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Green Finance Policy and Firm Productivity in the Green Transition: Evidence from China's Pilot Zones

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Abstract

Green finance has become an important policy instrument for promoting sustainable development, but its effects on firm productivity may vary across firms with different environmental attributes. This study develops a theoretical framework in which green finance incorporates environmental performance into credit allocation and capital pricing, thereby reshaping firms' financing conditions, innovation incentives, and resource allocation efficiency. The framework suggests that green finance may create productivity-enhancing incentives for green firms while imposing transition-related pressures on heavily polluting firms. Using data on Chinese A-share listed firms from 2009 to 2024, this study exploits China's Green Finance Reform and Innovation Pilot Zones policy as a quasi-natural experiment and combines a triple-difference (DDD) model with a Double Machine Learning (DDML) framework to identify the policy's productivity effects. The results show that the policy significantly increases the total factor productivity of green firms but reduces that of heavily polluting firms. Mechanism analysis indicates that the policy reduces both green technological innovation and capital allocation efficiency among heavily polluting firms. For green firms, the policy promotes green technological innovation but reduces capital allocation efficiency. Heterogeneity analysis shows that these effects vary with government subsidies, organizational slack, and industry asset intensity. Further analysis suggests that digital transformation may mitigate the policy's adverse productivity effect on heavily polluting firms, while the policy improves governance among green firms by reducing earnings management and controlling-shareholder expropriation. These findings suggest that green finance policy should balance environmental constraints with support for firms' green transition, adopt differentiated policy designs, and strengthen governance mechanisms to promote sustainable productivity growth and an inclusive green transition.

Keywords: green finance policy; firm productivity; sustainable development; green technological innovation; capital allocation efficiency; green transition

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1. Introduction

Total factor productivity (TFP) reflects a firm's overall capability in technological progress, management innovation, resource allocation efficiency, and long-term competitiveness, and constitutes an important micro-level foundation for sustained economic growth [1–3]. For a long period of time, many economies promoted industrialization and output growth by expanding inputs of capital, labor, and energy. However, this growth model also generated problems such as environmental pollution and the accumulation of climate risks [4]. As resource and environmental constraints continue to intensify, economic

growth increasingly needs to shift from factor input expansion toward improvements in resource allocation efficiency, technological progress, and the transformation of production modes. As the main agents of resource use, technological innovation, and production organization adjustment, firms' ability to improve TFP is directly related to whether they can maintain production efficiency while undertaking green transformation [5,6].

Finance performs a resource reallocation function and can substantially shape firms' production decisions. Some studies argue that financial expansion reduces financing costs and encourages firms to expand production scale, thereby increasing energy consumption and environmental pollution [7–9]. In recent years, an increasing number of scholars have emphasized the role of finance in promoting the green allocation of resources [10,11]. Among various financial instruments, green finance combines the dual attributes of resource allocation and environmental protection. By identifying environmental risks and resource values, it can guide capital toward green sectors [12]. This makes green finance an important instrument for promoting firms' green transformation and improving firm TFP.

Against this background, many countries have implemented green finance practices. In 2018, the European Commission released the Action Plan: Financing Sustainable Growth, aiming to reduce greenhouse gas emissions, develop the circular economy, and strengthen waste prevention and recycling. In 2019, the United Kingdom issued the Green Finance Strategy, which established three core priorities, namely "greening finance", "financing green", and "capturing the opportunity", and proposed promoting green investment and financing through a combination of government guidance and market leadership. While these policies support the development of green firms, they may also intensify financing constraints for heavily polluting firms and increase their pressure to transform. How, then, does green finance affect different types of firms? Do its effects vary across firm and industry characteristics? Through what mechanisms does it operate? What mitigation measures and economic consequences may arise? Existing research has paid limited attention to these questions. Addressing them is important not only for objectively evaluating the performance of green finance policies but also for improving and extending green finance institutions in the future.

China offers a useful setting for addressing these gaps in the literature. As the world's largest developing country, China has implemented the Green Finance Reform and Innovation Pilot Zones policy. In 2017, the People's Bank of China and several other government departments established green finance reform and innovation pilot zones in five provinces and ten cities, including Huzhou and Quzhou in Zhejiang Province; Guiyang and Anshun in Guizhou Province; Ganzhou and Jiujiang in Jiangxi Province; Guangzhou in Guangdong Province; and Hami, Changji Prefecture, and Karamay in the Xinjiang Uygur Autonomous Region. This policy is hereafter referred to as the "green finance pilot policy." In 2019 and 2022, Lanzhou City in Gansu Province and Chongqing Municipality, respectively, were included in the second and third batches of pilot regions. The policy promotes innovation and diversification in green financial products by improving the design of green financial instruments, including green credit, green bonds, green insurance, and green funds. It also supports the gradual improvement of the green finance development system through measures such as establishing green project databases and information service platforms, as shown in Table A1 of Appendix A.

Against this backdrop, this study exploits China's green finance pilot policy as a quasi-natural experiment to examine the effects of green finance on heavily polluting firms and green firms. It further investigates the heterogeneity, underlying mechanisms, mitigating factors, and economic consequences of these effects. The study makes four main contributions.

First, this study extends the literature on the relationship between the green finance pilot policy and firm productivity by examining heterogeneity in firms' environmental attributes. Existing studies have extensively examined the effects of the green finance pilot policy on firms' total factor productivity (TFP), but their findings remain mixed. Some studies find that the policy improves firm TFP, whereas others suggest that it may have an adverse effect on productivity [13–15]. These divergent findings highlight the need to examine how firms with different environmental attributes respond to green finance policy. However, existing research has primarily focused on changes in the productivity of listed firms as a whole, while some studies have further investigated the effects on heavily polluting firms [16]. Few studies have compared productivity changes among green firms, heavily polluting firms, and other firms within a unified analytical framework. To address this gap, this study incorporates firms with different environmental attributes into a common framework and systematically examines the heterogeneous effects of the green finance pilot policy on their TFP. The results show that the policy increases the TFP of green firms but reduces that of heavily polluting firms, highlighting firms' environmental attributes as an important dimension for understanding the productivity effects of green finance policy.

Second, this study extends the understanding of the mechanisms through which green finance affects firm-level TFP. Whereas prior research has mainly emphasized channels related to financing, firm governance, and environmental investment [17–19], this study focuses on capital allocation efficiency and green technological innovation to explain why the policy exerts different effects on the TFP of green firms and heavily polluting firms.

Third, this study extends the methodological approach to evaluating the green finance pilot policy by incorporating Double Machine Learning (DDML) into a triple-difference (DDD) identification framework. Existing studies have primarily employed difference-in-differences models to evaluate the effects of the green finance pilot policy [14,16,17]. However, firm TFP is jointly influenced by multiple factors at the firm, industry, and regional levels, and its relationships with these factors may be complex and nonlinear. Under such circumstances, conventional parametric models, which rely on prespecified functional forms, may not fully capture these relationships. To address this limitation, this study incorporates DDML into the DDD framework, using Lasso to estimate high-dimensional nuisance functions and applying Neyman orthogonalization and cross-fitting to mitigate the nuisance function estimation error, regularization bias, and overfitting. After accounting for high-dimensional covariates and potential nonlinear associations, this framework further enables us to examine the robustness of the heterogeneous effects of the green finance pilot policy.

Fourth, this study explores the boundary conditions and economic consequences of the relationship between green finance and firm TFP. Existing research has largely focused on the financing constraints imposed by green finance on heavily polluting firms [16,17] and the financing incentives provided to green firms [20,21]. This study shows that digital transformation can mitigate the adverse effects of green finance on the TFP of heavily polluting firms. It also finds that, under the green finance pilot policy, green firms exhibit significantly lower levels of earnings management and controlling shareholder expropriation.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 develops the theoretical framework and proposes the research hypotheses. Section 4 introduces the empirical methodology. Section 5 reports the main empirical results. Section 6 presents further analyses. The final section concludes and provides policy recommendations.

2. Literature Review

As the green transition continues to deepen, a growing body of research has examined the relationship between green finance and firm total factor productivity. Section 2.1 reviews this literature. Section 2.2 then discusses the methodological advantages and applicability of machine learning methods in policy analysis.

2.1. Green Finance and Firm Production Efficiency

Existing studies have not reached a consensus on whether green finance improves firms' total factor productivity. The literature can be broadly divided into three strands: the promotion view, the inhibition view, and the mixed-effect view.

The first strand argues that green finance can improve firms' total factor productivity [13,22], although the mechanisms differ across firm types. For heavily polluting firms, green finance operates mainly through financing constraints, which may compel firms to engage in R&D innovation, improve resource-use efficiency, and enhance environmental performance [23–25]. For green firms, green finance functions more as a financing incentive. Green bonds and sustainability-linked loans can reduce financing costs, attract long-term investors, and strengthen firms' R&D investment and green innovation capacity [20,21,26,27].

The second strand suggests that green finance may reduce financing scale, increase financing costs, and weaken innovation effectiveness, thereby inhibiting firms' total factor productivity [28]. As financial resources are increasingly allocated to firms with stronger environmental performance, heavily polluting firms face stricter financing conditions [29,30]. If financing pressure fails to translate into incentives for transformation, green finance is more likely to operate as a cost shock than as innovation compensation [16]. At the same time, after receiving greater financial support, green firms may emphasize the quantity rather than the quality of innovation, and may even engage in low-quality strategic innovation that does not translate into technological progress capable of improving productivity [26,31].

Beyond these two perspectives, existing research also shows that the effect of green finance on firms' total factor productivity is stage-specific and conditional [14,32]. Differences in existing findings may arise from variations in policy instruments, firm characteristics, and institutional environments [13,27]. For example, green credit places greater emphasis on financing constraints and induced adjustment, whereas green bonds are more closely related to optimizing long-term financing structures, improving market reputation, and alleviating capital constraints [20,33,34]. In addition, firms' green attributes, size, industry environment, regional development level, and policy enforcement conditions may all shape the effects of green finance [10,13,35].

2.2. Application of Machine Learning Models in Policy Analysis

In modern econometric research, scholars often face settings with many covariates, nonlinear relationships among variables, or complex interaction effects. Traditional linear regression models are prone to model misspecification or unstable estimation in such settings, which may affect the identification of causal effects [36]. By contrast, machine learning methods can efficiently handle a large number of covariates and capture nonlinear effects and complex interactions among variables [37]. Therefore, using machine learning methods to estimate the conditional expectations of the treatment and outcome variables given covariates can improve the precision of target causal parameter estimates and reduce bias caused by model misspecification [38]. Chernozhukov et al. further proposed Double Machine Learning, which combines Neyman orthogonalization with cross-fitting to effectively mitigate regularization bias and overfitting bias arising from the use of machine learning to estimate nuisance parameters [39].

In recent years, Double Machine Learning has increasingly been combined with classical identification strategies such as instrumental variables and difference-in-differences, and has been widely applied in policy analysis [40]. Dube et al. [41], in their study of online labor supply elasticity on MTurk, used machine learning to model heterogeneity in task characteristics and estimated the target treatment effect through cross-fitted residual regressions. Wang et al. [42] employed a Double Machine Learning model to examine the effects of rural households' digital capabilities, reducing potential bias from traditional linear regressions when controlling for multidimensional household characteristics. Zhou et al. [43] combined the Double Machine Learning model with the Difference-in-Differences model to address potential endogeneity, nonlinearity, and complex interactions in energy efficiency analysis. Ding et al. [44] applied a causal forest method to overcome the limitations of conventional policy evaluation in handling complex urban characteristics, high-dimensional control variables, and policy heterogeneity. These studies suggest that Double Machine Learning provides a more robust causal identification tool for policy evaluation in settings characterized by high dimensionality, nonlinearity, and complex interactions, and has therefore attracted increasing scholarly attention.

