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Does green finance policy promote green total factor productivity? Evidence from a quasi-natural experiment in the green finance pilot zone

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Abstract

The establishment of Green Finance Reform and Innovation Pilot Zones represents a novel endeavor aimed at paving a "bottom-up" pathway for the advancement of green finance and, consequently, holds immense significance in fostering economic growth that is environmentally sustainable. Drawing on data spanning the years 2013–2019 from 278 prefecture-level cities across China, we delve into the influence of the Green Finance Reform and Innovation Pilot policy on urban Green Total Factor Productivity. We found that: Firstly, the Green Finance Reform and Innovation Pilot policy has demonstrated a discernible enhancement in Green Total Factor Productivity within the designated pilot regions. Secondly, there is heterogeneity in the promotion effect of this pilot policy on Green Total Factor Productivity. As the geographical advantage and economic development level decrease, this promotional effect gradually diminishes. Thirdly, it is evident that the Green Finance Reform and Innovation Pilot policy primarily elevates Green Total Factor Productivity in the pilot regions by improving resource allocation efficiency, fostering innovation in green technologies, and facilitating the upgrading of industrial structures. This research not only underscores the efficacy of green finance in the context of economic transition but also provides empirical substantiation for the strategic utilization of pilot zones to propel nationwide initiatives aimed at sustainable green development.
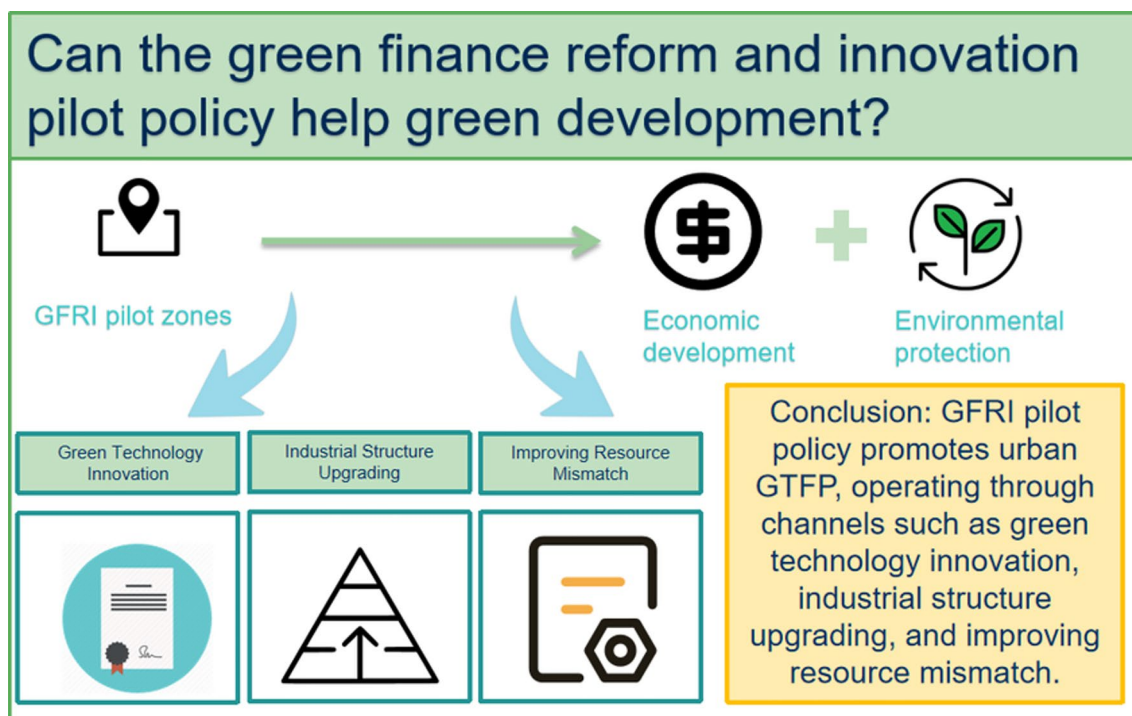
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Graphical abstract

Keywords Green finance · Green total factor productivity · Resource misallocation · Green technology innovation · Industrial structure upgrading

Introduction

The global economy has experienced remarkable growth during the past few decades, coupled with a rapid pace of industrialization and urbanization. However, this trajectory has come at the cost of an expanding ecological footprint and the persistent degradation of the natural environment. Particularly, the prevalent extensive development model has given rise to environmental challenges of considerable magnitude, prompting both the governments and the public to grapple with the imperative of sustainable economic development (Ma et al. 2021). Consequently, the conundrum of achieving economic prosperity while safeguarding the environment and conserving resources has become a paramount challenge facing the government. Based on data from the Wind database and the "World Energy Statistical Yearbook 2022," it is evident that China's GDP has surged from 367.87 billion yuan in 1978 to 1,143,669.72 billion yuan in 2021, as illustrated in Fig. 1. Adjusting for the influence of price factors, this represents an increase of over 300 times, positioning China as the world's second-largest economy, trailing only the USA. However, China's carbon

dioxide emissions have exhibited a linear upward trend. In 2021, the total emissions exceeded twice that of the USA, catapulting China to the top spot globally, while US carbon dioxide emissions have remained relatively stable. This underscores the pressing challenge for China to address the reduction in carbon emissions, mitigate environmental pollution, and propel economic transformation toward green and low-carbon practices. Achieving this transformation, which balances environmental protection and resource conservation while fostering economic growth, has become an urgent imperative for China's economic development. Against this backdrop, in 2017, the State Council designated Zhejiang, Jiangxi, Guangdong, Guizhou, and Xinjiang as the first pilot provinces and autonomous regions for Green Finance Reform and Innovation Pilot Zones (GFRIs). In 2019 and 2022, Gansu Province's Lanzhou New Area and Chongqing City were subsequently included in the pilot program. The introduction of Green Finance Reform and Innovation Pilot policy (GFRI pilot policy) highlights China's determination to employ financial instruments in supporting green and low-carbon development. The policy's objective is to achieve a "win–win" scenario by utilizing financial tools to drive both
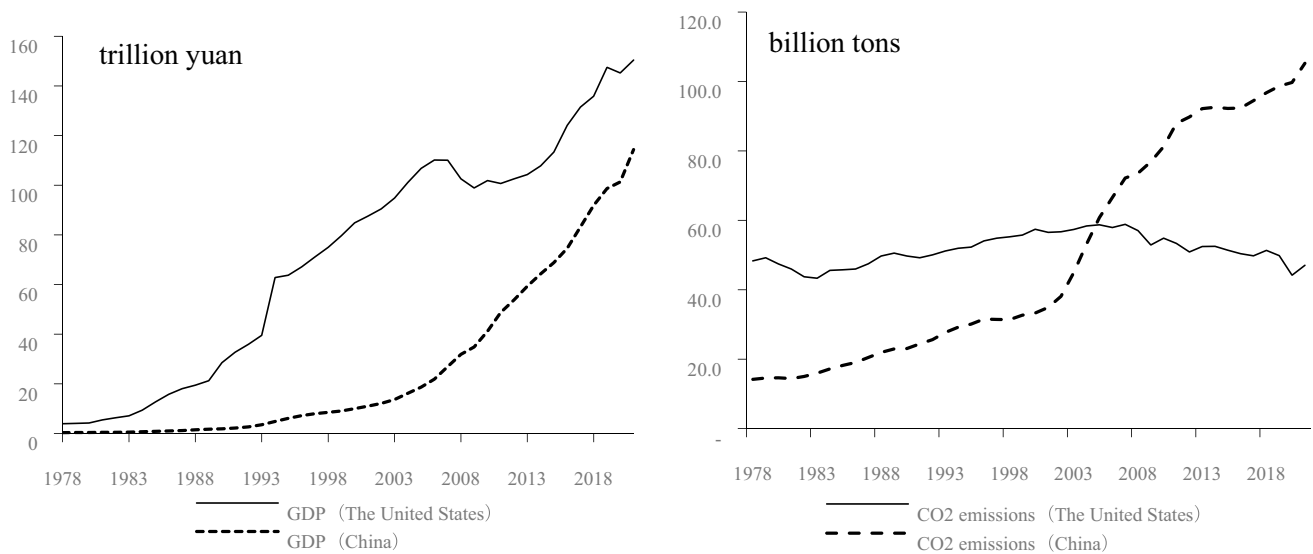
Fig. 1 Comparison between China and the USA

economic growth and environmental protection, thereby fostering sustainable economic development. Therefore, the establishment of GFRIs raises crucial questions: Can these zones simultaneously drive economic growth within their jurisdictions while prioritizing environmental protection? What is the underlying mechanism at play? These inquiries are pivotal in assessing the effectiveness of the GFRI pilot policy and informing the subsequent progression of these policies.

Green Total Factor Productivity (GTFP) extends the traditional total factor productivity framework by taking into account the impact of environmental factors and energy consumption (Mohtadi 1996). Therefore, GTFP is considered a suitable indicator for measuring the sustainable development of a country or region (Li and Liao 2020). The establishment of GFRIs provides conditions for enhancing GTFP in these pilot regions. In comparison with non-experimental zones, commercial banks in the experimental zones set higher environmental entry thresholds in their credit activities, and their implementation of differentiated pricing strategies for different enterprises is more stringent. On the one hand, they offer preferential low-interest loans to energy-saving and environmentally friendly enterprises, providing these enterprises with better advantages in market access, resource acquisition, project support, and regulatory flexibility. On the other hand, they impose punitive high-interest rates on loans to high-pollution and high-energy-consuming enterprises, withholding financing from these enterprises (Yao et al. 2021). The polluting enterprises, concerned about being blacklisted and attracting attention from the government and banks, engage in pollution control and low-carbon transformation. Therefore, the GFRI pilot policy, through the allocative function

of the financial market at the micro level, guides funds toward resource-efficient and environmentally friendly enterprises (Zhang et al. 2021a, b), profoundly influencing business decisions and innovation behavior of enterprises. This, in the end, will lead to the realization of sustainable economic and social development. Based on this, the present study will use various prefecture-level cities in China as research samples to delve into the impact of the GFRI pilot policy on GTFP.

In the existing literature, studies on the relationship between green finance policies and GTFP can be summarized as follows. Firstly, most research analyzes the impact of environmental regulatory tools on GTFP and finds a non-linear threshold effect (Tian and Feng 2022). In the short term, environmental regulations may increase pollution control costs, additional production costs, and sunk costs of innovation failure, thereby reducing GTFP (Zhang et al. 2020). However, with the accumulation of knowledge, human capital, and technological progress, environmental regulatory tools gradually enhance GTFP (Zheng and Chen 2023). Some studies have also analyzed the impact of green finance policies on GTFP, revealing that green credit policies incentivize financing for green enterprises and impose financial penalties on highly polluting enterprises (Wang et al. 2022a, b). This, in turn, can drive enterprises to engage in emission reduction activities, ultimately enhancing GTFP (Wang and Zhi 2016). However, there is limited research on the analysis of GFRI pilot policy, and there is also a lack of theoretical model analysis regarding the impact of this policy on GTFP. On the one hand, the GFRI pilot policy can comprehensively govern its jurisdiction compared to green credit policies. On the other hand, the construction and analysis of theoretical models can better grasp the

process and mechanism through which the GFRI pilot policy enhances GTFP. Secondly, regarding the analysis of green finance policies, most studies only examine the differences between different regions. Green finance policies can significantly promote GTFP in the eastern region, but the impact is less apparent in the central and western regions (Wang and Wang 2023). However, these studies have not further conducted model analysis and attempted to identify the reasons for these regional differences. Finally, the research on the mechanisms between green finance policies and GTFP is also incomplete, with most studies mainly exploring the effects of innovation and structural effects (Li et al. 2023a, b). Green finance policies can reduce pollution emissions at the source by guiding low-cost funds into the research and development of green innovation, thereby increasing GTFP. At the same time, green finance policies can force polluting enterprises to transform and upgrade, promoting the shift of the secondary industry structure toward environmental protection, ecology, and green upgrades (Hu et al. 2022). However, these studies overlook the importance of green finance pilot policies in improving resource allocation and thereby enhancing GTFP.

