

Article

National Reserve Forest Policy and Forestry Green Total Factor Productivity: Evidence from Prefecture-Level Cities in China

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Abstract

Against the backdrop of global forest degradation and timber supply constraints, improving green production efficiency in forestry while securing timber supply is an important challenge for sustainable forest management. Treating China's National Reserve Forest Policy (NRFP) as a quasi-natural experiment, this study uses panel data for 114 prefecture-level cities from 2011 to 2022, including 67 treated and 47 control cities. We employ a staggered difference-in-differences estimator based on group-time average treatment effects, together with transmission-channel analysis, difference-in-difference-in-differences (DDD), and a spatial difference-in-differences-spatial Durbin model (Spatial DID-SDM). The baseline estimates yield an overall ATT of 0.0149, indicating an average increase of 0.0149 index points in forestry GTFP for treated cities relative to the estimated counterfactual without the NRFP. This effect is approximately 1.49% of the sample mean of forestry GTFP (0.998) and remains stable across multiple robustness and sensitivity checks. NRFP implementation is separately associated with increases in capital deepening (CD) and physical labor productivity (PLP), while the lagged values of CD and PLP are each positively associated with forestry GTFP; these results are consistent with CD and PLP as potential transmission channels. The estimated NRFP effect is significantly weaker in resource-based cities and significantly stronger in economy-efficiency-oriented regions. Spatial effect decomposition shows that both the direct and indirect effects of the NRFP are positive and statistically significant. Under the alternative spatial weight matrix, both effects retain their direction and statistical significance, while the magnitude of the indirect effect remains broadly stable, suggesting that the positive spatial spillover effect of the NRFP on forestry GTFP is reasonably robust to the spatial weight matrix specification. These findings provide city-level empirical evidence for evaluating NRFP performance and informing differentiated policy design.



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1. Introduction

Global forest resources are facing severe challenges from ongoing degradation and loss, with illegal logging and unsustainable management practices remaining key drivers [1,2]. This trend not only contributes to biodiversity loss and exacerbates climate change [3], but also threatens the stability of global timber supply. Economies that rely heavily on timber

imports are therefore particularly exposed to supply-chain risks arising from fluctuations in timber availability and uncertainties in international sourcing [4]. China is one of the world's largest timber importers and consumers. Its dependence on imported timber exceeds 50%, and the country accounts for more than one-third of global log imports [5]. This high level of import dependence closely links China's domestic timber supply security to the sustainable management of global forest resources.

Against this background, increasing domestic timber supply cannot rely solely on expanding production. Rather, it needs to be pursued within a sustainable forest management framework that balances timber supply, resource-use efficiency, and ecological protection. Given limited forest land resources and the need to maintain ecosystem services, a key challenge for China's forestry sector is how to improve timber supply security and economic benefits without compromising ecological objectives, providing an important context for evaluating large-scale forest management policies.

To evaluate forestry production performance under resource and environmental constraints, a measure that accounts for both economic output and environmental costs is needed. Although traditional total factor productivity is widely applied, its accounting framework often does not fully account for resource and environmental constraints, especially undesirable outputs generated during production, making it difficult to fully reflect the green performance of production activities [6]. This limitation has driven the development of the concept of green total factor productivity (GTFP). GTFP integrates desirable and undesirable outputs into a unified analytical framework and evaluates productivity changes in the relationship between factor inputs and economic outputs while accounting for environmental costs [7]. When applied to the forestry sector, GTFP jointly accounts for factor inputs, desirable outputs, and undesirable outputs in forestry production, providing a comprehensive indicator for evaluating forestry green production efficiency under resource and environmental constraints.

China's NRFP is a key policy initiative for promoting sustainable forest management and coordinating timber supply with ecological protection objectives. The policy adheres to the principle of ecological priority and implements systematic measures such as intensive plantation cultivation, improvement of existing forests, and tending of young and middle-aged forests to develop industrial raw material forests and medium- to large-diameter timber forests. The NRFP encourages exploring the efficient use of reserve forest resources and understory spaces and supports the development of non-timber forest products, understory planting and breeding, and multifunctional forest management [8]. These measures may not only alleviate domestic timber supply constraints by increasing forest growing stock and enhancing timber supply capacity, but also create favorable conditions for maintaining ecosystem services, conserving biodiversity, and enhancing forest resilience. In addition, long-term investment in forest development may support mechanized operations and the adoption of digital forestry technologies, thereby improving forest management and supply-chain coordination efficiency. According to statistics from the National Forestry and Grassland Administration (NFGA), by the end of 2022, more than RMB 140 billion had been invested in NRFP construction, and more than 6.13 million hectares of national reserve forests had been established. The total forest growing stock in the project construction areas had increased by 270 million cubic meters, with an average annual growing stock increment of approximately 10.8 cubic meters per hectare, and the cumulative timber output through national reserve forests had reached about 150 million cubic meters [9]. These figures reflect the scale of NRFP construction and the progress achieved to date in increasing forest growing stock and timber supply. However, whether the policy can, as strategically envisioned, enhance timber supply capacity, coordinate economic benefits with ecological protection, and improve forestry GTFP remains to be rigorously evaluated.

Therefore, this study treats the NRFP as a quasi-natural experiment. Based on panel data from 114 prefecture-level cities in China spanning 2011 to 2022, we first employ a difference-in-differences (DID) approach designed for staggered treatment adoption to estimate the average treatment effect of the NRFP on forestry GTFP based on group-time average treatment effects (group-time ATTs). Subsequently, we conduct a transmission-channel analysis to examine the potential roles of capital deepening (CD) and physical labor productivity (PLP) in transmitting the effect of the NRFP on forestry GTFP. Further, we use a difference-in-difference-in-differences (DDD) approach to examine the heterogeneity of policy effects across dimensions such as resource-based city status and policy zoning. Finally, we employ a spatial difference-in-differences–spatial Durbin model (Spatial DID-SDM) to examine the spatial spillover effects of the NRFP and further characterize the spatial patterns of its policy effects.

This study makes three main contributions. First, it provides policy-specific city-level evidence on the relationship between the NRFP and forestry GTFP, offering an evaluation of the policy from the perspective of green production efficiency under resource and environmental constraints. Second, it goes beyond the average policy effect by providing further evidence on capital deepening and physical labor productivity as potential transmission channels and on how the estimated effect varies across resource-based city status and policy zoning conditions. Third, it extends the evaluation beyond implementing cities by explicitly considering inter-city spatial linkages and providing evidence that the policy effect may spill over across city boundaries.

The remainder of this paper is structured as follows. Section 2 presents the policy background and literature review. Section 3 provides the theoretical analysis and research hypotheses. Section 4 describes the model specification and data sources. Section 5 reports the empirical results and analysis. Section 6 offers a discussion. Section 7 concludes the study and discusses its limitations and directions for future research.

2. Policy Background and Literature Review

2.1. NRFP Background

The NRFP was initiated in 2012, with pilot projects led by the NFGA. As illustrated in Figure 1, the policy evolved through distinct stages, transitioning from local pilots to regional expansion and then to a nationwide policy, with its policy framework continuously refined. After 2021, the NRFP further demonstrated targeted and differentiated governance features [10]. Taking into account the actual conditions of different regions, the policy divided construction regions into key and moderate construction regions. It also defined multiple coordinated objectives, including carbon sink enhancement, soil and water conservation, biodiversity protection, precious tree species reserves, and non-timber forest product development. Given data availability, this study uses data from 2011 to 2022 to evaluate the effects of the NRFP from the launch of its pilot program in 2012 through the end of the sample period in 2022. After the sample period, the institutional framework of the NRFP continued to evolve. In May 2025, the NFGA, in conjunction with the National Development and Reform Commission (NDRC), released the Implementation Plan for National Reserve Forest Construction (2025–2028). This plan further emphasizes quality improvement, industrial development, livelihood benefits, green finance, ecological civilization development, and national timber resource security in national reserve forest construction. The plan continues and further develops the policy directions established in earlier phases of national reserve forest development, while further highlighting the policy objectives of coordinating timber supply, economic efficiency, and ecological sustainability.

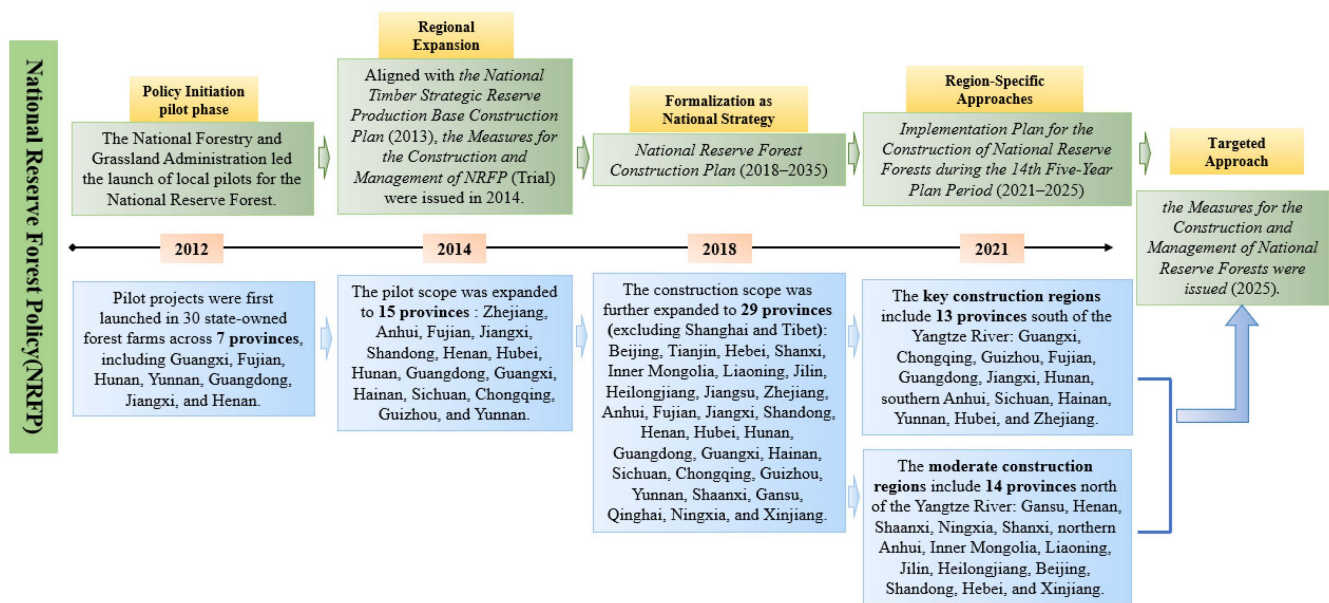


Figure 1. Timeline of the NRFP (2012–2025).

2.2. Literature Review

A rigorous evaluation of forestry policy effects provides an important basis for optimizing forest resource allocation and promoting green development. In terms of evaluation paradigms, the field has gradually shifted from a focus on single objectives toward greater emphasis on coordination among multiple objectives. Studies on sustainable forest management emphasize that forest management should not only maintain long-term timber production capacity but also account for ecosystem services, biodiversity conservation, and the sustainable use of forest resources [11]. Correspondingly, the valuation of forest ecosystem services has increasingly incorporated non-market ecological benefits, such as carbon sequestration, water conservation, soil retention, and habitat protection, into assessments of forest management performance [12]. In terms of production efficiency, existing research has examined both productivity and its determinants in the forestry sector, while increasingly incorporating resource consumption and environmental impacts into frameworks for evaluating eco-efficiency and green productivity [13]. Meanwhile, the expansion and intensification of planted forests have been regarded as important means of increasing forest productivity and timber supply capacity and are closely related to the stability of timber supply and resource security. However, intensified forest management and policy interventions may also generate environmental externalities, including potential impacts on biodiversity, ecosystem services, and resource and environmental pressures [14]. Against this background, forestry policy evaluation has gradually expanded from economic outcomes such as timber supply [15], ecological benefits such as carbon sequestration [16], and social impacts such as farmers' willingness to participate and the distribution of benefits among multiple stakeholders [17] toward a more comprehensive assessment of multidimensional policy performance and associated trade-offs.

Within this broader shift, GTFP has gradually become an important measure of economic efficiency and environmental performance in the forestry sector. Existing studies have mainly used forestry GTFP for regional efficiency comparisons [18] or as a dependent variable to examine the effects of economic development, resource endowments, and other macro-level factors on green productivity [19]. Focusing on the National Reserve Forest Policy (NRFP), existing studies have examined its implementation effects from multiple perspectives, including forest growing stock and timber supply [20], carbon sequestration effects [21], and the characteristics of investment returns during policy implementation [22].

Spatial effects also provide an important perspective for understanding the externalities of regional policies. According to the principle of spatial dependence [23], economic activities and environmental quality in neighboring or geographically proximate regions often exhibit spatial correlation, while knowledge and technology diffusion and the flow of production factors may generate cross-regional effects [24,25].