2.3. Literature Review Summary

Existing studies have developed a substantial discussion of the relationship between green finance and firms' total factor productivity, but several issues remain open for further investigation. First, most studies focus on all firms or on a single type of firm, with limited attention to comparing the effects of green finance on the total factor productivity of different types of firms within a unified framework. Second, although prior research has examined mechanisms such as financing constraints, technological innovation, and environmental investment, it still lacks a systematic explanation of why green finance generates differentiated productivity effects across firms. Third, while theoretical research on the use of machine learning models for causal inference has expanded rapidly, empirical studies that combine these frontier methods with conventional econometric approaches remain relatively limited. Fourth, existing research has paid limited attention to the mitigating measures that may alleviate the adverse effects of green finance on heavily polluting firms, as well as to the economic consequences of green finance for green firms. Against this background, this study takes China's green finance pilot policy as the research setting and embeds Double Machine Learning into a triple-difference framework to systematically examine the effects, heterogeneity, mechanisms, mitigation measures, and economic consequences of the green finance pilot policy on the total factor productivity of different types of firms. In doing so, it provides micro-level empirical evidence for improving the green finance policy system and optimizing policy design.

3. Theoretical Analysis and Research Hypotheses

This section develops a parsimonious equilibrium analysis framework. Within this framework, green finance changes the relative financing conditions faced by firms with different environmental attributes and, through this transmission channel, affects firm total factor productivity. The framework integrates three theoretical mechanisms that underpin the core empirical questions of this study. First, because the allocation of external finance is characterized by information frictions and regulatory screening, policy intervention can alter both the interest rates and the scale of credit available to different firms [45,46]. Second, total factor productivity depends not only on technological capability in a narrow sense, but also on whether capital is allocated to firms and projects with higher marginal returns. Financing distortions may therefore translate into distortions in total factor productivity [47,48]. Third, green transformation is an endogenous innovation process, and the profitability of

clean technologies depends on the strength of policy incentives and firms' ability to obtain long-term funding [49–51]. This study considers a closed economy consisting of representative households, a competitive final goods sector, competitive banks, and a continuum of monopolistically competitive firms indexed by $j \in [0,1]$. Firms are classified into two types according to their environmental attributes, $h \in \{g,b\}$, where g denotes green firms and b denotes heavily polluting firms. Representative households supply labor, hold deposits, and receive profit income. Their budget constraint is given by

$$C_t + D_{t+1} = w_t L_t + (1 + r_t^d) D_t + \Pi_t \tag{1}$$

where C_t denotes household consumption, D_t denotes household deposits, w_t is the wage rate, r_t^d is the deposit interest rate, and Π_t denotes aggregate profit income. Final goods are produced competitively using differentiated intermediate goods, with the production function specified as

$$Y_t = \left[\int_0^1 y_t(j)^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1 \tag{2}$$

This production function implies that the product of each firm satisfies a standard downward-sloping demand curve.

The green finance pilot policy is represented by the following policy vector:

$$\mathcal{D}_t = (s_t, \tau_t, \Gamma_t) x \tag{3}$$

where $s_t \geq 0$ denotes the intensity of policy support associated with green credit; $\tau_t \geq 0$ denotes the regulatory penalty and regulatory burden faced by commercial banks when financing heavily polluting firms; and $\Gamma_t \geq 0$ denotes the transformation cost and compliance burden borne by heavily polluting firms. Commercial banks absorb deposits from households and independently allocate credit across different types of firms. Let B_t^g and B_t^b denote the total amount of loans issued by banks to green firms and heavily polluting firms, respectively. The representative bank's optimal decision problem is

$$\max_{B_t^g, B_t^b} (r_t^g - r_t^d + s_t) B_t^g + (r_t^b - r_t^d - \tau_t) B_t^b - \Phi_g(B_t^g) - \Phi_b(B_t^b) \tag{4}$$

subject to

$$D_t = B_t^g + B_t^b \tag{5}$$

where $\Phi_h(\cdot)$ is a convex intermediation cost function. The first-order conditions are

$$r_t^g = r_t^d - s_t + \Phi'_g(B_t^g), \quad r_t^b = r_t^d + \tau_t + \Phi'_b(B_t^b) \tag{6}$$

Equation (6) shows that the green finance pilot policy reduces the equilibrium financing cost of compliant green firms while increasing the equilibrium financing cost of heavily polluting firms. If information frictions further induce credit rationing, the borrowing constraint for type h firms can be written as

$$B_{ht}(j) \leq \overline{B}_h(\mathcal{D}_t), \quad \frac{\partial \overline{B}_g}{\partial s_t} > 0, \quad \frac{\partial \overline{B}_b}{\partial \tau_t} < 0 \tag{7}$$

Hence, the policy affects both the interest rate faced by firms and the quantity of external finance they can obtain.

A firm of type h produces according to

$$y_{ht}(j) = A_{ht}(j) k_{ht}(j)^{\alpha} l_{ht}(j)^{1-\alpha}, \qquad 0 < \alpha < 1 \tag{8}$$

where $A_{ht}(j)$ denotes firm-specific productivity, $k_{ht}(j)$ denotes capital input, and $l_{ht}(j)$ denotes labor input. Pollution intensity is assumed to satisfy $e_b > e_g \geq 0$. Firms use internal funds $a_{ht}(j)$ and bank loans $B_{ht}(j)$ to finance capital input and green technological innovation input $c_{ht}(j)$. The current-period resource constraint of firms is

$$k_{ht}(j) + c_{ht}(j) + \mathbf{1}\{h = b\}\Gamma_t e_h y_{ht}(j) \leq a_{ht}(j) + B_{ht}(j) \tag{9}$$

Compared with green firms, heavily polluting firms need to allocate additional available funds because compliance costs and transformation expenditures consume part of their financial resources.

The productivity evolution equation is specified as

$$A_{h,t+1}(j) = A_{ht}(j)\exp\left[-\kappa_h(\mu_{ht}(j) - \overline{\mu}_t)^2 + \eta_h(c_{ht}(j)\overline{c}_{ht})^{\xi}\right],\ 0 < \xi < 1 \tag{10}$$

where $\overline{c}_{ht}$ denotes the average green technological innovation input of type h firms, and

$$\mu_{ht}(j) \equiv \frac{\alpha p_{ht}(j) y_{ht}(j)}{(1 + r_t^d)k_{ht}(j)} \tag{11}$$

is the marginal product of capital returns relative to the general financing benchmark. The first term in Equation (10) captures capital allocation efficiency. The further a firm's capital return deviates from the common benchmark, the greater the resource allocation distortion and the lower its next-period productivity. The second term captures productivity returns from green technological innovation, including R&D investment, technological improvement, and knowledge integration.

The dynamic optimization problem of firms is

$$V_h(A_{ht}(j)) = \max\left\{p_{ht}(j)y_{ht}(j) - w_t l_{ht}(j) - (1 + r_t^h)B_{ht}(j) - \frac{\psi_h}{2}c_{ht}(j)^2 + \beta V_h(A_{h,t+1}(j))\right\} \tag{12}$$

subject to Equations (7)–(10). General equilibrium requires labor market clearing:

$$L_t = \int_0^1 l_t(j)dj \tag{13}$$

in the credit market,

$$D_t = \int_0^1 B_t(j)dj \tag{14}$$

and in the aggregate resource constraint,

$$Y_t = C_t + I_t + \mathcal{C}_t + \mathcal{A}_t \tag{15}$$

where C_t denotes household consumption, I_t denotes productive investment, $\mathcal{C}_t$ denotes total green technological innovation input, and $\mathcal{A}_t$ denotes transformation and compliance expenditures.

The first implication of the model follows directly from the bank's optimal equilibrium conditions. An increase in s_t shifts credit supply toward green firms, whereas an increase in τ_t reduces credit supply to heavily polluting firms. Because these changes affect both borrowing costs and credit quotas, the green finance pilot policy endogenously creates asymmetric financing conditions between firms with different environmental attributes.

Proposition 1. *In equilibrium, the green finance pilot policy reduces the actual financing distortion of green firms while increasing the actual financing distortion of heavily polluting firms.*

Combining Proposition 1 with the firms' resource constraint and productivity evolution equation directly yields the productivity effect of the policy. A reduction in financing

distortions expands the feasible boundary of production investment and innovation investment for green firms. In contrast, heavily polluting firms face not only higher financing distortions but also compliance burdens, which further compress their feasible investment space. Therefore, the model does not support a uniform average treatment effect of the policy across all firms. Instead, firm-level total factor productivity exhibits directional divergence: the productivity of green firms increases, whereas that of heavily polluting firms decreases. This leads to the first empirical hypothesis of this study.

Hypothesis 1. *The green finance pilot policy increases the total factor productivity of green firms but reduces the total factor productivity of heavily polluting firms.*

To clarify the internal logic underlying the heterogeneous effects on total factor productivity, we next analyze the technological innovation dimension. According to Equation (12), the first-order condition for firms' green technological innovation input $c_{ht}(j)$ can be derived as

$$\psi_h c_{ht}(j) = \beta \frac{\partial V_h(A_{h,t+1}(j))}{\partial A_{h,t+1}(j)} A_{h,t+1}(j) \eta_h \xi (c_{ht}(j)\bar{c}_{ht})^{\xi-1}\bar{c}_{ht} - \lambda_{ht}(j) \tag{16}$$

Equation (16) shows that firms' green technological innovation input increases with the discounted marginal value of future productivity and decreases with the shadow price of internal funds. When the policy alleviates financing frictions for green firms, the scarcity value of funds declines, allowing firms to allocate more resources to green technology R&D, green technology improvement, and knowledge integration. Because next-period productivity $A_{h,t+1}(j)$ increases with relative innovation input $(c_{ht}(j)\bar{c}_{ht})^{\xi}$, green technological innovation further amplifies the improvement in total factor productivity among green firms.

For heavily polluting firms, however, financing distortions and transformation burdens work in the opposite direction. The green finance pilot policy increases the opportunity cost of allocating scarce funds to green technological innovation. At the same time, firms are forced to bear compliance costs, which reduces the expected private returns to long-term green transformation projects. As a result, heavily polluting firms reduce their equilibrium green technological innovation input, weakening the innovation-driven component of productivity growth.

Proposition 2. *In equilibrium, the green finance pilot policy encourages green firms to undertake green technological innovation while crowding out green technological innovation activities among heavily polluting firms.*

Proposition 2 provides mechanism-level implications. For green firms, the positive productivity effect of the green finance pilot policy can be partly explained by an increase in green technological innovation. Conversely, for heavily polluting firms, the negative productivity effect of the green finance policy partly stems from the suppression of green technological innovation activities. These implications are formulated as Hypotheses 2 and 3.