In light of this, we take 278 prefecture-level cities in China from 2013 to 2019 as the research sample, aiming to empirically investigate the impact and mechanisms of the GFRI pilot policy on the GTFP of each city. The marginal contributions of this paper are as follows. First, we provide a theoretical analytical framework for the relationship between green finance policies and GTFP by constructing a theoretical model, and we empirically validate this framework through model testing. This elucidates the significance of green finance policies in the process of achieving economic sustainability. Second, we analyze the regional heterogeneity in the impact of the GFRI pilot policy on GTFP and further conduct model analyses for each pilot zone based on the research findings, offering evidence for the economic development imbalances across different regions in China. Third, we enhance the mechanism analysis between green finance policies and GTFP. We comprehensively examine the role of the GFRI pilot policy in urban GTFP from the perspectives of green technological innovation, industrial structure upgrading, and improved resource allocation. This serves as a valuable supplement to the literature on the intersection of finance and green economic development.

The rest of this paper is organized as follows. Section "Research hypothesis" introduces research assumptions. Section "Data and variable" presents data and variable. Section "Model and result analysis" provides model and result analysis. Section "Further discussion" presents further discussion. Section "Conclusion and implications" presents conclusions and implications.

Research hypothesis

The GFRI pilot policy and the GTFP

The elevation of urban GTFP necessitates the constraint of pollution behavior among micro-level entities, predominantly businesses. Drawing upon the theory of externalities, the pollution emissions from enterprises exhibit strong negative externalities, resulting in a decrease in overall societal welfare and economic efficiency. However, these polluting enterprises do not compensate for these negative externalities (Fu et al. 2021). The environmental costs incurred by pollution emissions are borne by society, and the GFRI pilot policy can internalize these external costs (Wang and Wang 2021). This is achieved by placing polluting enterprises on a priority monitoring list, subjecting them to continuous scrutiny. Based on the enterprises' emission reduction plans and the attainment of emission reduction targets, the government and commercial banks will decide whether to continue providing loans, increase credit interest rates, or even retrieve existing credit facilities (Zhang 2021). This directly raises the financing costs for polluting enterprises. For investors, a reduction in credit implies that, as entities constrained under current macroeconomic policy regulations, these enterprises cannot fundamentally alter the status quo to meet pollution reduction goals and environmental quality requirements in the short term. Negative environmental news spreading in the capital markets influences investor expectations, leading to a lower valuation for the enterprise and further escalating its capital market financing costs (Zhao et al. 2023). Through this institutional arrangement, the GFRI pilot policy intricately links the environmental costs of pollution emissions with financing costs, compelling high-pollution enterprises to scrutinize their social and environmental responsibilities actively. Lowering the loan thresholds for green environmental enterprises and providing tax subsidies also encourage polluting enterprises to channel more funds into research and development, facilitating their own transformation and upgrading (Huang et al. 2019). Thus, by controlling the direction of credit, the GFRI pilot policy can eliminate or restructure polluting industrial sectors, thereby promoting green economic growth. Furthermore, the development of green environmental enterprises and the research and development of green technology innovation in polluting enterprises require substantial capital investment and financial support (Huang and Zhang 2021). The implementation of the GFRI pilot policy can assist regions in accumulating more infrastructure and green technology conditions while providing ample financial support for enterprises. This, in turn, propels the green development of micro-level enterprises, ultimately elevating the region's GTFP.

In the appended theoretical models, exogenous shocks denote the effects induced by the GFRI pilot policy. These effects hinge on the degree of variation in the punitive measures (γ) concerning corporate environmental pollution, which exerts distinct influences on multiple facets of enterprise operations, including the optimal age distribution of production equipment, emission levels, and productivity. The principal outcomes manifest as follows: the GFRI pilot policy's impact triggers a reduction in the steady-state optimal production equipment quantity and a decline in the optimal equipment age distribution for enterprises. Consequently, this engenders a transformation in the operational landscape of these enterprises. On the one hand, these alterations in production equipment contribute to a reduction in total emissions, thereby yielding a positive environmental impact. Conversely, the retirement of outdated production equipment drives an upswing in the average productivity of enterprises. Consequently, as per the model's derivations, the enactment of the GFRI pilot policy leads to a shift in the behavior of enterprises operating within the pilot zone, ultimately resulting in a reduction in overall pollution emissions and an upswing in productivity. These outcomes, in turn, are reflected in an augmentation of the pilot zone's GTFP. Based on the above analysis, we propose the following hypotheses:

H1 The GFRI pilot policy fosters the enhancement of GTFP within the pilot area.

Mechanism analysis

Green technology innovation mechanism

The GFRI pilot policy has the capacity to induce innovation in green technologies within polluting enterprises by elevating the environmental pollution costs, thereby contributing to the enhancement of GTFP. Throughout the course of economic development, technological progress assumes a central and paramount role, serving as a fundamental catalyst for economic expansion, as posited by Solow (1956). This role extends to its significant impact on augmenting GTFP, as corroborated by Wang et al. (2021). The GFRI pilot policy is designed to redirect funds from polluting enterprises toward green environmental enterprises. This redirection serves to elevate the environmental pollution costs for polluting enterprises. Concurrently, the impetus for green technological innovation is provided as a condition for polluting enterprises to secure financing (Wang and Wang 2021). From a dynamic competition perspective, Porter's hypothesis posits that moderate environmental regulations can stimulate businesses to engage in green technological innovation. The research and development of green technological innovation not only enhance a firm's competitiveness and market share but also offset the costs incurred during the process, yielding an innovation compensation effect (Porter and Van der Linde 1995). On another front, as enterprises apply the developed green technological innovations to their production processes, there is an effective reduction in pollution emissions. The government and commercial banks, based on the achievement of emission reduction targets, are then prompted to make decisions regarding continuous provision of loans, reduction in credit interest rates, or even provision of research and development subsidies (Zhang et al. 2022a, b). Therefore, the GFRI pilot policy serves to foster innovative activities within enterprises, particularly by promoting green technological innovation. Furthermore, through the theoretical model derivation presented in this paper, it is discerned that the GFRI pilot policy induces enterprises to scale down production by cutting and delaying cash expenditures for fixed asset investments. This involves the removal of more old production equipment with low productivity, high operating costs, and large pollutant emissions from the production process. Subsequently, the integration of green technologies into new production equipment occurs, effectively reducing pollution emissions and enhancing overall enterprise productivity. Ultimately, this approach contributes to the elevation of the GTFP within the pilot zone.

Industrial structure upgrading mechanism

The reallocation of financial resources plays a pivotal role in advancing environmental governance through the avenues of green finance, as highlighted by Wang and Wang (2021). This transformative process, often referred to as the industrial structure upgrading mechanism, primarily materializes through the lens of financial resource reallocation. It functions by strategically reallocating financial components, effectively curbing the expansion of low-efficiency and high-pollution industries while concurrently fostering the growth of high-tech and environmentally sustainable sectors. This strategic redirection of financial assets applies pressure on polluting enterprises, compelling them to embark on a path of transformation and modernization.

Firstly, under the current circumstances, the GFRI pilot policy instigates commercial banks to implement distinct loan interest rates and eligibility thresholds tailored to different categories of enterprises. Beneficial loan terms are extended to environmentally conscious enterprises characterized by minimal pollution and energy consumption, whereas stringent, high-interest rates are imposed upon highly polluting and energy-intensive counterparts (Su and Lian 2018). This maneuver effectively diminishes the financial lifelines accessible to polluting enterprises, thereby impacting their production scale and compelling them to undertake transformative measures.

Secondly, when viewed through a long-term perspective, the green finance policy conveys a resounding signal of

China's resolute commitment to cultivating a green economy (Nedopil 2022). This signal resonates not only in the realm of contemporary business operations and management practices but also permeates the contours of future developmental planning. On the one hand, the punitive ramifications for highly polluting and energy-intensive enterprises will progressively intensify, constricting their scope for survival. On the other hand, the government's support for green enterprises will beckon a greater influx of enterprises toward the domain of environmentally friendly initiatives (Wei 2023). Embedded within this signaling framework, a growing number of enterprises will align themselves with green development as the cornerstone of their future growth strategies, thus catalyzing widespread business transformation and modernization.

Thirdly, with regard to optimizing the industrial structure, each nation is inherently predisposed to an ideal industrial composition, primarily contingent upon the intrinsic resource endowment (Lin and Zhang 2007). In the present context, China's economic model is predominantly tilted toward the secondary and tertiary sectors, with the secondary sector's value-added component comprising the largest share among the triad. The development of these sectors heavily relies on credit-based funding, with their profitability serving as a boon for financial institutions, giving rise to a mutually reinforcing loop (Xu et al. 2018). Nevertheless, this loop, while beneficial for economic development, has historically sidestepped environmental consequences, culminating in environmental deterioration. The inception of the pilot zones integrates environmental considerations into this reinforcing loop, thereby amplifying its impact. Within the confines of these pilot zones, commercial banks and the government judiciously factor in regional economic and environmental conditions, harmonizing their initiatives with the dual carbon objectives of "peak carbon" and "carbon neutrality"(Huang and Zhang 2021). This harmonization entails interest rate adjustments, tax reductions, and a medley of other measures geared toward championing the development of high-tech industries and eco-friendly environmental sectors. As these enterprises garner increased credit-based funding, their competitive prowess burgeons, perpetuating a more robust cycle of bank loans.

Simultaneously, industries characterized by low efficiency and elevated pollution levels, which have historically thrived at the expense of environmental degradation, face measures designed to curtail their expansion. Punitive high interest rates, penalties, and other regulatory measures compel these enterprises to embark on transformational journeys (Zhang et al. 2022a, b). Through these feedback mechanisms and credit-driven incentives, regional industries gravitate toward greener, low-carbon, and highly efficient trajectories, ultimately uplifting the GTFP of the region.

Improving resource mismatch mechanism

The GFRI pilot policy can enhance GTFP by facilitating the transfer of production factors and addressing resource misallocation. In recent years, a key impediment to the overall factor productivity enhancement of enterprises across China has been the pervasive issue of resource misalignment in the market (Wei and Li 2017). Optimal resource allocation, marked by equilibrium and effectiveness, hinges on the unobstructed flow of economic resources such as labor, materials, and technology. It is this fluidity that cultivates a rational elemental allocation structure, thereby augmenting resource allocation efficiency and consequently elevating total factor productivity (Wen et al. 2021). However, when the natural flow of resources encounters market frictions, bureaucratic directives, and other factors, it may veer away from the optimal state, resulting in resource misalignment. The irrational allocation of capital and labor, among other production factors, emerges as a prominent contributor to diminished enterprise productivity (Hsieh and Klenow 2009). This predicament significantly reverberates through the GTFP landscape of different regions. From an ecological economics standpoint, irrational resource allocation impairs the production efficiency of high-performing enterprises while fostering resource wastage in their low-efficiency counterparts. This, in turn, curtails resource utilization efficiency and begets amplified environmental pollution. In essence, resource misalignment often culminates in inefficient resource deployment and market tumult, eroding the foundations of sustainable economic development (Uras 2014). Furthermore, resource misalignment also offers a glimpse into the economy's adaptability, hinting at missed opportunities and superior economic outcomes (Karabarbounis and Macnamara 2021). Therefore, steering policy-driven resource reallocation to rectify resource misalignment emerges as a potent avenue for fortifying GTFP.

