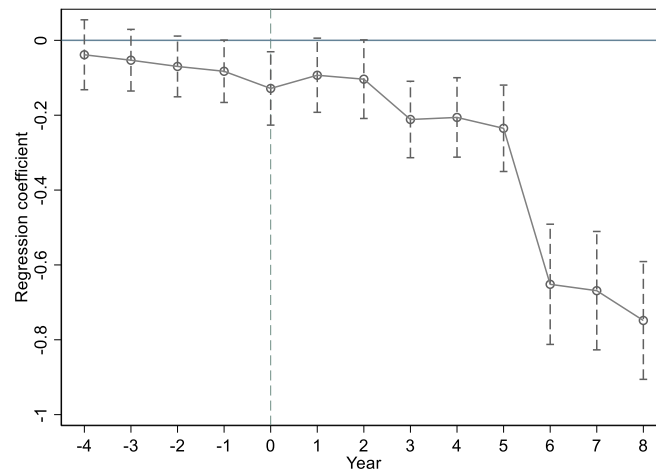


Figure 4. Common trend test chart.

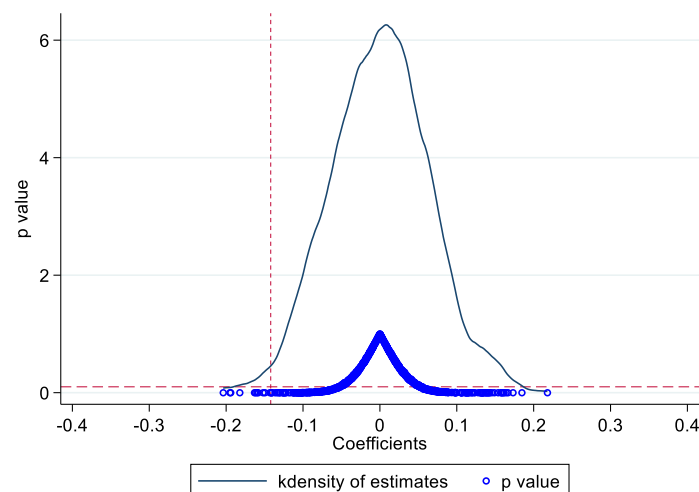


Figure 5. Placebo test chart.

4.3.2. Propensity Score Matching-Difference-in-Difference (PSM-DID)

When using the DID method for policy evaluation, it is important to ensure that the experimental and control groups are similar in characteristics. However, given the significant variation in factors such as economic development and informatization levels among Chinese cities, there is a risk of sample self-selection bias. To address this, the paper employs the PSM-DID method. First, this paper uses population density (PD), foreign direct investment intensity (FDI), R&D investment intensity (RD), gross domestic product ($PGDP$), environmental regulation (ER), and urbanization rate (UR) as matching variables, and calculates propensity scores using Probit model regression. The experiment and control groups are then matched based on the propensity score values, and results are regressed and estimated by DID model on the matched samples. The paper uses both nearest neighbor matching and caliper matching methods. The results of PSM-DID in Table 3 demonstrate that the impact of NEDC policy on energy saving is significantly negative in both matching methods. This further supports the empirical findings that the NEDC policy has significantly achieved energy-saving effects in the pilot cities.

4.3.3. Instrumental Variables Method

The results of benchmark regression may be biased by endogenous problems. For example, the choice of NEDC pilots can be due to energy problems. To address this, a two-stage least squares regression using the instrumental variables method is presented in this paper. Many studies have used historical information as the main strategy to address endogenous problems [44]. The growth of e-commerce is closely linked to internet technology, which is a continuation of traditional communication technology. The telecommunications infrastructure affects the subsequent development and application of subsequent internet technology [45]. Communication tools such as fixed telephones and post offices are essential media for traditional trading transactions, and regions with historically developed communication have relatively high levels of e-commerce development. Therefore, this study selects the number of fixed telephones and post offices in 1984 as instrumental variables for NEDC construction [46]. However, because the raw data are cross-sectional, previous studies have used the multiplied terms of internet penetration in the previous year in each city with the number of fixed phones in 1984 and the number of post offices in 1984 as the final instrumental variables [47,48], which are denoted by $Tele \times IPR$ and $Post \times IPR$, respectively. The internet penetration is characterized by the number of internet broadband access subscribers in the region. Columns (1) and (2) of Table 4 present the results for instrumental variable $Tele \times IPR$, and columns (3) and (4) present the results for instrumental variable $Post \times IPR$. Columns (1) and (3) are the first stage of the two-stage least squares regression and the results indicate that both instrumental variables are valid. Columns (2) and (4) are the second-stage regression results, and the coefficients $Treat_i \times Time_t$ are both significantly negative, consistent with the benchmark regression results of the impact of e-commerce on energy saving.

Table 3. Regression results of PSM-DID.

	(1)	(2)
	Nearest Neighbor Matching	Caliper Matching
	EC	EC
$Treat_i \times Time_t$	−0.118 * (0.062)	−0.135 *** (0.028)
Control	YES	YES
Constant	5.534 *** (0.259)	3.541 *** (0.127)
Year-FE	YES	YES
City-FE	YES	YES
Obs.	548	3937
R-squared	0.953	0.918

Note: robust standard errors in parentheses. * and *** represent the significance at 10% and 1% levels, respectively.