Hypothesis 2. *The green finance pilot policy inhibits green technological innovation among heavily polluting firms, thereby reducing their total factor productivity.*

Hypothesis 3. *The green finance pilot policy promotes green technological innovation among green firms, thereby improving their total factor productivity.*

The model also reveals a second mechanism: allocation efficiency. Let $\lambda_{ht}(j)$ denote the Lagrange multiplier associated with the resource constraint in Equation (9). The first-order condition for capital input is

$$\alpha p_{ht}(j) A_{ht}(j) k_{ht}(j)^{\alpha-1} l_{ht}(j)^{1-\alpha} = \lambda_{ht}(j) \tag{17}$$

with

$$\lambda_{ht}(j) = 1 + r_t^h + \chi_{ht}(j) \tag{18}$$

where $\chi_{ht}(j) \geq 0$ denotes the shadow cost when a firm faces a binding borrowing constraint. Equations (17) and (18) show that the effective cost of capital use increases as loan interest rates rise and financing constraints tighten. Therefore, any policy-induced change in the loan interest rate r_t^h or the shadow cost $\chi_{ht}(j)$ alters firms' investment decisions and, in turn, affects the extent of capital allocation distortions $(\mu_{ht}(j) - \overline{\mu}_t)^2$.

For green firms, Proposition 1 indicates that the green finance pilot policy reduces financing costs and improves access to funds. The alleviation of financing constraints helps reduce investment deviations caused by insufficient funding. However, improved access to funds may also induce investment expansion, thereby increasing the likelihood of overinvestment. Consequently, the effect of green finance on capital allocation efficiency among green firms depends on the relative strength of these two effects. For heavily polluting firms, the green finance pilot policy increases financing costs, tightens credit conditions, and intensifies pressures arising from compliance and transition expenditures. These changes may cause firms' investment to deviate from its normal level, thereby reducing capital allocation efficiency.

Proposition 3. *If a certain number of firms face binding financing constraints, the green finance pilot policy will exacerbate capital allocation distortions among heavily polluting firms, while its effect on capital allocation distortions among green firms remains uncertain.*

Proposition 3 further yields implications for the capital allocation channel. For heavily polluting firms, tighter financing conditions and greater transition expenditure pressures may cause actual investment to deviate from its normal level, thereby reducing capital allocation efficiency and adversely affecting firm productivity. Accordingly, this study proposes Hypothesis 4.

For green firms, the green finance pilot policy reduces financing costs and improves access to funds, creating conditions conducive to more efficient capital allocation. On the one hand, alleviated financing constraints help firms obtain the funds needed for production and operations and technological upgrading, thereby potentially improving capital allocation efficiency. On the other hand, improved financing conditions do not necessarily lead to greater capital allocation efficiency. If investment expansion is not matched by adequate project screening, risk assessment, and managerial capabilities, additional capital may fail to flow effectively toward higher-productivity uses, potentially reducing capital allocation efficiency instead. Thus, the net effect of the green finance pilot policy on capital allocation efficiency among green firms depends on the relative strength of these two effects, and its direction remains uncertain. Capital allocation efficiency is one channel through which firm total factor productivity (TFP) is affected. Changes in this efficiency may promote or impede productivity growth, but do not necessarily determine the overall effect of the policy on firm TFP. Accordingly, this study proposes Hypotheses 5a and 5b.

Hypothesis 4. *The green finance pilot policy reduces capital allocation efficiency among heavily polluting firms, thereby lowering their total factor productivity.*

Hypothesis 5a. *The green finance pilot policy improves capital allocation efficiency among green firms, thereby increasing their total factor productivity.*

Hypothesis 5b. *The green finance pilot policy reduces capital allocation efficiency among green firms, thereby lowering their total factor productivity.*

In summary, the model indicates that the productivity effects of green finance arise from the combined effects of differentiated credit pricing, endogenous capital reallocation, and heterogeneous firm responses in innovation. By changing financing conditions, innovation investment, and capital allocation behavior across different types of firms, the policy generates heterogeneous productivity effects. Together, these mechanisms shape the productivity effects of green finance policy and provide a theoretical foundation for the subsequent empirical analysis.

4. Research Design

4.1. Data Sources

This study uses data on Chinese A-share listed firms in Shanghai and Shenzhen from 2009 to 2024 as the research sample. Based on China's green finance pilot policy, it examines the impact of green finance on the total factor productivity of heavily polluting firms and green firms.

For the identification of heavily polluting firms, this study follows the Guidelines for the Industry Classification of Listed Companies, the Classified Management Catalogue of Industries for Environmental Verification of Listed Companies, and the Guidelines for Environmental Information Disclosure of Listed Companies. Industries including thermal power, steel, cement, electrolytic aluminum, coal, metallurgy, building materials, mining, chemicals, petrochemicals, pharmaceuticals, light industry, textiles, and leather are classified as heavily polluting industries. Firms belonging to these industries are defined as heavily polluting firms.

For the identification of green firms, this study follows the Green Industry Guidance Catalogue (2019 Edition) and the Green and Low-Carbon Transformation Industry Guidance Catalogue (2024 Edition), and identifies green firms using the main business descriptions disclosed in listed firms' annual reports. The detailed procedures are reported in Appendix B. Because green firms and heavily polluting firms are identified using different criteria, a small number of firms in the original classification may satisfy the criteria for both categories. To ensure that the firm categories are mutually exclusive, green firms are excluded from the analysis of heavily polluting firms, while heavily polluting firms are excluded from the analysis of green firms. Other firms are defined as those that belong to neither the green-firm category nor the heavily polluting-firm category.

In addition, the data are processed as follows: (1) firms with abnormal listing status during the sample period are excluded; (2) firms with asset–liability ratios greater than 1 or less than 0 are excluded; (3) firms with zero total assets or zero operating revenue are excluded; and (4) real estate firms and banking firms are excluded. Missing values are handled using a two-step procedure. First, linear interpolation is performed using available observations from preceding and subsequent years for the same firm or city. Second, values that remain missing after interpolation are imputed using the annual industry mean for firm-level variables and the annual provincial mean for city-level variables.

The final sample comprises 4936 listed firms and 43,180 firm-year observations, including 1382 heavily polluting firms with 13,263 firm-year observations, 192 green firms with 1596 firm-year observations, and 3362 other firms with 28,321 firm-year observations. As this study separately examines the effects of the green finance pilot policy on the total factor

productivity (TFP) of heavily polluting firms and green firms, two separate estimation samples are constructed. In the sample used to examine the policy's effect on TFP among heavily polluting firms, heavily polluting firms constitute the treatment group and other firms constitute the control group, while green firms are excluded. This sample contains 41,584 firm-year observations. In the sample used to examine the policy's effect on TFP among green firms, green firms constitute the treatment group and other firms constitute the control group, while heavily polluting firms are excluded. This sample contains 29,917 firm-year observations.

Firm-level and industry-level data are primarily obtained from the China Stock Market and Accounting Research (CSMAR) database, while city-level data are primarily obtained from the China City Statistical Yearbook. To further illustrate the sample composition, Table 1 reports the numbers of green firms, heavily polluting firms, and other firms in pilot and non-pilot regions.

Table 1. Number of firms by firm type and pilot-zone location.

Firm Type	Pilot-Zone Firms	Non-Pilot-Zone Firms	Total
Green firms	8	184	192
Heavily polluting firms	89	1293	1382
Other firms	168	3194	3362
Total	265	4671	4936

Notes: The table reports the number of unique firms. Firms are classified as pilot-zone firms if they are exposed to the green finance pilot policy during the sample period; otherwise, they are classified as non-pilot-zone firms. Each firm is counted only once.

4.2. Variable Measures

Dependent variable: TFP_{it} denotes the total factor productivity (TFP) of firm i in year t. This study employs the LP method proposed by Levinsohn and Petrin [52] to estimate firm TFP. Following the basic logic of the proxy-variable approach, this method uses intermediate inputs as a proxy for unobservable productivity, thereby mitigating the endogeneity problem arising from the simultaneous determination of firms' input choices and unobservable productivity. Accordingly, the LP method is adopted to measure firm TFP. Specifically, the following Cobb–Douglas production function is specified:

$$Y_{it} = \beta_L L_{it} + \beta_K K_{it} + \beta_M M_{it} + \omega_{it} + \varepsilon_{it} \tag{19}$$

where Y_{it}, K_{it}, L_{it}, and M_{it} denote firm output, capital, labor, and intermediate inputs, respectively. ω_{it} represents the productivity component that firms can observe when making input decisions but that researchers cannot directly observe, while ε_{it} denotes the random disturbance term. Operating revenue is used to measure output, the number of employees to measure labor input, net fixed assets at year-end to measure capital input, and cash paid for goods purchased and services received to measure intermediate inputs. Each variable is transformed using the natural logarithm of its value plus one.

The LP method exploits the monotonic relationship between intermediate inputs and firm productivity to express unobservable productivity as a function of capital and intermediate inputs, thereby addressing the endogeneity problem arising from the simultaneous determination of firm productivity and input choices. This study approximates the unknown function using a fourth-order polynomial and estimates the production function parameters based on firm-level panel data. The standard errors of the parameter estimates are calculated using 50 bootstrap replications. After estimating the coefficients on labor, capital, and intermediate inputs, firm TFP is calculated as follows:

$$TFP_{it} = Y_{it} - \hat{\beta}_L L_{it} - \hat{\beta}_K K_{it} - \hat{\beta}_M M_{it} \tag{20}$$

where TFP_{it} represents firm total factor productivity after deducting the estimated contributions of labor, capital, and intermediate inputs.

Core explanatory variables: $Treat_i$ is a treatment-group indicator that equals 1 if firm i is located in a pilot region and 0 otherwise. $Time_{it}$ is a post-treatment indicator determined by the actual policy implementation year of each pilot region. It equals 1 in the implementation year and thereafter, and 0 otherwise. $Type_i$ is a firm-type indicator that equals 1 if firm i is classified as either a heavily polluting firm or a green firm, and 0 if it is classified as another firm. The triple interaction term $Treat_i \times Time_{it} \times Type_i$ identifies the heterogeneous effects of the green finance pilot policy on TFP across different firm types.

Firms are assigned to cities according to their registered addresses and matched to the pilot regions. For the first batch of pilot regions, established in 2017, firms registered in these regions are considered exposed to the policy from 2017 onward. For the second batch, established in 2019, firms registered in the relevant regions are considered exposed to the policy from 2019 onward. Because firms may change their registered addresses during the sample period, this study further examines whether relocation changes their policy treatment status. Firms that relocate across cities and consequently switch from untreated to treated status, or vice versa, are excluded from the sample. Relocations completed before policy implementation and those that do not change a firm's treatment status are retained.

In addition, Chongqing was designated a Green Finance Reform and Innovation Pilot Zone only in August 2022. As the sample period ends in 2024, only two complete years of post-policy observations are available. To ensure a sufficiently long policy observation period for the pilot regions, firms in Chongqing are excluded from the sample. Previous studies have adopted similar approaches by excluding subsequent pilot regions whose policies were implemented relatively late and whose policy exposure during the sample period was insufficient [53,54].

Mechanism variables: (1) Capital allocation efficiency. This study employs the investment model developed by Richardson [55] to estimate firms' normal investment levels and uses the residual between actual and expected investment, ε_{it}, to measure investment deviations. When $\varepsilon_{it} > 0$, actual investment exceeds expected investment, indicating overinvestment. For the overinvestment subsample, $|\varepsilon_{it}|$ is used to measure the degree of overinvestment ($OverInvest$); a larger value indicates more severe overinvestment. When $\varepsilon_{it} < 0$, actual investment falls below expected investment, indicating underinvestment. For the underinvestment subsample, $|\varepsilon_{it}|$ is used to measure the degree of underinvestment ($UnderInvest$); a larger value indicates more severe underinvestment. This study further constructs $Inveff_{it} = -|\varepsilon_{it}|$ as an indicator of capital allocation efficiency. A higher value of this index indicates greater capital allocation efficiency. (2) Green technological innovation. Following Amore and Bennedsen [56], this study measures firms' green innovation using the number of green invention patent applications ($GreInv_{it}$) and applies the natural logarithmic transformation of the count plus one.