The establishment of these pilot zones provides an auspicious platform for grappling with this quandary. In this context, both the government and financial institutions, including commercial banks, can choreograph the flow of funds. This can be accomplished through measures such as tax incentives and adjustments to loan interest rates, effectively curbing capital allocation to polluting enterprises while channelling a more substantial financial influx into green and eco-friendly sectors. The consequential shift in the current of credit resources will invariably impact the distribution of other pivotal production elements like labor, land, and energy (Fan and Li 2022). The GFRI pilot policy sends a resounding signal that China is unequivocally championing the development of a green economy. Consequently, as it steers credit resources into the green environmental protection sector, it simultaneously triggers the migration of other production factors, including labor,
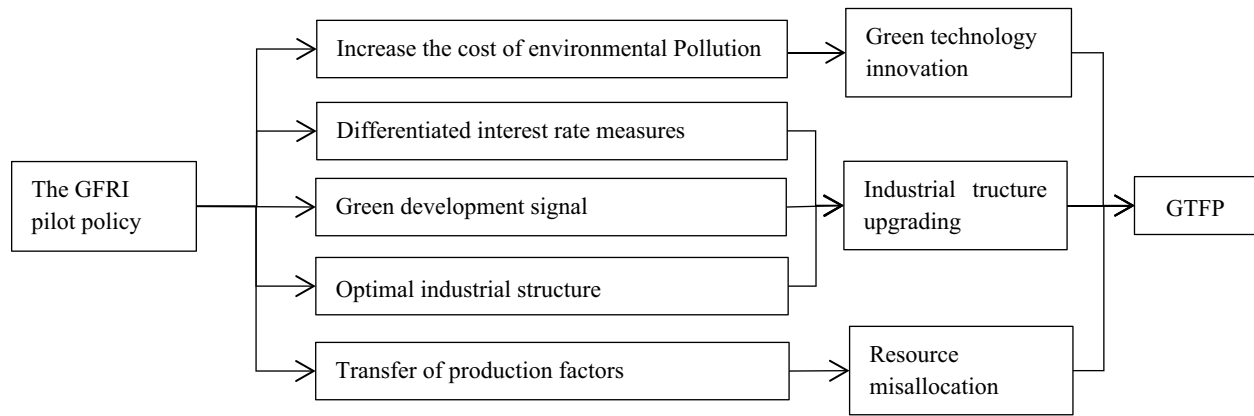
Fig. 2 Conduction mechanism diagram

land, and energy. The transformation and revitalization of polluting enterprises, coupled with the burgeoning influx of green-oriented enterprises, will necessitate augmented inputs of land, labor, energy, and other critical production factors. This transformative wave heralds an era of enhanced resource allocation, liberating the production factors from their erstwhile concentration within industrial enterprises marked by low production efficiency, extensive tax bases, and grave pollution. Ultimately, this paradigm shift augments the comprehensive utilization of production factors, bolsters resource allocation, and culminates in the heightened GTFP of the pilot zone region.

Based on the analysis above, the GFRI pilot policy can induce pollution enterprises to innovate in green technologies by increasing environmental pollution costs. Industrial structure upgrading can be facilitated through measures such as differential interest rates, signals for green development, and adjustments to industrial structures. By addressing resource misallocation through the transfer of production factors, the GFRI pilot policy ultimately contributes to the enhancement of GTFP (refer to Fig. 2). Further integrating the model derivation in appendix, the GFRI pilot policy can improve the resource allocation mechanism by raising environmental pollution costs ($C\gamma$). In this context, enterprises are compelled to remove more old production equipment, reduce the optimal age distribution of production equipment (α), invest in research and development for green technological innovation, drive their transformation and upgrading, and consequently reduce pollution emissions while enhancing productivity. This, in turn, leads to an increase in the region's GTFP.

H2 The GFRI policy is expected to bolster GTFP within the pilot regions by enhancing resource allocation mechanisms, nurturing green technological innovation, and facilitating industrial structure upgrading.

Data and variable

Sample selection and data

We conducted an analysis using panel data from Chinese prefecture-level cities for the years 2013–2019. The empirical data used in this study primarily came from the China National Research Data Service Platform (CNRDS), CSMAR database, Wind database, "China City Statistical Yearbook," and "China Statistical Yearbook." Specifically, the CNRDS contained relevant data on green patents for various prefecture-level cities; the "China City Statistical Yearbook" and "China Statistical Yearbook" provided characteristic data for these cities; the CSMAR and Wind databases supplied data for listed companies. After data collection and processing, we finally obtained 1945 observations of 278 prefecture-level cities. The data processing in this study is described as follows: (1) The samples with significant data gaps were excluded. (2) The samples with individual missing values in the data were supplemented using interpolation. (3) To remove the influence of extreme values, the upper and lower 1% of values for the continuous variables are winsorized.

Variable selection

(1) GTFP (*GP*). In line with Fukuyama and Weber's (2009) research, we will employ the SBM directional distance function and the Malmquist–Luenberger index for computation. Regarding the selection of input and output variables, building upon the findings of He and Qi (2022), Lee and Lee (2022), and Li and Li (2021), we not only incorporate the conventional input variables but also introduce an energy consumption input variable to capture environmental resource utilization. Additionally, we employ economic development as the desired output variable and pollution

Table 1 Description of variables

Panel A: Definition of variables		
Variable types	Variable Abbreviations	Variable specifications
Dependent variables	GP	Derived through the SBM-DDF model calculation
Explanatory variables	Treat*t	Interaction of policy location and policy time
	GDP	The logarithm of per capita regional GDP
	GDP^2	The square of the logarithm of per capita regional GDP
	FG	Foreign Direct Investment divided by GDP (%)
	GI	Fiscal expenditure divided by GDP (%)
Control variables	Swu	The comprehensive utilization rate of industrial solid waste (%)
	SE	Scientific expenditure divided by GDP (%)
	EE	Education expenditure divided by GDP (%)
	Em	The logarithm of the number of employed people
	LM	The number of students in higher education institutions divided by the number of employed people (%)

Panel B: Descriptive statistics						
Variable	N	Mean	SD	Median	Min	Max
GP	1945	0.9480	0.1380	0.8370	0.9280	1.0400
GDP	1945	10.7700	0.5520	10.3600	10.7400	11.1300
GDP^2	1945	116.3000	11.9600	107.3000	115.4000	123.8000
FG	1945	0.0160	0.0159	0.0032	0.0116	0.0232
GI	1945	0.2050	0.0979	0.1370	0.1810	0.2440
Swu	1945	75.0300	28.6800	63.2300	87.2000	95.7300
SE	1945	0.0028	0.0024	0.0013	0.0020	0.0037
EE	1945	0.0348	0.0169	0.0231	0.0304	0.0426
Em	1945	13.6300	0.8640	13.0400	13.5300	14.1100
LM	1945	0.0663	0.0606	0.0271	0.0476	0.0830

emissions as the undesired output variable to gauge the pollution levels associated with the development process of each prefecture-level city.

Regarding the specific indicators chosen, labor input is quantified by the total employed population in each city, while capital input is assessed based on fixed asset investment in each city. The perpetual inventory method is employed to convert fixed asset investment into stock indicators, accounting for depreciation at a rate of 15% (Bai et al. 2015). Energy consumption is measured using electricity consumption data for each city. Desired output is determined by the actual economic production value in each city, while undesired output encompasses industrial emissions such as sulfur dioxide, wastewater, and smoke and dust emissions in each city's industrial sector. Furthermore, to standardize input and output variables and eliminate dimension-related influences stemming from different units of measurement, this study normalizes each variable.

(2) Policy variables of GFRIs. We use two dimensions of province–year to construct a DID model to identify the implementation effect of this pilot policy. Specifically, we

study the five provinces of Zhejiang, Jiangxi, Guangdong, Guizhou, and Xinjiang Uygur Autonomous Region as the treatment group, which have established pilot zones, and the remaining provinces are considered as the control group. Therefore, if the sample enterprises are located in the aforementioned five provinces, *Treat* = 1; otherwise, *Treat* = 0. The five provinces built pilot zones on June 23, 2017, so we determine 2017 as the year when the policy plays take effect, and if the year is before 2017, *t* = 0. Otherwise, *t* = 1 (Table 1).

(3) Control variables. In order to mitigate the influence of these relevant factors, following the studies of Li and Li (2021) and Dai and Luo (2022), we mainly control for the following variables.① Per capita regional gross domestic product (*GDP*) and the square term of per capita regional gross domestic product (*GDP²*). According to the theories of new institutional economics and the Environmental Kuznets Curve, the level of economic development is a crucial factor affecting the efficiency of urban green economic activities.② Foreign direct investment (*FG*). Foreign

Table 2 Descriptive comparison of pilot zones and non-pilot areas

Variable	Pilot zones	Non-pilot areas	Difference
Before	0.8947	0.9084	−0.0137
After	1.0193	0.9997	0.0197
Difference	0.1246	0.0913	0.0333

direct investment can influence China's green development through channels related to capital and technology. ③ Government intervention (*GI*) and pollution control measures (*Swu*). Given China's "30·60" dual-carbon goals, intensified government oversight and efforts in pollution control are expected to impact the overall green productivity. ④ Scientific expenditure (*SE*). Science and technology play a vital role in the process of green development in a region. ⑤ Educational expenditure (*EE*), employment status (*Em*), and human capital (*LM*). The educational landscape and the state of the labor market can contribute to the availability of skilled professionals for urban green economic development. Simultaneously, to enhance the scientific rigor and robustness of the empirical regression, we also include individual fixed effects and year fixed effects separately, in order to control for unobservable individual differences and time trends that might affect the analysis.[1] All variable definitions are provided in Table 1.

Description of important variables

To enhance the robustness and persuasiveness of the empirical findings, we initiate by offering a descriptive comparison of GTFP (*GP*) variables across different cities. This comparison aims to delineate the disparities between pilot and non-pilot areas both before and after the GFRI pilot policy implementation. The relevant findings are presented in Table 2, revealing the following insights: (1) In general, there exists a discernible disparity in GTFP between pilot and non-pilot areas, albeit with relatively modest variations in data characteristics on average. (2) In terms of specific values, the average GTFP in non-pilot areas surpasses that in pilot areas before the policy was implemented. However, when considering the trend, it becomes evident that following the introduction of the GFRI pilot policy, the rate of GTFP enhancement for pollution-intensive enterprises in pilot areas significantly outpaces that in non-pilot areas. Consequently, based on this descriptive analysis of GTFP data from diverse cities, a preliminary inference can be drawn: The GFRI pilot policy appears to have yielded

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[1] Due to space limitations, the descriptive statistics of each variable are not shown in this paper. Please contact the author if you need detailed information.

Table 3 Benchmark regression results

Variable	*GP*	
	(1)	(2)
Treat×t	0.1012*** (12.2778)	0.0251*** (3.6225)
GDP	0.5031* (1.8181)	0.6613*** (2.7875)
GDP^2	−0.0187 (−1.4437)	−0.0290*** (−2.6529)
FG	0.2380 (0.5109)	0.4936 (1.3840)
GI	0.0339 (0.3400)	−0.1505** (−2.0198)
Swu	−0.0005*** (−3.6968)	0.0000 (0.1503)
SE	3.8317 (1.1649)	4.4536** (2.0243)
EE	−1.8967** (−2.0865)	1.6911*** (2.6525)
Em	−0.0183 (−0.9873)	−0.0067 (−0.5314)
LM	−0.3899** (−2.1890)	−0.1551 (−1.2013)
Firm	Y	Y
Year	N	Y
Constant	−1.9492 (−1.3545)	−2.7513** (−2.1579)
R^2	0.0800	0.4728
N	1945	1945

t statistics in parentheses (corrected for firm-level clustering), ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

favorable outcomes in advancing GTFP across these cities. This preliminary observation suggests that the policy has contributed to the reduction in pollution emissions in various urban centers, the augmentation of enterprise productivity, and ultimately, the elevation of overall GTFP. To further substantiate this observation, the study will employ an empirical model, controlling for potential influencing factors, thereby fortifying the scientific rigor and dependability of the research findings.

