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# Impact and Spatial Effect of Government Environmental Policy on Forestry Eco-Efficiency—Examining China's National Ecological Civilization Pilot Zone Policy

**Yingzheng Yan [1], Ziwei Zhou [1], Liupeng Chen [2] and Yuanzhu Wei [3,*]**

[1] College of Economics and Management, Fujian Agriculture and Forestry University, Fuzhou 350002, China; fjyyz@fafu.edu.cn (Y.Y.); zzw1224@fafu.edu.cn (Z.Z.)
[2] College of Rural Revitalization, Fujian Agriculture and Forestry University, Fuzhou 350002, China; clp2000@fafu.edu.cn
[3] College of Economics and Management, Ningde Normal University, Ningde 352100, China
* Correspondence: weiyz@ndnu.edu.cn

**Abstract:** Can government environmental policy harmonize environmental protection with economic output? We explore this issue from the perspective of forestry eco-efficiency, using China's National Ecological Civilization Pilot Zone Policy (NECP), an environmental policy promulgated by the government of China, as the subject of this study. The study introduces forestry eco-efficiency as an indicator to assess the balance between economic development in the forestry sector and environmental conservation. The indicator, grounded in sustainable development theory, employs a super-efficiency SBM model that includes undesirable outputs to evaluate efficiency. Additionally, we empirically analyze the impact of NECP on forestry eco-efficiency by using the difference-in-difference (DID) model with provincial panel data from 2011 to 2020. Ultimately, we analyze the effects of spatial spillover by employing the spatial Durbin model (SDM). Our study yields the following conclusions. (1) In this paper, through hotspot clustering analysis, forestry eco-efficiency in each province is categorized into three categories: effective, semi-effective and ineffective. Our findings suggest that China's average forestry eco-efficiency falls into the ineffective category, highlighting the need to optimize resource allocation within the sector. (2) NECP significantly enhances forestry eco-efficiency, with robust findings across various stability tests. Thus, implementing government environmental policies can have a multiplier effect on forestry, i.e., it can synergize its economic development with environmental protection. (3) In provinces with a strong ecological foundation, the NECP significantly enhances forestry eco-efficiency. However, in other provinces, the improvement is only moderate. Furthermore, while the NECP has a substantial positive impact in the eastern region, it has yet to show a discernible effect in other regions. (4) The positive impacts of NECP implementation on forestry eco-efficiency have spatial spillover effects due to demonstration effects and comparative advantages.

**Keywords:** ecological civilization; sustainable development; economic and environmental harmonization; spatial Durbin double-fixation model



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## 1. Introduction

The cornerstone of achieving global sustainable development is effectively harmonizing economic growth with environmental conservation [1,2]. The United Nations' SDGs also include the goal of harmonizing the global economy with the environment [3]. In recent years, countries have gradually accepted and thoughtfully implemented the concept of sustainable development. Countries are keenly aware of forestry's prominent role in sustainable development. All countries try to maximize the dual function of economic production and environmental protection that forestry possesses [4]. For example, the United States enacted the Multiple-Use Forest Management Policy, emphasizing sustainable yields, community participation and ecosystem health [5]. The EU proposes a forest strategy to enhance sustainable forest management, improve biodiversity and support the rural economy [5]. Finland employs an integrated approach with strict regulations, forest certification and financial incentives to promote sustainable forest management [6]. Indonesia has adopted the landscape approach, which integrates forestry, agriculture and environmental protection to reduce deforestation and combat climate change [7]. In 2020, forests covered 5% of the global land area in China [8]. This substantial coverage underscores China's forestry industry's critical role in the global quest for economic and environmental balance. Eco-efficiency measures the synergistic relationship between environmental impact and economic performance [9]. Measuring forestry eco-efficiency becomes a fundamental basis for exploring how to optimally utilize the dual functions of forestry. However, in agroforestry economics, the study of agroecological benefits is richer in breadth [10]. Scholars need to emphasize the importance of research in the forestry eco-efficiency field.

The concept of eco-efficiency was originally introduced by Schaltegger and Sturm [11]. Since then, it has become a tool many scholars use to measure the degree of harmonization between ecological environment and economic development [12–14]. Generally speaking, eco-efficiency optimizes economic production while minimizing resource use and pollutant emissions [15]. Based on the definition, initially, some scholars used the single-indicator ratio approach to measure eco-efficiency [16]. The establishment of a system of indicators soon replaced this single measure. In addition to focusing on economic and environmental output, resource inputs and pollutant discharges are also considered in the indicator system [17]. Eco-efficiency is the efficiency of inputs and outputs derived by considering resource and environmental constraints [18]. Such a measure is more comprehensive and rigorous than its predecessor.

The DEA models have been extensively applied in research exploring eco-efficiency metrics [19]. Charnes et al. introduced the DEA model, which has gained extensive utilization [20]. However, some things could be improved in the traditional DEA model. First, traditional DEA models do not emphasize negative environmental output indicators but only consider economic output indicators, which is an inaccurate way of measurement [21]. Second, classical models of economic efficiency analysis are essentially radial models that expect inputs or outputs to change proportionally. This model could make the calculated efficiency values higher than the actual values [22]. Finally, traditional DEA models are unable to estimate the resource allocation efficiency of decision-making units (DMUs) exceeding 1, leading to a situation where DMUs with an efficiency score of 1 cannot be differentiated. The literature review reveals that the SBM model, which considers unwanted outcomes, is highly effective and addresses many of the limitations of the standard DEA model [23]. This model can calculate eco-efficiency more scientifically and reasonably [24]. Studies on topics such as renewable energy efficiency [25,26], urban water resources' greening rate [27], industrial green development efficiency [28] and water utilization [29] frequently employ the super-efficient SBM model. This model's widespread application across various research areas is well documented. In addition, using the method at a constant scale, the combined efficiency is calculated. Aggregate efficiency considers the scale factor and the technical progress factor, which better reflects the comprehensive nature of efficiency. In the existing literature, most of the measures of forestry eco-efficiency are based on the DEA models [23], which will lead to a relatively homogeneous choice of measurement methods. Therefore, this paper lays the foundation for the study by using a super-efficient SBM model. The model integrates undesirable outputs of constant size to effectively measure explanatory variables.

Is government environmental policy formulation a powerful tool for addressing environmental challenges and influencing economic growth? There has yet to be a consensus in the academic community on this question. On the one hand, many scholars have supported the view that environmental regulation can effectively harmonize economic production and environmental protection through many empirical studies [24,30,31]. This view supports Porter's hypothesis [32]. On the other hand, some scholars are opposed to this view [33,34].

This view supports the neoclassical school of economic theory [35]. Based on this, this paper will explore this topic of debate.