Methodologically, DID is a commonly used quasi-experimental approach for policy evaluation, and its causal interpretation relies on identification assumptions such as parallel trends, no anticipation, and the appropriate construction of treated and comparison groups. When policy adoption is staggered across regions, particular attention is needed to heterogeneity in treatment effects across cohorts and periods. Related studies have shown that when treatment effects are heterogeneous across cohorts or over time, conventional two-way fixed-effects (TWFE) DID with multiple treatment periods may produce difficult-to-interpret or biased estimates because of inappropriate comparisons across groups [26]. Recently developed staggered DID estimators are designed to address this issue by constructing more appropriate comparison groups for different treatment cohorts and periods [27]. For spatial effect analysis, incorporating spatial structure into the DID framework makes it possible to further examine spatial dependence and cross-regional spillovers in policy effects. A Spatial DID-SDM can be used to analyze the direct effects and spatial spillover effects of a policy [28]. For heterogeneity analysis, difference-in-difference-in-differences (DDD) introduces a third dimension of differencing and can be used to examine differences in policy effects across resource-based city status and policy zoning conditions [29].

Overall, existing studies have provided valuable insights into the effects of the NRFP on forest growing stock, timber supply, carbon sequestration, and investment returns, laying an important foundation for understanding its policy effects. However, systematic empirical evidence remains limited on whether the NRFP improves forestry GTFP, whether capital deepening and physical labor productivity may constitute potential transmission channels through which the NRFP affects forestry GTFP, whether policy effects vary with resource-based city status and policy zoning, and whether cross-city spatial effects exist. Methodologically, existing studies on the NRFP have paid relatively limited attention to staggered treatment timing and treatment-effect heterogeneity associated with phased policy implementation, while potential spatial interdependence across cities has also rarely been incorporated into policy evaluation.

3. Theoretical Analysis and Research Hypothesis

3.1. *The Direct Effect of the NRFP on Forestry GTFP*

The potential positive effect of the NRFP on forestry GTFP can be understood in terms of its policy objectives and the externalities associated with forest ecosystem services. The NRFP is a forestry policy arrangement with the important objectives of ensuring timber supply security, improving forest quality, and enhancing timber supply capacity. Forest ecosystem services have significant public goods attributes and positive externalities [30]. Their ecological value is difficult to fully realize through market transactions, which may lead to insufficient social investment and inadequate provision of ecosystem services [31]. Against this background, the NRFP incorporates forest ecological benefits into policy objectives and forest management processes through fiscal funding, policy-based financial support, and long-term construction planning, which helps to mitigate insufficient market incentives for forest ecosystem services to some extent. From the perspective of the GTFP accounting framework, the policy may promote greener and more efficient forestry production by increasing desirable outputs, improving factor allocation, and reducing resource and environmental costs.

In addition to the effects discussed above, the NRFP's long-term institutional arrangements may also affect forestry GTFP by improving the intertemporal allocation of resources in forest management. Multiple-objective conflicts in forestry production mainly arise from the trade-off between the need to ensure short-term timber supply and long-term ecological security [32], as well as the incentive incompatibility between the economic benefits of forest managers and their ecological protection responsibilities. Timber supply security emphasizes sustained improvements in timber production and supply capacity, whereas ecological security emphasizes maintaining the stability and resilience of forest ecosystems and their ecosystem service functions. Traditional forestry management often tends to prioritize harvesting over cultivation, making it difficult to balance current timber output with the long-term sustainability of forest resources [33]. By allocating forest resources across different cultivation cycles and providing long-term development planning and sustained investment, the NRFP may help alleviate the conflict between short-term harvesting returns and long-term forest cultivation, improve the intertemporal allocation of resources in forest management, and thereby create favorable conditions for improving forestry GTFP.

However, these potential benefits may also come with costs, and the implementation of the NRFP may involve certain economic costs and ecological risks. National reserve forest development is characterized by substantial upfront investment, long construction periods, and delayed biological returns. Large-scale capital investment in forest establishment, tending, and infrastructure construction may increase short-term production costs and, under capital constraints, crowd out other forestry investments. The long-term occupation of forest land for reserve forest development may also entail opportunity costs of land [34]. Excessive reliance on a single tree species or homogeneous stand configurations during project implementation may increase the risks of biodiversity loss, pest and disease spread, and exposure to forest fires, potentially weakening the stability and resilience of forest ecosystems [35]. The NRFP may also alter local timber harvesting intensity or supply structures, causing some harvesting activities to shift to other regions and thereby generating spatial displacement or leakage effects [36].

Overall, the actual effect of the NRFP on forestry GTFP reflects the combined influence of policy benefits, implementation costs, and potential ecological risks. Given that its policy objectives and institutional arrangements emphasize the coordination of timber supply, forest quality improvement, and long-term sustainable forest management, this study proposes the following hypothesis:

H1. *The NRFP has a significant positive effect on forestry GTFP.*

3.2. Potential Transmission Channels of the NRFP's Impact on Forestry GTFP

To analyze the potential transmission channels through which the National Reserve Forest Policy (NRFP) affects forestry green total factor productivity (GTFP), this study discusses two conceptual dimensions: technological progress and technical efficiency improvement [37,38]. Technological progress is typically reflected in an outward shift in the production frontier, that is, an increase in the potential maximum output under a given level of inputs, and is mainly associated with technology adoption, knowledge accumulation, and improvements in factor quality. Technical efficiency improvement, by contrast, is reflected in the movement of actual output toward the existing production frontier, indicating more efficient allocation and utilization of existing resources, technologies, and production factors. The intensive forest management promoted by the NRFP may affect forestry GTFP through capital equipment and technology adoption, as well as improvements in factor allocation and production organization. Based on this theoretical logic, the following analysis examines capital deepening (CD) and physical labor productivity (PLP) as two observable channels through which the NRFP may affect forestry GTFP.

3.2.1. Capital Deepening

In policy implementation cities, the NRFP channels large-scale, targeted funds into the forestry sector through central government funding and development finance loans. These investments are mainly directed toward activities such as intensive plantation cultivation, improvement of existing forests, and tending of young and middle-aged forests [8], and may stimulate the acquisition and construction of mechanical equipment, forest infrastructure, and other long-term productive assets, thereby increasing the intensity of capital investment in forestry. As the capital stock per unit of forest area increases, the degree of CD in policy implementation areas increases accordingly. The potential influence of CD on forestry production may arise not only from an increase in the capital stock itself, but also from the introduction of production technologies and management tools embodied in new capital [39]. Mechanical equipment, forest roads, and irrigation facilities can improve operating conditions in forest establishment, tending, harvesting, and transportation, while capital investment may also facilitate the adoption of digital forestry technologies for forest-resource monitoring and inventory, production planning, and timber traceability. These improvements may enhance resource assessment, management decisions, supply-chain coordination, and operational efficiency. Conceptually, the improvements in capital equipment and associated technology adoption reflected by CD are consistent with the technology adoption and production-capacity improvements emphasized in the technological progress dimension. CD can therefore serve as a potential observable transmission channel through which the NRFP affects forestry GTFP.

3.2.2. Physical Labor Productivity

The NRFP may improve the allocation and utilization efficiency of production factors such as land, capital, and labor in forest management by promoting high-quality seedlings, valuable native tree species, and efficient cultivation and tending techniques. On the one hand, the use of high-quality seedlings and suitable tree species can improve tree growth quality and output per unit area, thereby increasing the effective output generated by labor input when labor input remains relatively stable [40]. On the other hand, the adoption of cultivation and tending techniques, such as pruning, thinning, and fertilization, together with related technical training, can improve forest workers' operational skills and the standardization of operations, reduce ineffective or repetitive labor, and improve the efficiency of production organization in forest cultivation and tending [41]. These changes may be reflected in higher actual output per unit of labor input. Accordingly, this study uses PLP to characterize the relationship between labor input and actual output in forestry production. An increase in PLP reflects an improvement in actual output for a given level of labor input. This is conceptually consistent with the technical efficiency dimension, which emphasizes better resource allocation and the movement of production activities toward the existing production frontier. PLP can therefore serve as an observable transmission channel for examining how the NRFP may improve factor utilization and management efficiency.

H2. *The NRFP may improve forestry GTFP by promoting CD and increasing PLP as two potential transmission channels.*

3.3. Heterogeneity Analysis of the NRFP's Impact on Forestry GTFP

The effects of the NRFP may vary with regional initial conditions and structural characteristics, resulting in heterogeneous policy effects. This study discusses this potential heterogeneity along two dimensions: resource-based city status (RE) and policy zoning (PZ). Resource-based city status captures structural differences between resource-based

and non-resource-based cities in development paths, industrial structures, and historical environmental pressures, whereas policy zoning captures differences in forest management objectives and functional orientations across construction regions.

3.3.1. Resource-Based City Status

Resource-based and non-resource-based cities differ substantially in their economic development paths, industrial structures, and historical environmental pressures. These structural characteristics may affect the conditions under which policy inputs from the NRFP are translated into improvements in forestry production efficiency.

Resource-based cities have long relied on the extraction and processing of non-renewable resources such as minerals and are typically characterized by strong industrial path dependence and substantial historical environmental burdens [42]. On the one hand, traditional resource-based industries account for a relatively large share of local economic activity and factor allocation, which may limit the scope for allocating additional capital, land, and other production factors to the forestry sector. On the other hand, environmental pressures generated by existing energy-intensive and high-emission industries may increase the costs of regional green transformation [43]. Existing studies also show that factor allocation and industrial organization in resource-based regions tend to be closely associated with traditional resource-based industries [44,45]. This may result in higher adjustment costs for the forestry sector when absorbing additional capital, adopting management technologies, and reorganizing production. Consequently, these structural constraints may reduce the extent to which NRFP inputs are translated into improvements in forestry production efficiency, thereby constraining its positive effect on forestry GTFP to some extent. In contrast, non-resource-based cities tend to exhibit weaker path dependence on traditional resource-based industries, and their industrial structures and factor allocation may provide greater scope for forestry capital investment, the adoption of management technologies, and adjustments in production organization. Under these conditions, capital investment, improvements in forest management, and the reallocation of production factors associated with the NRFP may be more readily translated into improvements in forestry production efficiency. Therefore, the positive effect of the NRFP on forestry GTFP is theoretically expected to be more pronounced in non-resource-based cities.

3.3.2. Policy Zoning

The NRFP adopts a clear regional classification. Based on natural geographical conditions and primary ecological functions, the key construction regions are further classified into three major regional zones: the Southeast Coastal Region, the Southwest Region, and the Middle and Lower Reaches of the Yangtze River Region. Among these, the Southeast Coastal Region and the Middle and Lower Reaches of the Yangtze River Region share a high degree of consistency in policy orientation. Both prioritize enhancing timber production capacity and ensuring the supply of industrial raw materials, reflecting a distinct economy-efficiency orientation. In contrast, while ensuring timber supply, the Southwest Region places greater emphasis on biodiversity conservation, the cultivation of valuable tree species, and mountain ecological barrier functions, demonstrating a more pronounced ecology-conservation orientation. Accordingly, this study collectively refers to the Southeast Coastal Region and the Middle and Lower Reaches of the Yangtze River Region as the economy-efficiency-oriented region, and the Southwest Region as the ecology-conservation-oriented region. This differentiation in policy objectives may constitute an important source of potential regional heterogeneity in the effects of the NRFP.

The construction tasks in the economy-efficiency-oriented region are primarily focused on cultivating medium- and short-cycle industrial raw material forests, with greater

emphasis on fast-growing and high-yielding tree species. These regions also have certain advantages in hydrothermal conditions, market accessibility, and the forestry industry base [46]. Under these policy objectives and regional conditions, the capital investment, intensive forest management, and technology adoption associated with the NRFP may be translated more rapidly into improvements in timber output and production efficiency.

In the ecology-conservation-oriented region, the improvement of existing forests and the cultivation of long-cycle, large-diameter timber forests account for a relatively prominent share of construction tasks. The region also places greater emphasis on the cultivation of valuable native tree species, while pursuing multiple objectives such as biodiversity conservation and the maintenance of mountain ecological barrier functions. These areas tend to have greater ecological sensitivity and more complex natural conditions [47]. Forest management may therefore require longer-term coordination among timber production, resource reserves, and ecological protection. Corresponding investments in capital, technology, and management may be directed more toward forest quality improvement, ecological protection, and long-term resource reserves, and their economic and production-efficiency effects may take longer to fully materialize. Therefore, the positive effect of the NRFP on forestry GTFP is expected to be more pronounced in the economy-efficiency-oriented region.

H3. *The effect of the NRFP on forestry GTFP exhibits heterogeneity: it is stronger in non-resource-based cities than in resource-based cities, and stronger in economy-efficiency-oriented regions than in ecology-conservation-oriented regions.*

3.4. The Spatial Spillover Effect of NRFP on Forestry GTFP

The impacts of the NRFP may not be confined to implementing cities. Forest management activities exhibit substantial cross-regional linkages in natural conditions, production factors, timber markets, and ecosystems. Therefore, policy implementation may affect forestry GTFP in neighboring regions through knowledge and technology diffusion, factor and market reallocation, and ecological externalities.