4.3.4. Excluding the Influence of Other Policies

The energy-saving effect may be influenced by other policies implemented during the same period. We exclude policies that could potentially affect energy consumption to further investigate whether the situation of NEDC saving energy still exists. China implemented three batches of national low-carbon city pilot policies (LCCP) in 2010, 2012, and 2017 to address climate change. In 2011, China initiated pilot projects for carbon emissions trading (CETP). The Broadband China Pilot Policy (BCPP) was launched in 2013, and three batches of 120 BCPP pilot cities were selected in 2014, 2015, and 2016. Additionally, in 2017, China created green finance reform and innovation pilot zones (GFPZ) in six provinces and energy consumption rights trading (ECRT) pilot zones in four provinces. The effects of LCCP, CETP, BCPP, GFPZ, and ECRT on energy have been proven [49–53]. Only the impact of the NEDC policy is considered in column (1), while the other columns of Table 5 show the regression results after including LCCP, CETP, BCPP, GFPZ, and ECRT, respectively. After considering the five policies mentioned above separately, the NEDC

policy still significantly achieves energy saving, which further confirms the validity of the baseline empirical results.

Table 4. Regression results of the instrumental variables method.

Variables	(1)	(2)	(3)	(4)
	<i>Tele</i> × <i>IPR</i>		<i>Post</i> × <i>IPR</i>	
	<i>Treat_i</i> × <i>Time_t</i>	<i>EC</i>	<i>Treat_i</i> × <i>Time_t</i>	<i>EC</i>
<i>Treat_i</i> × <i>Time_t</i>		−0.675 *** (0.185)		−0.620 *** (0.171)
<i>Tele</i> × <i>IPR</i>	0.0000009 *** (0.0000001)			
<i>Post</i> × <i>IPR</i>			0.0000021 *** (0.0000003)	
Control	YES	YES	YES	YES
Constant	0.151 *** (0.054)	1.846 *** (0.156)	0.155 *** (0.054)	1.842 *** (0.155)
Year-FE	YES	YES	YES	YES
City-FE	YES	YES	YES	YES
Obs.	3962	3962	3962	3962
R-squared	0.593	0.910	0.593	0.911

Note: robust standard errors in parentheses. *** represents the significance at 1% level.

Table 5. Regression results of excluding other policies.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	<i>EC</i>	<i>EC</i>	<i>EC</i>	<i>EC</i>	<i>EC</i>	<i>EC</i>
<i>Treat_i</i> × <i>Time_t</i>	−0.142 *** (0.028)	−0.139 *** (0.029)	−0.141 *** (0.028)	−0.111 *** (0.028)	−0.142 *** (0.028)	−0.145 *** (0.028)
LCCP		−0.015 (0.025)				
CETP			−0.017 (0.031)			
BCPP				−0.136 *** (0.028)		
GFPZ					0.007 (0.052)	
ECRT						−0.083 * (0.044)
Control	YES	YES	YES	YES	YES	YES
Constant	3.581 *** (0.125)	3.589 *** (0.126)	3.585 *** (0.126)	3.572 *** (0.123)	3.580 *** (0.126)	3.572 *** (0.127)
Year-FE	YES	YES	YES	YES	YES	YES
City-FE	YES	YES	YES	YES	YES	YES
Obs.	3962	3962	3962	3961	3962	3962
R-squared	0.917	0.917	0.917	0.917	0.917	0.917

Note: robust standard errors in parentheses. * and *** represent the significance at 10% and 1% levels, respectively.

4.3.5. Other Robustness Test

The paper draws on Ji [54] in replacing the explanatory variable to verify the robustness of the estimation results. This paper uses the energy consumption intensity (*ECI*) to replace the logarithm of energy consumption (*EC*). The regression results are presented in Table 6. The establishment of NEDC policy significantly reduces energy consumption intensity by 1.3% in the pilot cities. Hypothesis 1 is again verified.

The use of DID assumes a common trend in the experimental and control groups, but it is impossible to verify whether the common trend is satisfied due to sample size and variable limitations. Referring to Arkhangelsky et al. [55], we further tested the robustness of the baseline results using the synthetic difference-in-difference (SDID) method. The SDID method is weighted for the control group so that the weighted time trend is as consistent as possible with the experimental group. The advantage of SDID is that it can control the individual fixation effect and time fixation effect while synthesizing comparable

control groups. The SDID method is a general estimation with two-way fixed effects and individual and time weights. Compared with DID, SDID has dual robustness. The regression coefficients of *EC* in Table 7 remain significantly negative, again verifying the robustness of the benchmark regression.

Table 6. Robustness test: replacing the explanatory variables.

Variables	(1)	(2)
	<i>ECI</i>	<i>ECI</i>
$Treat_i \times Time_t$	−0.025 *** (0.006)	−0.013 ** (0.006)
<i>PD</i>		−0.001 (0.002)
<i>FDI</i>		−0.028 (0.097)
<i>RD</i>		−0.000 (0.001)
<i>PGDP</i>		−0.009 *** (0.003)
<i>ER</i>		0.005 (0.004)
<i>UR</i>		0.146 ** (0.061)
Constant	0.101 *** (0.002)	0.063 * (0.034)
Year-FE	YES	YES
City-FE	YES	YES
Obs.	3962	3962
R-squared	0.525	0.533

Note: robust standard errors in parentheses. *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Table 7. Regression results of SDID.

	ATT	Std. Err.	<i>t</i>	<i>p</i>
<i>EC</i>	−0.123	0.061	−2.83	0.005 ***

Note: Robust standard errors in parentheses. *** is significant at the 1% level.