In coordinating economic production and environmental protection, China has explored institutional models for sustainable development by promulgating environmental policies relating to pilot ecological civilization zones. China issued the "Opinions on Establishing Unified and Standardized National Ecological Civilization Pilot Zones" (later referred to as the "Opinions") in 2016 [36]. The pilot area includes Fujian, Jiangxi and Guizhou (three provinces). The measures proposed in the "Opinions" and their effectiveness are specifically six points [36,37]. First, quantitative red lines were set according to the characteristics of forests and other ecosystems, and a red line control system was established. As of 2020, approximately 311,500 square kilometers, or 31% of China's national territory, has been designated for ecological protection. Second, market-based mechanisms were explored to promote ecological environmental protection, implementing opinions to foster market players in environmental governance and ecological protection. By 2020, the national eco-environmental protection industry had already boasted an output value of CNY 8 trillion. Third, improvements were made to the compensation mechanism for ecological public welfare forests, implementing a forest ecological benefits compensation mechanism that links provincial and national levels and combines categorized compensation with graded subsidies. By 2020, the total amount of compensation reached CNY 10 billion. Fourth, a mechanism was established to seamlessly integrate administrative enforcement and criminal justice for severe environmental protection and natural resource use law violations. In 2020, the number of cases referred to the judiciary for environmental violations increased by 30% year on year. Fifth, a property rights system for natural resources has been established. According to statistics, by the end of 2020, the area of China's natural resource rights registration had exceeded 500,000 square kilometers. Sixth, the green development indicator system will be incorporated into the performance appraisal of regional leading cadres. By 2020, the weight of green development indicators in government appraisals increased to over 20%.

Since the release of the 2016 "Opinions", numerous scholars have evaluated the policy's effectiveness using it as a quasi-natural experiment. These studies have demonstrated that the policy can positively impact ecological, social and economic development [24,38,39]. However, fewer scholars have explored the multiplier effects of this policy by establishing a comprehensive system of evaluation indicators. Therefore, this paper examines this by creating a comprehensive measurement system. In addition, we analyze heterogeneity and spatial spillover effects, thus contributing to research in this area.

## 2. Hypotheses

### *2.1. NECP and Forestry Eco-Efficiency*

At the policy level, on the one hand, the three pilot provinces should promote cooperation between the government and social capital. They are obtaining social capital to protect and conserve ecological environment allocation resources. The "Opinions", on the other hand, also call for the cultivation of ecological market players. The measures taken by the three provinces in this regard include the following. Fujian Province has launched a pilot forestry carbon trading program, studied forestry carbon trading rules and methods and explored trading models. Jiangxi has promoted eco-industrialization and supported eco-forestry development, eco-tourism and other green industries to increase farmers' incomes. Guizhou has enhanced its green financial system by advancing green insurance, green credit and other financial innovations to support ecological construction projects [36]. Therefore, it can be judged that the NECP belongs to market-incentive-based environmental regulation [40]. Market-incentive-based environmental regulation through market-oriented means guides enterprises in choosing the most cost-effective means of environmental management to create a good situation of optimal allocation of industrial resources and the lowest cost of environmental management [41]. The theory of property rights in the new economic institutionalism can explain the reasons for such a favorable situation. The theory of property rights holds that under the conditions of clear property rights and non-zero transaction costs, placing commodities with clear property rights on the market for trading, market players will optimize the allocation of resources through market-based means to reduce transaction costs.

Such a mechanism would allow the negative externalities of public goods to be internalized, avoiding the tragedy of the commons and achieving an efficient allocation of resources [40]. In the "Opinions", the tasks of furthering the forestry rights reform and cracking the contradiction between ecological protection and the interests of forest farmers are put forward. The "Opinions on Improving the Collective Forest Rights System", released by the State Council of China, suggest that adopting a market-based approach to reasonably compensating forest rights owners is one of the fundamental ways to resolve this contradiction. Under the regulation of the market-oriented environment of the NECP, the governments where the pilot areas are located will explore the market-oriented mechanism to promote the protection of the forestry ecological environment [42]. For one thing, specifically, the use of market mechanisms by the government to promote ecological environmental protection can enable forestry to allocate resources efficiently in the development process. Another thing is that it will make forestry less costly regarding environmental management in the development process. Ultimately, this will promote economic and environmental complementarity, enhancing forestry eco-efficiency.

At the local government level, the performance appraisal system for officials in China has also incorporated environmental indicators into the new appraisal system and is gradually replacing the old system centered on economic growth. As the percentage of environmental achievements in performance appraisals continues to increase, local governments have more significant incentives to promote environmental protection within their jurisdictions [43]. The tournament theory suggests that local officials are incentivized to advance to higher positions. Therefore, if higher levels of government offer higher positions as performance incentives in a new evaluation system, local governments will be promoted by improving the effectiveness of coordinating economic growth and environmental protection within their jurisdictions [44].

The "Opinion" puts forward that the state will accelerate the construction of the performance appraisal system of local officials with the ecological civilization performance evaluation assessment as the core and not purely with the economic assessment as the core. This approach aims to increase the emphasis on environmental performance among government officials. Forestry's sustainable development is crucial to national economic development and ecological protection. It is also emphasized in the "Opinions" that forest ecological protection mechanisms must be reflected in officials' assessment process. Forestry eco-efficiency is one of the indicators that can reflect environmental performance. As a result, forestry eco-efficiency has become one of the most critical indicators for local officials to focus on in their appraisals. With the introduction of the NECP, local officials are incentivized to improve their environmental performance, which can be demonstrated through enhanced forestry eco-efficiency.

At the forestry development level, higher levels of government exert pressure on local officials to meet environmental performance standards through regulatory policies. This pressure is often distributed among enterprises within their jurisdictions [45], particularly those with high pollution levels. The "Opinions" also mandate that pilot zone governments accelerate the growth of leading enterprises in the environmental protection industry. This creates transformational pressure on local officials and firms, aligning with Porter's hypothesis. According to this hypothesis, reasonable environmental regulatory policies can spur enterprise innovation, leading to industry upgrading and high-quality development [46]. Since many forestry enterprises are significant polluters, local officials should focus more on forestry, increasing environmental protection measures within the industry to promote high-quality forestry development [45]. Eco-efficiency is critical for such development [14]. Therefore, this paper posits that the NECP will positively impact forestry eco-efficiency.

**H1:** *The implementation of the NECP can enhance forestry eco-efficiency.*

*2.2. The Spatial Spillover Effect*

At the level of spatial spillover effects, as the weight of environmental achievements in the performance appraisal system of regional officials continues to increase, officials around the world tend to compete with neighboring regions regarding economic growth and environmental protection to maintain their personal promotion advantages. Therefore, when implementing environmental policies, the decisions of various local governments influence each other [44]. In other words, establishing the NECP Area will bring about a demonstration effect within a specific scope. After the pilot region achieves success by implementing environmental policies, neighboring regions, under the influence of profit seeking, will imitate the policies. On the other hand, when neighboring regions impose stricter environmental regulations, the region also tends to increase the stringency of regulatory enforcement [47]. In addition, the establishment of the NECP Area may also bring about a specific range of comparative advantage effects. There are endowment gaps and development gaps across regions. Consequently, this will lead to developing a specific center in the region first and then spreading to the surrounding regions through various channels. The comparative advantage effect will bring about a clustering around human capital, service facilities and high-tech enterprises, reducing the waste of resources and energy and generating positive spatial spillover effects [48]. The logical hypotheses are shown schematically in Figure 1.