Control variables: Following Yao et al. [17], Zhao et al. [10], and related studies, this study selects control variables at the firm, industry, and regional levels. Firm-level controls include firm age (Age), analyst attention ($Analyst$), operating cash flow level ($Cash$), CEO duality ($Dual$), fixed asset investment ($FixAssIn$), institutional investor shareholding ratio (IO), leverage ratio (Lev), R&D scale (RD), profitability (ROA), financing constraints (SA), ownership type (SOE), firm size ($Size$), and the shareholding ratio of the top ten shareholders ($TopTen$). Industry-level controls include industry competition (HHI), total industry operating revenue ($Income$), and the number of firms in the industry ($Number$). City-level controls include financial development level (Fin), economic development level ($PerGdp$), fiscal expenditure ($Protect$), industrial structure ($SecGdp$), and fiscal expenditure on science and technology ($SciProtect$).

Detailed definitions of the variables are provided in Table A2 of Appendix C.

4.3. Descriptive Statistics

Table 2 reports descriptive statistics for the main variables by firm type. Green firms have the highest mean TFP of 16.80, compared with 16.72 for heavily polluting firms and 16.53 for other firms. Green firms also exhibit the highest level of green innovation, with a mean of 0.77, exceeding the corresponding values for other firms (0.35) and heavily polluting firms (0.21). By contrast, the mean capital allocation efficiency index is approximately −0.02 for all three firm types, indicating relatively small differences across groups in the descriptive statistics. The descriptive statistics for the remaining variables are broadly consistent with those reported in the existing literature and are therefore not discussed further.

Table 2. Summary statistics.

Variable	Heavily Polluting Firms				Green Firms				Other Firms			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
TFP	16.72	1.04	14.50	19.74	16.80	1.02	14.69	20.13	16.53	1.07	14.50	19.74
Inveff	−0.02	0.02	−0.13	0	−0.02	0.02	−0.13	0	−0.02	0.02	−0.13	0
GreInv	0.21	0.56	0	3.33	0.77	0.82	0	2.08	0.35	0.71	0	3.33
Age	2.95	0.32	1.95	3.58	2.89	0.35	1.79	3.61	2.910	0.35	1.95	3.58
Analyst	1.96	0.81	0.69	3.74	1.93	0.81	0.69	3.74	1.94	0.80	0.69	3.74
Cash	0.11	0.15	−0.47	0.62	0.06	0.20	−0.48	0.63	0.09	0.16	−0.47	0.62
Dual	0.29	0.45	0	1	0.36	0.48	0	1	0.34	0.47	0	1
FixAssIn	0.03	0.06	−0.08	0.23	0.02	0.05	−0.07	0.21	0.02	0.04	−0.08	0.23
IO	0.45	0.25	0	0.92	0.40	0.25	0	0.91	0.41	0.25	0	0.92
Lev	0.39	0.20	0.05	0.88	0.49	0.19	0.05	0.88	0.40	0.20	0.05	0.88
RD	17.85	1.51	13.70	21.89	18	1.50	13.83	22.03	17.94	1.44	13.70	21.89
ROA	0.04	0.06	−0.23	0.20	0.02	0.06	−0.24	0.18	0.04	0.06	−0.23	0.20
SA	−3.85	0.26	−4.52	−3.16	−3.82	0.28	−4.55	−3.16	−3.83	0.27	−4.52	−3.16
SOE	0.35	0.48	0	1	0.18	0.39	0	1	0.29	0.45	0	1
Size	22.28	1.32	19.77	26.10	22.27	1.23	19.74	26	21.98	1.24	19.77	26.10
TopTen	0.60	0.16	0.23	0.95	0.60	0.16	0.23	0.96	0.59	0.16	0.23	0.95
HHI	0.10	0.09	0.02	0.88	0.13	0.11	0.03	0.90	0.15	0.16	0.03	0.88
Income	26.90	1.02	22.55	29.01	26.71	1.64	22.33	29.30	26.82	1.54	22.55	29.01
Number	4.22	0.82	1.61	5.41	4.11	0.93	1.39	5.51	4.17	0.98	1.61	5.51
Fin	3.73	0.29	2.77	4.17	3.60	0.34	2.74	4.11	3.63	0.33	2.77	4.17
PerGdp	11.34	0.57	9.98	12.29	11.63	0.47	10.14	12.34	11.61	0.48	9.98	12.29
Protect	15.85	1.11	13.87	18.38	16.55	1.07	14.10	18.38	16.52	1.10	13.87	18.38
SecGdp	0.42	0.11	0.15	0.63	0.38	0.11	0.14	0.60	0.39	0.11	0.15	0.63
SciProtect	12.22	1.79	8.79	15.55	13.41	1.62	9.19	15.55	13.35	1.630	8.79	15.55

4.4. Empirical Model Specification

4.4.1. Triple-Difference (DDD) Model

To examine the effects of the green finance pilot policy on the TFP of different types of firms, this study draws on the triple-difference identification framework of Olden and Møen [57] and the approach adopted by Li et al. [58]. A triple-difference model is constructed along three dimensions: policy implementation region, policy implementation period, and firm type. The model is specified as follows:

$$TFP_{it} = \alpha_0 + \alpha_1 Treat_i \times Time_{it} \times Type_i + \alpha_2 Treat_i \times Time_{it} + \alpha_3 X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (21)$$

where i and t denote firms and years, respectively, and TFP_{it} represents the total factor productivity of firm i in year t. $Treat_i$ is a treatment-group indicator that equals 1 if firm i is located in a pilot region and 0 otherwise. $Time_{it}$ is a post-treatment indicator determined by

the actual policy implementation year of each pilot region. It equals 1 in the implementation year and thereafter, and 0 otherwise. $Type_i$ is a firm-type indicator used to identify the effects of the policy on heavily polluting firms and green firms, respectively. The triple interaction term $Treat_i \times Time_{it} \times Type_i$ is the main variable of interest, and its coefficient, α_1, measures the differential effects of the green finance pilot policy on TFP across firm types. X_{it} denotes the vector of control variables, λ_t and μ_i represent year and firm fixed effects, respectively, and ε_{it} is the random error term.

Because $Treat_i$, $Type_i$, and $Treat_i \times Type_i$ do not vary over time, they are perfectly collinear with firm fixed effects and are therefore absorbed. Under the coding rule for $Time_{it}$, this indicator is always zero for firms in non-pilot regions. Consequently, $Treat_i \times Time_{it}$ coincides with $Time_{it}$, while $Treat_i \times Time_{it} \times Type_i$ coincides with $Time_{it} \times Type_i$. Equation (21) retains $Treat_i \times Time_{it}$ and $Treat_i \times Time_{it} \times Type_i$, without separately including the corresponding duplicate terms. Given that the green finance pilot policy is implemented at the city level, firms within the same city may face common policy shocks and correlated disturbances. Accordingly, standard errors are clustered at the city level.

4.4.2. Double Machine Learning (DDML) Model

Existing studies suggest that appropriately accounting for potential nonlinear relationships and other complex functional forms can improve a model's ability to characterize the research setting when multiple factors interact [59,60]. Compared with conventional parametric estimation methods, DDML uses machine learning to flexibly estimate high-dimensional nuisance functions and applies Neyman orthogonalization and cross-fitting to mitigate the effects of nuisance-function estimation errors, regularization bias, and overfitting on the estimation of the target parameter [39]. To improve the model's ability to capture potential nonlinear relationships, this study further includes squared terms of the control variables. Accordingly, DDML is embedded within the DDD framework to assess the robustness of the estimated heterogeneous effects of the green finance pilot policy on firm TFP.

Specifically, this study follows the DDML framework of Chernozhukov et al. [39] and draws on the implementation approach of Ahrens et al. [61]. Lasso is used to estimate the nuisance functions, and five-fold cross-fitting is implemented. The sample is randomly divided into five subsamples. In each iteration, four subsamples are used to estimate the conditional expectations of the outcome and the core treatment variable given the high-dimensional nuisance covariates, while out-of-sample predictions are generated for the remaining subsample. This procedure is repeated until all five subsamples have served as the prediction sample. The Lasso penalty parameter is selected through internal five-fold cross-validation, using mean squared prediction error as the selection criterion. The cross-fitting procedure employs conventional random five-fold splits. Subsequently, a low-dimensional linear regression is performed using the orthogonalized outcome and core treatment variable to obtain an estimate of the effect parameter, β_0. The model is specified as follows:

$$TFP_{it} = \beta_0 D_{it} + g(W_{it}) + U_{it} \tag{22}$$

$$E(U_{it}|D_{it},W_{it}) = 0 \tag{23}$$

$$D_{it} = m(W_{it}) + V_{it} \tag{24}$$

$$E(V_{it}|W_{it}) = 0 \tag{25}$$

where $D_{it} = Treat_i \times Time_{it} \times Type_i$ is the triple interaction term of interest, and β_0 represents the effect of the green finance pilot policy on TFP across different firm types. W_{it} denotes the high-dimensional nuisance-function covariate set, which includes $Treat_i \times Time_{it}$, $Treat_i \times$

$Type_i$, $Treat_i$, and $Type_i$, as well as firm-level, industry-level, and city-level control variables, squared terms of continuous control variables, and firm and year indicators.

Because Lasso may select or shrink the coefficients on firm and year indicators in the DDML model, $Treat_i$, $Type_i$, and $Treat_i \times Type_i$ are retained in W_{it} alongside the firm and year indicators. This allows the model to exploit firm-level and year-level information, as well as information distinguishing pilot regions and firm types, when estimating the high-dimensional nuisance functions. Moreover, under the variable construction adopted in this study, $Treat_i \times Time_{it}$ coincides with $Time_{it}$, and $Treat_i \times Time_{it} \times Type_i$ coincides with $Time_{it} \times Type_i$. Accordingly, $Time_{it}$ and $Time_{it} \times Type_i$ are not separately included in W_{it}. The functions $g(W_{it})$ and $m(W_{it})$ denote the high-dimensional nuisance functions in the outcome and treatment equations, respectively, while U_{it} and V_{it} denote their corresponding error terms. The detailed orthogonalization procedure and mathematical derivations are provided in Appendix D. Given that the green finance pilot policy is implemented at the city level, firms within the same city may face common policy shocks and correlated disturbances. Accordingly, standard errors are clustered at the city level.

5. Empirical Results

5.1. Benchmark Results

Columns (1) and (2) of Table 3 report the regression results based on the triple-difference (DDD) model. In Column (1), the coefficient on the triple interaction term is −0.103, statistically significant at the 5% level. This result indicates that the green finance pilot policy significantly reduced the total factor productivity (TFP) of heavily polluting firms. In Column (2), the coefficient on the triple interaction term is 0.080, statistically significant at the 1% level. This finding indicates that the policy significantly increased the TFP of green firms.

Table 3. Results of benchmark regression.