First, knowledge and technology diffusion may generate positive spatial spillovers. Neighboring regions often share similarities in natural conditions, tree species composition, and forest management practices, providing a basis for the cross-regional diffusion of management experience and production technologies [48]. The intensive management techniques, selection of improved varieties, and management experience developed during NRFP implementation may spread to surrounding regions through channels such as technical cooperation, personnel exchanges, demonstration and extension, and interfirm linkages. Existing studies suggest that forestry technology innovation may generate spatial spillover effects through interregional learning, information exchange, and technology diffusion, thereby affecting management decisions and technology adoption in neighboring regions [49]. Therefore, such knowledge spillovers may reduce the costs for neighboring regions to access and adopt advanced management technologies and improve their forestry production efficiency.

Second, factor mobility and timber market linkages may generate spatial effects in opposite directions. On the one hand, cross-regional industrial-chain cooperation, timber flows, and supply-chain integration may strengthen linkages between production regions and processing markets and improve the efficiency of timber procurement, transportation, and allocation [50]. On the other hand, the additional investment and production demand generated in NRFP-implementing cities may alter the regional allocation of capital, labor, and related industries. If implementing cities attract forestry investment, specialized labor, and processing capacity, neighboring regions may experience factor outflows, investment displacement, or industrial relocation. Meanwhile, additional timber supply and industrial

agglomeration may intensify competition among regional producers and contribute to the relocation or concentration of forestry-related factors across regions [51]. Therefore, market and factor linkages may improve allocative efficiency through regional specialization and cooperation, but they may also weaken forestry production capacity in neighboring regions through competition for production factors and siphoning effects.

Third, adjustments in forest resource use may lead to cross-regional production displacement and leakage effects. When the NRFP changes the timber supply structure, harvesting arrangements, or land-use patterns in implementing regions, regional timber demand and production activities may be redistributed accordingly. If restrictions or supply adjustments in one region cause some harvesting activities, timber production, or land-development pressures to shift to other regions, harvesting displacement or land-use leakage may occur, increasing pressure on forest resources and environmental costs in receiving regions [52]. Therefore, improvements in forest management conditions in implementing regions do not necessarily imply a corresponding reduction in resource and environmental pressures at the broader spatial scale.

Finally, forest ecological processes themselves have cross-regional characteristics. Forest ecosystem services generate significant spatial externalities [53]. Ecological benefits arising from improvements in forest quality, including hydrological regulation, climate regulation, and biodiversity conservation, may extend beyond the administrative boundaries where forests are located and affect ecological and environmental conditions in other regions [54]. At the same time, these cross-regional linkages may also transmit ecological risks. Forest fires and pest outbreaks can propagate across landscape and administrative boundaries, and their spatial dynamics are influenced by forest connectivity, host distribution, and climatic conditions [55]. Therefore, ecological linkages among forests may generate cross-regional ecological synergies, but may also serve as channels for the spread of disturbance risks.

Overall, the effect of the NRFP on forestry GTFP in neighboring regions depends on the combined influence of multiple spatial channels. Knowledge and technology diffusion, industrial-chain cooperation, and spillovers of ecosystem services may generate positive effects, whereas competition for production factors, investment and industrial relocation, land-use and harvesting leakage, and the spread of ecological risks may generate effects in the opposite direction. Therefore, the net spatial effect of the NRFP depends on the relative strength of these positive and negative channels. Given the potential for regional diffusion of forest management knowledge and technologies, cross-regional industrial-chain linkages between timber production and processing, and the positive externalities of forest ecosystem services across administrative boundaries, this study expects the positive effects to outweigh the potential negative effects overall and proposes the following testable hypothesis:

H4. *The NRFP has a positive spatial spillover effect on forestry GTFP.*

3.5. Comprehensive Theoretical Analysis Framework

Based on the above analysis, this study develops an integrated theoretical framework for analyzing how the NRFP affects forestry GTFP, as illustrated in Figure 2. The NRFP may affect the economic and ecological performance of forestry production by improving market incentives for forest ecosystem services and strengthening incentives for long-term forest management, thereby influencing forestry GTFP. In this process, CD and PLP may constitute two potential transmission channels, reflecting changes in capital equipment and technology adoption, and in factor utilization and production organization efficiency, respectively. Meanwhile, the effects of the NRFP may vary with RE and PZ. In addition, because knowledge and technology, production factors, timber markets, and

forest ecosystems are interconnected across regions, the NRFP may also affect neighboring regions through channels such as technology diffusion, market and factor reallocation, resource-use displacement, and ecological externalities.

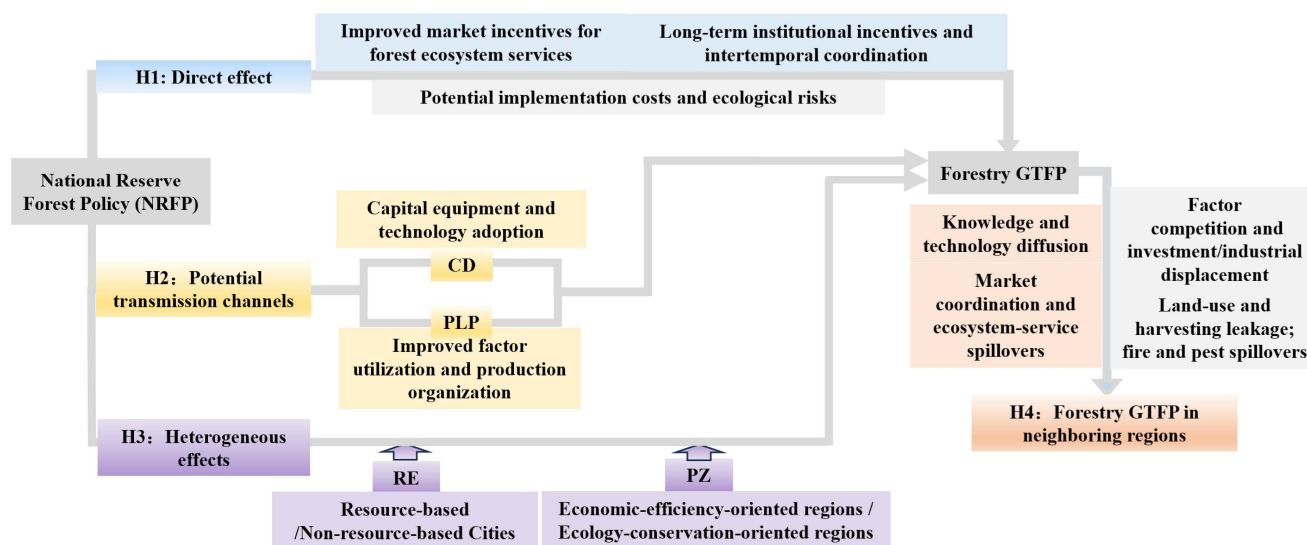


Figure 2. Theoretical framework of NRFP's impact on forestry GTFP.

4. Materials and Methods

4.1. Model Specification

4.1.1. DID with Staggered Treatment Adoption

Given that the NRFP was implemented in different cities at different times, this study adopts the group-time average treatment effect (group-time ATT) framework proposed by Callaway and Sant'Anna [27] for staggered treatment adoption to estimate the effect of the NRFP on forestry GTFP. Let G_i denote the year in which city i first adopted the NRFP. In the sample, treated cities adopted the NRFP in 2012, 2014, 2018, or 2021; therefore, $G_i \in \{2012, 2014, 2018, 2021\}$. For cities that did not adopt the NRFP during 2011–2022, $G_i = 0$. Accordingly, the policy treatment status of city i in year t is defined as

$$NRFP_{it} = \begin{cases} 1, & t \geq G_i, G_i > 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $NRFP_{it} = 1$ indicates that city i had implemented the NRFP by year t , and $NRFP_{it} = 0$ otherwise. For cities that first entered NRFP treatment in year g , this study further estimates the group-time average treatment effect in calendar year t , denoted by $ATT(g, t)$ and defined as

$$ATT(g, t) = E[GTFP_{it}(g) - GTFP_{it}(0) | G_i = g] \quad (2)$$

where $GTFP_{it}(g)$ denotes the potential forestry GTFP of city i in year t if it first receives NRFP treatment in year g , and $GTFP_{it}(0)$ denotes its potential forestry GTFP in year t if it remains untreated throughout the sample period. $ATT(g, t)$ therefore represents the average treatment effect in year t for cities that first receive NRFP treatment in year g .

Under identification conditions including conditional parallel trends, no anticipation, and overlap, cities that did not adopt the NRFP during the 2011–2022 sample period are used as the comparison group. The doubly robust inverse probability weighting (DRIPW) estimator is employed to estimate $ATT(g, t)$. The estimated $ATT(g, t)$ values are then aggregated across treatment cohorts and calendar years to obtain the overall ATT. They

are also aggregated by relative time since policy implementation to examine dynamic treatment effects. Unless otherwise specified, all panel regressions use city-level clustered standard errors.

4.1.2. Transmission-Channel Analysis

To examine the potential roles of CD and PLP in transmitting the effect of the NRFP on forestry GTFP, this study conducts a transmission-channel analysis. First, CD and PLP are separately treated as outcome variables, and the staggered treatment DID framework described in Section 4.1.1 is applied to examine changes in these two variables following NRFP implementation. For treatment cohort g , the group-time average treatment effect on channel variable MV in year t is defined as

$$ATT_{MV}(g, t) = E[MV_{it}(g) - MV_{it}(0) | G_i = g], MV \in \{CD, PLP\} \quad (3)$$

where $MV_{it}(g)$ denotes the potential value of the channel variable for city i in year t if it first receives NRFP treatment in year g , whereas $MV_{it}(0)$ denotes its potential value in year t if it remains untreated throughout the sample period. $ATT_{MV}(g, t)$ measures the average effect of the NRFP on the corresponding channel variable in year t for treatment cohort g .

Because adjustments in capital investment, production organization, and labor productivity may occur with a time lag, this study further examines the relationship between the one-period lagged values of CD and PLP and forestry GTFP. The model is specified as follows:

$$GTFP_{it} = \eta_0 + \eta_1 MV_{it-1} + \eta_2 NRFP_{it} + \sum_{k=1}^K \alpha_k Control_{kit} + u_i + v_t + \varepsilon_{it} \quad (4)$$

where $MV_{i,t-1}$ denotes the one-period lagged value of CD or PLP, and u_i and v_t denote city and year fixed effects, respectively. This study considers the estimated average treatment effect of the NRFP on the corresponding channel variable together with the association between its one-period lagged value and forestry GTFP to assess whether the results provide empirical evidence consistent with CD or PLP serving as a potential transmission channel.

4.1.3. DDD Model

To examine whether the effect of the NRFP varies with regional conditions, this study employs a difference-in-difference-in-differences (DDD) specification [29]. The model is specified as follows:

$$GTFP_{it} = \gamma_0 + \gamma_1 (NRFP_{it} \times HV_i) + \eta_2 NRFP_{it} + \sum_{k=1}^K \alpha_k Control_{kit} + u_i + v_t + \varepsilon_{it} \quad (5)$$

where HV_i is alternatively specified as RE_i and PZ_i to examine heterogeneity by resource-based city status and policy zoning, respectively. $RE_i = 1$ for resource-based cities and $RE_i = 0$ for non-resource-based cities. $PZ_i = 1$ for the economy-efficiency-oriented region and $PZ_i = 0$ for the ecology-conservation-oriented region. Because RE_i and PZ_i are time-invariant, their main effects are absorbed by the city fixed effects. The coefficient γ_1 captures the difference in the NRFP effect between cities with $HV_i = 1$ and those with $HV_i = 0$, while γ_2 captures the NRFP effect for the reference group with $HV_i = 0$. The NRFP effect for cities with $HV_i = 1$ is given by $\gamma_2 + \gamma_1$. City and year fixed effects are denoted by u_i and v_t , respectively, and ε_{it} is the error term.

4.1.4. Spatial DID-SDM

To examine the spatial dependence and cross-regional spillover effects associated with the NRFP, this study constructs a Spatial DID-SDM. Given that forestry production activities

and the movement of production factors are influenced by both geographic proximity and economic linkages across regions, this study employs a geographical–economic nested spatial weight matrix to characterize spatial interdependence among cities.

The geographical inverse-distance weight matrix W^{geo} is constructed based on the latitude and longitude coordinates of city centroids. The spherical distance between cities i and j is calculated using the Haversine formula:

$$d_{ij} = 2R \arcsin \left[\sqrt{\sin^2 \left(\frac{\phi_i - \phi_j}{2} \right) + \cos \phi_i \cos \phi_j \sin^2 \left(\frac{\lambda_i - \lambda_j}{2} \right)} \right] \quad (6)$$

where R denotes the mean radius of the Earth, and ϕ_i and λ_i denote the latitude and longitude of city i , respectively. The geographic weights are defined as

$$W_{ij}^{geo} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \quad (7)$$

The economic weight matrix W^{eco} is constructed based on differences in cities' average per capita GDP over the sample period. Let $\overline{GDP}_{pci}$ denote the average per capita GDP of city i over 2011–2022. The economic weights are defined as

$$W_{ij}^{eco} = \begin{cases} \frac{1}{|\overline{GDP}_{pci} - \overline{GDP}_{pcj}| + \kappa}, & i \neq j \\ 0, & i = j \end{cases} \quad (8)$$

where κ is a small positive constant introduced to avoid an undefined value when the economic distance is zero and is set to 10^{-6} in this study. No two cities in the sample have exactly the same average per capita GDP; therefore, this adjustment does not affect the actual ordering of the economic weights.