4.4. Impact Mechanism

We use Equations (2) and (3) to verify the impact mechanisms. As discussed in Part 2 above, the NEDC policy impacts energy saving through technological innovation, industrial restructuring, and economic agglomeration. The regression results are presented in Table 8.

The regression results for technological innovation (*TI*) as a mediating variable are shown in columns (1) and (2). The regression coefficient of column (1) is significantly positive at the 1% level, indicating that NEDC construction significantly increases the level of technological innovation in the pilot cities. Moreover, the regression coefficient of energy consumption is −0.096, which is significantly negative, indicating that improved technological innovation significantly achieves energy saving. This is because the NEDC policy enhances the speed of information transfer and feedback, which enables companies to accelerate technological innovation. Further, technological innovation is an essential way for enterprises to save energy. Hypothesis 2 is verified.

Columns (3) and (4) verify the mediation effect of industrial structure optimization. From the significant positive coefficient of *IS*, it can be determined that the proportion of tertiary industry to secondary industry in the demonstration cities has increased obviously and the industrial structure has been optimized significantly. As indicated by the significant regression coefficient of −0.138 in column (4) of Table 8, the optimization of industrial structure significantly achieves energy saving. Industrial structure optimization increases

the proportion of tertiary industry with less energy consumption and realizes the role of energy saving. Hypothesis 3 is supported.

Table 8. Regression results of impact mechanism.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Technological Innovation		Industrial Restructuring		Economic Agglomeration	
	TI	EC	IS	EC	EA	EC
$Treat_i \times Time_t$	0.747 *** (10.235)	−0.096 *** (−3.442)	0.061 *** (3.238)	−0.138 *** (−4.942)	2.000 *** (5.849)	−0.131 *** (−5.355)
Intermediate variable		−0.062 *** (−5.705)		−0.058 * (−1.854)		−0.016 *** (−5.052)
Control	YES	YES	YES	YES	YES	YES
Constant	0.406 ** (2.477)	3.606 *** (29.060)	0.910 *** (14.583)	3.633 *** (27.756)	3.574 *** (4.427)	3.635 *** (29.501)
Year-FE	YES	YES	YES	YES	YES	YES
City-FE	YES	YES	YES	YES	YES	YES
Obs.	3962	3962	3962	3962	3962	3962
R-squared	0.780	0.917	0.835	0.917	0.880	0.920

Note: robust standard errors in parentheses. *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

Columns (5) and (6) validate the regression results with economic agglomeration (EA) as a mediating variable. The regression coefficient of column (5) suggests that NEDC policy significantly promotes economic agglomeration at the 1% level, which indicates that the implementation of the NEDC attracts infrastructure development and e-commerce enterprises to migrate to pilot cities to present economic spatial agglomeration patterns. As can be seen, the regression coefficient of EC is significantly negative, which means the scale effect of economic agglomeration plays an important role in saving energy. Hypothesis 4 is confirmed.

4.5. Heterogeneity Test

The preceding analysis proves that NEDC policy has remarkable energy-saving benefits. Nevertheless, the implementation of policies is often regionally specific, and the effects vary due to the vast size of China and the large regional differences in economic levels, human capital, and resource endowments [56]. Therefore, this paper further analyzes the heterogeneous influence of the NEDC on energy consumption from four dimensions: human capital, information infrastructure level, city type, and business environment.

4.5.1. Heterogeneity of Human Capital

According to Li et al. [57], this study applies the ratio of higher education students in the population to characterize the human capital level. Human capital promotes regional innovation levels by absorbing information and knowledge and producing innovative results. Cities with higher levels of human capital tend to have higher levels of green technological innovation [58]. Innovation is beneficial for promoting energy-saving technology development and improving production efficiency. Consistent with the results of the mechanism analysis, the development of technological innovation significantly achieves energy saving. According to human capital level, the study divides the sample into two groups: high and low. Table 9 reports the heterogeneous impact of NEDC policy on energy saving under different levels of human capital. The regression coefficient $Treat_i \times Time_t$ in column (2) is significantly negative, indicating that in cities with higher levels of human capital, the construction of NEDC policy can significantly save energy. However, the implementation of EDCP in cities with low levels of human capital is not significant in saving energy.

4.5.2. Heterogeneity of Information Infrastructure

A sound information infrastructure is an important factor in promoting the e-commerce growth. On the basis of the information infrastructure level, all samples are divided into

two separate regression groups. The regression results are indicated by Table 10. Overall, the implementation of NEDC policy in cities with high levels of information infrastructure significantly achieves energy saving; however, energy consumption increases in regions with poor information infrastructure. Complete information infrastructure is the material basis for the growth and scaling of e-commerce. According to the above analysis, the construction of NEDC policy can save energy through direct or indirect paths. Cities with relatively poor information infrastructure are probably in the initial stage of e-commerce industry, which is the stage of small-scale production. Initial production has not yet developed scale effects and energy benefits. On the contrary, the increased production of new industries makes energy consumption increase.

Table 9. Regression results of human capital heterogeneity.

Variables	(1)	(2)
	EC	EC
	Low	High
$Treat_i \times Time_t$	−0.059 (0.064)	−0.072 *** (0.028)
Control	YES	YES
Constant	3.092 *** (0.196)	4.092 *** (0.142)
Year-FE	YES	YES
City-FE	YES	YES
Obs.	1974	1988
R-squared	0.894	0.921

Note: robust standard errors in parentheses. *** represents the significance at 1% level.

Table 10. Regression results of information infrastructure heterogeneity.