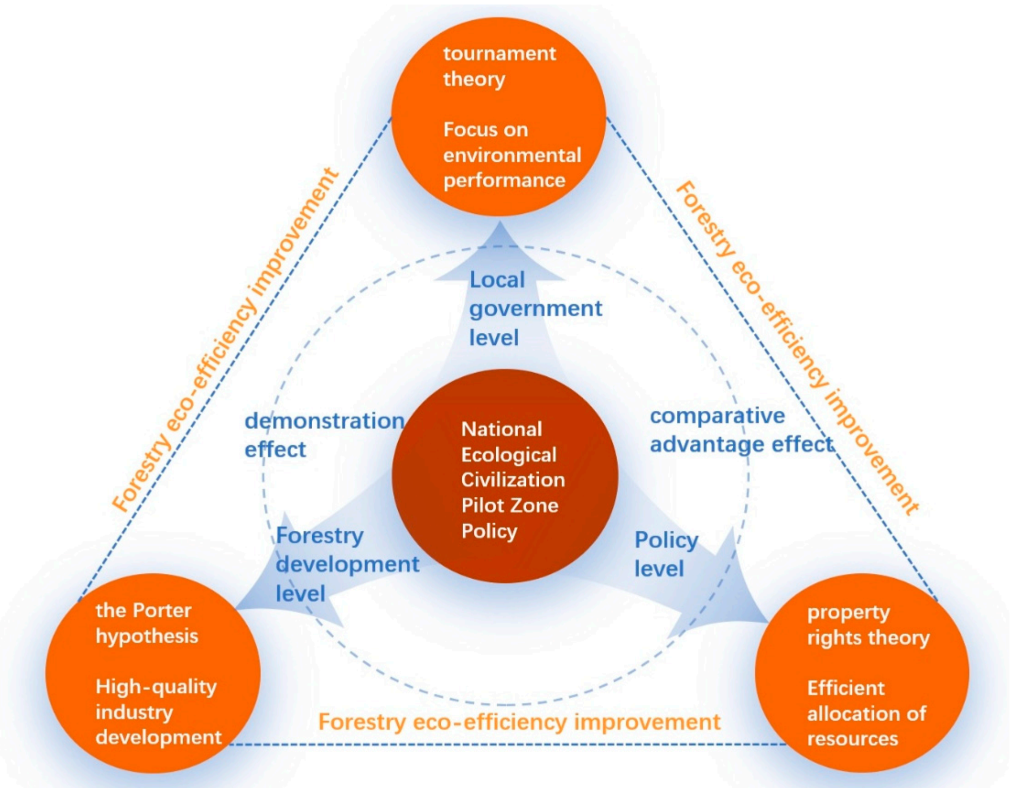


**Figure 1.** Logical schematic of the hypothesis.

**H2:** *The implementation of the NECP has spatial spillover effects on forestry eco-efficiency.*

## 3. Model and Data

To measure the ecological benefits of forestry, this paper employs a super-efficiency SBM model with undesirable outputs, as detailed in Section 3.1, and utilizes the forestry eco-efficiency indicators described in Section 3.4.1. Provincial panel data from 2011 to 2022 were analyzed, with data processing conducted using Matlab version 2022. Additionally, this study uses the ChiPlot academic website for hotspot mapping to present the data. The hierarchical clustering method employed is complete-linkage clustering, with Euclidean distance as the metric.

To analyze the impacts of the NECP on forestry eco-efficiency, the DID model in Section 3.2 and the spatial Durbin model in Section 3.3 were utilized, with data processing conducted using Stata version 17. Sections 4.2, 4.3 and 4.5 detail these analyses.

### 3.1. Super-Efficiency SBM Model

Referring to the related literature [49,50], the formulation of this model is shown in Equation (1).

$$\begin{gathered}\rho^{*}=min\frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{p_1+p_2}\left(\sum_{r=1}^{p_1}\frac{\overline{y_r^a}}{y_{r0}^a}+\sum_{q=1}^{p_2}\frac{\overline{y_q^b}}{y_{q0}^b}\right)}\\ \text{s.t.}\overline{x}\geqslant\sum_{j=1,\neq k}^{n}\lambda_j x_j\\ \overline{y^a}\leqslant\sum_{j=1,\neq k}^{n}\lambda_j y_j^a\\ \overline{y^b}\geqslant\sum_{j=1,\neq k}^{n}\lambda_j y_j^b\\ \overline{x}\geqslant x_0,\overline{y^a}\leqslant y_0^a,\overline{y^b}\geqslant y_0^b,\lambda\geqslant 0\end{gathered}\tag{1}$$

In Equation (1), $x_{ij}$ is the inputs; $y_{qj}^b$ is the undesired outputs; and $y_{rj}^a$ is the desired outputs. $\lambda$ is a weight vector indicating the weight of each DUM. $x_{i0}$ is an indicator of the inputs; $y_{q0}^b$ is an indicator of the undesired outputs; $y_{r0}^a$ is an indicator of the desired outputs. $s_i^-$ is the slack variable for the inputs; $s_q^b$ is the slack variable for the undesired outputs; $s_r^a$ is the slack variable for the desired outputs. Forestry eco-efficiency is defined in the article as $\rho$. The slack variables $s_i^-$, $s_q^b$, $s_q^b$ in the objective function are strictly decreasing. In the SBM model with undesired outputs $\rho \in [0,1]$, when DUM is in effect, $\rho = 1$. The $\rho^*$ in Equation (1) is the value of efficiency with calculations.

### 3.2. DID Model

Referring to related research [51], the model equation is as follows.

$$FEE_{i,t}=\beta_0+\beta_1\cdot treat\_post_{i,t}+\beta_2\cdot Controls_{i,t}+\mu_i+\lambda_t+\varepsilon_{i,t}\tag{2}$$

In the model, the dependent variable $FEE_{i,t}$ denotes forestry eco-efficiency in province $i$, year $t$. "*treat*" is a dummy variable for experimental and control groups, while "*post*" signifies policy implementation. $\beta_1$ is the coefficient of "*treat_post*". The name "*Controls*" refers to the collection of control variables. The remaining symbols represent province fixed effects, time fixed effects and random error terms in the order in which they appear in Equation (2).

### 3.3. Spatial Model

Referring to related research [51,52], the neighboring matrix is expressed as Equation (3).

$$W_{ij}=\left\{\begin{array}{ll}1, & \text{Provinces i and j are geographically linked}\\ 0, & \text{Provinces i and j are not geographically linked}\end{array}\right.\quad(\text{i}\neq\text{j})\tag{3}$$

Referring to related research [53], the spatial Durbin model is expressed as Equation (4).

$$\begin{gathered}FEE_{i,t}=\beta_0+\rho WFEE_{\text{it}}+\beta_1\cdot treat\_post_{i,t}+\\ \sum\beta\cdot Controls_{i,t}+\theta_1 Wtreat\_post_{i,t}+\sum\theta_2 WControls_{i,t}+\lambda_t+\mu_i+\varepsilon_{i,t}\end{gathered}\tag{4}$$

In Equation (4), W is the constructed adjacency space matrix; $\rho WFEE_{\text{it}}$ is the spatially lagged term of the explanatory variables; $\theta_2 WControls_{i,t}$ is the spatially lagged variable of the average observations in neighboring provinces.

### *3.4. Data Sources and Variable Measurement*

#### 3.4.1. Dependent Variable: *Forestry Eco-Efficiency*

The sustainable development theory emphasizes the compatibility of economic growth and environmental sustainability [54]. Thus, it is essential to consider both economic and environmental outputs and energy consumption. Figure 2 illustrates the logical framework for establishing specific forestry eco-efficiency indicators. Based on relevant theories, the selected indicators are grounded in the literature [55,56].