Model and result analysis

Model

To test the above assumptions, we first constructed the basic econometric model as follows:

$$\text{GP}_{i,t} = \beta_0 + \beta_1 \text{Treat}_{i,t} + \beta_2 t_{2017} + \beta_3 \text{Treat}_{i,t} * t_{2017} + \gamma_1 X_{i,t} + \alpha_i + \varphi_t + \varepsilon_{i,t} \quad (1)$$

where GP_{it} represents the GTFP of each city, $Treat_{it}$ is the policy location dummy variable, t_{2017} is the policy time dummy variable, X_{it} is a series of control variables, α is the individual fixed effect, φ is the time fixed effect, and ε is a random disturbance term. We focus on the coefficient β_3 of the interaction term $Treat_{it} \times t_{2017}$ to further identify the implementation effect of the GFRI pilot policy.

Fig. 3 Parallel test results

Benchmark regression

Table 3 provides the benchmark regression results. Column (1) reports the model estimation results of GTFP with the inclusion of control variables and only controlling for individual fixed effects. Column (2) further considers the impact of time variation by adding time fixed effects on top of the specifications in column (1). The regression results demonstrate that, regardless of the treatment approach, the estimated coefficient of the policy variable $Treat \times t$ on urban GTFP (GP) is significantly positive. In particular, the estimated coefficient of the policy variable $Treat \times t$ in column (2) is 0.0251 (significant at the 1% level). This finding strongly suggests that the implementation of the GFRI pilot policy exerted a substantial positive impact on GTFP within the pilot areas. This affirms the beneficial influence of the policy on GTFP in the pilot areas, thereby corroborating Hypothesis H1.

In terms of control variables, the regression coefficients of the control variables roughly align with expectations, indicating the relative robustness and reliability of the empirical results. On the one hand, both GDP and GDP^2 show positive and negative correlations with GP, respectively, both passing significance tests at the 1% level. This indicates a nonlinear impact of regional economic development on urban GTFP, mainly exhibiting an inverted U-shaped relationship, consistent with reality. When the economic development level is low, as it increases, various public services and infrastructure gradually improve, collaborative capabilities enhance, and environmental pollution

is largely absent, thereby boosting urban GTFP. However, with further economic development, people may prioritize economic growth at the expense of the environment, leading to a decline in urban GTFP. The estimated coefficient of GI on GP is significantly negative at the 5% level, suggesting that increased government intervention has a detrimental impact on urban GTFP. Excessive government intervention can hinder economic development and result in unclear effects on pollution reduction. The coefficients of SE and EE on GP are both significantly positive, indicating that increased research investment and higher education levels contribute to the enhancement of urban GTFP. On the other hand, the estimated coefficient of FG on GP is not significant. This might be attributed to the fact that while foreign direct investment can drive economic green development through capital and technology channels, profit-oriented requirements may also lead to increased pollution emissions by enterprises. The coefficients of Swu, Em, and LM on GP are also not significant. This could be attributed to the notion that pollution governance, employment conditions, and human capital exert prolonged effects on urban economic green development, with their short-term impact being less apparent.

Dynamic effect analysis

To increase the reliability of the empirical results, we further conducted a parallel trend test on the DID model. Based on the event study approach proposed by Jacobson et al. (1993)

Table 4 Dynamic effect analysis results

Variable	GP
Treat×t2013	−0.0039 (−0.1948)
Treat×t2014	0.0004 (0.0152)
Treat×t2015	0.0209 (1.3572)
Treat×t2017	0.0017 (0.0908)
Treat×t2018	0.0542** (2.1805)
Treat×t2019	0.0364* (1.8982)
Controls	Y
Firm	Y
Year	Y
Constant	−2.6684** (−2.0939)
R^2	0.4746
N	1945

t statistics in parentheses (corrected for firm-level clustering), ***$p<0.01$, **$p<0.05$, *$p<0.1$

to test the dynamic effects of the GFRI pilot policy, the following model was constructed:

$$GP_{i,t} = \beta_0 + \sum_{t=2012}^{2020} \beta_t Treat_{i,t} \times t_{2017} + \gamma_1 X_{i,t} + \alpha_i + \varphi_t + \varepsilon_{i,t}$$

(2)

where 2016 is the base year before the pilot policy, β_t represents the estimated coefficients during the sample period from 2013 to 2019; other variables are consistent with Model (1).

Figure 3 represents the parallel trend plot, and Table 4 presents the results of the dynamic effects analysis. It can be observed that the estimated coefficients β_t for the years 2013–2015 are not statistically significant, indicating that there were no significant differences between the pilot and non-pilot areas before the implementation of the GFRI pilot policy, thus satisfying the parallel trends assumption. Furthermore, the urban GTFP shows a significant increase only in the second year after the implementation of the GFRI pilot policy. This suggests the presence of a certain lagged effect in the impact of the policy on GTFP.

Heterogeneity analysis

The imbalance in regional economic development has led to significant disparities in various aspects, including the scale of financial development, the status of industrial development, and the degree of urbanization across different regions (Liu et al. 2018). To test the difference in the impact of the pilot policy effect in various regions, we divide urban samples into eastern, central, and western categories and then

Table 5 Heterogeneity analysis results

Variable	GP		
	(Eastern)	(Central)	(Western)
Treat×t	0.0358*** (4.2140)	0.0026 (0.1529)	−0.0162 (−1.4354)
Controls	Y	Y	Y
Firm	Y	Y	Y
Year	Y	Y	Y
Constant	−6.9521*** (−3.1155)	−3.6319 (−1.5913)	6.7376** (2.4461)
R^2	0.4317	0.5504	0.5107
N	685	756	504

t statistics in parentheses (corrected for firm-level clustering), ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 6 Regression results of each pilot zone

Variable	GP				
	Guangdong (Eastern)	Zhejiang (Eastern)	Jiangxi (Central)	Guizhou (Western)	Xinjiang (Western)
Treat×t	0.0541*** (4.4897)	0.0585*** (3.6152)	0.0516** (2.2886)	0.0304** (2.1510)	0.0247 (0.7631)
Controls	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
Constant	0.8057 (0.3988)	−2.3276 (−0.4881)	1.5366 (0.4022)	3.9871 (1.2392)	−19.2713* (−1.8984)
R^2	0.6088	0.4331	0.5430	0.5472	0.3927
N	398	307	329	252	126

t statistics in parentheses (corrected for firm-level clustering)

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

Table 7 PSM-DID analysis results

Variable	GP	
	DID	PSM—DID
Treat×t	0.0251*** (3.6225)	0.0245*** (3.3837)
Controls	Y	Y
Firm	Y	Y
Year	N	Y
Constant	−2.7513** (−2.1579)	−2.4281* (−1.6937)
R^2	0.4728	0.4980
N	1945	1662

t statistics in parentheses (corrected for firm-level clustering)

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

perform group regression on them. The relevant results are shown in Table 5. We can find that the pilot policy has a stronger promotion effect on GTFP in the eastern region, but not significant in the central and western regions. This result is consistent with the findings of Wang et al. (2022a, b).

In order to explore the underlying factors, we conducted additional grouped regressions by matching each experimental province with three provinces from same regions, having similar economic development levels. The results are presented in Table 6. On the one hand, the GFRI pilot policy in the provinces of Guangdong (Eastern), Zhejiang (Eastern), Jiangxi (Central), and Guizhou (Western) has all demonstrated a promotional effect on urban GTFP. This suggests that the GFRI pilot policy significantly enhances the GTFP in the pilot regions, and this improvement is more pronounced for provinces with similar geographical locations and economic development levels. On the other hand, as we move from Eastern to Western experimental provinces, the estimated coefficients and significance of $Treat×t$ on GP decrease. This implies that as the regional economic development level decreases, financial development lags behind, creating substantial disadvantages in various aspects such as talent, capital, and infrastructure, thereby hindering the desired effectiveness of green financial policies. Moreover, in Xinjiang, located deep in the Western region, there is less demand for green finance, and project financing faces greater challenges. Hence, the impact of green financial experimental policies is less apparent.

Robustness tests

PSM-DID estimation results

To mitigate potential selection bias in the city samples, we adopt the propensity score matching method to select matched samples and subsequently re-estimate using the difference-in-differences model. During the propensity score

matching process, the study controls for city-level characteristic variables such as per capita gross domestic product (GDP), squared per capita GDP (GDP^2), foreign direct investment (FG), government intervention (GI), pollution control (Swu), research and development expenditure (SE), educational expenditure (EE), employment status (Em), and human capital (LM). A Logit model is constructed to ascertain whether a city is situated in a pilot province of the pilot zone. The nearest neighbor 1:1 matching technique is employed to establish matched pairs, and the model estimation is executed using the matched sample.

Table 7 presents the outcomes of the model estimation employing the matched sample. The results reveal that, subsequent to the propensity score matching process and the utilization of the difference-in-differences model, the estimated coefficients of the difference-in-differences interaction term, $Treat×t$, concerning urban GTFP (GP), remain remarkably positive (0.0251 and 0.0245). The level of statistical significance remains consistent, with negligible numerical variations. This indicates the resilience of the earlier empirical findings, even after addressing potential sample selection bias.

Placebo test

To further account for unobservable variables and minimize the impact of human factors on the model while improving the precision of our empirical findings, we adopt an approach akin to that of Li et al. (2016). In this approach, cities situated within pilot provinces of the pilot zone are randomly selected. Following this, random instances of policy implementation timing are generated, and a randomized experiment is conducted at both the temporal and municipal levels. To bolster the credibility of our randomized experiment outcomes, this procedure is iterated 500 times. Subsequently, the distribution of the estimated coefficient for the difference-in-differences interaction term, $Treat×t$, concerning urban GTFP (GP), is graphically represented in Fig. 4.

Due to the random selection of the experimental group samples and the timing of policy implementation, a randomly simulated placebo experiment should not exhibit significant policy effects. If the estimated coefficient distribution under randomization is centered around 0, it implies that the spurious policy variable has not significantly impacted urban GTFP. This suggests that the observed effects in the baseline analysis are indeed induced by the policy innovation of the GFRI pilot policy. The estimated coefficient distribution plot in Fig. 4 illustrates that the spurious regression coefficients are concentrated around 0, far from the baseline regression coefficients in this study. This, to some extent, indicates that the conclusions drawn in the baseline regression are not influenced by unobserved random factors, ensuring the robustness of the earlier findings.