Variables	(1) DDD	(2)	(3) DDML	(4)
	TFP	TFP	TFP	TFP
Treat × Time × Type	−0.103 **	0.080 ***	−0.091 *	0.028 *
	(−2.026)	(4.536)	(−1.796)	(1.729)
Treat × Time	−0.030 *	−0.033 *	Included in W	
	(−1.711)	(−1.852)		
Other lower-order terms	Absorbed/Omitted		Included in W	
Linear term of control variables	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	YES	YES
Constant	0.184	−1.220	0.001	0.001
	(0.277)	(−1.467)	(0.741)	(0.618)
Observations	41,584	29,917	41,584	29,917
R^2	0.941	0.940	—	—
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

Notes: t-statistics are reported in parentheses. Standard errors are clustered at the city level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. In the DDML specifications, the corresponding lower-order terms are included in the high-dimensional nuisance covariate set W, and their coefficients are not reported separately. Because DDML estimates the target parameter using the orthogonalized outcome and treatment variables, the conventional regression R^2 is not reported. "—" indicates that the corresponding statistic is not reported. Unless otherwise stated, these conventions apply to all subsequent regression tables, with the DDML-specific explanations applying only to DDML specifications

To further assess the robustness of the DDD results, this study conducts an additional test using the Double Machine Learning (DDML) model, incorporating squared terms of the control variables. Columns (3) and (4) of Table 3 report the DDML results. In Column (3), the coefficient on the triple interaction term is −0.091, statistically significant at the 10% level, indicating that the green finance pilot policy also reduced the TFP of heavily polluting firms. In Column (4), the coefficient is 0.028, statistically significant at the 10% level, indicating that the policy also increased the TFP of green firms. Overall, the DDD and DDML results are consistent: the green finance pilot policy reduces the TFP of heavily polluting firms but increases that of green firms. These findings support Hypothesis 1.

5.2. Robustness Checks

This study may still be subject to limitations related to the parallel trends assumption, sample selection bias, measurement error in variables, interference from other environmental policies, and model specification bias. Accordingly, we systematically assess the robustness of the baseline results using an event-study approach, PSM-DDD/DDML tests, alternative measures of the dependent variable, controls for major environmental policies, and alternative model specifications.

5.2.1. Event-Study Analysis

To examine pre-policy trends and capture the dynamic effects of the green finance pilot policy, this study draws on Jacobson et al. [62] and Sun and Abraham [63] and employs an interaction-weighted event-study estimator. Because the green finance pilot policy was not implemented simultaneously across all regions, conventional two-way fixed-effects event studies may use already-treated regions as comparison groups for later-treated regions under staggered implementation, potentially resulting in inappropriate comparisons. To address this issue, firms are classified into treatment cohorts according to the year in which their respective regions were first exposed to the green finance pilot policy, and the dynamic policy effects are estimated separately for each implementation cohort. The model is specified as follows:

$$TFP_{it} = \sum_{g} \sum_{k \neq k_0} \beta_{gk} \mathbf{1}(G_i = k) \mathbf{1}(t - G_i = k) + \gamma X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{26}$$

where G_i denotes the first year in which the region where firm i is located was exposed to the green finance pilot policy. The pilot regions in the sample began implementing the policy in 2017 and 2019, respectively, allowing firms to be classified into treatment cohorts according to their initial policy implementation year. Firms that remained unexposed to the pilot policy throughout the sample period serve as the control group. The term $k = t - G_i$ denotes time relative to the policy implementation year, and k_0 is the reference period. The coefficient β_{gk} captures the dynamic policy effect for cohort g in relative period k.

Following Sun and Abraham [63], the interaction-weighted estimator first estimates the treatment effects for each implementation cohort at each relative period and then aggregates the estimates across cohorts using the corresponding weights for each relative period:

$$\beta_k^{IW} = \sum_{g} w_{gk} \beta_{gk} \tag{27}$$

where w_{gk} denotes the weight assigned to implementation cohort g in relative period k. This approach avoids the potentially inappropriate comparisons that can arise in conventional two-way fixed-effects event studies under staggered policy implementation, making it more suitable for the phased introduction of China's green finance pilot policy.

This study conducts interaction-weighted event-study analyses separately for the samples of heavily polluting firms, green firms, and other firms, with standard errors

clustered at the city level. The seventh pre-policy period and all earlier periods are used as the reference period. *Pre_6–Pre_1* denote the six periods preceding policy implementation, from the sixth to the first pre-policy period; *Current* denotes the implementation period; and *Post_1–Post_7* denote the first through seventh post-policy periods. Table 4 reports the estimation results.

Table 4. Parallel trends test results.

Variables	(1) Heavily Polluting Firms TFP	(2) Green Firms TFP	(3) Other Firms TFP
Pre_6	0.013	−0.015	0.041
	(0.609)	(−0.172)	(0.986)
Pre_5	0.006	0.154	0.032
	(0.183)	(1.503)	(0.703)
Pre_4	0.029	0.117	0.055
	(0.806)	(0.978)	(0.748)
Pre_3	0.055	−0.005	−0.047
	(1.521)	(−0.043)	(−0.570)
Pre_2	−0.026	0.014	0.027
	(−0.592)	(0.118)	(0.249)
Pre_1	0.014	0.005	−0.079
	(0.289)	(0.042)	(−0.700)
Current	−0.065 *	0.136	0.026
	(−1.886)	(1.507)	(0.443)
Post_1	−0.083 **	0.163 **	−0.012
	(−2.238)	(2.515)	(−0.229)
Post_2	−0.063 *	0.207 ***	−0.046
	(−1.872)	(3.197)	(−1.049)
Post_3	−0.118 ***	0.063	−0.085
	(−3.162)	(1.362)	(−1.480)
Post_4	−0.139	0.017	−0.117
	(−1.619)	(0.343)	(−1.437)
Post_5	−0.105	0.096	−0.071
	(−1.257)	(0.974)	(−0.877)
Post_6	−0.176 *	−0.015	−0.060
	(−1.920)	(−0.106)	(−0.738)
Post_7	−0.231 **	0.137	−0.134
	(−2.590)	(0.883)	(−1.432)
Linear term of control variables	YES	YES	YES
Quadratic term of control variables	YES	YES	YES
Observations	13,235	1594	28,234
R^2	0.947	0.933	0.847
Firm fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES

Before policy implementation, none of the estimated coefficients for the three firm groups exhibits a statistically significant change across the respective pre-policy periods. Furthermore, tests of the linear combinations of the coefficients for the fourth through first pre-policy periods yield a test statistic of −0.57 ($p = 0.57$) for heavily polluting firms, −0.46 ($p = 0.64$) for green firms, and 0.06 ($p = 0.95$) for other firms. These results fail to reject the parallel-trends assumption for all three groups. Taken together, the estimates show no clear evidence of systematic pre-policy changes.

The dynamic effects indicate substantial differences in the productivity responses of different firm types to the green finance pilot policy. For heavily polluting firms, TFP generally declines after policy implementation. The negative effects are not statistically significant in the fourth and fifth post-policy years but become statistically significant again thereafter. For green firms, the effect is not statistically significant in the implementation

period. The positive effects strengthen over the following two years but begin to weaken from the third post-policy year onward and are no longer statistically significant. For other firms, TFP exhibits no discernible change following policy implementation.

These differences in dynamic effects may reflect the reallocation of financial resources induced by the green finance policy. For heavily polluting firms, financial institutions may strengthen environmental risk assessments and raise financing thresholds after policy implementation, causing these firms to face tighter financing conditions relatively early and suppressing their productivity. As policy constraints continue to intensify, the adverse effects may deepen. For green firms, the reallocation of financial resources toward green activities can help ease financing constraints and support equipment renewal, technological upgrading, and research and development. However, these investments require time to translate into productivity gains, so the positive effects emerge gradually after policy implementation. As financing constraints ease, the marginal contribution of additional financial resources diminishes, and the positive effects consequently weaken. Other firms generally have lower pollution emissions and are not the primary targets of the policy. Accordingly, the policy has relatively limited direct effects on their productivity.

5.2.2. Propensity Score Matching with Triple-Difference and Double Machine Learning Models

Given that firms in pilot and non-pilot cities may differ systematically in firm characteristics and regional development levels, this study further conducts robustness checks using propensity score matching combined with the DDD and DDML models (PSM-DDD and PSM-DDML, respectively). To avoid potential post-treatment bias arising from the use of firm characteristics measured after policy implementation, all firm-level control variables in 2016, before policy implementation, are used as covariates. A Logit model is employed to estimate the propensity scores of firms being located in pilot cities. Matching is then performed within the common support region using a caliper of 0.01, followed by balance tests. The results show that the standardized biases for most covariates are below 20% after matching, and the differences between the treatment and control groups in all covariates are no longer statistically significant. These findings indicate that the two groups are reasonably comparable in terms of observable characteristics after matching.

After identifying the successfully matched firms, this study merges the matching results with the original panel data and retains all valid observations for matched firms over the sample period. The DDD and DDML models are then re-estimated separately. The results are reported in Table 5. Columns (1) and (3) present the estimates for heavily polluting firms. The coefficients on the triple interaction term are −0.106 and −0.102, respectively, and are statistically significant at the 5% and 10% levels, respectively. These results indicate that the negative effect of the green finance pilot policy on the TFP of heavily polluting firms persists in the matched sample. Columns (2) and (4) report the results for green firms. The corresponding coefficients on the triple interaction term are 0.051 and 0.033, respectively, both positive and statistically significant at the 5% and 10% levels, respectively. These findings indicate that the positive effect of the green finance pilot policy on the TFP of green firms also persists in the matched sample. Overall, the DDD and DDML estimates have consistent signs and are statistically significant, suggesting that the main conclusion regarding the heterogeneous effects of the green finance pilot policy on the two types of firms remains robust after improving the comparability of observable characteristics between firms in pilot and non-pilot cities.

Table 5. PSM-DDD/DDML test results.

Variables	(1) DDD TFP	(2) DDD TFP	(3) DDML TFP	(4) DDML TFP
Treat × Time × Type	−0.106 **	0.051 **	−0.102 *	0.033 *
	(−2.020)	(2.214)	(−1.758)	(1.653)
Treat × Time	−0.031	−0.019	Included in W	
	(−1.365)	(−0.836)		
Other lower-order terms	Absorbed/Omitted		Included in W	
Linear term of control variables	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	YES	YES
Constant	−0.079	−0.962	0.000	−0.000
	(−0.107)	(−1.084)	(0.331)	(−0.261)
Observations	27,859	19,806	27,859	19,806
R^2	0.936	0.933	—	—
Firm fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES

5.2.3. Excluding Interference from Other Environmental Policies

During the sample period, the Chinese government successively introduced several environmental policies, including the carbon emissions trading pilot policy, the low-carbon city pilot policy, the Green Credit Guidelines, the environmental protection fee-to-tax reform policy, and the new energy city pilot policy. These policies may affect firms' low-carbon transition activities and, in turn, their total factor productivity (TFP). To rule out potential confounding effects from these policies, this study incorporates the corresponding policy variables into the baseline regression models and re-estimates the specifications. The results are reported in Table 6.

Table 6. Test results after excluding other environmental policies.