The geographical–economic nested spatial weight matrix is obtained by taking the Hadamard product of the geographic and economic weights matrices:

$$W_{ij}^* = W_{ij}^{geo} \times W_{ij}^{eco} \quad (9)$$

To avoid introducing subjective weighting parameters between the geographic and economic dimensions, the nested matrix is row-standardized as follows:

$$W_{ij} = \frac{W_{ij}^*}{\sum_{j \neq i} W_{ij}^*}, W_{ii} = 0 \quad (10)$$

Accordingly, the off-diagonal elements in each row sum to one. Because the city centroids do not overlap, no zero geographic distance exists between different cities. The spatial autoregressive parameter ρ is further required to lie within the admissible parameter space that ensures the nonsingularity of $I_n - \rho W$. For the row-standardized spatial weights matrix used in this study, $|\rho| < 1$ provides a sufficient stability condition.

LM tests are used to examine the presence of spatial dependence, while LR and Wald tests are used to determine whether the SDM can be simplified to alternative spatial specifications. The Hausman test is used to determine the fixed-effects specification. The test results support a static Spatial Durbin Model that includes spatial lags of both the dependent and explanatory variables and controls for city and year fixed effects. Accordingly, the Spatial DID-SDM is specified as follows:

$$\begin{aligned}
 GTFP_{it} = & \rho \sum_{j=1}^n w_{ij} GTFP_{jt} + \beta NRFP_{it} + \theta \sum_{j=1}^n w_{ij} NRFP_{jt} \\
 & + \sum_{k=1}^K \gamma_k \text{Control}_{kit} + \sum_{k=1}^K \delta_k \sum_{j=1}^n w_{ij} \text{Control}_{kjt} + u_i + v_t + \varepsilon_{it}
 \end{aligned} \quad (11)$$

where w_{ij} denotes the geographical–economic weight between cities i and j , and ρ is the spatial autoregressive coefficient. β and θ are the coefficients on $NRFP_{it}$ and its spatial lag, respectively. γ_k and δ_k are the coefficients on the k th control variable and its spatial lag, respectively. u_i and v_t denote city and year fixed effects, respectively, and ε_{it} is the error term.

To account for spatial feedback effects, this study uses partial-derivative effect decomposition to calculate the direct, indirect, and total effects of the NRFP. The reported direct, indirect, and total effects are average marginal impacts obtained from the partial-derivative effect decomposition. The direct effect captures the average effect of the policy on forestry GTFP in implementing cities, whereas the indirect effect captures its spatial spillover effect on other cities transmitted through inter-city spatial linkages. The total effect is the sum of the direct and indirect effects.

4.2. Variables

4.2.1. Dependent Variable

To evaluate forestry production performance under resource and environmental constraints, this study employs forestry GTFP as the dependent variable. Following existing studies [56,57], we select capital, land, labor, and energy as input factors. The desirable outputs include the total output value of the forestry sector and the volume of timber harvested from planted forests. Pollutant emissions and carbon emissions, which represent environmental costs, are treated as undesirable outputs. The specific indicator system is presented in Table 1. Specifically, forestry pollutant emissions are estimated by multiplying the total industrial wastewater, waste gas, and solid waste emissions by the share of the wood processing and wood products manufacturing industry in total industrial output value. This proxy assumes that the share of forestry-related industrial pollution is approximately proportional to the output share of the wood-processing sector in total industry. This estimation aims to reflect the potential environmental pressure associated with forestry industrial activities. Forestry carbon emissions refer to direct carbon dioxide emissions from forestry production activities. These activities encompass two core sectors: (1) timber harvesting and transportation, and (2) the processing of wood, bamboo, rattan, palm, and grass products.

Table 1. Forestry GTFP measurement indicators.

Types	Indicators	Definition
Inputs	Capital	Forestry fixed asset investment (10,000 yuan)
	Land	Forestry land area (square kilometers)
	Labor	Number of forestry employees (10,000 people)
	Energy	Forestry energy consumption (10,000 tons of standard coal)
Desirable outputs	Economic output	Total output value of the forestry sector (10,000 yuan)
	Physical timber output	Timber harvest volume from planted forests (cubic meters)
Undesirable outputs	Environmental pollution	Forestry pollutant emissions (tons)
	Carbon emissions	Forestry carbon emissions (tons)

China imposed a nationwide ban on commercial logging of natural forests (NFLB) starting in 2017. To maintain a consistent definition of the physical output indicator used in the GTFP measurement, we adjusted the physical output indicator. Specifically, for the pre-2017 period, we estimated the volume of timber harvested from planted forests based on each city's share of planted forest area. This estimation assumes that, in the absence of city-level harvest data by forest type, the planted-forest area share can approximate the contribution of planted forests to local timber harvest. Given that the Natural Forest Protection Project, implemented in China since 1998, has resulted in strict regulation and gradual reduction in logging in natural forests [58], this estimation is used to distinguish planted-forest timber output from total timber harvest in the pre-2017 period.

This study employs a super-efficiency slacks-based measure (Super-SBM) model incorporating undesirable outputs to measure forestry production efficiency and further uses the Global Malmquist–Luenberger (GML) index to characterize intertemporal changes in forestry GTFP [59,60]. The Super-SBM model simultaneously incorporates input excesses, desirable-output shortfalls, and undesirable-output excesses into the efficiency evaluation and further distinguishes cities on the production frontier through the super-efficiency specification. A non-oriented specification is adopted, simultaneously considering input reduction, desirable-output expansion, and undesirable-output reduction. Given differences across cities in forest resource endowments, forestry production scale, and input structures, variable returns to scale (VRS) are assumed. The calculations are performed using MaxDEA 8.0. For decision-making unit q_0 , the Super-SBM model incorporating undesirable outputs is specified as follows:

$$\min \rho_{q_0}^* = \frac{1 + \frac{1}{V} \sum_{v=1}^V \frac{s_v^{x-}}{x_{vq_0}}}{1 - \frac{1}{R+P} \left(\sum_{r=1}^R \frac{s_r^{g+}}{x_{rq_0}^g} + \sum_{p=1}^P \frac{s_p^{b-}}{y_{pq_0}^b} \right)} \quad (12)$$

Subject to

$$\begin{cases} \sum_{q=1, q \neq q_0}^Q \tau_q x_{vq} \leq x_{vq_0} + s_v^{x-}, v = 1, \dots, V \\ \sum_{q=1, q \neq q_0}^Q \tau_q y_{rq}^g \geq y_{rq_0}^g - s_r^{g+}, r = 1, \dots, R \\ \sum_{q=1, q \neq q_0}^Q \tau_q y_{pq}^b \leq y_{pq_0}^b - s_p^{b-}, p = 1, \dots, P \\ \sum_{q=1, q \neq q_0}^Q \tau_q = 1 \\ \tau_q \geq 0, s_v^{x-} \geq 0, s_r^{g+} \geq 0, s_p^{b-} \geq 0 \end{cases} \quad (13)$$

where Q denotes the number of decision-making units, and V , R , and P denote the numbers of inputs, desirable outputs, and undesirable outputs, respectively. x_{vq} , y_{rq}^g , and y_{pq}^b denote the input, desirable output, and undesirable output of decision-making unit q , respectively. τ_q denotes the intensity weight assigned to each decision-making unit in constructing the production frontier. s_v^{x-} , s_r^{g+} , and s_p^{b-} denote the slack variables for input excesses, desirable-output shortfalls, and undesirable-output excesses, respectively. Forestry pollutant emissions and carbon emissions are incorporated into the production possibility set as undesirable outputs. This study adopts a non-oriented specification without imposing a single exogenous directional vector. Instead, the adjustment directions of inputs, desirable outputs, and undesirable outputs are jointly determined by their corresponding slack variables, which are used to measure the deviation of each decision-making unit from the production frontier. For zero values in the GTFP measurement indicators, following the treatment proposed by Tone [59], zero observations are replaced with one-hundredth of the minimum positive value of the corresponding indicator, while all other observations remain unchanged, to ensure the computability of the Super-SBM model.

To measure intertemporal changes in forestry GTFP, this study further employs the GML index. The GML index constructs an intertemporal reference frontier based on a unified global technology set. Specifically, all city-year input and output observations from 2010 to 2022 are incorporated into the global technology set:

$$T^G = \text{conv}\left(\bigcup_{t=2010}^{2022} T^t\right) \quad (14)$$

where T^t denotes the production technology set in year t , and T^G denotes the global reference technology set jointly constructed from all years used in the GTFP measurement. The unified global technology set provides a consistent technological benchmark for comparing changes in forestry productivity across years. Forestry pollutant emissions and carbon emissions are incorporated into the GML measurement as undesirable outputs to reflect the environmental costs associated with forestry production. Based on the global technology set, the GML index for city q_0 from year t to year $t + 1$ is defined as

$$GML_{q_0}^{t,t+1} = \frac{E^G(x_{q_0}^{t+1}, y_{q_0}^{g,t+1}, y_{q_0}^{b,t+1})}{E^G(x_{q_0}^t, y_{q_0}^{g,t}, y_{q_0}^{b,t})} \quad (15)$$

where $E^G(\cdot)$ denotes the Super-SBM efficiency score calculated relative to the global technology set T^G , and x , y^g , and y^b denote the input, desirable-output, and undesirable-output vectors, respectively. $GML_{q_0}^{t,t+1} > 1$ indicates an increase in forestry GTFP for city q_0 from year t to year $t + 1$, whereas $GML_{q_0}^{t,t+1} < 1$ indicates a decrease.

To construct annual city-level GTFP indices for the 2011–2022 empirical sample, this study uses 2010 as the index base year and sets

$$GTFP_{i,2010} = 1 \quad (16)$$

The GML indices for adjacent years are then chain-linked as follows:

$$GTFP_{i,t} = GTFP_{i,t-1} \times GML_i^{t-1,t}, t = 2011, \dots, 2022 \quad (17)$$

This procedure yields annual city-level GTFP indices for 2011–2022. The year 2010 is used only as the index base year for GTFP construction and is not included in the empirical regression sample. The GTFP index for city i in year t is then matched with the NRFP treatment status of the same city and year in the subsequent panel estimations.

4.2.2. Independent Variable

The core explanatory variable is a dummy variable for the NRFP. As defined in Section 4.1.1, $NRFP_{it} = 1$ from the year in which city i first entered NRFP treatment onward, and $NRFP_{it} = 0$ otherwise. As described in Section 2.1, the NRFP was implemented in successive stages, including the pilot phases in 2012 and 2014 and subsequent expansion in 2018 and 2021. The Implementation Plan for the Construction of National Reserve Forests during the 14th Five-Year Plan Period (2021–2025) further defined the key construction regions for national reserve forests, covering Guangxi, Chongqing, Guizhou, Fujian, Guangdong, Jiangxi, Hunan, southern Anhui, Sichuan, Hainan, Yunnan, Hubei, and Zhejiang. These key construction regions constitute the geographical scope of the empirical analysis.

At the prefecture-city level, treatment timing is determined by the year in which a city was documented as having entered NRFP construction and initiated implementation. The relevant information is compiled from multiple types of publicly available documentary sources, including government documents, official government websites, authoritative

media reports and project-related records. Cities within the key construction regions that initiated NRFP implementation during the study period are classified as treated cities, whereas cities that remained untreated throughout the sample period and had sufficiently complete data are used as the comparison group. Detailed treatment timing and supporting documentary evidence for treated and comparison cities are reported in Supplementary Tables S1 and S2, respectively.

Some cities within the key construction regions are excluded from the final empirical sample because their treatment status or implementation timing could not be reliably established, the available implementation evidence was ambiguous, or administrative and longitudinal data comparability limitations prevented the construction of a consistent city-level panel. The initial pool consisted of 135 cities in the study area. After excluding 21 cities, the final empirical sample consists of 114 prefecture-level cities, including 67 treated cities and 47 control cities. The excluded cities and the corresponding reasons are reported in Supplementary Table S3.

4.2.3. Transmission-Channel Variables

Based on Section 3.2, we use CD and PLP as potential transmission-channel variables through which the NRFP may affect forestry GTFP. CD is proxied by the estimated level of forestry mechanization, calculated by multiplying the total mechanization level in agriculture, forestry, animal husbandry, and fishery by the share of forestry output value in the total output value of these sectors. This indicator reflects the intensity of mechanized capital input in forestry production. The total level of mechanization in agriculture, forestry, animal husbandry, and fishery is a continuously reported indicator of mechanization intensity in China's official statistics. After adjustment by the forestry output share, it is used as a proxy for the level of mechanization and capital deepening in the forestry sector. To mitigate potential measurement errors arising from this estimation, we further use forestry fixed asset investment per unit of forest area as an alternative indicator for CD in the robustness checks.