Variables	(1)	(2)
	EC	EC
	Low	High
$Treat_i \times Time_t$	0.135 (0.109)	−0.156 *** (0.026)
Control	YES	YES
Constant	3.099 *** (0.173)	3.999 *** (0.170)
Year-FE	YES	YES
City-FE	YES	YES
Obs.	1988	1974
R-squared	0.855	0.933

Note: robust standard errors in parentheses. *** represents the significance at 1% level.

4.5.3. Heterogeneity of City Type

In 2013, China's State Council issued a "national sustainable development plan" for resource-based cities, identifying 262 resource-based cities with mining and processing natural resources as the primary industry in the region. According to the different resource endowments, we separate all samples into resource-based cities and non-resource-based cities and then regress them separately. From the analysis in Table 11, it's clear that non-resource-based cities achieve significant positive energy benefits at the 1% level after the implementation of NEDC, in contrast to resource-based cities that instead experience a small increase in energy consumption after the implementation of NEDC. The issue of how to promote the economic transition of resource-based cities and achieve sustainable growth has always been a problem of focus in China. The resource-based cities always suffer from the problem of excessive dependence of industrial development on resources. Slow development of high-tech industries, poor human and capital gathering capacity, and low

level of innovation are also major obstacles to the transition to green economy in resource-based cities. The failure to achieve the expected purpose after the establishment of NEDC in resource-based cities may be due to the hindered and poorly developed e-commerce.

Table 11. Regression results of city type heterogeneity.

Variables	(1)	(2)
	EC	EC
	Non-Resource-Based Cities	Resource-Based Cities
$Treat_i \times Time_t$	−0.226 *** (0.028)	0.086 (0.098)
Control	YES	YES
Constant	3.675 *** (0.170)	3.390 *** (0.169)
Year-FE	YES	YES
City-FE	YES	YES
Obs.	2352	1610
R-squared	0.938	0.870

Note: robust standard errors in parentheses. *** represents the significance at 1% level.

4.5.4. Heterogeneity of Business Environment

A favorable business environment not only promotes the introduction of e-commerce enterprises and related talents but also signifies a better investment and financing environment. The results of business environment heterogeneity are shown in Table 12, where column (1) represents the results for the group with a relatively poor business environment, and column (2) represents the results for the group with a relatively good business environment. The results indicate that, compared to cities with a relatively poor business environment, a favorable business environment makes the NEDC's effect on saving energy more significant. Specifically, in cities with a good business environment, NEDC policies can reduce consumption energy by 18.5%. Overall, the optimization of the business environment promotes the improvement of regional innovation performance, providing technical support for energy conservation through innovation.

Table 12. Regression results of business environment heterogeneity.

Variables	(1)	(2)
	EC	EC
	Low	High
$Treat_i \times Time_t$	−0.088 * (0.053)	−0.185 *** (0.034)
Control	YES	YES
Constant	3.413 *** (0.166)	3.785 *** (0.187)
Year-FE	YES	YES
City-FE	YES	YES
Obs.	2170	1792
R-squared	0.898	0.922

Note: robust standard errors in parentheses. * and *** represent the significance at 10% and 1% levels, respectively.

4.6. Further Analysis

E-commerce can break the spatial barriers of market segmentation and factor mobility, exhibiting strong externalities. This study further considers the spatial effects of NEDC policy on energy saving and conducts an analysis. On the one hand, technological innovation often appears in the form of information and knowledge, exhibiting noticeable positive externalities. According to the research on mechanism effects, it has been shown

that NEDC policy achieves energy savings by promoting technological innovation. Technological innovation in pilot areas has a spatial spillover effect on the technological innovation of surrounding areas, leading to energy savings in surrounding areas. On the other hand, the implementation of NEDC provides policy advantages for the e-commerce industry. The goal of NEDC is to achieve energy savings and develop a green economy, so the pilot areas will focus on developing the e-commerce industry, which will attract capital, talent, and other production factors to the third industry with low energy consumption. High energy-consuming industries have been squeezed out to non-pilot cities in the surrounding areas, causing energy consumption in these areas to increase. Therefore, the potential spillover effects of e-commerce development on energy saving in neighboring regions are uncertain. Thus, this study employs a spatial econometric model to examine the spillover effects of the NEDC policy. The spatial econometric model is shown in Equation (5).

$$EC_{it} = \beta_0 + \rho_1 W \ln EC_{it} + \beta_1 Treat_i \times Time_t + \rho_2 W Treat_i \times Time_t + \beta_n Control_{it} + \varphi W Control_{it} + \delta_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where ρ_1 represents the spatial autocorrelation coefficient, ρ_2 is the influence coefficient of the spatial lag term, and W is the spatial weight matrix.

The spatial weight matrices selected in this paper are the spatial adjacency matrix (W_1) and the geographic distance matrix (W_2). Columns (1)–(3) of Table 13 are the results of using W_1 , and columns (4)–(6) are the results of using W_2 . Columns (1) and (3) display the direct effects using the two matrices, and the results indicate that the policy effect of NEDC on saving energy remains significant after considering spatial correlation factors. Columns (2) and (5) represent the indirect effect, and the results are remarkably positive at the 10 % level, suggesting that the construction of NEDC has increased energy consumption in the surrounding areas. This finding suggests that the NEDC policy has negative external benefits for surrounding areas. The possible reason is that NEDC policy only has a positive impact on industrial structure upgrading within the pilot cities, while energy-intensive industries may transfer to surrounding areas, resulting in the increase in energy consumption in these areas. The overall effect is not significant, indicating that the negative direct effect and the positive indirect effect offset each other. It is worth noting that the positive effect of the NEDC on energy saving is still mainly within the pilot areas, and regional integration of energy saving still needs to be strengthened.