Variables	(1) DDD TFP	(2) DDD TFP	(3) DDML TFP	(4) DDML TFP
Treat × Time × Type	−0.091 *	0.063 *	−0.094 **	0.089 ***
	(−1.755)	(1.780)	(−2.001)	(3.518)
Treat × Time	−0.034 *	−0.033 *	Included in W	
	(−1.705)	(−1.699)		
Other environmental policies	YES	YES	YES	YES
Other lower-order terms	Absorbed/Omitted		Included in W	
Linear term of control variables	YES	YES	YES	YES
Quadratic term of control variables	NO	YES	NO	YES
Constant	−0.032	−1.534 *	0.000	0.000
	(−0.048)	(−1.773)	(0.066)	(0.321)
Observations	41,584	29,917	41,584	29,917
R^2	0.941	0.940	—	—
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

Columns (1) and (3) report the results for heavily polluting firms. The coefficients on the triple interaction term are −0.091 and −0.094, respectively, and are statistically significant at the 10% and 5% levels, respectively. These findings indicate that the negative effect of the green finance pilot policy on the TFP of heavily polluting firms persists after accounting for other environmental policies. Columns (2) and (4) report the results for green firms. The

corresponding coefficients are 0.063 and 0.089, respectively, and are statistically significant at the 10% and 1% levels, respectively. These results indicate that the positive effect of the green finance pilot policy on the TFP of green firms also persists after accounting for other environmental policies. Overall, the DDD and DDML estimates have consistent signs and are statistically significant, suggesting that the main conclusion regarding the heterogeneous effects of the green finance pilot policy on the TFP of the two types of firms remains robust after controlling for other environmental policies.

5.2.4. Alternative Measurement of the Dependent Variable

To mitigate potential endogeneity arising from measurement error, this study adopts an alternative measure of intermediate inputs, calculated as the sum of operating costs, selling expenses, administrative expenses, and financial expenses, minus depreciation and amortization and cash paid to and on behalf of employees. The resulting measure is transformed using the natural logarithm of its value plus one, and firm total factor productivity (TFP) is re-estimated using the LP method.

The results are reported in Table 7. Columns (1) and (3) present the results for heavily polluting firms, with triple-interaction coefficients of −0.110 and −0.113, significant at the 10% and 5% levels, respectively. Columns (2) and (4) report the results for green firms, with corresponding coefficients of 0.111 and 0.094, significant at the 5% and 1% levels, respectively. Thus, the DDD and DDML estimates consistently indicate that the green finance pilot policy reduces the TFP of heavily polluting firms but increases that of green firms, supporting the robustness of the baseline findings to alternative measurement of the dependent variable.

Table 7. Test results using alternative measures of the dependent variable.

Variables	(1)	(2)	(3)	(4)
	DDD		DDML	
	TFP	TFP	TFP	TFP
Treat × Time × Type	−0.110 *	0.111 **	−0.113 **	0.094 ***
	(−1.810)	(2.365)	(−2.025)	(3.347)
Treat × Time	−0.055	−0.058	Included in W	
	(−1.299)	(−1.292)		
Other lower-order terms	Absorbed/Omitted		Included in W	
Linear term of control variables	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	YES	YES
Constant	2.238 ***	0.948	0.000	0.001
	(3.040)	(1.080)	(0.127)	(0.420)
Observations	41,584	29,917	41,584	29,917
R^2	0.892	0.899	—	—
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

5.2.5. Alternative Double Machine Learning Specifications

To mitigate potential specification bias in the DDML model, this study conducts robustness checks by varying the sample-splitting ratio and the machine-learning algorithm. First, the original five-fold cross-fitting is adjusted to four-fold cross-fitting and six-fold cross-fitting to examine whether changes in sample partitioning affect the baseline results. Second, neural networks and elastic net are used as alternative prediction algorithms to replace the original Lasso regression algorithm, allowing the sensitivity of the baseline results to different prediction algorithms to be assessed.

The results are reported in Table 8. Columns (1), (3), (5), and (7) report the estimates for heavily polluting firms, with triple-interaction coefficients of −0.090, −0.096, −0.084, and −0.092, respectively, significant at the 10%, 10%, 1%, and 10% levels, respectively. These results indicate that the negative effect of the green finance pilot policy on the TFP of heavily polluting firms persists when the sample-splitting ratio and prediction algorithm are varied. Columns (2), (4), (6), and (8) report the estimates for green firms, with corresponding coefficients of 0.024, 0.040, 0.014, and 0.030, respectively, significant at the 10%, 1%, 10%, and 10% levels, respectively. These findings indicate that the positive effect of the policy on the TFP of green firms also persists under these alternative DDML specifications. Overall, the estimates remain consistent in sign with the baseline DDD results and are statistically significant across the reported specifications, supporting the robustness of the conclusion that the green finance pilot policy has heterogeneous effects on the productivity of heavily polluting firms and green firms.

Table 8. Test results using alternative machine learning model specifications.

Variables	(1) 4-Fold Cross-Fitting	(2) 4-Fold Cross-Fitting	(3) 6-Fold Cross-Fitting	(4) 6-Fold Cross-Fitting	(5) Neural Net	(6) Neural Net	(7) Elastic Net	(8) Elastic Net
	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Treat × Time × Type	−0.090 *	0.024 *	−0.096 *	0.040 ***	−0.084 ***	0.014 *	−0.092 *	0.030 *
	(−1.746)	(1.697)	(−1.900)	(2.769)	(−7.745)	(1.753)	(−1.818)	(1.885)
Treat × Time	Included in W							
Other lower-order terms	Included in W							
Linear term of control variables	YES	YES	YES	YES	YES	YES	YES	YES
Quadratic term of control variables	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.001	0.001	0.001	0.001	−0.066 ***	−0.155 ***	0.001	0.001
	(0.565)	(0.824)	(0.506)	(0.632)	(−26.198)	(−37.169)	(0.727)	(0.611)
Observations	41,584	29,917	41,584	29,917	41,584	29,917	41,584	29,917
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES

5.2.6. Controlling for City-by-Year and Firm-Type-by-Year Fixed Effects

Time-varying city-level shocks and year-specific shocks that affect different types of firms differently may confound the baseline estimates. For example, changes in local economic conditions, credit supply, and environmental regulation may jointly affect the productivity of firms within the same city. Meanwhile, changes in market demand, technology, and related policies may affect heavily polluting firms, green firms, and other firms differently. If these factors are correlated with the timing of the green finance pilot policy and firms' environmental attributes, the baseline estimates may be subject to confounding influences. To address this concern, this study further incorporates city-by-year and firm-type-by-year fixed effects into the baseline regression models. City-by-year fixed effects control for time-varying shocks shared by firms within the same city in a given year, while firm-type-by-year fixed effects control for year-specific shocks common to firms of the same type, allowing different firm types to follow different annual trajectories.

The results are reported in Table 9. Columns (1) and (3) present the estimates for heavily polluting firms, with triple-interaction coefficients of −0.101 and −0.089, respectively, both statistically significant at the 10% level. These results indicate that the negative effect of the green finance pilot policy on the TFP of heavily polluting firms persists after controlling for time-varying shocks at the city and firm-type levels. Columns (2) and (4) report the estimates for green firms, with corresponding coefficients of 0.094 and 0.027, respectively, statistically significant at the 5% and 1% levels. These findings indicate that the positive effect of the policy on the TFP of green firms also persists after accounting for these time-varying shocks. Overall, the DDD and DDML estimates have consistent signs and are statistically significant, suggesting that the main conclusion regarding the heterogeneous productivity

effects of the green finance pilot policy remains robust to controlling for city-by-year and firm-type-by-year fixed effects.

Table 9. Regression Results Controlling for City-by-Year and Firm-Type-by-Year Fixed Effects.

Variables	(1)	(2)	(3)	(4)
	DDD		DDML	
	TFP	TFP	TFP	TFP
Treat × Time × Type	−0.101 *	0.094 **	−0.089 *	0.027 ***
	(−1.946)	(2.260)	(−1.653)	(11.328)
Treat × Time	Absorbed/Omitted		Included in W	
Other lower-order terms	Absorbed/Omitted		Included in W	
Linear term of control variables	YES	YES	YES	YES
Quadratic term of control variables	YES	YES	YES	YES
Constant	0.966 *	0.172	0.001	0.001
	(1.866)	(0.285)	(0.877)	(0.400)
Observations	41,584	29,917	41,584	29,917
R^2	0.950	0.949	—	—
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
City-by-year fixed effects	YES	YES	YES	YES
Firm-type-by-year fixed effects	YES	YES	YES	YES

5.3. Heterogeneity Analyses

The preceding analysis has established the effects of the green finance pilot policy on the total factor productivity of different types of firms. However, the actual effects of the policy may vary with government support, slack resources, and factor allocation. In light of this possibility, this section further examines the implementation effects of the green finance pilot policy from three dimensions: government subsidies, organizational slack, and industry asset intensity.

5.3.1. Heterogeneity by Government Subsidies

Government subsidies serve both as a source of financial support and as a signaling mechanism. On the one hand, subsidies directly increase firms' available funds and alleviate financing constraints. On the other hand, government support may send positive signals to financial institutions, thereby improving firms' external financing conditions [64,65]. To examine whether the effects of the green finance pilot policy on firm total factor productivity (TFP) vary with government subsidies, this study measures subsidy intensity as the ratio of government subsidies received to operating revenue and divides the sample at the median.

The results are reported in Table 10. Columns (1) and (5) present the estimates for heavily polluting firms receiving higher levels of government subsidies. The coefficients on the triple interaction term are −0.031 and −0.017, respectively, neither of which is statistically significant. Columns (2) and (6) report the results for heavily polluting firms receiving lower levels of government subsidies, with coefficients of −0.153 and −0.151, significant at the 10% and 5% levels, respectively. One possible explanation is that heavily polluting firms receiving higher levels of government subsidies can use these funds to cushion the financing pressures associated with the green finance pilot policy and signal government support to external investors, potentially mitigating the policy's adverse effects on their TFP. By contrast, firms receiving fewer government subsidies have more limited fiscal support and may be less able to offset the financing pressures induced by the policy. Consequently,

policy-induced financing constraints may more readily affect their productive investment and resource allocation, leading to lower TFP.

Table 10. Heterogeneity test results by government subsidies.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DDD				DDML			
	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Treat × Time × Type	−0.031	−0.153 *	0.115 ***	0.036	−0.017	−0.151 **	0.054 ***	0.001
	(−1.461)	(−1.926)	(4.224)	(0.998)	(−0.541)	(−2.154)	(3.192)	(0.149)
Treat × Time	−0.012	−0.018	−0.015	−0.009	Included in W			
	(−0.642)	(−0.430)	(−0.661)	(−0.233)				
Other lower-order terms	Absorbed/Omitted				Included in W			
Linear term of control variables	YES	YES	YES	YES	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	NO	NO	YES	YES	YES	YES
Constant	2.501 ***	−0.640	1.790 *	−2.380 *	0.005 ***	−0.004 **	0.005 ***	−0.004 *
	(3.175)	(−0.637)	(1.941)	(−1.808)	(3.522)	(−1.998)	(2.631)	(−1.720)
Observations	20,792	20,792	14,958	14,959	20,792	20,792	14,958	14,959
R^2	0.946	0.947	0.946	0.946	—	—	—	—
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES

Columns (3) and (7) present the results for green firms receiving higher levels of government subsidies. The coefficients on the triple interaction term are 0.115 and 0.054, respectively, both statistically significant at the 1% level. Columns (4) and (8) report the results for green firms receiving lower levels of government subsidies, with coefficients of 0.036 and 0.001, respectively, neither of which is statistically significant. One possible explanation is that higher government subsidies enable green firms to share the risks associated with research and development and green transition investments, allowing them to translate the financing support associated with green finance into technological progress and productivity gains more effectively. By contrast, lower subsidy levels provide less financial support for research and development and transition activities and weaken the government-support signal conveyed to financial institutions. As a result, the positive effects of green finance on green technological upgrading and productivity growth may be less fully realized.