Fig. 4 Placebo test results
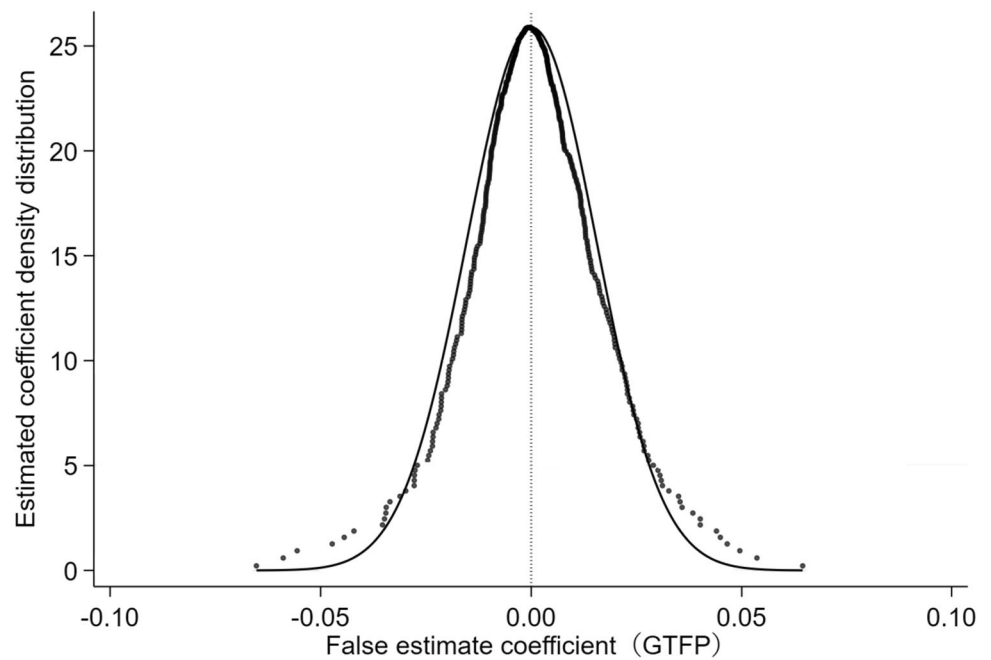
Table 8 Estimated results excluding policy interference

Variable	GP			
	(1)	(2)	(3)	(4)
Treat×t	0.0250*** (3.6510)	0.0155* (1.6855)	0.0279*** (4.1631)	0.0242*** (3.2340)
Envipro	−0.0128* (−1.8018)			
Controls	Y	Y	Y	Y
Firm	Y	Y	Y	Y
Year	Y	Y	Y	Y
Constant	−3.2569** (−2.4460)	−2.3470 (−1.6247)	−3.0846** (−2.3158)	−3.2191* (−1.9120)
R^2	0.4732	0.4576	0.4850	0.5076
N	1945	1707	1595	1099

t statistics in parentheses (corrected for firm-level clustering)

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

Eliminate significant policy interferences

In accordance with the "Notice on the Implementation of the Ambient Air Quality Standards (GB3095-2012)," the revised "Ambient Air Quality Standards" were implemented in stages, specifically: in 2012, in key regions such as Beijing-Tianjin-Hebei, the Yangtze River Delta, the Pearl River Delta, as well as in municipalities directly under the central government and provincial capitals; in 2013, in 113 key environmental protection cities and national environmental model cities; in 2015, in all cities at or above the prefecture level; and as of January 1, 2016, nationwide implementation of the new standards. Based on this, we introduce *Envipro* into the model, where a city implements the new standards, it is coded as 1; otherwise, it is coded as 0. The results in Table 8, column (1), indicate that the regression coefficient

of *Treat×t* on *GP* remains significantly positive. This suggests that the influence of the "Ambient Air Quality Standards" on the empirical conclusions of this study is minimal.

In 2013 and 2014, China officially launched carbon emissions trading pilot programs in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen. To eliminate potential interference from carbon emissions trading pilot programs on the empirical results of this study, we conducted regressions after excluding samples from pilot areas. The results in Table 8, column (2), show that the regression coefficient of *Treat×t* remains significantly positive, suggesting that the carbon emissions trading pilot policy did not excessively interfere with the empirical conclusions of this study.

In 2014, the Ministry of Environmental Protection issued the "Interim Measures for the Ministry of Environmental

Table 9 Reassessing the estimated results of GTFP

Variable	GP2
Treat×t	0.0291*** (4.5122)
Controls	Y
Firm	Y
Year	Y
Constant	−2.6690** (−2.2174)
R^2	0.5268
N	1945

t statistics in parentheses (corrected for firm-level clustering)

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

Protection to Talk to Local Governments," which involved interviewing local government leaders for inadequate environmental performance and using command-and-control environmental regulation methods to urge companies to reduce pollution emissions. During the study period, a total of 73 cities were interviewed. To eliminate potential interference from environmental interviews on the conclusions of this study, we conducted regressions after excluding cities that were interviewed. The results in Table 8, column (3), show that the regression coefficient of *Treat×t* on *GP* remains significantly positive, indicating that the environmental interview policy did not excessively interfere with the empirical conclusions of this study.

On January 1, 2018, China officially implemented the "Environmental Protection Tax Law of the People's Republic of China." This environmental tax reform may impact the pollution emissions of heavily polluting enterprises, thereby interfering with the baseline regression results of this study. Specifically, during the implementation of the environmental tax reform, 12 provinces increased their tax standards, while the remaining provinces maintained the original pollutant discharge fee collection standards as the environmental tax standards.[2] To eliminate the interference of the environmental tax reform on the empirical results of this study, the provinces that raised the environmental tax standards were excluded from the analysis, and the regression was conducted again. The results in column (4) of

Table 8 indicate that the regression coefficient of *Treat×t* on *GP* remains significantly positive. This suggests that after excluding the interference of the environmental tax reform, the core conclusion remains robust.

Re-measure GTFP

In the calculation of urban GTFP, we replace the industrial dust emissions in the non-desired output with PM2.5 and then re-apply the SBM directional distance function and Malmquist–Luenberger index method to calculate the GTFP of each city. Subsequently, the model (4–1) is re-estimated, and the results are presented in Table 9. It can be observed that the estimated coefficient of the difference-in-differences interaction term Treat×t for urban GTFP (*GP2*) remains significantly positive (0.0291), with no change in the level of significance, and the specific numerical change is minimal. These findings are consistent with those in Table 3, indicating that the conclusions drawn earlier remain robust.

Further discussion

The mechanisms discussed above elucidate that within the framework of establishing GFRIs, policies will reshape the allocation of resources, stimulate transformation and upgrading among enterprises in these pilot zones, boost investments in green technological innovation, facilitate the transition of more enterprises from labor-intensive to capital and technology-intensive sectors, decrease the presence of polluting enterprises, and promote the growth of green enterprises. Consequently, these measures culminate in the enhancement of urban GTFP. To corroborate these claims, the present study conducts separate assessments of the impact of the GFRI pilot policy on urban GTFP, considering the pathways of green technological innovation, industrial structure upgrading, and improved resource allocation.

Mechanism model

We constructed the mechanism model as follows:

$$GP_{i,t} = \beta_1 + \beta_1 Treat_{i,t} + \beta_2 t_{2017} + \beta_3 Treat_{i,t} \times t_{2017} \times ReM_{i,t}/GInno_{i,t}/ISU_{i,t}$$
$$+\beta_4 ReM_{i,t}/GInno_{i,t}/ISU_{i,t} + \gamma_1 X_{i,t} + \alpha_i + \varphi_t + \varepsilon_{i,t}$$

(3)

In Model (5–1), *GP* represents the proxy variable for urban GTFP; $Treat_{it}$ is the province dummy variable; t_{2017} is the policy dummy variable; *ReM* stands for the proxy variable for city resource misallocation; *ISU* represents the proxy variable for city industrial structure upgrading; *GInno* represents the proxy variable for city green technological innovation; other variable definitions are consistent with Model (4–1).

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[2] The 12 provinces that increased their tax standards during the process of environmental tax reform include Hebei, Henan, Jiangsu, Shandong, Hunan, Sichuan, Chongqing, Guizhou, Hainan, Guangxi, Shanxi, and Beijing.

Table 10 Results of transmission mechanisms

	GP				
	(1)	(2)	(3)	(4)	(5)
	ReM	GInno_In	GInno_Um	Iss	Isr
Treat×t× ReM	−0.0208* (−1.7483)				
Treat×t× GInno_In		0.0313** (2.2977)			
Treat×t× GInno_Um			0.0130 (0.7174)		
Treat×t× Iss				0.0385** (2.4671)	
Treat×t× Isr					−0.0082 (−0.4698)
Treat× t	0.0395*** (3.9732)	0.0052 (0.4284)	0.0163 (1.0552)	0.0000 (0.0027)	0.0287*** (2.9463)
ReM	0.0056 (0.5304)				
GInno_In		0.0211* (1.9348)			
GInno_Um			−0.0054 (−0.5280)		
Iss				−0.0020 (−0.1772)	
Isr					0.0011 (0.1272)
Controls	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
Constant	−2.7118** (−2.1252)	−2.8298** (−2.1811)	−2.8428** (−2.2302)	−3.2348** (−2.4376)	−2.8567** (−2.1437)
R^2	0.4730	0.4744	0.4729	0.4735	0.4728
N	1945	1945	1945	1945	1945

t statistics in parentheses (corrected for firm-level clustering),

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

Regarding the selection of the city resource misallocation (*ReM*) variable, we will draw on the practices of Han et al. (2017) and use the dispersion of productivity to measure resource misallocation. Enterprise productivity is calculated based on comprehensive input and output situations as well as all other factors, making the measurement of resource misallocation more accurate when considering the dispersion of enterprise productivity. We will use the LP method to calculate the productivity of all listed companies and then measure resource misallocation by the standard deviation of productivity for all listed companies within each city.

For the selection of the green technological innovation (*GInno*) variable, we will represent it with the number of applications for green invention patents (*GInno_In*) and green utility model patents (*GInno_Um*) in each city.

In terms of variable selection for Industrial Structure Upgrading (*ISU*),[3] we draw on the research of Sun et al. (2022) by using two measures, namely Industrial Structure Sophistication (*Iss*) and Industrial Structure Rationalization (*Isr*), to quantify industrial structure upgrading. The calculation formula is as follows:

$$Iss_{it} = \sum_{m=1}^{3} y_{imt} \times mm = 123 \tag{4}$$

$$Isr_{it} = \sum_{m=1}^{3} y_{imt} \ln\left(y_{imt}/l_{imt}\right) m = 1, 2, 3 \tag{5}$$

In Eqs. (5–2) and (5–3), *Iss* represents the proxy variable for city industrial structure advancement, while *Isr* represents the proxy variable for city industrial structure rationalization. y_{imt} denotes the proportion of city *i*'s output value from the *m* industry to the regional GDP in year *t*, and l_{imt} similarly represents the proportion of city *i*'s employment in the *m* industry to the total employment in year *t*. The industrial structure advancement index (*Iss*) reflects the evolution process of the three categories of industries. A value of *Iss* closer to 3 indicates a higher level of industrial structure development in the city. The industrial structure rationalization index (*Isr*) reflects whether the city's industrial structure is at a reasonable level. A calculated value of 0 implies that the city's industrial structure is in equilibrium; otherwise, it deviates from the balanced state.[4]

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[3] It is worth noting that the Industrial Structure Upgrading (ISU) is primarily measured based on three major industries (*m*=1 for agriculture, *m*=2 for industry, *m*=3 for service industry).

[4] In calculating the industrial structure rationalization index, for analytical convenience, this study uniformly takes the absolute value of the calculated result.

During the model construction process, the article takes the medians of the yearly sample city mechanism variables (*ReM*, *GInno_In*, *GInno_Um*, *Iss*, and *Isr*) as standards. If a mechanism variable is greater than the median, its value is set to 1; otherwise, it is set to 0. Subsequently, the mechanism variables and their interaction terms with the policy variable are introduced into the model.

Mechanism results analysis

Table 10 presents the empirical findings from the mechanism analysis conducted in this study. In Column (1), we examine the mechanism related to resource allocation improvement. The estimated coefficient of the interaction term $Treat \times t \times ReM$ on city GTFP (*GP*) is significantly negative (−0.0208) at a 10% significance level. These results suggest that the GFRI pilot policy primarily enhances city GTFP by rectifying resource misallocation. This implies that the policy, by redistributing financial resources, redirects more funds toward green enterprises, consequently improving the allocation of credit resources. This, in turn, triggers adjustments in the allocation of other production factors, mitigating resource misallocation, restraining the disorderly expansion of polluting enterprises, fostering the growth potential of green enterprises, and ultimately elevating city GTFP.

Columns (2) and (3) present the outcomes of the investigation into the green technological innovation mechanism. The estimated coefficient of the interaction term $Treat \times t \times GInno\_In$ on city GTFP (*GP*) is significantly positive (0.0313) at a 5% significance level, while the coefficient of the interaction term $Treat \times t \times GInno\_Um$ is not statistically significant. These findings indicate that the establishment of GFRI pilot zones substantially increases environmental pollution costs ($C\gamma$), incentivizing enterprises to embark on green technological innovation endeavors. As more enterprises invest in the research and development of green technological innovation, a cumulative green technological innovation effect ensues, ultimately augmenting regional GTFP. The insignificance of the impact of green utility model patents can be attributed to their lower input of capital, labor, and technological factors required for research and development, as compared to green invention patents. Additionally, their integration into enterprise production activities has proved less effective in curbing pollution emissions.