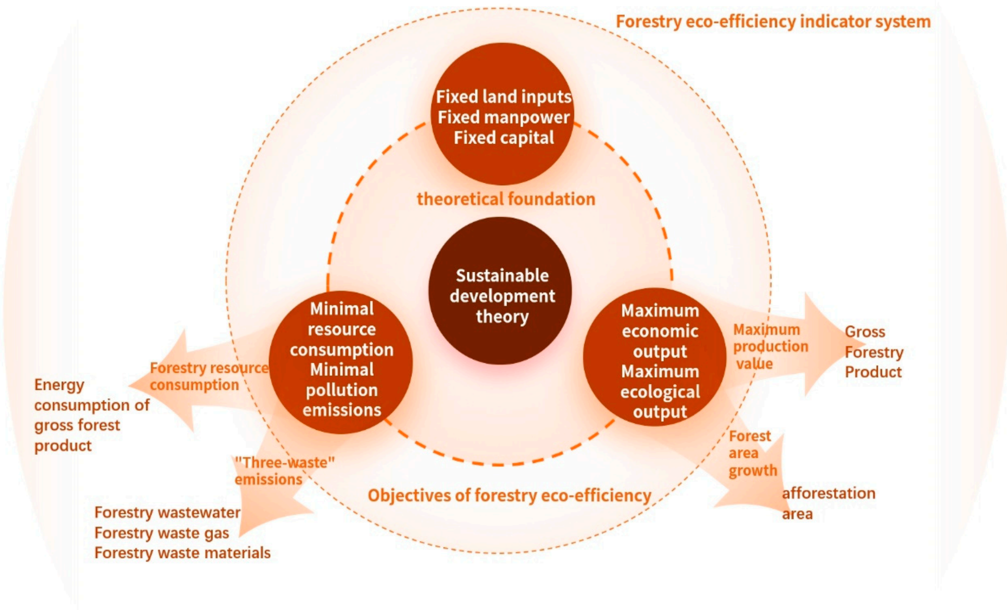


**Figure 2.** Theoretical basis and process of establishing forestry ecological indicators.

The input variables comprise land, human capital and energy. The measurement of land input is determined by the extent of land dedicated to forestry. The quantification of human contribution is determined by the total workforce working in the forestry sector at the end of the year [57]. Capital input is quantified by the perpetual inventory approach, which measures completed investment in fixed assets associated with forestry. The value of σ is 9.6% based on relevant studies [58]. The energy input is determined by considering the overall energy consumption associated with forestry output. This was calculated by multiplying the total consumption in each district by the overall forestry output and dividing it by the GDP of each district.

The desired outputs include economic and ecological benefits. For the economic output, gross forestry product is chosen, with 2011 as the base year for constant price calculations [56]. For the ecological output, afforestation area is selected, as it directly correlates with the ecological benefits of forestry [56].

The undesired outputs are exhaust emissions, solid waste emissions and wastewater emissions, based on references [50,55]. These are calculated using secondary industry output values and relevant industrial waste indicators. For example, forestry $SO_2$ emissions are calculated as industrial $SO_2$ emissions × forestry secondary production value/total industrial production value. Similar formulae are used for solid waste and wastewater outputs. Secondary forestry industry output is used as the primary source for these calculations, as most forestry waste emissions originate from this sector. Table 1 lists the specific indicators.

**Table 1.** Forestry eco-efficiency indicator components.

| Indicator Type | Indicator | Unit | Definition | Sources |
|---|---|---|---|---|
| Inputs | Land | Hectares | Forestry land area | China Forestry Statistical Yearbook [1] |
| | Labor | People | Number of workers in the forestry system at year's end | China Forestry Statistical Yearbook |
| | Capital | CNY 10,000 | Finished forestry fixed asset investment | China Forestry Statistical Yearbook |
| | Energy | Tons of standard coal | Energy consumption of total forestry output value | China Forestry Statistical Yearbook, China Energy Statistical Yearbook [2], China Statistical Yearbook [3] |
| Desired outputs | Economic output | CNY 10,000 | Gross forestry product | China Statistical Yearbook |
| | Ecological output | Hectares | Afforestation area | China Forestry Statistical Yearbook |
| Undesired outputs | Forestry exhaust gas | Tons | $SO_2$ emissions from regional forestry | China Environmental Statistics Yearbook, China Statistical Yearbook |
| | Forestry solid waste | Tons | Regional forestry solid waste generation | China Environmental Statistics Yearbook [4], China Statistical Yearbook |
| | Forestry wastewater | Tons | Total amount of wastewater discharged from forestry in the region | China Environmental Statistics Yearbook, China Statistical Yearbook |

Data sources: [1] https://www.forestry.gov.cn/c/www/tjnj.jhtml (accessed on 17 May 2024). [2] https://cnki.ctbu.edu.cn/CSYDMirror/Trade/yearbook/single/N2023050100?z=Z023 (accessedon 17 May 2024). [3] https://www.stats.gov.cn/sj/ndsj/ (accessed on 17 May 2024). [4] https://cnki.nbsti.net/CSYDMirror/area/Yearbook/Single/N2021070128?z=D26 (accessed on 17 May 2024).

The "China Forestry Statistical Yearbook", "China Statistical Yearbook", "China Environmental Statistical Yearbook", "China Energy Statistical Yearbook" and the official websites of provincial and local governments are the sources of all the data in Section 3.

3.4.2. Independent Variable: Interaction Term *"treat_post"*

The article identifies three provinces in the pilot region of eco-civilization as the treatment group. The remaining provinces are the control group. Due to the limited data for Tibet, the province is not included. The year 2016 is the time point of policy implementation, with the pre-implementation group before 2016 and the post-implementation group after 2016 [59].

3.4.3. Control Variables

Based on relevant literature [51,52], the following control variables are selected: Industrial Scale (*IS*), Forestry Pests Area *(lnFPA*), Urbanization Level (*UL*), Government Support (*lnGS*) and Environmental Governance Level (*EGL*).

3.4.4. Descriptive Statistics

Table 2 shows the descriptive statistics of this paper. Table 2 shows the article's data, which contains 300 observations from 30 provinces from 2011 to 2020. Among the variables, the most central variables are "treat_post" and FEE. The former represents the implementation status of the policy pilot, with a mean of 0.0500, a standard deviation of 0.218, a minimum value of 0 and a maximum value of 1. The latter represents the efficiency level of forestry ecology, with a mean of 0.631, a standard deviation of 0.399, a minimum value of 0.0901 and a maximum value of 2.105. This suggests excellent variations in the ecological efficiency among the observations.

**Table 2.** Descriptive statistics.

| Variable Type | Variable | Description | Unit | Obs | Mean | St | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Independent variable | treat_post | Policy pilot dummy variable | – | 300 | 0.0500 | 0.218 | 0 | 1 |
| Dependent variable | FEE | Forestry eco-efficiency | – | 300 | 0.631 | 0.399 | 0.0901 | 2.105 |
| Control variables | IS | Ratio of the year-end GDP to the total value of forestry output | % | 300 | 7.779 | 5.646 | 0.130 | 33.94 |
| | EGL | Ratio of total investment in industrial pollution control to year-end industrial GDP | % | 300 | 0.00313 | 0.00308 | 0.0000166 | 0.0280 |
| | UL | Ratio of the overall population to that of the urban area | % | 300 | 59.01 | 12.22 | 35.03 | 89.60 |
| | lnFPA | Provincial forest pests and diseases at the end of the year | Hectares | 300 | 10.03 | 1.693 | 3.332 | 13.10 |
| | lnGS | Government forestry investments at year's end | CNY 10,000 | 300 | 13.04 | 0.852 | 9.873 | 15.18 |

## 4. Results

### *4.1. Forestry Eco-Efficiency Calculations*

Table 3 displays the ultimate recorded values of forestry eco-efficiency for each province in China throughout the specified period. Figure 3 displays the hotspot map of these data, providing a visual representation of the overall data. China's forestry eco-efficiency experienced a decline between 2011 and 2014. The eco-efficiency of forestry reached its highest level in 2016, with a value of 0.8327, but has since been declining. The average eco-efficiency of China's forestry sector has yet to reach a practical level, defined as being less than 1. Hence, China's forestry sector must enhance the balance between economic and environmental inputs and outputs and actively work toward improving the ecological efficiency of forestry to achieve tangible benefits.