5.3.2. Heterogeneity by Organizational Slack

Organizational slack refers to resources retained by firms beyond those required for their routine operations [66,67]. Absorbed organizational slack typically comprises resources committed to administration, organizational coordination, and internal operations, which may provide firms with room to adjust when operational pressures increase. To examine whether the effects of the green finance pilot policy on firm total factor productivity (TFP) vary with absorbed organizational slack, this study measures absorbed organizational slack as the ratio of administrative expenses to operating revenue minus the corresponding industry mean and divides the sample at the median.

The results are reported in Table 11. Columns (1) and (5) present the estimates for heavily polluting firms with higher levels of absorbed organizational slack. The coefficients on the triple interaction term are 0.032 and −0.008, respectively, neither of which is statistically significant. Columns (2) and (6) report the results for heavily polluting firms with lower levels of absorbed organizational slack, with coefficients of −0.159 and −0.137, respectively, both statistically significant at the 10% level. One possible explanation is that greater absorbed organizational slack may cushion the operational impact of the green finance pilot policy on heavily polluting firms, thereby mitigating its effect on their TFP. By contrast, heavily polluting firms with lower levels of absorbed organizational slack may have less capacity to withstand external policy shocks and may therefore be less able to

cushion the policy's adverse effects on their TFP. Columns (3) and (7) present the estimates for green firms with higher levels of absorbed organizational slack. The coefficients are 0.169 and 0.173, respectively, both statistically significant at the 1% level. Columns (4) and (8) report the results for green firms with lower levels of absorbed organizational slack, with coefficients of −0.012 and −0.000, respectively, neither of which is statistically significant. One possible explanation is that greater absorbed organizational slack provides green firms with a resource buffer for production adjustments and green transition activities, helping them make better use of the financing support associated with green finance policy to improve technology and productivity. In contrast, green firms with less absorbed organizational slack have fewer resources available for production adjustments and green transition activities and may therefore find it more difficult to translate policy-related financing support into productivity gains.

Table 11. Heterogeneity test results by organizational slack.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DDD				DDML			
	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Treat × Time × Type	0.032	−0.159 *	0.169 ***	−0.012	−0.008	−0.137 *	0.173 ***	−0.000
	(0.736)	(−1.681)	(6.248)	(−0.336)	(−0.182)	(−1.695)	(21.804)	(−0.047)
Treat × Time	−0.083 ***	0.036	−0.060 **	0.025	Included in W			
	(−4.056)	(0.925)	(−2.393)	(0.629)				
Other lower-order terms	Absorbed/Omitted				Included in W			
Linear term of control variables	YES	YES	YES	YES	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	NO	NO	YES	YES	YES	YES
Constant	0.883	0.568	−0.819	0.203	0.004 **	−0.002	0.007 ***	−0.003
	(0.958)	(0.476)	(−0.765)	(0.143)	(2.352)	(−1.102)	(3.673)	(−1.467)
Observations	20,772	20,772	14,944	14,945	20,772	20,772	14,944	14,945
R^2	0.944	0.959	0.932	0.961	—	—	—	—
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES

5.3.3. Heterogeneity by Industry Asset Intensity

Asset-intensive industries typically have high asset specificity and sunk costs, which can lead to capital lock-in and path dependence, thereby reducing firms' flexibility in reallocating resources and adjusting their business activities [68,69]. To examine whether the effects of the green finance pilot policy vary across industries with different levels of asset intensity, this study measures industry asset intensity as the ratio of net fixed assets to total assets at the industry level and divides the firm sample at the median.

The results are reported in Table 12. Columns (1) and (5) present the estimates for heavily polluting firms in high-asset-intensity industries, with triple-interaction coefficients of −0.148 and −0.156, respectively, both statistically significant at the 10% level. Columns (2) and (6) report the results for heavily polluting firms in low-asset-intensity industries, with coefficients of 0.078 and 0.020, respectively, neither of which is statistically significant. One possible explanation is that heavily polluting firms in low-asset-intensity industries face less capital lock-in and lower asset adjustment costs, allowing them to adjust their production inputs more flexibly in response to policy requirements. Consequently, the policy shock does not translate into a statistically significant decline in TFP. By contrast, firms in high-asset-intensity industries face stronger capital lock-in and higher asset adjustment costs, making it more difficult to restructure production and undertake a green transition in the short run. They may therefore be more susceptible to the policy, resulting in a statistically significant decline in TFP. Columns (3) and (7) present the estimates for green firms in high-asset-intensity industries. The coefficients are 0.022 and 0.014, respectively, neither of which is statistically significant. Columns (4) and (8) report the results for green firms in low-asset-intensity industries, with coefficients of 0.124 and 0.041, respectively, both statistically

significant at the 1% level. One possible explanation is that green firms in low-asset-intensity industries face lower asset adjustment costs and enjoy greater operational flexibility, enabling them to allocate funds more flexibly and advance technological upgrading. They can therefore translate the financing support associated with green finance policy into productivity gains more quickly. By contrast, green firms in high-asset-intensity industries often face higher adjustment costs associated with equipment renewal and technological upgrading, meaning that the productivity benefits of green finance support may take longer to materialize and are not yet statistically significant.

Table 12. Heterogeneity test results by industry asset intensity.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DDD				DDML			
	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP
Treat × Time × Type	−0.148 *	0.078	0.022	0.124 ***	−0.156 *	0.020	0.014	0.041 ***
	(−1.937)	(0.986)	(0.730)	(5.527)	(−1.744)	(0.373)	(0.610)	(3.396)
Treat × Time	−0.018	−0.037	0.030	−0.078 ***	Included in W			
	(−0.624)	(−1.133)	(1.040)	(−3.069)				
Other lower-order terms	Absorbed/Omitted				Included in W			
Linear term of control variables	YES	YES	YES	YES	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	NO	NO	YES	YES	YES	YES
Constant	2.246 ***	−2.386 *	0.292	−2.175	0.001	0.000	0.003	0.001
	(2.768)	(−1.929)	(0.291)	(−1.369)	(0.493)	(0.320)	(1.629)	(0.519)
Observations	20,599	20,985	14,958	14,959	20,599	20,985	14,958	14,959
R^2	0.955	0.941	0.954	0.947	—	—	—	—
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES

5.4. Mechanism Analysis

The preceding results show that the development of green finance improves the total factor productivity of green firms but reduces that of heavily polluting firms. What explains this pattern? This study examines how the green finance pilot policy affects firms' green technological innovation and capital allocation efficiency, thereby generating differentiated effects on the total factor productivity of different types of firms.

5.4.1. Mechanism Test for Green Technological Innovation

The regression results are reported in Table 13. Columns (1) and (3) present the results for heavily polluting firms, with coefficients on the triple interaction term of −0.217 and −0.215, respectively, both statistically significant at the 1% level. These findings indicate that the green finance pilot policy significantly reduces green technological innovation among heavily polluting firms. Columns (2) and (4) report the results for green firms, with corresponding coefficients of 0.356 and 0.376, respectively, both statistically significant at the 1% level. These results indicate that the policy significantly promotes green technological innovation among green firms. Thus, the findings are consistent with the theoretical predictions of Hypotheses 2 and 3. Combined with existing evidence that green technological innovation is closely associated with firm productivity [70], these findings provide supportive evidence that green technological innovation may be a channel through which the green finance pilot policy affects firm productivity.

Table 13. Mechanism test results for green technological innovation.

Variables	(1) DDD	(2)	(3) DDML	(4)
	GreInv	GreInv	GreInv	GreInv
Treat × Time × Type	−0.217 ***	0.356 ***	−0.215 ***	0.376 ***
	(−4.856)	(6.920)	(−4.649)	(16.065)
Treat × Time	0.119 **	0.078	Included in W	
	(2.302)	(1.528)		
Other lower-order terms	Absorbed/Omitted		Included in W	
Linear term of control variables	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	YES	YES
Constant	1.062	−1.162 *	0.000	0.001
	(1.233)	(−1.656)	(0.188)	(0.706)
Observations	41,584	29,917	41,584	29,917
R^2	0.664	0.642	—	—
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

5.4.2. Mechanism Test for Capital Allocation Efficiency

Tables 14 and 15 report the capital allocation efficiency mechanism tests based on the DDD and DDML models, respectively. Columns (1)–(3) of Tables 14 and 15 report the results for heavily polluting firms, while Columns (4)–(6) report the results for green firms.

Table 14. Mechanism test results for capital allocation efficiency (DDD).

Variables	(1)	(2)	(3) Heavily Polluting Firms	(4)	(5)	(6) Green Firms
	Inveff	OverInvest	UnderInvest	Inveff	OverInvest	UnderInvest
Treat × Time × Type	−0.008 ***	0.014 ***	0.003	−0.009 ***	0.027 ***	−0.002 *
	(−3.272)	(2.682)	(1.113)	(−5.909)	(10.532)	(−1.816)
Treat × Time	0.004 *	−0.007 ***	−0.001	0.003 *	−0.007 **	0.000
	(1.919)	(−2.859)	(−0.342)	(1.689)	(−2.179)	(0.116)
Other lower-order terms	Absorbed/Omitted					
Linear term of control variables	YES	YES	YES	YES	YES	YES
Quadratic term of control variables	YES	YES	YES	YES	YES	YES
Constant	−0.095 ***	0.197 **	0.059 **	−0.072 **	0.129	0.030
	(−3.084)	(2.548)	(2.166)	(−2.217)	(1.622)	(1.430)
Observations	38,252	14,646	23,606	27,284	10,244	17,040
R^2	0.338	0.458	0.381	0.365	0.493	0.400
Firm fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES

For heavily polluting firms, the coefficients on the triple interaction term in Column (1) of Tables 14 and 15 are −0.008 and −0.007, respectively, both statistically significant at the 1% level. These results indicate that the green finance pilot policy significantly reduces capital allocation efficiency among heavily polluting firms. When investment deviations are further distinguished by direction, the corresponding coefficients in Column (2) of Tables 14 and 15 are 0.014 and 0.010, respectively, significant at the 1% and 5% levels. By contrast, the coefficients reported in Column (3) of Table 14 and Column (3) of Table 15 are 0.003 and 0.002, respectively, neither of which is statistically significant. These findings suggest that the decline in capital allocation efficiency among heavily polluting firms is primarily reflected in increased overinvestment, while the change in underinvestment is not statistically significant.

Table 15. Mechanism test results for capital allocation efficiency (DDML).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Heavily Polluting Firms			Green Firms		
	Inveff	OverInvest	UnderInvest	Inveff	OverInvest	UnderInvest
Treat × Time × Type	−0.007 ***	0.010 **	0.002	−0.005 ***	0.003 ***	−0.003 ***
	(−3.291)	(2.303)	(1.079)	(−6.440)	(6.222)	(−4.704)
Treat × Time	Included in W					
Other lower-order terms	Included in W					
Linear term of control variables	YES	YES	YES	YES	YES	YES
Quadratic term of control variables	YES	YES	YES	YES	YES	YES
Constant	−0.000	0.000	0.000	−0.000	0.000	0.000
	(−0.256)	(0.111)	(0.114)	(−0.173)	(0.021)	(0.074)
Observations	38,252	14,646	23,606	27,284	10,244	17,040
Firm fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES

For green firms, the coefficients on the triple interaction term in Column (4) of Tables 14 and 15 are −0.009 and −0.005, respectively, both statistically significant at the 1% level. These results indicate that the green finance pilot policy also significantly reduces capital allocation efficiency among green firms. When investment deviations are further distinguished by direction, the coefficients reported in Column (5) of Table 14 and Column (5) of Table 15 are 0.027 and 0.003, respectively, both statistically significant at the 1% level. The corresponding coefficients in Column (6) of Tables 14 and 15 are −0.003 and −0.002, respectively, significant at the 10% and 1% levels. These findings suggest that the policy exacerbates overinvestment among green firms while alleviating underinvestment. One possible explanation is that the policy improves financing conditions for green firms, enabling some investment projects that were previously constrained by insufficient funding to proceed and thereby alleviating underinvestment. However, improved financing conditions do not necessarily translate into better investment decisions. The expansion of investment by green firms may also involve additional low-return projects, thereby exacerbating overinvestment.