Columns (4) and (5) unveil the results of the examination of the industrial structure upgrading mechanism. The estimated coefficient of the interaction term $Treat \times t \times Iss$ on city GTFP (*GP*) is significantly positive (0.0385) at a 5% significance level, whereas the coefficient of the interaction term $Treat \times t \times Isr$ does not exhibit statistical significance. These outcomes signify that the GFRI pilot policy predominantly bolsters city GTFP by propelling advancements in

the industrial structure of cities. However, the impact of industrial structure rationalization is not statistically significant. This implies that the policy reduces the number of labor-intensive and polluting enterprises, while concurrently elevating the presence of technology-intensive and green enterprises. This transformative effect enhances the level of industrial structure development and, consequently, augments city GTFP. The absence of significance in the impact of industrial structure rationalization can be attributed to the influence of upgrading the city's industrial structure on the labor market. This shift has led to a diminished demand for low-skilled workers and an increased demand for high-skilled workers. Nevertheless, the training of high-skilled workers entails specific thresholds and a lengthier period, resulting in a diminished alignment between the labor market and the upgraded city industrial structure. This ultimately leads to an insignificant effect of the GFRI pilot policy on GTFP through industrial structure rationalization.

Conclusion and implications

Utilizing the policy framework of GFRIs as a foundation, we establish a quasi-natural experiment to investigate the ramifications of the pilot zone's inception on GTFP. We employ data from 278 prefecture-level cities in China spanning the years 2013 to 2019. The research findings yield the following insights: Firstly, the GFRI pilot policy has led to an enhancement in the GTFP of the pilot areas. This assertion remains robust even after the incorporation of dynamic effect analysis, propensity score matching analysis, placebo tests, and GTFP reassessment. Secondly, regional heterogeneity analysis reveals that the GFRI pilot policy has a stronger promotion effect on GTFP in the eastern region, but not significant in the central and western regions. Further stratified matching based on geographical location and economic development level demonstrates that the policy significantly enhances GTFP in provinces of the central and western regions, albeit with a diminishing effect as the economic development level decreases. Thirdly, the policy's influence in augmenting GTFP within pilot areas is primarily attributed to three mechanisms: amelioration of resource misallocation, stimulation of green technological innovation, and promotion of industrial structure upgrading. In terms of rectifying resource misallocation, the policy reshapes the allocation of financial resources, directing a greater portion toward green enterprises, and thereby optimizing the allocation of credit resources, ultimately bolstering city GTFP. Concerning green technological innovation, the policy stimulates a surge in green invention patents, consequently elevating GTFP. The impact of green utility model patents is comparatively less pronounced. Regarding industrial structure upgrading, the policy chiefly fosters advanced industrial

structures in cities, leading to enhanced GTFP. However, the influence of industrial structure rationalization is less conspicuous.

Drawing practical implications from the study results: Firstly, with the precondition of achieving good results in the construction of the GFRIs, its demonstrative role should be fully utilized. The expansion of the pilot zone should be steadily promoted to comprehensively enhance the effectiveness of the GFRI pilot policy. Drawing on beneficial experiences from pilot areas, the number of pilot projects can be increased appropriately. Simultaneously, based on the characteristics of different regions, a progressive green finance policy can be gradually implemented, exploring more valuable pilot experiences for the comprehensive implementation of GFRI pilot policy. In the subsequent expansion of pilot areas, a more targeted and guiding GFRI pilot policy should be formulated, incorporating clear restraint mechanisms, incentive mechanisms, and technological transformation plans tailored to heavily polluting industries. This will improve the policy's specificity and guidance to better achieve green, low-carbon economic development.

Secondly, in the process of advancing the GFRI pilot policy, the heterogeneity of policy effects should be fully considered. Through precise measures, the efficiency of green finance in promoting green economic development can be enhanced. Differences in geographical location and economic development level will affect the effectiveness of the GFRI pilot policy. Therefore, a one-size-fits-all reform model will significantly impact the process of promoting green finance for economic low-carbon transformation. Consideration should be given to differences in geographical location, economic development status, financial development scale, industrial development, and urbanization levels. Different complementary policies should be implemented in different regions. Simultaneously, gradual and focused special green finance policies should be implemented in underdeveloped areas, prioritizing development and, as a secondary goal, environmental protection. This approach avoids repeating the mistakes of sacrificing the environment for economic gains while promoting economic development.

Thirdly, resource misallocation is a significant factor leading to low GTFP in regions. Therefore, it is essential to further promote the innovative development of green financial products and services in the GFRIs. Continuously expanding green finance channels, while increasing the financing threshold for polluting enterprises, should include providing appropriate support policies for enterprises with green practices. This approach not only improves the allocation of credit resources but also enhances the role of green finance, guiding and reinforcing environmental awareness among enterprises, and promoting green technological innovation. Additionally, the government should strengthen supervision of both polluting and green environmental

protection enterprises. This includes preventing the excessive withdrawal of credit resources from environmentally responsible enterprises and avoiding the diversion of credit resources into high-return projects that do not comply with credit standards, undermining the original intent of policy implementation.

However, it is imperative to acknowledge the limitations of this study. On the one hand, while the GFRI pilot policy has enhanced GTFP within the experimental zones, the impact on environmental amelioration remains unaddressed. On the other hand, owing to temporal and data constraints, the sample period encompasses the years 2013 to 2019. The study primarily concentrates on the short-term implementation effects of the pilot policies, leaving questions pertaining to long-term effects and their implications for the sustained development of the national economy unexplored. These inquiries beckon as promising avenues for future research.

Appendix

Model assumptions

Based on the model provided by Xepapadeas and de Zeeuw (1999), Wan et al. (2021), and Zhang et al. (2022a, b), this paper will conduct theoretical model derivation and analysis on the impacts brought about by the GFRI pilot policy. Before the model derivation, the following assumptions are proposed:

(1) The market environment in the model derivation is a perfectly competitive market. There is no information asymmetry between enterprises, banks, and the government, especially banks and the government can obtain information about enterprises' environmental behaviors, such as pollution and green technology innovation.

(2) The number of firms in the market is infinite. For ease of understanding, we assume that there are two types of enterprises in the market, and in the analysis, we only consider two firms (Firm *i* and Firm *j*).

(3) Loan contracts can be further extended after the expiration, and we assume the discount factor is 0 in the analysis.[5] In the context of economic green and low-carbon transformation, many green projects of enterprises often have long-term characteristics with a longer return cycle. In comparison with traditional

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[5] It should be noted that setting the discount factor as 0 only simplifies the model analysis without changing the conclusions of this paper.

loans, green loans provided by commercial banks also have long-term investment characteristics. Therefore, we assume that under the background of the pilot zone construction, all loans granted by banks to enterprises are long-term loans with a discount factor of 0, and enterprises will not repay the principal in our model.

Model inferences and propositions

Based on the above assumptions, this paper will examine the impact of the GFRI pilot policy on the behavior of Firm i to simulate the behavioral changes of enterprises in the pilot zone, and ultimately analyze the changes in the GTFP in the pilot zone.

(1) Basic situation of enterprises.

Before the GFRI pilot policy, Firm i and Firm j were in the same external environment, and their fundamental situations were similar. Taking Firm j as an example, we assume that Firm j owns production equipment manufactured at different times, and the pollution emissions of these production equipment are related to the technical factors of their manufacturers and the years of usage. The α is used to measure the years of usage of production equipment, where $\alpha \in [0, h]$, and h represents the maximum age the production equipment can reach before being scrapped. As the years of usage of production equipment increase, its operating costs and pollution emissions will gradually increase, while the output of production will gradually decrease, which is consistent with the reality. That is, if $v(\alpha)$, $c(\alpha)$, and $s(\alpha)$, respectively, represent the output, operating costs, and pollution emissions of the production equipment, then $v'(\alpha) \leq 0$, $c'(\alpha) \geq 0$, and $s'(\alpha) \geq 0$. On this basis, the total output, total operating costs, and total pollution emissions of Firm j in the t year can be represented as follows:

$$Q(t) = \int_0^h v(\alpha)x(t, \alpha)d\alpha \qquad (6)$$

$$C(t) = \int_0^h c(\alpha)x(t, \alpha)dy \qquad (7)$$

$$S(t) = \int_0^h s(\alpha)x(t, \alpha)d\alpha \qquad (8)$$

In Eqs. (6), (7), and (8), $x(t, \alpha)$ represents the quantity of production equipment with an age of α that Firm j is using

in year t. $Q(t)$, $C(t)$, and $S(t)$, respectively, denote the total output, total operating costs, and total pollution emissions of Firm j in year t. Therefore, it can be observed that the annual output, operating costs, and pollution emissions of a production equipment will vary with the increase in the equipment's years of usage.

Furthermore, based on the fundamental assumption (1) that the market is perfectly competitive, the market price of production equipment with an age of α will not change due to the demand and supply of individual enterprises. The market price b will differ based on the age of production equipment: as the age α increases, the performance and production efficiency of production equipment decrease, pollution emissions increase, and the market price becomes lower. Conversely, the market price becomes higher, i.e., $b'(\alpha) \leq 0$, and $b(h) = 0$. Assuming that manufacturing enterprise j buys or sells a total quantity of production equipment $u(t, \alpha)$ in the market in year t, where $u(t, \alpha) > 0$ indicates the quantity purchased by Firm j in year t, otherwise, it represents the quantity sold. Therefore, the total cost for manufacturing enterprise j to buy and sell production equipment in the market in year t is given by:

$$T(t) = b(\alpha)u(t\alpha) + \frac{1}{2}u^2(t\alpha) \qquad (9)$$

In equation (9), $b(\alpha)u(t, \alpha)$ represents the direct purchasing cost of production equipment, and $u^2(t, \alpha)/2$ denotes the adjustment cost for buying and selling production equipment, including transaction, installation, and debugging expenses, among others.

Assuming that the market price for the products produced by Firm j is p, the firm can choose to buy or sell production equipment at different times to maximize its profits.[6] At this point, the paper can further derive the profit maximization objective function for Firm j:

$$\max_{u(t\alpha)} \pi = \int_0^\infty \int_0^h \left\{ [pv(\alpha) - c(\alpha)]x(t\alpha) - \left[b(\alpha)u(t\alpha) + \frac{1}{2}u^2(t\alpha) \right] \right\} d\alpha dt \qquad (10)$$

$$s.t. \frac{\partial x(t\alpha)}{\partial t} = -\frac{\partial x(t\alpha)}{\partial \alpha} + u(t\alpha) \qquad (11)$$

$$x(00) = 0x(t\alpha) \geq 0 \forall t\alpha \qquad (12)$$

Equations (10), (11), and (12) depict an infinite-horizon optimal control problem with transfer dynamics described by a system of local linear differential equations (Carlson

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[6] The basic assumption (3) assumes a discount factor of 0. Therefore, the purchase or sale of production equipment with an age of α at any time will not affect its market price, as the market price of production equipment is only related to its age.

et al. 1991). Equation (10) represents the objective function for profit maximization. Equations (11) and (12) are both constraints: Equation (11) shows that the rate of change in the quantity of production equipment with an age of α in Firm j is determined by two factors: first, the decrease in the stock of production equipment due to aging and scrapping $-\frac{\partial x(t,\alpha)}{\partial \alpha}$; second, the variation in the quantity of production equipment caused by buying or selling production equipment with an age of α in the market $u(t, \alpha)$. Equation (12) indicates that the quantity of production equipment with an age of α owned by Firm j at any time is non-negative, and the firm does not possess the latest production equipment at the beginning of its operation.