**Table 3.** Presentation of forestry eco-efficiency.

| Province | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|---|---|---|
| Beijing | 0.5216 | 0.4563 | 0.3040 | 0.2965 | 0.3639 | 0.3764 | 0.5567 | 0.3717 | 0.3358 | 0.4497 |
| Tianjin | 0.6387 | 0.5513 | 0.5239 | 0.5265 | 0.5262 | 0.7310 | 1.1496 | 0.4016 | 1.0801 | 0.1798 |
| Hebei | 0.6722 | 0.6806 | 0.6507 | 0.7164 | 0.8997 | 1.0875 | 0.9554 | 1.0638 | 0.7072 | 0.8059 |
| Shanxi | 0.4978 | 0.3017 | 0.2638 | 0.2583 | 0.4147 | 0.4834 | 0.4739 | 0.2984 | 0.2762 | 0.7424 |
| Inner Mongolia | 0.3283 | 0.3277 | 0.3079 | 0.4065 | 0.7070 | 0.5856 | 0.4727 | 0.2421 | 0.2280 | 0.3203 |
| Liaoning | 0.7134 | 0.8962 | 0.9460 | 0.8445 | 0.8159 | 0.7380 | 0.6945 | 0.5763 | 0.5357 | 0.6449 |
| Jilin | 0.1623 | 0.1165 | 0.3992 | 0.2011 | 0.4217 | 0.5295 | 0.6129 | 0.2489 | 0.1850 | 0.2684 |
| Heilongjiang | 0.1405 | 0.2122 | 0.1653 | 0.1356 | 0.1483 | 0.1049 | 0.1081 | 0.1291 | 0.1350 | 0.1493 |
| Shanghai | 1.2148 | 0.5124 | 0.2194 | 0.2264 | 0.7813 | 1.1320 | 0.5736 | 0.5147 | 0.4754 | 0.5151 |
| Jiangsu | 1.2196 | 0.9578 | 0.4884 | 0.4301 | 1.7675 | 1.1845 | 1.1323 | 0.4268 | 0.4120 | 0.8395 |
| Zhejiang | 0.2876 | 0.3522 | 0.2645 | 0.2468 | 0.6829 | 1.2980 | 1.0178 | 0.4667 | 0.6333 | 1.2121 |
| Anhui | 0.2941 | 0.2458 | 0.7122 | 0.9723 | 1.0147 | 1.1586 | 1.2330 | 1.1200 | 0.6718 | 0.6986 |
| Fujian | 0.8271 | 0.4020 | 0.4285 | 0.3324 | 1.4292 | 1.3309 | 1.4492 | 1.1189 | 0.8553 | 1.1594 |
| Jiangxi | 0.5082 | 0.4750 | 0.6225 | 0.4874 | 0.5642 | 1.1799 | 1.1919 | 0.9882 | 0.9589 | 0.9225 |
| Shandong | 0.8141 | 1.9823 | 1.0342 | 0.8569 | 2.0995 | 2.0000 | 1.9312 | 1.5999 | 0.8251 | 0.8293 |
| Henan | 1.6364 | 0.7923 | 0.7905 | 0.7747 | 0.7895 | 0.6591 | 0.6896 | 0.7444 | 0.7497 | 0.8343 |

**Table 3.** *Cont.*

| Province | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|---|---|---|
| Hubei | 0.6471 | 0.6170 | 0.7060 | 0.6543 | 0.7775 | 0.6722 | 0.8714 | 0.7642 | 0.6273 | 0.7389 |
| Hunan | 0.7923 | 0.6993 | 0.6119 | 0.6434 | 0.8160 | 0.7927 | 0.6926 | 0.8693 | 0.8952 | 0.9239 |
| Guangdong | 1.5256 | 1.7591 | 0.5661 | 0.4245 | 2.0000 | 2.1050 | 1.8530 | 0.8180 | 0.6367 | 0.8599 |
| Guangxi | 0.2463 | 0.2166 | 0.2017 | 0.1927 | 0.3082 | 0.5144 | 0.4307 | 0.4328 | 0.3885 | 0.3952 |
| Hainan | 0.1842 | 0.1659 | 0.1157 | 0.0901 | 0.2002 | 0.1593 | 0.1336 | 0.1225 | 0.1550 | 0.1400 |
| Chongqing | 1.4535 | 0.6521 | 0.6973 | 0.5149 | 1.0736 | 1.1742 | 1.1298 | 1.1083 | 1.0037 | 1.1370 |
| Sichuan | 0.4429 | 0.2686 | 0.3085 | 0.2738 | 0.8909 | 0.6995 | 0.7054 | 0.6348 | 0.6113 | 0.7679 |
| Guizhou | 0.3116 | 0.3611 | 0.3035 | 0.3171 | 0.6367 | 1.0505 | 1.1142 | 0.8776 | 0.9891 | 0.7832 |
| Yunnan | 0.4469 | 0.3266 | 0.3747 | 0.4105 | 0.6021 | 0.5533 | 0.6074 | 0.5397 | 0.4952 | 0.6609 |
| Shannxi | 0.6175 | 0.4624 | 0.3926 | 0.4191 | 0.5779 | 0.5694 | 0.7535 | 0.5253 | 0.4550 | 0.5287 |
| Gansu | 0.3177 | 0.3340 | 0.2848 | 0.2793 | 0.4567 | 0.5248 | 0.5335 | 0.3862 | 0.3095 | 0.3335 |
| Qinghai | 1.5123 | 0.3091 | 0.2633 | 0.1777 | 0.2254 | 0.2971 | 0.2695 | 0.1953 | 0.3516 | 1.2852 |
| Ningxia | 0.5051 | 0.2908 | 0.2580 | 0.1944 | 0.4180 | 0.5741 | 0.4322 | 0.2208 | 0.1659 | 0.2698 |
| Xinjiang | 0.4729 | 0.4944 | 0.4692 | 0.3795 | 0.7330 | 0.7153 | 0.5464 | 0.3849 | 0.3029 | 0.3439 |
| Mean | 0.6651 | 0.5406 | 0.4558 | 0.4228 | 0.7714 | 0.8327 | 0.8105 | 0.6064 | 0.5484 | 0.6580 |