PLP is measured as the volume of timber harvested from planted forests per employee in the forestry sector. This indicator reflects the physical timber output associated with each unit of labor input and may reflect changes in labor productivity associated with improved varieties, intensive cultivation, and tending management. Accordingly, PLP is used as a proxy for the pathway through which changes in production organization and factor utilization may contribute to forestry GTFP.

4.2.4. Heterogeneity Grouping Variables

To examine whether the effect of the NRFP varies with a city's dependence on traditional natural resources, we introduce a dummy variable for RE. This variable is constructed based on the National Sustainable Development Plan for Resource-Based Cities issued by the State Council of China. If city i is a resource-based city, then $RE_i = 1$ throughout the study period; otherwise, $RE_i = 0$.

To examine whether the effect of the NRFP varies with policy zoning, we construct a dummy variable based on the regional classification in the Implementation Plan for the Construction of National Reserve Forests during the 14th Five-Year Plan Period (2021–2025). Specifically, the economy-efficiency-oriented category comprises the Southeast Coastal Region and the Middle and Lower Reaches of the Yangtze River Region. Cities located in these regions are assigned $PZ_i = 1$ during the study period. The ecology-conservation-oriented region refers to the Southwest Region, and cities located in this region are assigned $PZ_i = 0$.

4.2.5. Control Variables

Drawing on relevant studies [56,61] and considering the characteristics of intensive forest management and the ecological-priority principle of the NRFP, we control for other observable factors that may affect forestry GTFP, including economic fundamentals (ECO), industrial structure (ISU), government support (GOS), institutional environment (INE), and climatic factors (CLF).

Specifically, ECO is measured by GDP per capita, as the overall development level of a region affects its capacity for technology adoption and the resource base for green transformation. ISU is measured by the share of forestry output value in regional GDP, reflecting the relative importance of forestry in the local economic structure, which may influence the priority of resource allocation and policy attention. GOS is measured by forestry fiscal expenditure, capturing the intensity of public funding directed toward the forestry sector. INE is measured using the marketization index [62], since a well-functioning institutional environment promotes the rational flow of forestry production factors. CLF is measured by average daily precipitation, as water availability is a key climatic factor affecting forest growth and ecosystem functioning [63].

4.3. Data Sources and Descriptions

This study uses panel data from 114 prefecture-level cities in China's key construction regions of the NRFP over the period 2011–2022, yielding 1368 observations. The study period is selected to provide a pre-policy baseline before the first NRFP pilot in 2012 and to cover the successive policy implementation cohorts in 2012, 2014, 2018, and 2021. Moreover, 2022 is the most recent year for which relatively complete data are available, balancing temporal coverage and data quality.

Indicators related to the forestry sector, including forestry fixed asset investment, forestry employment, total forestry output value, timber harvest volume, and forestry energy consumption, are mainly sourced from the China Forestry and Grassland Statistical Yearbook, provincial forestry statistical yearbooks, and publicly available information from relevant municipal governments. The mechanization level of agriculture, forestry, animal husbandry, and fishery is obtained from the China Statistical Yearbook. Forest area data are derived from an annual land cover dataset generated from Landsat imagery [64], while planted forest area data are obtained from the National Ecological Science Data Center. Province-level forest area and growing stock data for planted and non-planted forests, which are used in the alternative estimation of pre-2017 planted-forest timber harvest, are obtained from China's forest resources inventory data. Forestry carbon emissions are sourced from the China Carbon Emission Accounts and Datasets. Industrial waste and socioeconomic data, including GDP and forestry fiscal expenditure, are mainly sourced from the China City Statistical Yearbook and various provincial statistical yearbooks. Daily precipitation data are obtained from the China National Meteorological Information Center. City-center coordinates used to construct the geographical inverse-distance weight matrix are obtained from the National Geomatics Center of China. To eliminate the effects of inflation on intertemporal comparability, forestry fixed asset investment and the total output value of the forestry sector are both deflated to constant 2005 prices. The total output value of the forestry sector is deflated using the provincial producer price indices for forestry products reported in the China Agricultural Product Price Survey Yearbook, while forestry fixed asset investment is deflated using the fixed asset investment price index. Specifically, the fixed asset investment price indices for 2019 and earlier years are obtained from the China Statistical Yearbook. Since the National Bureau of Statistics ceased publishing provincial fixed asset investment price indices in 2020, the indices for 2020–2022 are extrapolated using the geometric mean of the price indices over the preceding five years [65].

Missing observations in the sample are limited to two variables: forestry carbon emissions and forestry fiscal expenditure. For forestry carbon emissions, 58 observations are missing in 2015 and 2020, accounting for 4.24% of the observations for this variable. For forestry fiscal expenditure, 27 observations are missing, accounting for 1.97% of the observations for this variable, all of which occur in 2012. These missing observations are filled using linear interpolation. Missing forestry carbon emissions in 2015 are replaced by the arithmetic mean of the corresponding city's observations in 2014 and 2016, while those in 2020 are replaced by the arithmetic mean of the corresponding observations in 2019 and 2021. Missing forestry fiscal expenditure in 2012 is replaced by the arithmetic mean of the corresponding city's observations in 2011 and 2013. All missing observations are single-year gaps within the city-level time series, with no missing observations at the beginning or end of the sample period. Descriptive statistics for the variables used in the empirical analysis are reported in Table 2.

Table 2. Descriptive statistics of variables.

Types	Variables	Mean	SD	Min	Max
Dependent variable	GTFP	0.998	0.028	0.806	1.300
Independent variable	NRFP	0.273	0.446	0.000	1.000
Control variables	ISU	0.064	0.048	0.0002	0.288
	CLF	0.004	0.001	0.001	0.008
	Ln(ECO)	10.799	0.553	9.321	12.579
	INE	12.547	2.544	4.960	21.330
	GOS	5.129	5.995	0.011	47.770
Transmission-channel variables	CD	0.098	0.219	0.0001	2.045
	PLP	10.740	18.148	0.006	158.639
Heterogeneity variables	RE	0.684	0.465	0.000	1.000
	PZ	0.772	0.420	0.000	1.000

4.4. Addressing Potential Confounding Policies

To account for other major policies in effect during the study period that may also affect forestry GTFP, we consider policies that overlap with the NRFP in terms of timing or spatial implementation. This study focuses on the following three policies: (1) the Carbon Emissions Trading Scheme (ETS), launched as a pilot policy in 2011, which affects regional carbon emission costs through market mechanisms and may indirectly influence factor allocation and environmental efficiency; (2) the Central Environmental Inspection (CEI), initiated in 2016, which strengthens environmental regulation through administrative accountability and may affect forestry GTFP by influencing pollution emissions, which are included as undesirable outputs in the GTFP measurement; and (3) the Yangtze River Protection Forest Program (YRFP), initiated in 1989, a regional ecological program whose afforestation and tending activities in the Yangtze River Basin overlap with the NRFP's construction activities and may therefore affect forestry investment and ecological outcomes. To account for potential confounding influences from these policies, we separately include dummy variables for these policies as additional covariates in the group-time ATT estimation in Section 5.3. If the estimated overall ATT remains positive and similar in magnitude after accounting for these policies, this provides additional evidence that the baseline results are not primarily driven by these concurrent policy influences.

5. Results and Analysis

5.1. Forestry GTFP Analysis

To preliminarily illustrate the overall trends and group differences in forestry GTFP, Figure 3 presents the annual average trends for the full sample, grouped by treatment status (treated vs. control) and by policy zoning (economy-efficiency-oriented vs. ecology-conservation-oriented). From an overall trend perspective, forestry GTFP exhibited notable fluctuations during the study period. Specifically, from 2011 to 2016, forestry GTFP declined from 0.996 to 0.993. This may reflect the path dependence of the forestry sector on traditional extensive models amid increasing resource and environmental constraints, leading to a lagged transition [66,67]. During the 2016–2018 period, forestry GTFP rebounded to 1.000, indicating that the previous downward trend in forestry GTFP had been reversed. From 2019 to 2022, forestry GTFP remained generally above 1.000 despite some year-to-year fluctuations.

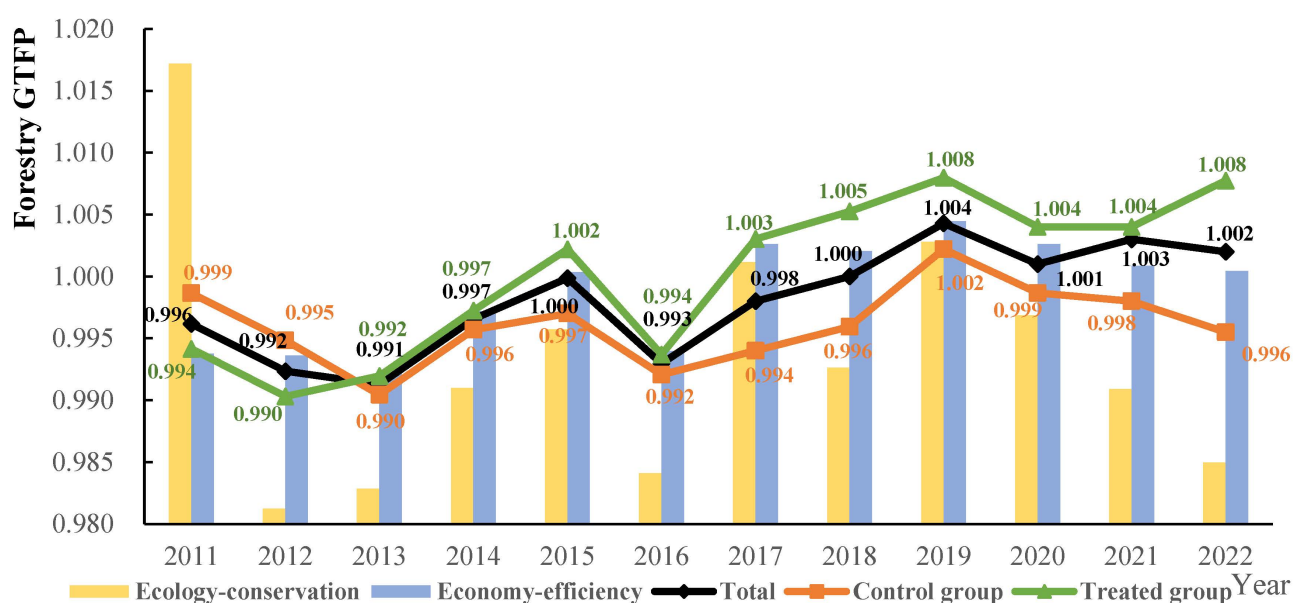


Figure 3. Trends in forestry GTFP from 2011 to 2022.

From the perspective of treatment status, the two groups exhibit different trends over the study period. During 2011–2012, forestry GTFP in the control group was slightly higher than that in the treated group. The first NRFP pilot projects were launched in 2012. From 2013 onward, forestry GTFP in the treated group remained higher than that in the control group. In 2015, the treated group's forestry GTFP increased to 1.002. The policy coverage expanded further in 2018, and the difference between the two groups became more pronounced after 2019.

From the perspective of policy zoning, forestry GTFP in the ecology-conservation-oriented region was higher than that in the economy-efficiency-oriented region in 2011. Since 2012, however, forestry GTFP in the economy-efficiency-oriented region has generally exceeded that in the ecology-conservation-oriented region, with the difference becoming more pronounced after 2019. This descriptive pattern suggests potential heterogeneity in forestry GTFP across policy-zoning categories.

5.2. Baseline Regression Results

The NRFP provides a quasi-natural experimental setting for this study. First, the key construction regions examined in this study were primarily designated based on long-term structural factors, such as hydrothermal conditions, natural geographical patterns,

ecological barrier functions, and the national timber logistics layout [10]. These factors mainly reflect long-term regional characteristics rather than short-term changes in forestry GTFP. Second, the timing of NRFP implementation across cities was gradually determined according to policy planning, implementation batches, and implementation arrangements. Given the staggered implementation of the NRFP across cities, this study employs the Callaway and Sant’Anna method designed for staggered treatment adoption to estimate the policy effect, thereby avoiding potentially inappropriate cross-cohort comparisons under conventional TWFE when treatment effects vary across cohorts and over time.

Table 3 reports the baseline estimates obtained using the Callaway and Sant’Anna staggered DID estimator. Column (1) excludes covariates, and the overall average treatment effect (overall ATT) is 0.0144, which is statistically significant at the 5% level. Column (2) includes covariates for economic fundamentals, industrial structure, government support, institutional environment, and climatic conditions. The overall ATT is 0.0149 and remains statistically significant at the 5% level. The estimates from the two specifications are similar in direction, statistical significance, and magnitude. Using Column (2) as the baseline specification, the overall ATT of the NRFP is equivalent to approximately 1.49% of the sample mean of forestry GTFP (0.998). The significantly positive overall ATT supports H1.

Table 3. Baseline estimates of the effect of the NRFP on forestry GTFP.