(2) Impact of the GFRI pilot policy.

The basic situations of Firm i and Firm j are the same as described above. Now, consider the situation after the implementation of the GFRI pilot policy. Firm j is located outside the pilot zone, and its behavior remains unchanged. On the other hand, Firm i is within the pilot zone and will be affected by the policy. Specifically, for Firm i in the pilot zone, the government and banks will impose penalties for its pollution behavior, including fines, higher loan interest rates, and stricter loan conditions. For analytical convenience, this paper assumes that the correlation coefficient between Firm i's environmental pollution costs and the degree of environmental pollution is denoted as γ. The magnitude of γ represents the severity of penalties imposed by the pilot zone for environmental pollution. In other words, the larger γ is, the higher the costs that Firm i incurs for causing environmental pollution. For Firm j outside the pilot zone, $\gamma = 0$. If we denote $C\gamma(t)$ as the environmental pollution cost for Firm i in the pilot zone, its formula can be written as:

$$C_\gamma(t) = \gamma S(t) = \int_0^h \gamma s(\alpha)x(t\alpha)d\alpha \tag{13}$$

In this case, compared to Firm j, the total cost for Firm i will further increase, i.e., the environmental pollution cost that Firm i bears for causing pollution will increase.[7] As a result, the profit maximization objective function for Firm i will also undergo changes:

$$\begin{aligned}max\pi \\ u(t\alpha)\end{aligned} = \int_0^\infty \int_0^h \left\langle \{pv(\alpha) - c(\alpha) - \gamma s(\alpha)\}x(t\alpha) - \left[b(\alpha)u(t\alpha) + \frac{1}{2}u^2(t\alpha)\right]\right\rangle d\alpha dt \tag{14}$$

$$s.t. \frac{\partial x(t\alpha)}{\partial t} = -\frac{\partial x(t\alpha)}{\partial \alpha} + u(t\alpha) or \frac{\partial x(t\alpha)}{\partial t} + \frac{\partial x(t\alpha)}{\partial \alpha} = u(t\alpha) \tag{15}$$

$$x(00) = 0 x(t\alpha) \geq 0 \tag{16}$$

In order to reduce environmental pollution costs and achieve profit maximization, Firm i initiates two approaches: on the one hand, the company starts researching and developing green technologies and further applies them to production equipment to reduce pollution emissions at the source; on the other hand, the company increases environmental protection investments for end-of-pipe treatment of pollution. We assume that the environmental management effect achieved by Firm i through these two approaches can be represented as:

$$G(t) = \int_0^h g_1 x(t\alpha)d\alpha + \int_0^h g_2 x(t\alpha)d\alpha = \int_0^h j(\gamma)x(t\alpha)d\alpha \tag{17}$$

In Equation (16), $G(t)$ represents the environmental management effect of Firm i in year t; $g_1 x(t, \alpha)$ represents the reduction in pollution emissions achieved by Firm i by introducing green technology into production equipment at age α; $g_2 x(t, \alpha)$ represents the reduction in environmental pollution achieved by Firm i through end-of-pipe treatment. This paper combines the two to express it as a function of the correlation coefficient γ between environmental pollution costs and the degree of environmental pollution, denoted as $j'(\gamma) \geq 0$, with $j(0) = 0$. For analytical convenience, this paper assumes that the funding cost for environmental management by Firm i through these two approaches is also denoted as $G(t)$. In other words, the level of funding invested by the firm in environmental management is positively correlated with the environmental management situation. The more funds Firm i invests in environmental management, the better the achieved environmental management effect. If the firm does not invest in any environmental management, then $G(t) = 0$. Under this condition, the level of environmental pollution caused by Firm i in year t can be expressed as:

$$EP(t) = S(t) - G(t) = \int_0^h \left[s(\alpha) - j(\gamma)\right]x(t\alpha)d\alpha \tag{18}$$

[7] It should be noted that both firms in the pilot zone and those outside the pilot zone will bear environmental pollution costs when they engage in environmental pollution behavior. The difference is that firms in the pilot zone bear higher costs. For the sake of clarity, we further assume that the environmental pollution cost for firms outside the pilot zone is 0.

Furthermore, as Firm i engages in environmental management, its environmental pollution costs will also change, and this can be expressed as:

$$C_\gamma(t) = \int_0^h j(\gamma) + \gamma[s(\alpha) - j(\gamma)]x(t\alpha)d\alpha \qquad (19)$$

$$\frac{dC_\gamma}{d\gamma} = \int_0^h \left[s(\alpha) - j(\gamma) + (1 - \gamma)\frac{dj(\gamma)}{d\gamma} \right] x(t\alpha)d\alpha > 0 \qquad (20)$$

Under these circumstances, the profit maximization objective function of Firm i changes to:

$$\max_{u(t\alpha)} \pi = \int_0^\infty \int_0^h \left\langle \left\{ pv(\alpha) - c(\alpha) - j(\gamma) - \gamma[s(\alpha) - j(\gamma)] \right\} x(t\alpha) - \left[b(\alpha)u(t\alpha) + \frac{1}{2}u^2(t\alpha) \right] \right\rangle d\alpha dt \qquad (21)$$

$$s.t. \frac{\partial x(t\alpha)}{\partial t} = -\frac{\partial x(t\alpha)}{\partial \alpha} + u(t\alpha) \ or \ \frac{\partial x(t\alpha)}{\partial t} + \frac{\partial x(t\alpha)}{\partial \alpha} = u(t\alpha) \qquad (22)$$

$$x(00) = 0 x(t\alpha) \geq 0 \qquad (23)$$

Further utilizing the Hamiltonian equation, the profit maximization objective function of Firm i can be rewritten as:

$$H = \left\{ pv(\alpha) - c(\alpha) - j(\gamma) - \gamma[s(\alpha) - j(\gamma)]x(t\alpha) \right\} - \left[b(\alpha)u(t\alpha) + \frac{1}{2}u^2(t\alpha) \right]$$
$$+ \lambda(t\alpha) \left[-\frac{\partial x(t\alpha)}{\partial \alpha} + u(t\alpha) \right] \qquad (24)$$

In the Hamiltonian equation shown in equation (23), the state variable is the quantity of production equipment with age α, denoted by $x(t, \alpha)$, and the control variable is the quantity of production equipment bought or sold with age α, denoted by $u(t, y)$. Therefore, in addition to equation (21), the first-order conditions for optimality can be expressed as:

$$\frac{\partial H}{\partial u} = 0 \ or - b(\alpha) - u(t\alpha) + \lambda(t\alpha) = 0 \qquad (25)$$

$$\frac{\partial \lambda(t\alpha)}{\partial t} = -\frac{\partial H}{\partial x} + \frac{\partial}{\partial \alpha}\frac{\partial H}{\partial x_\alpha} x_\alpha = \frac{\partial x}{\partial \alpha} \qquad (26)$$

The expression (25) can be further represented as:

$$\frac{\partial \lambda(t\alpha)}{\partial t} = -pv(\alpha) + c(\alpha) + j(\lambda) + \gamma[s(\alpha) - j(\gamma)] - \frac{\partial \lambda(t\alpha)}{\partial \alpha} \qquad (27)$$

To facilitate the analysis of the Hamiltonian equation (23), this study further considers the state of the firm at an economic steady state. At the steady state: the quantity of α-age production equipment owned by the firm, $x(t, \alpha)$, does not change over time, and the revenue from a single α-age production equipment, $\lambda(t, \alpha)$, also remains constant, denoted as $\partial x / \partial t = 0$ and $\partial \lambda / \partial t = 0$, respectively. Under these conditions, if we let $\dot{\lambda}(\alpha)$ represent $\partial \lambda / \partial \alpha$, and $\dot{x}(\alpha)$ represent $\partial \lambda / \partial \alpha$, the optimal conditions for the Hamiltonian equation at the steady state can be further expressed as:

$$u(\alpha) = \lambda(\alpha) - b(\alpha) \qquad (28)$$

$$\dot{\lambda}(\alpha) = -pv(\alpha) + c(\alpha) + j(\gamma) + \gamma[s(\alpha) - j(\gamma)] \qquad (29)$$

$$\dot{x}(\alpha) = u(\alpha) \qquad (30)$$

Therefore, at the steady state, the profit maximization objective function for enterprise i represented by Equation (20) can be simplified as follows:

$$\max_{u(\alpha)} \pi = \int_0^h \left\langle \left\{ pv(\alpha)x(\alpha) - [c(\alpha) + j(\gamma) + \gamma s(\alpha) - \gamma j(\gamma)]x(\alpha) \right\} - \left[b(\alpha)u(\alpha) + \frac{1}{2}u^2(\alpha) \right] \right\rangle d\alpha \qquad (31)$$

$$s.t.\dot{x}(\alpha) = u(\alpha)x(0) = 0x(\alpha) \geq 0 \forall y. \tag{32}$$

In theoretical model, exogenous shocks refer to the impacts brought about by the GFRI pilot policy, which leads to a change in enterprise i's profit maximization objective function from Equation (10) to Equation (30). The profit maximization objective function for enterprise i represents the changes in enterprise behavior under the GFRI pilot policy. This paper will further analyze the effects of these changes in enterprise behavior on the optimal age distribution of production equipment, productivity, and pollutant emissions for enterprise i. These changes will, in turn, determine the variations in the pilot zone's GTFP.

(3) Optimal quantity and optimal age distribution of enterprise production equipment

The profit maximization objective functions for enterprise i and enterprise j can be represented by Eqs. (30) and (10). Before calculating the optimal age distribution of production equipment for enterprise i, it is necessary to compute the revenue $\lambda(\alpha)$ brought by one α-age production equipment. The total revenue A generated by one α-age production equipment before it is scrapped can be divided into two parts: the revenue A_1 that cannot be obtained before installation and the revenue $\lambda(\alpha)$ that can be obtained after installation. The revenues A and A_1 can be expressed as follows:

$$A = \int_0^h \left\{ pv(\rho) - c(\rho) - j(\gamma) - \gamma \left[s(\rho) - j(\gamma) \right] \right\} d\rho \tag{33}$$

$$A_1 = \int_0^\alpha \left\{ pv(\rho) - c(\rho) - j(\gamma) - \gamma \left[s(\rho) - j(\gamma) \right] \right\} d\rho \tag{34}$$

According to Eqs. (32) and (33), it is possible to further derive the profit $\lambda(\alpha)$ for enterprise i installing a production equipment with age α and maintaining it until it reaches the maximum age h. This constitutes a boundary problem under the framework of local optimal control, with $\lambda(h) = 0$. Moreover, we can deduce the following:

$$\lambda(\alpha) = \int_\alpha^h \left\{ pv(\rho) - c(\rho) - j(\gamma) - \gamma \left[s(\rho) - j(\gamma) \right] \right\} d\rho \tag{35}$$

Compared to enterprise i, enterprise j does not incur costs related to environmental pollution, and its production equipment profit $\lambda_j(\alpha)$ can be expressed as:

$$\lambda_j(\alpha) = \int_\alpha^h \left[pv(\rho) - c(\rho) \right] d\rho \tag{36}$$

By using Eqs. (27), (34), and (35), we can further obtain the optimal purchase or sale quantities for enterprise i and enterprise j in year t, which are given by:

$$u*(\alpha) = \lambda(\alpha) - b(\alpha) = \int_\alpha^h \{ pv(\rho) - c(\rho) - j(\gamma)$$
$$- \gamma \left[s(\rho) - j(\gamma) \right] \} d\rho - b(\alpha) \tag{37}$$

$$u_j*(\alpha) = \lambda_j(\alpha) - b(\alpha) = \int_\alpha^h \left[pv(\rho) - c(\rho) \right] d\rho - b(\alpha) \tag{38}$$

$$u(\alpha), u_j(\alpha) \begin{smallmatrix} > \\ = \\ < \end{smallmatrix} 0, \text{ if and only if } \lambda(\alpha), \lambda_j(\alpha) \begin{smallmatrix} > \\ = \\ < \end{smallmatrix} b(\alpha) \tag{39}$$