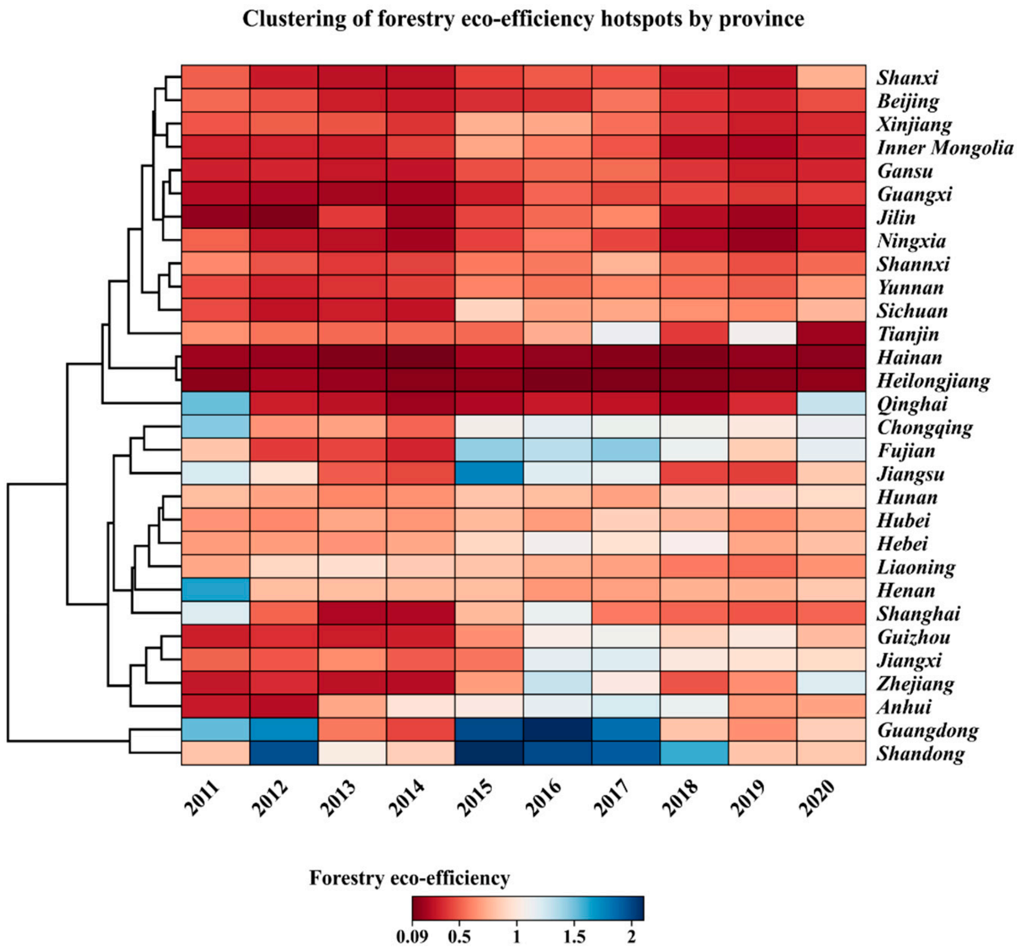


**Figure 3.** Hotspot clustering of forestry eco-efficiency.

In addition, a cluster analysis was conducted in this paper using the methodology described in Section III, and the results are shown in Figure 3. Depending on the outcome, this study categorized the ecological benefits of forestry in different regions into three categories. The first category of places, namely Shandong and Guangdong, have an average forestry eco-efficiency value of 1.3260, indicating that they operate efficiently. In forest areas where the second category of benefits is at a medium level, the average forestry eco-efficiency is 0.7427. The regions above encompass Chongqing, Fujian, Jiangsu, Hunan, Hubei, Hebei, Liaoning, Henan, Shanghai, Guizhou, Jiangxi, Zhejiang and Anhui. The third category comprises the following regions: Shanxi, Beijing, Xinjiang, Inner Mongolia, Gansu, Guangxi, Jilin, Ningxia, Shaanxi, Yunnan, Tianjin, Hainan, Heilongjiang and Qinghai. The mean eco-efficiency of forestry in these regions is 0.3913, indicating room for improvement. Among the pilot provinces proposed in the "Opinions", namely Fujian, Guizhou and Jiangxi, this eco-efficiency is only moderate compared to certain other provinces. Nevertheless, following the enactment of the legislation in 2016, the average forestry efficiency of the three provinces reached 1.0646, demonstrating its effectiveness.

### *4.2. Basic Regression Results*

Before performing the regression, the following tests were performed in this paper: (1) VIF test, (2) F-test and (3) Hausman test. The test results demonstrated that no multicollinearity exists between the variables. In addition, this paper chose a double-fixed model.

The primary regression findings are displayed in Table 4. Disregarding the control variables, it can be seen in Table 4, Column (1), that the explanatory variable is significant at the three-star level. This suggests that NECP enhances regional forestry's eco-efficiency and supports Hypothesis 1. After considering the control factors, the analysis of data in Table 4, Column (2), shows that the explanatory variable is statistically significant at the 1% level. Therefore, Hypothesis H1 is confirmed. The calculated coefficient for the NECP policy in China is 0.347. The data suggest that the ecological advantages of forestry in the test area, assuming all other factors remain constant, are 0.347 more significant than in the non-test area.

**Table 4.** Benchmark regression results.

| | **(1)** | **(2)** |
|---|---|---|
| treat_post | 0.456 *** | 0.347 *** |
| | (4.85) | (3.34) |
| Controls | No | YES |
| Constant | 0.665 *** | −0.255 |
| | (14.88) | (−0.31) |
| Year fixed effect | YES | YES |
| Provincial fixed effect | YES | YES |
| Observations | 300 | 300 |
| R-squared | 0.308 | 0.327 |
| Number of id | 30 | 30 |

*** $p < 0.01$.

### *4.3. Robustness Tests*

#### 4.3.1. Parallel Trend Test

A parallel trend test is required before regression is conducted, and only through this test can the subsequent study be conducted. The parallel trend test refers to relevant studies [60]. The test used 2011 as the reference group. The parallel trend test was successful, as indicated by the findings shown in Figure 4. Two conclusions can be inferred. (1) The issue of endogeneity, which arises when unobserved elements are not considered, can be partially resolved. (2) The initial regression analysis findings are again confirmed.

#### 4.3.2. Placebo Test

This paper conducted a placebo test to rule out the effect of other omitted variables. The specific steps were as follows. (1) We conducted a placebo test with random assignment and (2) re-evaluated the policy after 500 random samples. The results are shown in Figure 5, indicating that the outcomes are stable.