Table 13. Spatial effects regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	W_1	W_1	W_1	W_2	W_2	W_2
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
$Treat_i \times Time_t$	−0.145 *** (0.029)	0.103 * (0.059)	−0.042 (0.068)	−0.138 *** (0.029)	0.191 * (0.103)	0.053 (0.110)
PD	−0.002 (0.004)	−0.010 (0.009)	−0.012 (0.010)	−0.003 (0.004)	0.009 (0.015)	0.006 (0.016)
FDI	−0.245 (0.239)	0.444 (0.635)	0.199 (0.664)	−0.170 (0.239)	0.521 (0.875)	0.351 (0.890)
RD	−0.002 (0.017)	−0.009 (0.036)	−0.010 (0.040)	−0.001 (0.017)	−0.040 (0.073)	−0.041 (0.074)
PGDP	−0.017 *** (0.005)	0.029 *** (0.009)	0.012 (0.009)	−0.022 *** (0.005)	0.060 *** (0.013)	0.038 *** (0.012)
ER	0.002 (0.006)	−0.014 (0.014)	−0.012 (0.017)	0.002 (0.006)	0.018 (0.018)	0.020 (0.020)
UR	1.537 *** (0.188)	0.971 *** (0.347)	2.509 *** (0.368)	1.556 *** (0.187)	1.008 ** (0.483)	2.564 *** (0.489)
Obs.	3962	3962	3962	3962	3962	3962
R-squared	0.211	0.211	0.211	0.224	0.224	0.224
Control	YES	YES	YES	YES	YES	YES
Year-FE	YES	YES	YES	YES	YES	YES
City-FE	YES	YES	YES	YES	YES	YES

Note: robust standard errors in parentheses. *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

5. Conclusions and Policy Implications

5.1. Conclusions

Since the setting of China's first NEDC pilot in 2009, three batches totaling 70 NEDC pilots have been constructed in China. E-commerce has been an important driving force for Chinese economic growth, while the accelerated growth of e-commerce has led to substantial changes in economic forms and patterns. Concurrently, the large-scale development of e-commerce inevitably exerts a considerable impact on energy consumption. Therefore, this study, based on panel data of Chinese 283 prefecture-level cities between 2006 and 2019, employs the multi-period DID method to evaluate the effect and mechanisms of the NEDC policy on energy saving. Further, the research investigates the impact of the NEDC on heterogeneity across regions. The main findings are shown below.

- (1) On average, the NEDC policy has achieved energy savings in pilot cities of 14.2%. This conclusion remains valid following a range of robustness tests, such as the placebo test, PSM-DID, instrumental variables regression, and SDID. From the perspective of dynamic changes in policy effects, the energy saving impact of the NEDC policy becomes significant after two years of implementation and grows more pronounced over time.
- (2) From the indirect impact analysis, mechanism tests show that NEDC policy significantly promotes energy saving through technological innovation, industrial restructuring and economic agglomeration.
- (3) To enhance the practical value of this assessment, the paper further examines the heterogeneity of NEDC policy impacts by grouping the sample according to human capital level, information infrastructure level, city type, and business environment. The results of the heterogeneity analysis indicate that the energy-saving effect of NEDC policy is more pronounced in cities with high levels of human capital, well-developed information infrastructure, non-resource-based cities, and favorable business environments.
- (4) Further, we investigate the spatial spillover effect of NEDC policy, and the findings indicate that NEDC policy significantly saves energy in the pilot areas but increases energy consumption in the surrounding areas, and the total effect is not statistically significant. The NEDC policy lacks consideration for inter-regional coordination and unified management, and there is a possibility of negative energy impact on non-pilot areas.

5.2. Policy Recommendations

According to the above findings we make the following policy recommendations.

- (1) Given the empirical results indicating the significant role of NEDC policy in saving energy, the government should continue to provide support and introduction to the demonstration cities. For example, the government promulgates incentive policies and provides funding support to attract more enterprises, talents, and capital into the e-commerce industry, accelerating market construction and improvement. Moreover, it is important to review and summarize the experiences and lessons learned during the pilot process, not only to deepen the policy practice of pilot cities but also to provide references for non-pilot cities. The government should make a comprehensive plan on how to develop e-commerce in the whole region and prevent the phenomenon of monopoly and sacrificing the interests of non-pilot areas in exchange for the interests of pilot areas.
- (2) Considering that technological innovation, industrial structure optimization, and economic agglomeration are key channels for NEDC policy energy savings, the government should accelerate these pathways via policy promotion. Increasing investment and incentive policies to maintain a favorable innovation environment is feasible. The government can expedite the profound integration of e-commerce and traditional sectors on the basis of NEDC policy, promoting industrial structural

adjustment by transforming traditional industries into digital and network-based ones. This is not only a trend in contemporary industrial development, but also an important way to save energy and reduce resource waste. Furthermore, the government can enhance the coordination between economic agglomeration and environmental quality, thus promoting e-commerce agglomeration-based business. By building e-commerce industrial parks and development zones, as well as Taobao villages, the concentration of economic activities can be increased and the advantages of economic agglomeration in resource integration can be fully leveraged to accelerate the energy-saving effect of e-commerce development.