In Eqs. (36) and (37), $u*(\alpha)$ and $u_j*(\alpha)$ represent the optimal purchase or sale quantities for enterprise i and enterprise j. $\lambda(\alpha)$ and $\lambda_j(\alpha)$ denote the total profit generated by a production equipment of age α, while $b(\alpha)$ stands for the purchase price of a production equipment of age α. Furthermore, it is possible to derive the optimal quantity of production equipment of age α that enterprise i and enterprise j should possess in year t. This optimal quantity is determined by two factors: on the one hand, the purchase and sale quantities of production equipment for the enterprises in year t; on the other hand, the inventory situation of production equipment acquired and sold in previous years. From this, we can further deduce the optimal quantity of production equipment for both enterprise i and enterprise j:

$$x*(\alpha\gamma) = \int_0^\alpha \left\langle \int_z^h \left\{ pv(\rho) - c(\rho) - j(\gamma) - \gamma \left[s(\rho) - j(\gamma) \right] \right\} d\rho - b(z) \right\rangle dz \tag{40}$$

$$x*(\alpha 0) = \int_0^\alpha \left\langle \int_z^h \left[pv(\rho) - c(\rho) \right] d\rho - b(z) \right\rangle dz \tag{41}$$

From Eqs. (38) and (39), it can be observed that, in comparison with enterprise j, enterprise i incurs an additional environmental pollution cost. Therefore, the optimal quantity of production equipment can be further expressed as a function of the extent of penalties γ imposed on environmental pollution for the pilot region. By taking the partial derivative of both sides of equation (38) with respect to γ, we can further derive the marginal change of the optimal quantity of production equipment of age α for enterprise i with respect to the environmental tax γ:

$$\frac{\partial x * (\alpha\gamma)}{\partial \gamma} = -\int_0^\alpha \int_z^h \left[s(\rho) - j(\gamma) \right] + [1 - \gamma]\frac{dj(\gamma)}{d\gamma} d\rho dz < 0$$

(42)

From equation (40), it can be seen that γ (the impact of the GFRI pilot policy) reduces the quantity of production equipment in each age distribution within the inventory of enterprise i. This also demonstrates the reduction effect of the GFRI pilot policy on the daily production activities of polluting enterprises.

To further verify whether the average age of production equipment in enterprise i's inventory has also decreased, this paper assumes that enterprise i optimizes the age distribution of its production equipment based on the above conclusions. Therefore, the quantity of production equipment for each age is given by equation (37). The proportion of production equipment of age α among all ages of production equipment is defined as:

$$r(\alpha\gamma) = \frac{x(\alpha\gamma)}{\int_0^h x(\alpha\gamma)d\alpha}$$

(43)

From equation (41), it can be observed that this function is a density function, and $r(\alpha,\gamma) \in [0, 1]$, with $\int_0^h r(\alpha,\gamma) = 1$. Furthermore, we can deduce that the average age of production equipment for enterprise i is:

$$g(\gamma) = \int_0^h \alpha r(\alpha\gamma)d\alpha = \frac{\int_0^h \alpha x(\alpha\gamma)d\alpha}{\int_0^h x(\alpha\gamma)d\alpha}$$

(44)

It can be observed that under the GFRI pilot policy, the quantity of production equipment owned by enterprise i decreases. However, the average age of the production equipment may not necessarily decrease, because as the extent of penalties imposed on environmental pollution γ increases in the pilot zone, the reduction in the quantity of production equipment for each age group by enterprise i becomes uncertain. Therefore, the increase in γ will reduce the average age of production equipment for enterprise

i only if the change in the average age of the portion of equipment reduced due to the increase in γ is smaller than the optimal average age of equipment before the increase in γ.

$$\frac{\int_0^h \alpha x(\alpha\gamma)d\alpha}{\int_0^h x(\alpha\gamma)d\alpha} < \frac{\int_0^h \alpha\left[\partial x(\alpha\gamma)/\partial\gamma\right]d\alpha}{\int_0^h \left[\partial x(\alpha\gamma)/\partial\gamma\right]d\alpha}$$

(45)

This conclusion aligns well with reality and is easily comprehensible: as the extent of penalties imposed on environmental pollution γ increases in the pilot zone, enterprises will phase out older production equipment with lower productivity, higher operating costs, and greater emissions. In comparison with the average reduction in corresponding equipment quantities across different age groups, this approach, On the one hand, significantly reduces the total cost for enterprises and, on the other hand, decreases the overall reduction in output. As a result, the introduction of the GFRI pilot policy leads to a decrease in the average age of production equipment for enterprise i.

(4) The impact of GFRI pilot policy on enterprise pollution emissions and environmental management.

Equations (38) and (39) provide the optimal quantities of production equipment of various ages owned by enterprise i and enterprise j in year t. In this case, the pollution level caused by both enterprises to the environment can be expressed as:

$$EP(\gamma) = \int_0^h \left[s(\alpha) - j(\gamma) \right] x * (\alpha\gamma)d\alpha$$

(46)

$$EP_j(0) = \int_0^h s(\alpha)x * (\alpha 0)d\alpha$$

(47)

Furthermore, by taking the derivative of enterprise i's environmental pollution penalty γ, we can derive its marginal rate of change:

$$\frac{dEP(\gamma)}{d\gamma} = \int_0^\alpha \int_z^h -\left[s(\rho) - j(\gamma)\right]\left\{ \left[s(\rho) - j(\gamma)\right] + (1 - \gamma)\frac{dj(\gamma)}{d\gamma} \right\} - \frac{dj(\gamma)}{d\gamma}x * (\rho\gamma)d\rho dz$$

(48)

In equation (46), the right-hand side comprises two terms, and the signs of both terms are negative, indicating that the marginal rate of change of enterprise i's environmental pollution level with respect to γ is negative. It can be deduced that, compared to enterprise j, the pollution caused by enterprise i to the environment has decreased. This suggests that the GFRI pilot policy has led to a reduction in pollution

On the other hand, the marginal rate of change of enterprise environmental management with respect to the extent of penalties imposed on environmental pollution γ can be expressed as:

$$G(\gamma) = \int_0^h j(\gamma)x * (\alpha\gamma)d\alpha \qquad (52)$$

$$\frac{dG(\gamma)}{d\gamma} = \int_0^\alpha \int_z^h \frac{dj(\gamma)}{d\gamma} x * (\rho\gamma) - j(\gamma)\left\{ \left[s(\rho) - j(\gamma) \right] + (1-\gamma)\frac{dj(\gamma)}{d\gamma} \right\} d\rho dz \qquad (53)$$

emissions by enterprises, further enhancing pollution control efforts. In other words, the policy has brought about a positive impact on the environment.

Furthermore, within the model for enterprise i, the environmental pollution level can be divided into the total emissions and the environmental management part for the enterprise:

$$EP(\gamma) = S(\gamma) - G(\gamma) \qquad (49)$$

Among these, the marginal rate of change of enterprise pollution emissions with respect to the extent of penalties imposed on environmental pollution γ can be expressed as:

$$S(\gamma) = \int_0^h s(\alpha)x * (\alpha\gamma)d\alpha \qquad (50)$$

$$\frac{dS(\gamma)}{d\gamma} = -\int_0^\alpha \int_z^h s(\rho)\left\{ \left[s(\rho) - j(\gamma) \right] + [1-\gamma]\frac{dj(\gamma)}{d\gamma} \right\} d\rho dz < 0 \qquad (51)$$

From equation (49), it can be observed that under the GFRI pilot policy, the increase in the extent of penalties imposed on environmental pollution γ leads to a reduction in the total emissions of enterprises. Moreover, the higher the extent of penalties on environmental pollution, the lower the total emission volume of enterprises. By further combining the conclusion from equation (43), it can be noted that an increase in the extent of penalties on environmental pollution γ leads to a reduction in the optimal quantity of production equipment owned by enterprise i, a decrease in the average age of all production equipment, and a decrease in the total emissions of the enterprise. This phenomenon is consistent with reality.

The sign of equation (51) is difficult to determine, as it stems from the fact that the increase in the extent of penalties imposed on environmental pollution γ can be divided into two stages: the initiation of penalties on environmental pollution and further escalation of penalties. Therefore, the changes in enterprise environmental management with respect to the increase in γ require comprehensive analysis: when the GFRI pilot policy is introduced, enterprises begin to implement environmental management. Hence, $j(\gamma)$ increases, and $j'(\gamma) \geq 0$, indicating that enterprise i undertakes environmental management, involving financial investment, while enterprise j does not invest funds. Thus, the introduction of the GFRI pilot policy leads to an increase in enterprise environmental management. Furthermore, assuming a further increase in the extent of penalties imposed on environmental pollution γ, $j(\gamma)$ increases, and $j'(\gamma) \geq 0$. Combined with the conclusions from equations (43) and (49), the increase in γ leads to a reduction in the optimal quantity of production equipment, a decrease in the average age, and a decrease in total emissions, i.e., $x(t, \alpha)$ decreases. Therefore, changes in enterprise environmental management depend on the relative magnitude between the portion that increases due to the escalation of penalties on environmental pollution γ and the portion that decreases due to the reduction in production equipment quantity. If the former is greater than the latter, environmental management increases; otherwise, it decreases. Even if environmental management decreases, the reduction is smaller than the reduction in pollution emissions, meaning that the arrival of the GFRI pilot policy leads to a decrease in the pollution caused by enterprise i to the environment, indicating a positive impact on the environment in the region where the policy is implemented.

(5) The Impact of GFRI pilot policy on Enterprise Productivity.

An increase in the extent of penalties imposed on environmental pollution γ will lead enterprise i to phase out older production equipment with low productivity and high emissions, thus reducing the average age of production equipment. Utilizing this conclusion, the paper will further analyze the impact of the decrease in average age on enterprise productivity. The average productivity of production equipment can be defined as:

$$f(\gamma) = \frac{\int\limits_0^h v(\alpha)x(\alpha\gamma)d\alpha}{\int\limits_0^h x(\alpha\gamma)d\alpha} \tag{54}$$

Furthermore, based on the assumptions made earlier regarding the productivity of production equipment, there exists a negative correlation between production equipment productivity and age, denoted as $v'(\alpha) \le 0$. For the sake of analytical convenience, we will define its functional form as a general linearly decreasing production function: $v(\alpha) = a - \beta\alpha$. Thus, the marginal rate of change of the average productivity of production equipment with respect to the extent of penalties imposed on environmental pollution γ can be expressed as:

$$\frac{df}{d\gamma} = -\beta\frac{d}{d\gamma}\frac{\int\limits_0^h \alpha x(\alpha, \gamma)d\alpha}{\int\limits_0^h x(\alpha, \gamma)d\alpha} = -\beta\frac{dg(\gamma)}{d\gamma} > 0 \tag{55}$$

In equation (53), its derivative can be divided into two parts: the first part is $-\beta$, where $-\beta < 0$; the second part is $dg(\gamma)/d\gamma$, in conjunction with the conclusion from equation (43), indicating a decrease in the average age of all production equipment with an increase in the extent of penalties imposed on environmental pollution γ, thus $dg(\gamma)/d\gamma < 0$. Therefore, it can be observed that the average productivity of production equipment increases with an increase in the extent of penalties imposed on environmental pollution γ. This phenomenon is also quite intuitive: an increase in the extent of penalties on environmental pollution γ leads to a reduction in the optimal quantity of production equipment owned by enterprise i, where the equipment being phased out consists mostly of older production equipment with low productivity, high operating costs, and high emissions. This reduction in the average age of all production equipment, combined with $v'(\alpha) \le 0$, results in an increase in enterprise productivity. Thus, the GFRI pilot policy enhances enterprise i's productivity.

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Declarations

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