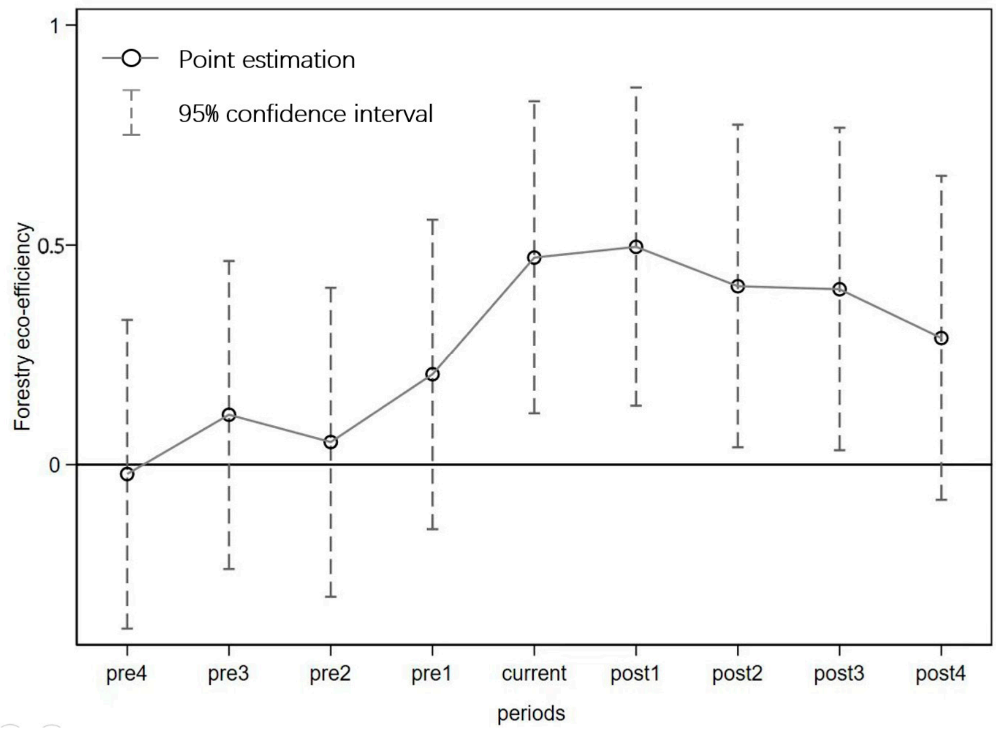


**Figure 4.** Parallel trend test results.

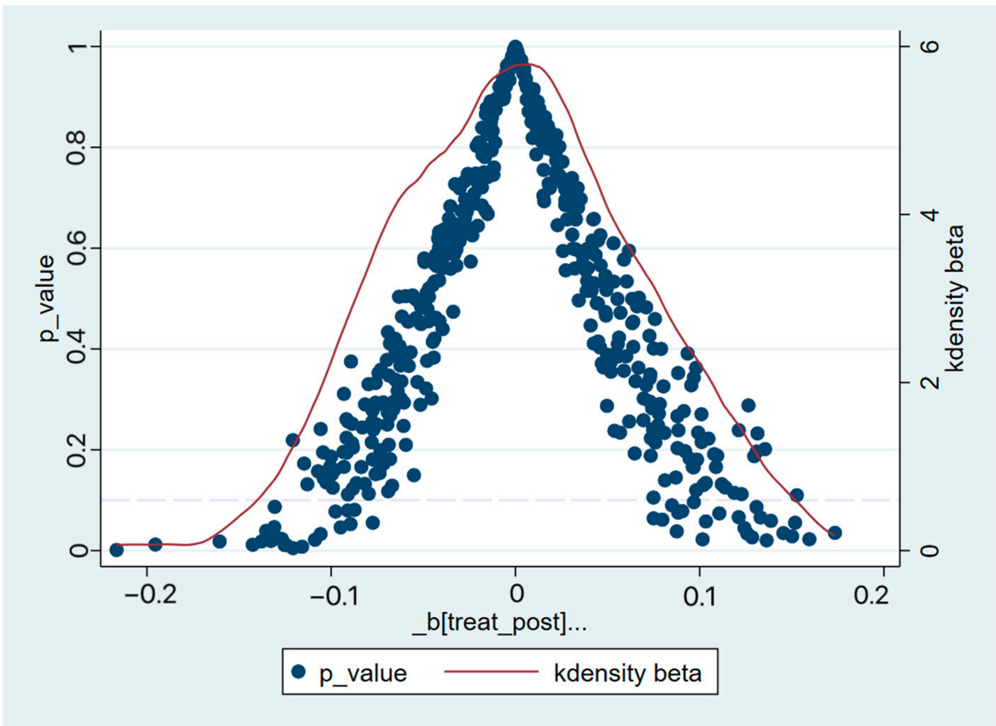


**Figure 5.** Placebo test results.

### 4.3.3. Counterfactual Tests

To rule out the possible effects of other unobserved shocks on the NECP, we advanced the NECP implementation dummy variables by 1–5 years, respectively, one at a time, and examined the effects of policies on forestry eco-efficiency by setting up a dummy policy shock year. If the estimated coefficient is insignificant, this means that it passes the placebo test, i.e., no other omitted confounding variables exist. Based on the outcome of the data, the observed coefficient estimated for each year of the initial implementation of the policy is not significant, as shown in Table 5. This satisfies the conditions for the test to be valid.

**Table 5.** Counterfactual test results.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Variables | treated1 | treated2 | treated3 | treated4 | treated5 |
| treat_post | −0.230 | −0.264 | −0.106 | −0.190 | −0.018 |
| | (−1.42) | (−1.64) | (−0.65) | (−1.19) | (−0.11) |
| Controls | YES | YES | YES | YES | YES |
| Year fixed effect | YES | YES | YES | YES | YES |
| Provincial fixed effect | YES | YES | YES | YES | YES |
| Observations | 300 | 300 | 300 | 300 | 300 |
| R-squared | 0.303 | 0.305 | 0.299 | 0.301 | 0.298 |

#### 4.3.4. Replacement of Core Explanatory Variables

This paper changes the explanatory variable to variable-scale forestry eco-efficiency (FEE1). The new explanatory variables are regressed, and the conclusions are reliable if the results are also significant. NECP continues to positively contribute to forestry eco-efficiency—a conclusion derived from data in the first column of Table 6.

**Table 6.** Replacement variables and excluded sample test results.

| | (1) | (2) |
|---|---|---|
| Variables | FEE1 | Rejection sample |
| treat_post | 0.167 * | 0.350 *** |
| | (1.79) | (3.49) |
| Controls | YES | YES |
| Constant | 0.076 | −0.287 |
| | (0.10) | (−0.35) |
| Year fixed effect | YES | YES |
| Provincial fixed effect | YES | YES |
| Observations | 300 | 280 |
| R-squared | 0.341 | 0.360 |

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

#### 4.3.5. Exclusion of Some Samples

There are disparities in resource endowments among China's provinces. Among them, there is a large gap between Qinghai and Xinjiang regarding forestry development and other provinces. This may lead to inconsistent effects of NECP. Therefore, this paper again excludes two provinces: Qinghai and Xinjiang. As can be seen from the data in Table 6, Column 2, the hypotheses of this paper are validated again.

### *4.4. Further Studies: Tests for Heterogeneity*

#### 4.4.1. Grouping by Ecological Basis

Forest cover in each province is an essential indicator of regional resource endowment. Therefore, the article takes the forest cover of each province in China in 2020 as the basis and divides the sample into two groups: good ecological base and general ecological base. This is the basis for studying the impact of different regional resource endowments on forestry eco-efficiency [59]. The results in Table 7, Columns 1 and 2, show that the pilot policy has significantly impacted forestry benefits in provinces with a better ecological base. However, this conclusion must be present in provinces with an average ecological base. This suggests that the NECP can effectively promote forestry eco-efficiency in provinces with an excellent ecological base. This may be because provinces with a better ecological base are rich in forest resources, and therefore, the region attaches relative importance to ecological conservation. After implementing the pilot policy, the government's emphasis on forestry development was further increased, and the investment in forestry construction was increased, leading to an increase in forestry eco-efficiency. In contrast, in provinces with an average ecological base—some rich in forest resources—these areas focus more on developing other industries. After implementing the environmental regulation policy, the government will also be the first to start regulating these industries, which leads to the need for clarity in implementing the pilot policy on forestry eco-efficiency in these areas.

**Table 7.** Heterogeneity results.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Variables | Good ecological base | General ecological base | The east | The middle | The west |
| treat_post | 0.363 *** | 0.034 | 0.416 * | 0.224 | 0.278 |
| | (2.68) | (0.15) | (1.95) | (1.56) | (1.40) |
| Controls | YES | YES | YES | YES | YES |
| Constant | −0.073 | −0.465 | −0.813 | 1.735 | −0.547 |
| | (−0.04) | (−0.44) | (−0.50) | (1.18) | (−0.29) |
| Observations | 100 | 200 | 110 | 80 | 110 |
| R-squared | 0.420 | 0.311 | 0.432 | 0.486 | 0.444 |

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

#### 4.4.2. Geographical Groupings

Geographic classification. Based on the outcomes of data in Table 7, Columns 4 and 5, it can be seen that the pilot strategy has significantly impacted forestry eco-efficiency in the east. However, in the middle and west regions, the impact was not significant.