- (3) In view of the obvious differences in policy effects across regions, it is recommended that the central government carry out the NEDC policy based on local conditions, rather than blindly implement pilot projects. Regional governments can issue policies to attract talent to improve the local human capital level, fully leveraging the role of human capital in promoting energy saving through technological innovation. In addition, internet infrastructure level is the foundation of e-commerce development, which further affects the effectiveness of NEDC policy in energy saving. Cities with a lower level of information infrastructure should prioritize investment, construction, and application of telecommunications infrastructure to overcome the developmental lag caused by the backwardness of infrastructure. Policy makers in resource-based cities should endeavor to identify the reasons for the failure to achieve the expected energy-saving effects, in order to avoid any negative impact on energy consumption from NEDC construction. Finally, the pilot regions should foster a favorable business environment for the growth of e-commerce and eliminate factors that may hinder the effective production and operation of e-commerce. For example, improving government efficiency, perfecting the legal system to ensure fair competition, and optimizing the financing environment to attract investment.

The frequently occurring abbreviations and variables are listed in Table 14.

Table 14. Abbreviations and variables summary table.

		Meaning
Abbreviations	NEDC	national e-commerce demonstration cities
	DID	difference-in-difference
	SDID	synthetic difference-in-difference
	PSM-DID	propensity score matching- difference-in-difference
Variables	EC	energy consumption
	$Treat_i \times Time_t$	interaction terms for policy dummy variable $Treat_i$ and time dummy variable $Time_t$
	PD	population density
	FDI	foreign direct investment intensity
	RD	research and development (R&D) investment intensity
	PGDP	gross domestic product per capita
	ER	environmental regulation
	UR	urbanization rate
	TI	technological innovation
	IS	industrial restructuring
	EA	economic agglomeration
	ECI	energy consumption intensity

Author Contributions: Conceptualization, M.L. and H.J.; methodology, M.L., H.J. and Y.H.; formal analysis, M.L., H.J. and Y.H.; data curation, M.L. and H.J.; writing—original draft preparation, M.L., H.J. and Y.H.; writing—review and editing, M.L. and H.J.; supervision, M.L. and H.J.; funding acquisition, M.L. and H.J. 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: The main data source for this study is China City Statistical Yearbook (<https://data.cnki.net/yearBook/single?id=N2022040095>, accessed on 20 December 2022).