Statistics	(1)	(2)
Overall ATT	0.0144 ** (0.0064)	0.0149 ** (0.0066)
95% CI	[0.0019, 0.0270]	[0.0020, 0.0278]
Covariates	No	Yes
Observations	1368	1368

Note: Standard errors clustered at the city level are reported in parentheses. ** denotes statistical significance at the 5% level.

To further examine the comparison structure underlying the conventional TWFE estimator in the context of staggered NRFP implementation, this study conducts a Goodman–Bacon decomposition based on the conventional TWFE specification without covariates [26], with the results reported in Table 4. Comparisons between treated and never-treated cities account for 62.44% of the total weight, while comparisons across different treatment cohorts account for 37.56%. Specifically, comparisons in which earlier-treated cohorts serve as the treated group while later-treated cohorts have not yet received treatment account for 13.84%, whereas comparisons between later-treated cohorts after treatment and already-treated earlier cohorts account for 23.72%. Thus, more than one-third of the weight in the conventional TWFE estimator comes from comparisons across different treatment cohorts. This result provides further support for using the Callaway and Sant’Anna method as the baseline estimation strategy to accommodate the staggered implementation of the NRFP and potential treatment-effect heterogeneity.

Table 4. Goodman–Bacon decomposition of the conventional TWFE estimator.

Comparison Type	Weight
Treated vs. never-treated	0.6244
Earlier treated vs. later-treated	0.1384
Later treated vs. earlier-treated	0.2372
Total	1.0000

Note: The decomposition is based on the conventional TWFE specification without covariates.

5.3. Staggered-Treatment Diagnostics and Dynamic Effects

5.3.1. Dynamic Treatment Effects and Pre-Treatment Trend Assessment

Figure 4 shows that the dynamic ATTs generally fluctuate around zero before NRFP implementation, with no evident systematic differential trend. After implementation, the ATTs become positive and generally increase, indicating that the positive treatment effect on forestry GTFP gradually emerges over time.

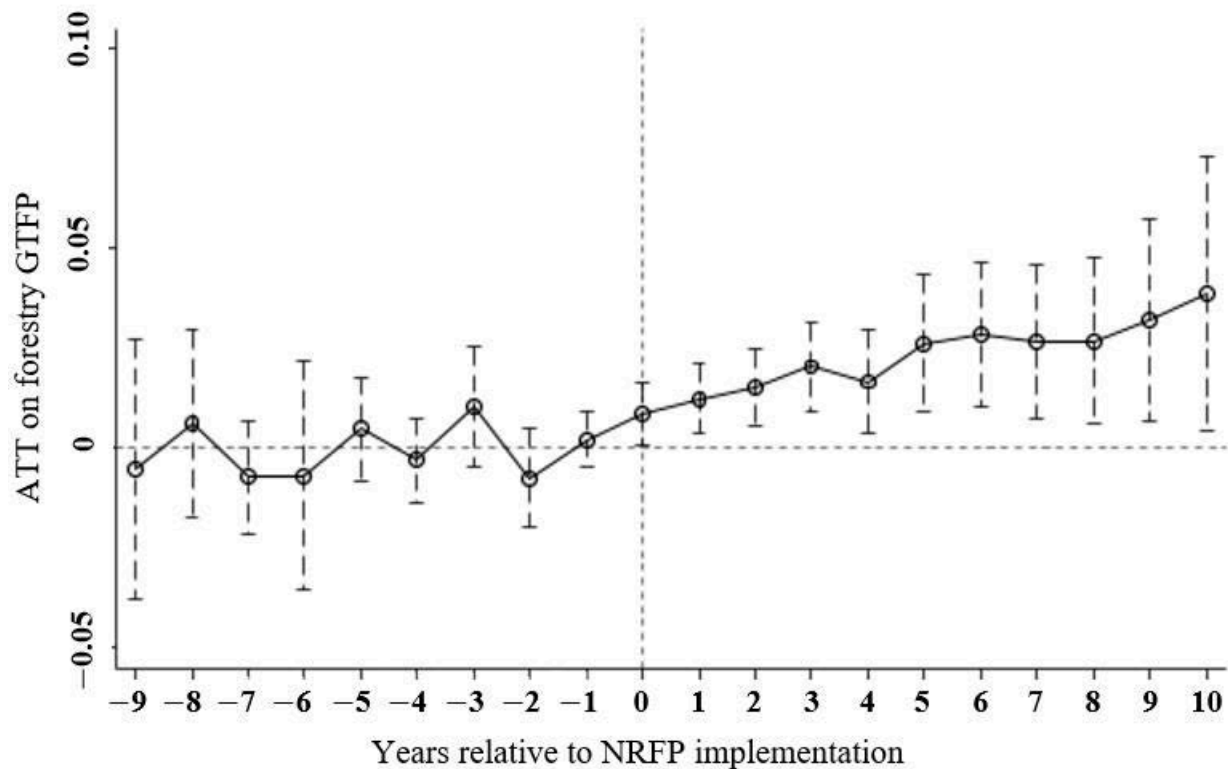


Figure 4. Dynamic treatment effects of the NRFP on forestry GTFP. Note: Points represent dynamic ATTs, and error bars indicate 95% confidence intervals. Estimates are obtained using DRIPW with never-treated cities as the comparison group and baseline covariates included; standard errors are clustered at the city level. Event time 0 denotes the first year of NRFP implementation.

Specifically, the 95% confidence intervals for the ATTs at all pre-treatment event times include zero. A joint test of the 17 estimable pre-treatment group-time ATTs fails to reject the null hypothesis that these pre-treatment ATTs are jointly equal to zero ($\chi^2(17) = 13.655$, $p = 0.691$). The average pre-treatment ATT is -0.0007 and is not statistically significant ($p = 0.587$). These results provide evidence consistent with the parallel-trends assumption. The average post-treatment ATT is 0.0230 and is statistically significant at the 1% level ($p = 0.003$). The ATTs in the first, second, and third years after implementation are 0.0123 , 0.0152 , and 0.0204 , respectively, indicating that the positive treatment effect strengthens during the first few years following implementation.

Figure 4 reports dynamic ATTs according to actual event time relative to NRFP implementation, without binning the endpoints. Under the Callaway and Sant'Anna specification used in this study, pre-treatment event periods are directly used to estimate dynamic ATTs rather than uniformly omitting one event period as the reference period. Because the sample begins in 2011, the theoretical event time of -10 cannot be estimated because the preceding observation required to construct the pre-treatment ATT is unavailable. The figure therefore reports estimates beginning at event time -9 . As event time moves farther from policy implementation, fewer treatment cohorts and cities contribute to the estimation. In particular, the estimates at event times $+9$ and $+10$ are identified only by the 18 cities in

the 2012 treatment cohort. The ATTs, 95% confidence intervals, contributing cohorts, and numbers of contributing cities at each event time are reported in Table S4.

5.3.2. Placebo Test

To examine whether the baseline estimates could be driven by random policy assignment, this study further conducts a randomization-based placebo test. Holding the actual treatment cohorts and the number of treated cities in each cohort fixed, the 67 treated cities and their treatment cohorts are randomly reassigned across the sample cities, with the numbers of treated cities in the 2012, 2014, 2018, and 2021 cohorts fixed at 18, 6, 12, and 31, respectively. After each random reassignment, the overall ATT is re-estimated using the same Callaway and Sant'Anna method as in the baseline estimation. This procedure is repeated 1000 times. Figure 5 shows that the placebo ATTs obtained from the random assignments are concentrated around zero, whereas the overall ATT under the actual policy assignment, 0.0149, lies in the right tail of the placebo ATT distribution. A two-sided empirical randomization test is further conducted by calculating the proportion of random assignments for which the absolute placebo ATT is at least as large as the absolute actual ATT. The resulting empirical randomization p -value is 0.021. This indicates that an estimate as or more extreme than the actual estimate is unlikely to arise under random policy assignment. This result provides further evidence of the robustness of the baseline estimate.

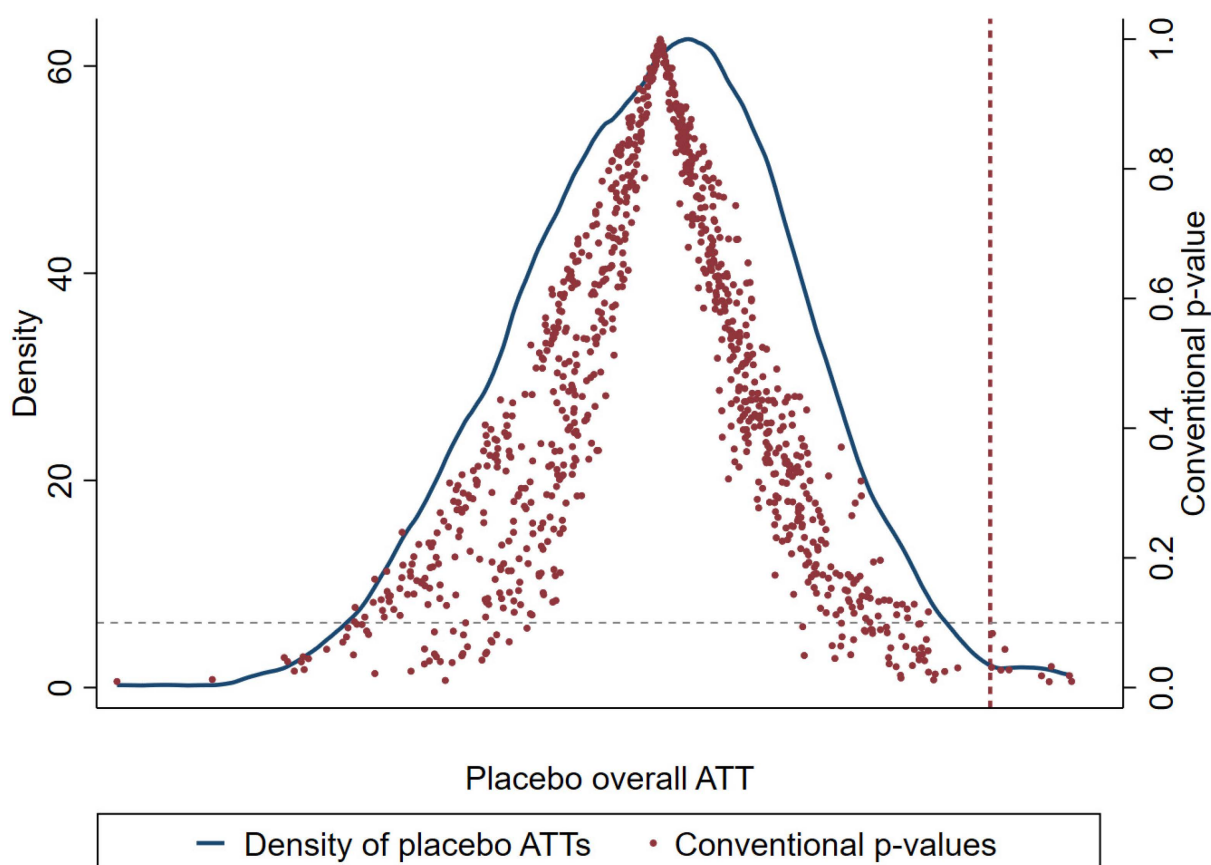


Figure 5. Placebo test based on randomized treatment assignment. Note: The solid line shows the kernel density of the placebo ATTs, and the dots represent the conventional p -values associated with the placebo estimates. The vertical dashed line indicates the overall ATT under the actual policy assignment, and the horizontal dashed line indicates $p = 0.10$.

5.3.3. Accounting for Concurrent Policies

As described in Section 4.4, to examine whether other major forestry or environmental policies during the study period may affect the baseline estimates of the NRFP, this study separately includes ETS, CEI, and YRFP as additional covariates in the group-time ATT estimation. As shown in Table 5, after separately accounting for these concurrent policies, the overall ATT of the NRFP remains significantly positive, ranging from 0.0148 to 0.0157, and is close to the baseline estimate of 0.0149. These results indicate that the baseline estimates remain stable after accounting for the potential influence of these concurrent policies.

Table 5. Estimates accounting for concurrent policies.

Statistics	(1) ETS	(2) CEI	(3) YRFP
Overall ATT	0.0157 ** (0.0069)	0.0149 ** (0.0066)	0.0148 ** (0.0066)
95% CI	[0.0022, 0.0292]	[0.0020, 0.0278]	[0.0019, 0.0277]
Covariates	Yes	Yes	Yes
Observations	1368	1368	1368

Note: Standard errors clustered at the city level are reported in parentheses. ** denotes statistical significance at the 5% level.

5.3.4. Additional Robustness and Sensitivity Analyses

To further examine the sensitivity of the baseline estimates to sample definition, variable measurement, comparison-group selection, and the treatment of missing values, this study conducts a series of sensitivity analyses and robustness checks. The sensitivity analyses use a sample selected based on stricter evidence for policy identification and an alternative measure of forestry GTFP that excludes the forestry pollution indicator. The robustness checks focus on the specification of the comparison group, the treatment of missing values, and the measurement of pre-2017 planted-forest timber harvest. Except for the adjustments to the sample, comparison group, or variable construction required for each test, all other settings remain consistent with the baseline estimation.