The following are possible explanations. The degree of regional economic growth is one of the most critical factors affecting the role of environmental regulatory laws in forestry eco-efficiency [61]. The central region has a greater capacity for economic development and innovation. Consequently, businesses in the area are more equipped to handle the extra expenses associated with safeguarding the environment, and industries in the region are more capable of synchronizing output with environmental preservation. On the other hand, in areas with lower economic growth, specific industries may be forced out of the market because of environmental regulations. This, in turn, impacts the enhancement of forestry eco-efficiency [62].

### *4.5. Further Studies: Spatial Spillover Effects*

This paper uses a spatial autocorrelation test and a spatial model selection test. The results of the tests are as follows. (1) All three indicators show significance at the three-star level, indicating the existence of spatial autocorrelation of forestry eco-efficiency in the 30 provinces of China. (2) The spatial Durbin model with double-fixed effects is the most effective when applying the data to the adjacency matrix.

Therefore, this paper can be tested further using the correlation model. The test of spatial spillover effects shown in Table 8 indicates that (1) NECP has a robust spatial spillover effect on forestry ecological benefits, thus verifying Hypothesis H2. (2) Through further decomposition analysis, this paper concludes that the direct, indirect and total effects are all significant.

The above conclusions indicate that the policy has substantial positive spatial impacts on forestry eco-efficiency at the regional level, which supports Hypothesis H2, and the observed spatial spillover effects are likely to be due to the strong demonstration and comparative advantage effects of the NECP.

**Table 8.** Spatial spillover effect results.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Variables | Main | Wx | Spatial | Variance | LR_Direct | LR_Indirect | LR_Total |
| treat_post | 0.258 *** | 0.896 *** | | | 0.329 *** | 1.252 *** | 1.581 *** |
| | (0.0731) | (0.265) | | | (0.110) | (0.331) | (0.359) |
| rho | | | 0.272 *** | | | | |
| | | | (0.0845) | | | | |
| sigma2_e | | | | 0.0565 *** | | | |
| | | | | (0.0141) | | | |
| Observations | 300 | 300 | 300 | 300 | | | |
| Controls | YES | YES | - | - | YES | YES | YES |
| R-squared | 0.030 | 0.030 | 0.030 | 0.030 | | | |

*** $p < 0.01$.

## 5. Discussion

This paper may present the following contributions. First, in this paper, NECP is chosen as the research object to study its impact on forestry eco-efficiency. The impact of environmental policies on the synergy between conservation and economic development is explored. This differs from current studies examining this multiplier effect [63,64]. Second, compared with the traditional DEA model used by other scholars [23,65], this paper adopts a more scientific and rigorous calculation method, making forestry ecological benefits more accurate. Finally, this paper provides further research on NECP, thus enhancing the depth of research in this area.

Table 9 provides a complete overview of the assumptions and results of this paper. The section that follows is based on the research findings.

**Table 9.** Hypotheses and results.

| Hypothesis | Result |
|---|---|
| H1: The implementation of the NECP can enhance forestry eco-efficiency. | Hypothesis is valid |
| H2: The implementation of the NECP has spatial spillover effects on forestry eco-efficiency. | Hypothesis is valid |

First, it is clear from evaluating China's forestry eco-efficiency that the country's average eco-efficiency has not yet achieved a practical level and urgently needs to be improved. This is consistent with Hanting Chen et al.'s findings [50], indicating that resource allocation in China's forestry sector needs to be more rational.

Second, given the above problems, exploring the ways to promote a rational allocation of resources is essential, so that the forestry economy can better utilize the multiplier effect. Our analysis validates that NECP policies positively influence forestry eco-efficiency, supporting Hypothesis H1. This suggests that government environmental policies can foster synergies between the forestry economy and the environment. This aligns with findings by Aziz Noshab et al. and Muhammad Salman et al., who, through different perspectives, showed that such policies reduce carbon footprints while promoting economic gains [66,67]. Therefore, governments around the world should emphasize forestry development as a sector that combines the dual functions of production and environmental protection and could become an essential component of integrated economic and environmental development.

Third, there is heterogeneity in the harmonizing effects of NECP policies. This finding highlights that while synergizing the economy and the environment is a common global goal, a single environmental policy cannot be universally applied. Different regions must develop policies tailored to their specific contexts. Policies from various regions can inspire countries around the world but should not be directly replicated.

Lastly, the spatial benefits of NECP policies support Hypothesis H2. This suggests that countries around the globe that want to achieve better multiplier effects can prioritize implementing environmental policies in specific regions and achieve this through spatial spillover effects. This is similar to the findings of Liu et al., who concluded that government environmental policies can curb carbon emissions in the manufacturing sector and that these effects have spatial spillovers [68]. The same conclusion can be drawn from different research perspectives: government environmental policies exhibit spatial spillover effects.

## 6. Conclusions

Harmonizing economic development with ecological and environmental protection is essential in the global quest for sustainable development [1,2]. This issue has garnered significant global attention, and the international community is eager to incorporate more policies and experiences that contribute to sustainable development [69,70]. As a crucial sector for global sustainable development, forestry requires a careful balance between economic progress and protection of the environment [4]. By 2022, China's forest area had reached 2.2 million square kilometers, accounting for 5% of the global land area. In terms of economic output, China's forestry output value exceeded CNY 590 billion in 2020, a 1.37-fold increase from 2015 [8]. It follows that China's advantage in forestry development and its experience in harmonizing economic and environmental objectives position it uniquely. In recent years, China has emphasized forestry development through various policies, including the NECP. This paper examined the NECP from the perspective of forestry eco-efficiency research, aiming to offer new insights for global sustainability. On the basis of the above research significance, we used provincial data from 2011 to 2020 to conduct an empirical analysis using the DID model and the spatial Durbin model and drew the following conclusions.

First, in this paper, through hotspot clustering analysis, forestry eco-efficiency in each province is categorized into three categories: effective, semi-effective and ineffective. Our findings suggest that China's average forestry eco-efficiency falls into the ineffective category, highlighting the need to optimize resource allocation within the sector.

Second, NECP significantly enhances forestry eco-efficiency, with robust findings across various stability tests. Thus, implementing government environmental policies can have a multiplier effect on forestry, i.e., it can synergize its economic development with environmental protection.

Third, in provinces with a strong ecological foundation, the NECP significantly enhances forestry eco-efficiency. However, in other provinces, the improvement is only moderate. Furthermore, while the NECP has a substantial positive impact in the eastern region, it has yet to show a discernible effect in other regions.

Lastly, the positive impacts of NECP implementation on forestry eco-efficiency have spatial spillover effects due to demonstration effects and comparative advantages.

The limitations of this paper and the future outlook are described first because forestry eco-efficiency may be characterized by a long period of effectiveness. This paper chose 10 years as the research period after referring to related research. However, our future direction is to adopt a more extended research period for related research. Second, in the construction of the indicators of forestry eco-efficiency, the non-expected output indicators applied in this paper were selected concerning relevant studies and data availability. However, when selecting such indicators, the limitation of data availability leads to a lack of comprehensiveness. This point will be the direction of our future research.

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**Data Availability Statement:** Data are contained within the article.

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