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

References

1. Naseer, S.; Khalid, S.; Parveen, S.; Abbass, K.; Song, H.M.; Achim, M.V. COVID-19 outbreak: Impact on global economy. *Front. Public Health* **2023**, *10*, 1009393. [CrossRef] [PubMed]
2. Liao, L.P.; Huang, C.K.; Du, M.Z. The Effect of Energy Quota Trading on Energy Saving in China: Insight from a Quasi-Natural Experiment. *Energies* **2022**, *15*, 8610. [CrossRef]
3. Xie, X.Y.; Wang, Y.H. Evaluating the Efficacy of Government Spending on Air Pollution Control: A Case Study from Beijing. *Int. J. Environ. Res. Public Health* **2019**, *16*, 45. [CrossRef] [PubMed]
4. Liu, B.Y. An analysis of energy efficiency of the Pearl River Delta of China based on super-efficiency SBM model and Malmquist index. *Environ. Sci. Pollut. Res.* **2023**, *30*, 18998–19011. [CrossRef]
5. Wang, K.; Lei, L.; Qiu, S.; Guo, S. Policy Performance of Green Lighting Industry in China: A DID Analysis from the Perspective of Energy Conservation and Emission Reduction. *Energies* **2020**, *13*, 5855. [CrossRef]
6. Zhang, H.; Wu, J.Y. The Energy Saving and Emission Reduction Effect of Carbon Trading Pilot Policy in China: Evidence from a Quasi-Natural Experiment. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9272. [CrossRef] [PubMed]
7. Ding, C.H.; Liu, C.; Zheng, C.Y.; Li, F. Digital Economy, Technological Innovation and High-Quality Economic Development: Based on Spatial Effect and Mediation Effect. *Sustainability* **2022**, *14*, 216. [CrossRef]
8. Zhang, X. Investigation of e-commerce in China in a geographical perspective. *Growth Chang.* **2019**, *50*, 1062–1084. [CrossRef]
9. Wang, H.; Li, Y.Y.; Lin, W.F.; Wei, W.D. How does digital technology promote carbon emission reduction? Empirical evidence based on e-commerce pilot city policy in China. *J. Environ. Manag.* **2023**, *325*, 116524. [CrossRef]
10. Williams, E.D. Energy efficiency of b2c e-commerce in Japan. In Proceedings of the International Symposium on Electronics and the Environment, San Francisco, CA, USA, 6–9 May 2002; pp. 38–43.
11. Palsson, H.; Pettersson, F.; Hiselius, L.W. Energy consumption in e-commerce versus conventional trade channels—Insights into packaging, the last mile, unsold products and product returns. *J. Clean. Prod.* **2017**, *164*, 765–778. [CrossRef]
12. Dost, F.; Maier, E. E-Commerce Effects on Energy Consumption: A Multi-Year Ecosystem-Level Assessment. *J. Ind. Ecol.* **2018**, *22*, 799–812. [CrossRef]
13. Weber, C.L.; Hendrickson, C.T.; Matthews, H.S.; Nagengast, A.; Nealer, R.; Jaramillo, P. Life Cycle Comparison of Traditional Retail and E-commerce Logistics for Electronic Products: A Case Study of buy.com. In Proceedings of the IEEE International Symposium on Sustainable Systems and Technology, Tempe, AZ, USA, 18–20 May 2009; pp. 254–259.
14. Reijnders, L.; Hoogeveen, M.J. Energy effects associated with a-commerce: A case-study concerning online sales of personal computers in The Netherlands. *J. Environ. Manag.* **2001**, *62*, 317–321. [CrossRef]
15. Peng, L.F.; Li, Q.; Zhang, X.F. In Optimism or pessimism: Environmental impacts of the e-commerce. In Proceedings of the Conference of the International-Society-for-Environmental-Information-Sciences on Environmental Informatics, Xiamen, China, 26–28 July 2005; pp. 263–269.
16. Cao, X.G.; Deng, M.; Li, H.K. How does e-commerce city pilot improve green total factor productivity? Evidence from 230 cities in China. *J. Environ. Manag.* **2021**, *289*, 112520. [CrossRef] [PubMed]
17. Zhang, Z.X.; Sun, Z.Y.; Lu, H. Does the E-Commerce City Pilot Reduce Environmental Pollution? Evidence From 265 Cities in China. *Front. Environ. Sci.* **2022**, *10*, 229. [CrossRef]
18. Wang, H.; Fang, L.; Mao, H.; Chen, S.J. Can e-commerce alleviate agricultural non-point source pollution?—A quasi-natural experiment based on a China's E-Commerce Demonstration City. *Sci. Total Environ.* **2022**, *846*, 157423. [CrossRef]
19. Bolla, R.; Bruschi, R.; Davoli, F.; Cucchiatti, F. Energy Efficiency in the Future Internet: A Survey of Existing Approaches and Trends in Energy-Aware Fixed Network Infrastructures. *IEEE Commun. Surv. Tutor.* **2011**, *13*, 223–244. [CrossRef]
20. Liu, D.S.; Chen, J.K.; Zhang, N. Political connections and green technology innovations under an environmental regulation. *J. Clean. Prod.* **2021**, *298*, 126778.
21. Mi, Z.F.; Pan, S.Y.; Yu, H.; Wei, Y.M. Potential impacts of industrial structure on energy consumption and CO₂ emission: A case study of Beijing. *J. Clean. Prod.* **2015**, *103*, 455–462. [CrossRef]
22. Wang, Y.A.; Yin, S.W.; Fang, X.L.; Chen, W. Interaction of economic agglomeration, energy conservation and emission reduction: Evidence from three major urban agglomerations in China. *Energy* **2022**, *241*, 122519. [CrossRef]
23. Goldfarb, A.; Tucker, C. Digital Economics. *J. Econ. Lit.* **2019**, *57*, 3–43. [CrossRef]
24. Zhang, M.; Li, B.; Yin, S. Is Technological Innovation Effective for Energy Saving and Carbon Emissions Reduction? Evidence From China. *IEEE Access* **2020**, *8*, 83524–83537. [CrossRef]
25. Ren, S.Y.; Hao, Y.; Xu, L.; Wu, H.T.; Ba, N. Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ.* **2021**, *98*, 105220. [CrossRef]
26. Zhu, B.; Shan, H.Y. Impacts of industrial structures reconstructing on carbon emission and energy consumption: A case of Beijing. *J. Clean. Prod.* **2020**, *245*, 118916. [CrossRef]