Table 6 reports the results of the sensitivity analyses. First, because the treatment status of cities is identified using information from multiple sources, including government departments, authoritative media, and enterprises undertaking NRFP projects, the sample definition may be sensitive to the sources of evidence used for policy identification. We therefore apply a stricter policy identification criterion by restricting the evidence to official government websites and formal government documents and retaining only cities whose treatment status can be directly confirmed by these two types of government sources. The resulting sample consists of 96 cities, including 52 treated cities and 44 control cities. The re-estimated overall ATT is 0.0153 and is statistically significant at the 5% level, which is very close to the baseline estimate of 0.0149. Second, because direct city-level statistics on forestry pollution emissions are unavailable, the baseline measurement estimates these emissions using a proportional approach. Differences in pollution intensity across industries may introduce measurement error into this proxy and, in turn, affect the measurement of forestry GTFP. To examine whether the baseline results depend on this pollution proxy, we exclude forestry pollution emissions from the undesirable outputs and recalculate forestry GTFP using the remaining indicators. The estimated overall ATT is 0.0136 and remains statistically significant at the 5% level. These results show that the overall ATT of the NRFP remains significantly positive when a stricter policy identification criterion is applied or when forestry pollution emissions are excluded from the measurement of forestry GTFP, indicating that the baseline findings are stable under these alternative specifications.

Table 6. Sensitivity analyses.

Statistics	(1) Strict Official-Source Sample	(2) Excluding the Forestry Pollution Indicator
Overall ATT	0.0153 ** (0.0070)	0.0136 ** (0.0065)
95% CI	[0.0017, 0.0290]	[0.0009, 0.0263]
Covariates	Yes	Yes
Observations	1152	1368

Note: The 1152 observations in Column (1) correspond to 96 cities retained under the strict official-source criterion over 2011–2022; Standard errors clustered at the city level are reported in parentheses. ** denotes statistical significance at the 5% level.

Table 7 reports the results of the robustness checks. We first examine the sensitivity of the baseline results to the choice of comparison group. The comparison group is changed from never-treated cities to not-yet-treated cities, so that cities that receive treatment in later periods can also serve as comparison units before they enter treatment. The re-estimated overall ATT is 0.0148 and is statistically significant at the 5% level.

Table 7. Robustness checks.

Statistics	(1) Not-Yet-Treated Comparison Group	(2) Excluding Imputed Observations	(3) Excluding Planted-Forest Timber Output	(4) Province-Specific Stock-Density Adjustment	(5) Post-2017 Sample
Overall ATT	0.0148 ** (0.0068)	0.0146 ** (0.0065)	0.0122 ** (0.0058)	0.0151 ** (0.0067)	0.0112 *** (0.0041)
95% CI	[0.0014, 0.0282]	[0.0019, 0.0273]	[0.0008, 0.0236]	[0.0020, 0.0282]	[0.0032, 0.0192]
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	1368	1303	1368	1368	540

Note: Column (2) excludes 65 unique city-year observations containing at least one interpolated value, leaving 1303 observations. Standard errors clustered at the city level are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

We then examine whether the interpolation of missing values affects the estimated policy effect. We exclude all 65 unique city-year observations containing at least one interpolated value. Specifically, there are 85 variable-level missing values in total, including 58 missing observations for forestry carbon emissions and 27 for forestry fiscal expenditure, with the two variables simultaneously missing in 20 city-years. After excluding these 65 city-year observations, the remaining sample contains 1303 observations. The estimated overall ATT is 0.0146 and remains statistically significant at the 5% level, which is broadly consistent with the baseline result.

A further set of robustness checks concerns the measurement of pre-2017 planted-forest timber harvest. Because planted-forest timber harvest before 2017 is estimated and is itself included as a desirable output in the measurement of forestry GTFP, we conduct three checks. First, we exclude physical planted-forest timber output from the desirable outputs and recalculate forestry GTFP using the remaining indicators. The re-estimated overall ATT is 0.0122 and is statistically significant at the 5% level. Second, we use an alternative method to estimate pre-2017 planted-forest timber harvest. Specifically, we calculate the growing stock per unit area of planted and non-planted forests at the provincial level and use their ratio to adjust the relative area weights of planted and non-planted forests across cities, thereby allowing for provincial differences in growing-stock density between the two forest types. Based on these adjusted weights, we re-estimate pre-2017 planted-forest timber harvest and recalculate forestry GTFP. The estimated overall ATT is 0.0151 and

is statistically significant at the 5% level, which is close to the baseline result. Third, to avoid reliance on estimated pre-2017 planted-forest timber harvest, we restrict the sample period to 2017–2022. Because the 2012 and 2014 treatment cohorts had already entered treatment before 2017, their pre-treatment periods cannot be observed in the shortened sample. This robustness check therefore retains only the 2018 and 2021 treatment cohorts and the never-treated cities, yielding 540 observations. The estimated overall ATT is 0.0112 and is statistically significant at the 1% level. Although the shortened sample contains fewer identifiable treatment cohorts and observations, the estimated effect remains positive and is similar in magnitude to the baseline estimate.

5.4. Potential Transmission-Channel Analysis

Table 8 reports the results of the potential transmission-channel analysis. Columns (1) and (3) employ the Callaway and Sant’Anna estimator to examine the effects of the NRFP on CD and PLP, respectively. The overall ATTs of the NRFP on CD and PLP are 0.2923 and 0.2950, respectively, and are statistically significant at the 5% and 10% levels. These results indicate that NRFP implementation is associated with increases in capital deepening and physical labor productivity in the forestry sector. Considering that adjustments in capital input and labor productivity may take time to be reflected in forestry GTFP, Columns (2) and (4) introduce the one-period lagged values of CD and PLP, respectively, to examine their associations with current forestry GTFP. The coefficient on one-period lagged CD is 0.0026 and is statistically significant at the 5% level, while the coefficient on one-period lagged PLP is 0.0029 and is statistically significant at the 10% level.

Table 8. Potential transmission-channel analysis.

Statistics/Variables	CD Channel		PLP Channel		Alternative CD Measure	
	(1) CD	(2) GTFP	(3) PLP	(4) GTFP	(5) Alternative CD	(6) GTFP
Overall ATT	0.2923 ** (0.1462)	—	0.2950 * (0.1543)	—	0.2254 ** (0.1075)	—
NRFP	—	0.0059 *** (0.0015)	—	0.0064 *** (0.0023)	—	0.0057 ** (0.0024)
CD _{t−1}	—	0.0026 ** (0.0013)	—	—	—	—
PLP _{t−1}	—	—	—	0.0029 * (0.0017)	—	—
Alternative CD _{t−1}	—	—	—	—	—	0.0024 * (0.0012)
Observations	1368	1254	1368	1254	1368	1254
R ²	—	0.1655	—	0.1708	—	0.1660
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	—	Yes	—	Yes	—	Yes
Year fixed effects	—	Yes	—	Yes	—	Yes

Note: Columns (1), (3), and (5) report overall ATTs using the Callaway and Sant’Anna estimator; Columns (2), (4), and (6) report fixed-effects estimates. The 1254 observations in Columns (2), (4), and (6) reflect the use of one-period lagged channel variables. City-clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

To further examine whether the evidence related to the capital deepening channel is sensitive to the specific measure of CD, we replace the baseline CD indicator with forestry fixed asset investment per unit of forest area. The results in Columns (5) and (6) show that the overall ATT of the NRFP on the alternative CD indicator is 0.2254 and is statistically significant at the 5% level. The coefficient on the one-period lagged alternative CD indicator is 0.0024 and is statistically significant at the 10% level. The consistency in the direction and statistical significance of the results across the two measures of CD indicates that the evidence for capital deepening as a potential transmission channel is reasonably robust to the specific measure of CD. Taken together, these results support H2.

5.5. Heterogeneity Analysis

To examine whether the effect of the NRFP on forestry GTFP varies across resource-based city status and policy zoning, we employ a DDD model. As shown in Columns (1) and (2) of Table 9, the coefficients of NRFP are significantly positive at the 1% and 5% levels, respectively, indicating that the NRFP has a significant positive effect on forestry GTFP in non-resource-based cities and ecology-conservation-oriented regions. The coefficient on NRFP $\times$ RE is significantly negative, indicating that the effect of the NRFP is significantly weaker in resource-based cities than in non-resource-based cities. In contrast, the coefficient on NRFP $\times$ PZ is significantly positive, indicating that the effect is significantly stronger in economy-efficiency-oriented regions than in ecology-conservation-oriented regions. These results indicate significant heterogeneity in the effect of the NRFP across resource-based city status and policy zoning and support H3.

Table 9. Heterogeneity analysis results.

Variables	(1) RE	(2) PZ
NRFP	0.0163 *** (0.0030)	0.0135 ** (0.0056)
NRFP $\times$ RE	−0.0211 *** (0.0042)	-
NRFP $\times$ PZ	-	0.0114 ** (0.0051)
Covariates	Yes	Yes
City fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1368	1368
R ²	0.0787	0.0601

Note: Standard errors clustered at the city level are reported in parentheses. RE = 1 denotes resource-based cities, and PZ = 1 denotes economy-efficiency-oriented regions. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

As a supplementary robustness check, this study further employs the Callaway and Sant’Anna staggered DID estimator to estimate the overall ATT separately for different subsamples, with the results reported in Table 10. The overall ATTs for non-resource-based and resource-based cities are 0.0270 and −0.0149, respectively, while those for ecology-conservation-oriented and economy-efficiency-oriented regions are 0.0129 and 0.0173, respectively. In terms of the relative magnitudes of the point estimates, the subgroup estimates exhibit a pattern consistent with the DDD results: the estimated effect is larger in non-resource-based cities than in resource-based cities and larger in economy-efficiency-oriented regions than in ecology-conservation-oriented regions. Therefore, the main heterogeneity pattern remains consistent when the staggered DID estimator is used.

Table 10. Subgroup estimates using the Callaway and Sant’Anna staggered DID estimator.

Statistic	RE = 0	RE = 1	PZ = 0	PZ = 1
Overall ATT	0.0270 *** (0.0091)	−0.0149 * (0.0082)	0.0129 ** (0.0060)	0.0173 ** (0.0070)
95% CI	[0.0091, 0.0449]	[−0.0309, 0.0011]	[0.0011, 0.0247]	[0.0036, 0.0310]
Covariates	Yes	Yes	Yes	Yes
Observations	432	936	312	1056

Note: RE = 0 and RE = 1 denote non-resource-based and resource-based cities, respectively; PZ = 0 and PZ = 1 denote ecology-conservation-oriented and economy-efficiency-oriented regions, respectively. Standard errors clustered at the city level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.6. Spatial Regression Analysis

Before estimating the Spatial DID-SDM, we examine the spatial autocorrelation of forestry GTFP using the global Moran's I [68]. Based on the nested weight matrix, the results are reported in Table 11. Moran's I is positive in all sample years and statistically significant in all years except 2012 and 2013, indicating positive spatial autocorrelation of forestry GTFP in most sample years. Although the magnitude of Moran's I is relatively small, the overall pattern suggests weak but statistically significant spatial dependence, supporting the consideration of spatial interactions in the subsequent analysis.

Table 11. Moran's I statistics for forestry GTFP from 2011 to 2022.

Year	Moran's I	Year	Moran's I
2011	0.0079 ** [0.0365]	2017	0.0099 *** [0.0000]
2012	0.0086 [0.9746]	2018	0.0095 *** [0.0048]
2013	0.0087 [0.7709]	2019	0.0096 *** [0.0003]
2014	0.0087 ** [0.0164]	2020	0.0102 *** [0.0000]
2015	0.0086 ** [0.0383]	2021	0.0100 *** [0.0000]
2016	0.0088 ** [0.0459]	2022	0.0098 *** [0.0004]

Note: *** and ** denote statistical significance at the 1% and 5% levels, respectively. [·] represents the *p*-value.

Table 12 reports the Spatial DID-SDM estimates and the decomposition of spatial effects. Column (1) uses the nested weight matrix. The estimated coefficient of the NRFP is positive and statistically significant at the 1% level. The estimated coefficients of the spatially lagged NRFP term ($W \times \text{NRFP}$) are significantly positive under both weight matrices. It should be noted that, because the Spatial DID-SDM involves spatial feedback effects, the coefficient of $W \times \text{NRFP}$ does not directly represent the spatial indirect effect. Therefore, we interpret the spatial effects of the NRFP primarily based on the partial-derivative effect decomposition. The decomposition results show that the direct effect of the NRFP is 0.0081 and is statistically significant at the 1% level. The indirect effect is 0.0942 and is also statistically significant at the 1% level, while the total effect is 0.1023 and is statistically significant at the 1% level.

Given that the indirect effect is substantially larger than the direct effect under the baseline specification, we further replace the baseline geographical-economic nested weight matrix with the geographical inverse-distance weight matrix W^{geo} (Equation (7)) to examine the sensitivity of the spatial effects to the specification of the spatial weight matrix. Column (2) shows that, under the alternative matrix, the direct, indirect, and total effects are 0.0300, 0.0920, and 0.1220, respectively, and all are statistically significant at the 1% level. In particular, the indirect effect changes from 0.0942 to 0.0920, while its direction, statistical significance, and magnitude remain stable. This result indicates that the positive spatial indirect effect of the NRFP is reasonably robust to the alternative specification of the spatial weight matrix. These results provide support for H4.

The spatial autoregressive coefficient ρ is significantly negative under both spatial weight matrices, with estimates of -0.6973 under the nested matrix and -0.2450 under the geographical inverse-distance weight matrix. Both estimates satisfy the spatial stability condition specified in Section 4.1.4. Although the absolute magnitude of ρ changes noticeably across the two spatial weight matrices, its sign and statistical significance remain consistent. This suggests that the negative spatial dependence in forestry GTFP is robust in direction, while its magnitude is somewhat sensitive to the specification of the spatial weight matrix.

Table 12. Spatial DID-SDM model estimates and effect decomposition.

Variables	(1) Nested Matrix	(2) Geographical Inverse-Distance Weight Matrix
NRFP	0.0131 *** (0.0038)	0.0140 *** (0.0042)
$W \times \text{NRFP}$	0.1605 *** (0.0348)	0.1379 *** (0.0370)
ρ	−0.6973 ** (0.2835)	−0.2450 *** (0.0750)
Covariates	Yes	Yes
City fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1368	1368
R^2	0.1711	0.1042
Direct effect	0.0081 *** (0.0031)	0.0300 *** (0.0115)
Indirect effect	0.0942 *** (0.0277)	0.0920 *** (0.0285)
Total effect	0.1023 *** (0.0267)	0.1220 *** (0.0290)

Note: Standard errors clustered at the city level are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

6. Discussion

The estimation results show that the NRFP significantly increases forestry GTFP. This result suggests that the NRFP, characterized by long-term investment and intensive forest management, is relevant not only to timber supply and forest resource cultivation but also to improvements in the overall green production efficiency of forestry, taking into account inputs, outputs, and environmental constraints. This finding is also consistent with previous studies showing that policy interventions can affect green productivity [69]. Compared with previous studies that have mainly examined the spatiotemporal evolution of forestry GTFP or its macro-level determinants, this study estimates the effect of the NRFP from a quasi-experimental perspective, providing further empirical evidence on the relationship between large-scale forest policies and green production efficiency in forestry.

The results for capital deepening and physical labor productivity provide further evidence for understanding the production adjustments that may accompany NRFP implementation. The channel analysis further shows that NRFP implementation is associated with increases in CD and PLP, while the lagged values of CD and PLP are each positively associated with forestry GTFP. From the input–output perspective of GTFP, these two sets of results reflect changes in different aspects of forestry production. An increase in CD reflects greater intensity of mechanized capital input in forestry. However, greater capital input does not necessarily lead to productivity improvements; whether it can be transformed into effective productive capacity and improve factor utilization efficiency is important for understanding the relationship between capital deepening and improvements in GTFP. An increase in PLP, by contrast, indicates greater physical output per unit of labor input, reflecting an improvement in the relationship between labor input and actual output. Previous studies have also shown that capital input, management technologies, and factor utilization efficiency are closely related to forest productivity [70]. Therefore, the results for CD and PLP provide complementary evidence from the perspectives of capital

input and labor output, respectively, for understanding the production changes that may occur during NRFP implementation. It should be noted that the construction of CD and PLP overlaps to some extent with the input or output information used to measure forestry GTFP, and the observed statistical relationships may therefore partly reflect correlations arising from indicator construction. Accordingly, we interpret CD and PLP as potential transmission channels consistent with the estimated effect of the NRFP.

In light of the estimates for capital deepening as a potential transmission channel, digital forestry provides a further perspective for understanding how long-term capital investment under the NRFP may support green productivity. Digital technologies can connect forest resource monitoring, management decision-making, and production operations. For example, remote sensing, unmanned aerial vehicles (UAVs), and LiDAR can improve forest resource inventories and dynamic monitoring; the Internet of Things (IoT) and artificial intelligence (AI) can support microclimate monitoring and forest growth and yield forecasting; and digital twins and geographic information systems (GIS) can support forest management planning and operational decision-making [71]. These applications may improve resource-use efficiency through better information acquisition, management decisions, and operational allocation. From this perspective, digital technologies can also strengthen the supply chain linking forest production with downstream utilization. Digital timber traceability, smart warehousing, and harvesting, transportation, and logistics optimization can improve information coordination across timber production, transportation, inventory management, processing, and utilization [72]. Therefore, long-term timber supply capacity depends not only on forest resource development and production efficiency but also on efficient coordination between forest production and downstream utilization.

Understanding the long-term green productivity effects of the NRFP also requires consideration of forest disturbance risks. For reserve forests with long growth cycles, fires, droughts, pests and diseases, and extreme climate events may cause losses in forest growing stock, increase carbon emissions, and disrupt timber supply, thereby affecting long-term forest productivity and forest resilience [73]. The forestry GTFP measured in this study captures productivity changes under the observable inputs, outputs, and environmental costs during the sample period, but does not directly incorporate expected losses from natural disturbances. Therefore, whether the observed productivity improvements would persist after accounting for disturbance risks and their potential losses remains an important issue for evaluating the long-term green productivity effects of the NRFP. Digital tools such as remote sensing, UAVs, thermal sensors, meteorological monitoring, and AI-based risk forecasting can provide technological support for forest disturbance detection, risk early warning, post-disturbance assessment, and recovery management [74], thereby providing a basis for incorporating production stability and forest resilience more fully into the long-term performance evaluation of the NRFP.

The heterogeneity analysis shows that the effect of the NRFP on forestry GTFP is significantly weaker in resource-based cities and significantly stronger in economy-efficiency-oriented regions. The weaker policy effect in resource-based cities may be related to the structural adjustment costs associated with the green transition in resource-dependent regions. Previous studies have shown that development patterns shaped by long-term resource dependence may increase the difficulty of shifting economic activities toward greener and more efficient modes of production [75]. This characteristic may affect the extent to which additional forestry investment is translated into observable productivity gains during the sample period. From this perspective, the productivity effect of the NRFP may depend not only on policy investment but also on the existing economic structure of a region. The results for policy zoning further suggest that differences in GTFP effects across regions need to be understood in relation to the alignment between policy objectives and the

dimensions captured by productivity measurement. Economy-efficiency-oriented regions place greater emphasis on timber supply capacity and management efficiency, and these policy outcomes can be more directly reflected in the economic output, physical timber output, and factor utilization captured by the GTFP measure used in this study. By contrast, some of the ecological objectives pursued in ecology-conservation-oriented regions are primarily reflected in ecosystem services such as biodiversity conservation, water conservation, and habitat maintenance. These services have substantial non-market value and are difficult to fully capture in conventional productivity accounting [76,77]. Therefore, the stronger GTFP effect observed in economy-efficiency-oriented regions may reflect both differences in productivity performance across policy zones and differences in the extent to which various policy outcomes are observable within the current GTFP evaluation framework.

The spatial analysis extends the understanding of the geographical scope of the NRFP's policy effects. It further suggests that the green productivity effects of long-term forest management policies need to be understood in the context of regional linkages. For the NRFP, one possible explanation is that large-scale and long-term reserve forest development may generate sustained demand for seedlings, machinery and equipment, specialized technical services, and harvesting, transportation, and processing capacity, while these production and service activities are not necessarily confined by city administrative boundaries [78]. As project implementation and forest management expand, changes in production demand and management activities in implementing cities may further affect regional forestry service systems and timber production networks, allowing policy effects to spread through economic linkages across cities [79]. Meanwhile, forestry capital, specialized labor, and processing capacity exhibit some degree of mobility across regions, and cities may also influence one another in their ability to attract and utilize these production factors [80]. Therefore, cross-regional policy effects and the conditional spatial dependence of forestry GTFP can coexist, reflecting the regional transmission of policy effects and spatial feedback in productivity across cities, respectively. Accordingly, evaluating the NRFP also requires attention to regional linkages arising from forest management activities that extend beyond administrative boundaries, providing a basis for cross-regional coordination of long-term forest management policies.

The findings of this study are based on China's specific forest governance and policy implementation context, and their international relevance is better understood in terms of the institutional conditions required for long-term forest management. Long-term forest investment generally requires financing arrangements aligned with forest growth cycles, stable and enforceable forest tenure and management rights [81], as well as sustained management planning, technical services, and regulatory capacity. Long-term performance evaluation also depends on a data infrastructure capable of supporting forest resource monitoring and policy evaluation [82]. Together, these conditions influence whether long-term capital investment can be translated into sustained forest management activities and whether long-term coordination can be achieved among timber supply, production efficiency, and ecological objectives. The spatial analysis in this study further suggests that when forest production and timber market linkages extend across administrative boundaries, policy implementation and performance evaluation need to consider inter-regional interactions, placing additional demands on cross-regional governance, information sharing, and the coordination of associated costs and benefits [83]. Therefore, other countries seeking to draw lessons from the NRFP should not focus on replicating its specific implementation model. Instead, they should develop long-term investment and sustained management mechanisms that are aligned with forest growth cycles and adapted to their own forest tenure arrangements, public fiscal capacity, and forest governance foundations, while coordinating timber production, regional interests, and ecological conservation.

7. Conclusions

Based on panel data from 114 prefecture-level cities in China from 2011 to 2022, this study systematically evaluates the impact of the NRFP on forestry GTFP. The findings are fourfold.

First, the NRFP significantly improves forestry GTFP in implementing cities. The baseline overall ATT is 0.0149, corresponding to approximately 1.49% of the sample mean of forestry GTFP, indicating that reserve forest construction contributes to greener and more efficient forestry development. Second, the channel analysis shows that the improvement in forestry GTFP is accompanied by capital deepening and higher physical labor productivity, suggesting that CD and PLP may serve as potential transmission channels through which NRFP investment is translated into productivity gains. Third, the policy effect exhibits clear regional heterogeneity, with stronger improvements in non-resource-based cities and economy-efficiency-oriented regions, indicating that the productivity effects of the NRFP vary across resource-based city status and policy zoning. Fourth, the spatial analysis reveals a positive cross-regional policy effect of the NRFP, indicating that its influence on forestry GTFP extends beyond implementing cities.

This study still has several limitations. First, although this study employs a DID estimator suited to staggered treatment adoption and conducts a series of related tests, the estimates still rely on the corresponding identification assumptions, and it remains difficult to completely rule out the possibility that unobserved time-varying factors, such as fiscal capacity, implementation readiness, and forest-resource conditions, may simultaneously affect NRFP implementation and forestry GTFP. Second, because of limitations in the availability of city-level forestry data, some indicators still need to be estimated or interpolated based on available information. Although this study verifies the stability of the main findings through tests that exclude the pollution indicator and interpolated observations, adjust the measurement of planted-forest timber output, and shorten the sample period, these data treatments may still affect the measurement accuracy of the relevant indicators. Third, the identification of NRFP treatment status and implementation timing remains constrained by the completeness of publicly available information. Meanwhile, publicly available information provides limited detail on differences in actual implementation intensity and execution across regions, and existing city-level data do not allow us to further characterize implementation differences in terms of construction area, investment scale, implementation progress, and specific management practices. Fourth, the current GTFP measurement does not fully incorporate non-market ecosystem services, such as biodiversity conservation, water regulation, and habitat protection, or potential long-term losses caused by natural disturbances such as fires, droughts, and pests and diseases. Therefore, the results of this study primarily reflect changes in green productivity within the existing input–output and environmental indicator framework. Finally, the spatial estimates may be sensitive to how the spatial weight matrix characterizes linkages across cities. Although the direction and magnitude of the NRFP's cross-regional policy effects remain generally stable under the alternative matrix, some spatial parameter estimates vary across matrix specifications.

Future research can further extend this study by improving data granularity, broadening the measurement of ecological performance, and refining the identification of spatial linkages. First, as city-level forestry statistics and project-level and micro-level management data on the NRFP become more comprehensive, future studies can characterize differences in implementation, such as construction scale, investment intensity, implementation progress, and management practices, in greater detail beyond city-level treatment status. More direct data on forestry pollution emissions and timber output can also be incorporated to improve the measurement accuracy of policy implementation characteristics and forestry GTFP. Second, future research can broaden the dimensions of forestry green

performance by incorporating biodiversity, ecosystem services, and natural disturbance risks, such as fires, droughts, and pests and diseases, to examine NRFP effects under broader ecological objectives and long-term disturbance risks. Finally, spatial networks based on more direct linkages, such as timber flows, technological connections, and ecological processes, can be used to further examine the cross-regional effects of the NRFP. Beyond statistical significance, future research can also assess the economic significance of the policy effects by considering policy investment costs, productivity gains, and long-term ecological benefits.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/f17091081/s1>, Table S1: Treatment Cities and Documentary Evidence on NRFP Implementation during 2011–2022; Table S2: Control Cities and Documentary Evidence Supporting Their Untreated Status during 2011–2022; Table S3: Sample Exclusions and Reasons for Exclusion; Table S4: Dynamic ATT Estimates and Cohort Composition.

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