27. Hornick, S.; Glaeser, E.L. Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier. *Foreign Aff.* **2011**, *90*, 164–172.
28. Gao, Y.N.; Li, M.; Xue, J.J.; Liu, Y. Evaluation of effectiveness of China's carbon emissions trading scheme in carbon mitigation. *Energy Econ.* **2020**, *90*, 104872. [[CrossRef](#)]
29. Yang, X.H.; Li, Y.; Liao, L. The impact and mechanism of high-speed rail on energy efficiency: An empirical analysis based on 285 cities of China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 23155–23172. [[CrossRef](#)]
30. Baron, R.M.; Kenny, D.A. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J. Personal. Soc. Psychol.* **1986**, *51*, 1173–1182. [[CrossRef](#)]
31. Xue, F.; Zhou, M.L.; Liu, J.Q. Are Cities Saving Energy by Getting Smarter? Evidence from Smart City Pilots in China. *Sustainability* **2023**, *15*, 2961. [[CrossRef](#)]
32. Yi, F.J.; Ye, H.J.; Wu, X.M.; Zhang, Y.Y.; Jiang, F. Self-aggravation effect of air pollution: Evidence from residential electricity consumption in China. *Energy Econ.* **2020**, *86*, 104684. [[CrossRef](#)]
33. Hu, Y.C.; Ren, S.G.; Wang, Y.J.; Chen, X.H. Can carbon emission trading scheme achieve energy conservation and emission reduction? Evidence from the industrial sector in China. *Energy Econ.* **2020**, *85*, 104590. [[CrossRef](#)]
34. Chen, Z.C.; Paudel, K.P.; Zheng, R.Q. Pollution halo or pollution haven: Assessing the role of foreign direct investment on energy conservation and emission reduction. *J. Environ. Plan. Manag.* **2022**, *65*, 311–336. [[CrossRef](#)]
35. Ren, Y.M. Industrial Investment Funds, Government R&D Subsidies, and Technological Innovation: Evidence From Chinese Companies. *Front. Psychol.* **2022**, *13*, 890208.
36. Huang, J.B.; Chen, X. Domestic R&D activities, technology absorption ability, and energy intensity in China. *Energy Policy* **2020**, *138*, 111184.
37. Zhou, X.X.; Xia, M.; Zhang, T.; Du, J.T. Energy- and Environment-Biased Technological Progress Induced by Different Types of Environmental Regulations in China. *Sustainability* **2020**, *12*, 7486. [[CrossRef](#)]
38. Wang, Z.; Cui, C.; Peng, S. How do urbanization and consumption patterns affect carbon emissions in China? A decomposition analysis. *J. Clean. Prod.* **2019**, *211*, 1201–1208. [[CrossRef](#)]
39. Xu, G.X.; Yang, Z.J. The mechanism and effects of national smart city pilots in China on environmental pollution: Empirical evidence based on a DID model. *Environ. Sci. Pollut. Res.* **2022**, *29*, 41804–41819. [[CrossRef](#)]
40. Yu, Q.Y.; Li, M.; Li, Q.; Wang, Y.A.; Chen, W. Economic agglomeration and emissions reduction: Does high agglomeration in China's urban clusters lead to higher carbon intensity? *Urban Clim.* **2022**, *43*, 101174. [[CrossRef](#)]
41. Kahn, M.E.; Li, P.; Zhao, D.X. Water Pollution Progress at Borders: The Role of Changes in China's Political Promotion Incentives. *Am. Econ. J. -Econ. Policy* **2015**, *7*, 223–242. [[CrossRef](#)]
42. Shao, S.; Tian, Z.H.; Yang, L.L. High speed rail and urban service industry agglomeration: Evidence from China's Yangtze River Delta region. *J. Transp. Geogr.* **2017**, *64*, 174–183. [[CrossRef](#)]
43. Beck, T.; Levine, R.; Levkov, A. Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *J. Financ.* **2010**, *65*, 1637–1667. [[CrossRef](#)]
44. Au, C.C.; Henderson, J.V. Are Chinese cities too small? *Rev. Econ. Stud.* **2006**, *73*, 549–576. [[CrossRef](#)]
45. Xie, C.; Liu, C.Z. The Nexus between Digital Finance and High-Quality Development of SMEs: Evidence from China. *Sustainability* **2022**, *14*, 7410. [[CrossRef](#)]
46. Zhou, J.; Lan, H.L.; Zhao, C.; Zhou, J.P. Haze Pollution Levels, Spatial Spillover Influence, and Impacts of the Digital Economy: Empirical Evidence from China. *Sustainability* **2021**, *13*, 9076. [[CrossRef](#)]
47. Nunn, N.; Qian, N. US Food Aid and Civil Conflict. *Am. Econ. Rev.* **2014**, *104*, 1630–1666. [[CrossRef](#)]
48. Wu, H.T.; Xue, Y.; Hao, Y.; Ren, S.Y. How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Econ.* **2021**, *103*, 105577. [[CrossRef](#)]
49. Hong, M.; Chen, S.L.; Zhang, K.X. Impact of the "Low-Carbon City Pilot" Policy on Energy Intensity Based on the Empirical Evidence of Chinese Cities. *Front. Environ. Sci.* **2021**, *9*, 717737. [[CrossRef](#)]
50. Hong, Q.Q.; Cui, L.H.; Hong, P.H. The impact of carbon emissions trading on energy efficiency: Evidence from quasi-experiment in China's carbon emissions trading pilot. *Energy Econ.* **2022**, *110*, 106025. [[CrossRef](#)]
51. Wang, Q.X.; Hu, A.; Tian, Z.H. Digital transformation and electricity consumption: Evidence from the Broadband China pilot policy. *Energy Econ.* **2022**, *115*, 106346. [[CrossRef](#)]
52. Zhang, H.F.; Wang, Y.X.; Li, R.; Si, H.Y.; Liu, W. Can green finance promote urban green development? Evidence from green finance reform and innovation pilot zone in China. *Environ. Sci. Pollut. Res.* **2022**, *30*, 12041–12058. [[CrossRef](#)]
53. Wang, Z.; Wu, M.Y.; Li, S.X.; Wang, C.J. The Effect Evaluation of China's Energy-Consuming Right Trading Policy: Empirical Analysis Based on PSM-DID. *Sustainability* **2021**, *13*, 11612. [[CrossRef](#)]
54. Ji, H.K. The impact of the anti-corruption campaign on energy efficiency: Evidence from prefecture-level cities in China. *Front. Environ. Sci.* **2022**, *10*, 1002578. [[CrossRef](#)]
55. Arkhangelsky, D.; Athey, S.; Hirshberg, D.A.; Imbens, G.W.; Wager, S. Synthetic Difference-in-Differences. *Am. Econ. Rev.* **2021**, *111*, 4088–4118. [[CrossRef](#)]
56. Chen, S.; Shi, A.N.; Wang, X. Carbon emission curbing effects and influencing mechanisms of China's Emission Trading Scheme: The mediating roles of technique effect, composition effect and allocation effect. *J. Clean. Prod.* **2020**, *264*, 121700. [[CrossRef](#)]

57. Li, Q.; Dong, A.; Zhang, B. Impact of the opening of high-speed rail on environmental pollution in the Yangtze River Economic Belt: Promoting or inhibiting? *Int. J. Environ. Sci. Technol.* **2022**, *19*, 11145–11160. [[CrossRef](#)]
58. Xu, H.; Qiu, L.; Liu, B.Z.; Liu, B.; Wang, H.; Lin, W.F. Does regional planning policy of Yangtze River Delta improve green technology innovation? Evidence from a quasi-natural experiment in China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 62321–62337. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.