Overall, the green finance pilot policy reduces capital allocation efficiency among both heavily polluting firms and green firms, although the specific patterns differ between the two groups. For heavily polluting firms, the decline in capital allocation efficiency is primarily reflected in increased overinvestment, while the change in underinvestment is statistically insignificant. For green firms, the policy alleviates underinvestment but exacerbates overinvestment, with an overall significant decline in capital allocation efficiency. These findings are consistent with the prediction of Hypothesis 4 and the theoretical expectation of Hypothesis 5b, but do not support Hypothesis 5a. Combined with existing evidence that capital allocation efficiency is closely related to firm productivity [48], the results provide supportive evidence that capital allocation efficiency may be a channel through which the green finance pilot policy affects firm productivity.

6. Further Analysis

The preceding analysis has shown that the green finance pilot policy has heterogeneous effects on the total factor productivity of different firms. Two issues therefore warrant further discussion: how to mitigate the adverse effect of green finance on the total factor productivity of heavily polluting firms, and what economic consequences may arise when green finance improves the total factor productivity of green firms.

6.1. Firm Digital Transformation

Information asymmetry between firms and financial institutions makes it difficult for financial institutions to accurately identify the green transition projects of heavily polluting firms, thereby affecting the availability of financing support for these projects [20,45]. In recent years, digital transformation has increasingly become an important means for firms to integrate operational information and reduce information asymmetry [71]. The application of digital technologies enables firms to record and integrate information on production, energy consumption, and pollutant emissions, improving its verifiability and comparability and helping financial institutions evaluate firms' green transition projects [72,73]. Digital transformation may therefore mitigate, to some extent, the negative effect of the green finance pilot policy on the TFP of heavily polluting firms. This study measures corporate digital transformation (*Dig*) as the ratio of digital-transformation-related intangible assets disclosed in the notes to financial statements to total assets at year-end. The digital transformation variable and its associated interaction terms are then incorporated into the DDD and DDML models to examine its moderating role.

The regression results are reported in Table 16. In Columns (1) and (4), the coefficients on the four-way interaction term are 25.087 and 18.874, respectively, both positive and statistically significant at the 10% level. These results provide preliminary evidence that digital transformation can mitigate the negative effect of the green finance pilot policy on the TFP of heavily polluting firms. In addition, the coefficient on *Treat* × *Time* × *Dig* is significantly positive, whereas the coefficients on *Dig*, *Treat* × *Type* × *Dig*, *Treat* × *Dig*, and *Type* × *Dig* are not statistically significant.

Table 16. Further analysis results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	DDD			DDML		
	TFP	RA	RPT	TFP	RA	RPT
Treat × Time × Type × Dig	25.087 *			18.874 *		
	(1.725)			(1.670)		
Dig	−0.389			Included in W		
	(−0.477)					
Treat × Time × Type	−0.114 **	−0.017 ***	−0.010 ***	Included in W	−0.007 **	−0.009 ***
	(−1.968)	(−4.450)	(−5.922)		(−2.248)	(−7.299)
Treat × Time × Dig	3.140 ***			Included in W		
	(3.160)					
Treat × Time	−0.039 **	0.000	−0.003		Included in W	
	(−2.118)	(0.111)	(−1.528)			
Treat × Type × Dig	−11.056			Included in W		
	(−0.763)					
Treat × Dig	−3.089			Included in W		
	(−1.604)					
Type × Dig	−2.670			Included in W		
	(−1.061)					
Other lower-order terms	Absorbed/Omitted				Included in W	
Linear term of control variables	YES	YES	YES	YES	YES	YES
Quadratic term of control variables	NO	NO	NO	YES	YES	YES
Constant	0.178	0.021	−0.055	0.000	−0.000	−0.000
	(0.269)	(0.287)	(−1.317)	(0.204)	(−0.053)	(−0.022)
Observations	41,584	29,801	29,917	41,584	29,801	29,917
R^2	0.941	0.285	0.518	—	—	—
Firm fixed effects	YES	YES	YES	YES	YES	YES
	YES	YES	YES	YES	YES	YES

To further examine how the moderating effect varies with the level of digital transformation, this study uses the DDD model to estimate the conditional policy effects at

the 25th, 50th, and 75th percentiles of (*Dig*), together with their 90% confidence intervals. The results are reported in Table 17. Panel A shows that the conditional effects of the green finance pilot policy on the TFP of heavily polluting firms are −0.1523, −0.1374, and −0.0998 at the 25th, 50th, and 75th percentiles, respectively, all statistically significant at the 1% level. The magnitude of the negative effect decreases as digital transformation increases. Further tests show that the difference in the estimated effects between the 75th and 25th percentiles is 0.0526, statistically significant at the 10% level. Panel B further examines the conditional DDD effects for heavily polluting firms relative to non-heavily polluting firms. The estimated coefficients at the 25th, 50th, and 75th percentiles are −0.1137, −0.1005, and −0.0670, respectively, all statistically significant at the 10% level. The negative effect likewise becomes smaller in magnitude as digital transformation increases. The difference in the estimated effects between the higher and lower levels of digital transformation is 0.0467, statistically significant at the 10% level. Overall, the decreasing magnitude of the negative conditional effects as digital transformation increases provides supportive evidence that digital transformation mitigates the adverse productivity effects of the green finance pilot policy.

Table 17. Conditional policy effects at different levels of digital transformation (DDD).

Dig Level	Dig Value	Marginal Effect	Std. Err.	t-Value	*p*-Value	90% CI
Panel A: Conditional Policy Effects on Heavily Polluting Firms						
P25	0.00001949	−0.1523	0.055	−2.77	0.006	[−0.2431, −0.0616]
P50	0.0005483	−0.1374	0.0488	−2.81	0.005	[−0.2179, −0.0569]
P75	0.00188134	−0.0998	0.0361	−2.77	0.006	[−0.1592, −0.0403]
P75−P25	—	0.0526	0.0274	1.92	0.056	[0.0074, 0.0977]
Panel B: Conditional DDD Effects Relative to Non-Heavily Polluting Firms						
P25	0.00001949	−0.1137	0.0577	−1.97	0.050	[−0.2089, −0.0185]
P50	0.00054830	−0.1005	0.0514	−1.95	0.051	[−0.1852, −0.0157]
P75	0.00188134	−0.0670	0.0377	−1.78	0.076	[−0.1292, −0.0048]
P75−P25	—	0.0467	0.0270	1.73	0.085	[0.0021, 0.0913]

Notes: This table reports conditional policy effects estimated from the DDD moderation model. Panel A presents the policy effects on heavily polluting firms, while Panel B reports the differential policy effects relative to non-heavily polluting firms. P25, P50, and P75 represent the 25th, 50th, and 75th percentiles of Dig in the estimation sample, respectively. P75−P25 denotes the difference in conditional effects between the two percentiles. Standard errors are clustered at the city level, and 90% confidence intervals are reported.

6.2. Analysis of Economic Consequences

Managers and controlling shareholders serve as the decision-making agents and ultimate controllers of firms, respectively. Driven by opportunistic motives, they may make decisions that deviate from the objective of firm value maximization [74]. Among such behaviors, earnings management and controlling shareholder expropriation have attracted considerable academic attention [75,76]. Accordingly, this study further examines the effects of the green finance pilot policy on green firms' corporate governance. Specifically, earnings management (*RA*) is measured by the absolute value of the residuals from the modified Jones model, while controlling shareholder expropriation (*RPT*) is measured by net other receivables as a proportion of total assets. Both the DDD and DDML models are employed in this analysis.

The regression results are reported in Table 16. Columns (2), (3), (5), and (6) report the results for green firms. Columns (2) and (5) present the earnings management results, with triple-interaction coefficients of −0.017 and −0.007, respectively, statistically significant at the 1% and 5% levels. These findings indicate that the green finance pilot policy is associated with a reduction in earnings management among green firms. Columns (3) and (6)

report the results for controlling shareholder expropriation, with corresponding coefficients of −0.010 and −0.009, respectively, both statistically significant at the 1% level. These results indicate that the policy is associated with a reduction in controlling shareholder expropriation among green firms. Overall, the findings suggest that the green finance pilot policy may benefit green firms partly by improving corporate governance practices.

7. Conclusions and Policy Recommendations

7.1. Main Conclusions

Using data on Chinese A-share listed firms in Shanghai and Shenzhen from 2009 to 2024, this study applies a Triple-Difference model and a Double Machine Learning model to examine the effects of the green finance pilot policy on the total factor productivity of heavily polluting firms and green firms. The main findings are as follows.

First, the green finance pilot policy increases the total factor productivity of green firms but reduces that of heavily polluting firms. This finding remains robust across a series of robustness checks.

Second, the mechanism tests indicate that the green finance pilot policy reduced both green technological innovation and capital allocation efficiency among heavily polluting firms. Among green firms, the policy reduced capital allocation efficiency but significantly increased green technological innovation.

Third, the heterogeneity analysis reveals that the negative effect of the green finance pilot policy on the total factor productivity of heavily polluting firms was more pronounced among firms receiving fewer government subsidies, with lower levels of organizational slack, and operating in more asset-intensive industries. In contrast, the positive effect on the total factor productivity of green firms was stronger among firms receiving more government subsidies, with higher levels of organizational slack, and operating in less asset-intensive industries.

Finally, further analysis provides suggestive evidence that firm digital transformation may mitigate the adverse effect of the green finance pilot policy on the total factor productivity of heavily polluting firms. The policy also significantly reduces earnings management and controlling-shareholder expropriation among green firms.

7.2. Policy Implications

First, financial support for heavily polluting firms should be improved. The purpose of the green finance pilot policy is not to reduce the total factor productivity of heavily polluting firms, but to encourage them to accelerate green transformation. Financial institutions should be encouraged to support firms that actively pursue transformation. Mechanisms for environmental information disclosure, information sharing on energy conservation and emission reduction, and credit tracking should also be improved to provide targeted financing for green transformation projects undertaken by heavily polluting firms.

Second, a long-term support mechanism for green firms should be established. Financial institutions should promote innovation in green financial products and increase financial support for green firms and green projects in energy conservation and environmental protection, low-carbon development, and the circular economy. This would further guide financial resources toward industries and firms characterized by lower energy consumption, lower pollution, and lower emissions.

Third, the digital transformation of heavily polluting firms should be advanced. Heavily polluting firms should be encouraged to incorporate digital transformation into their development strategies and gradually implement digital monitoring and management in key areas of production, management, and environmental protection. Financial institutions

also need to develop financing products for digital transformation to support firms in building digital management platforms and intelligent systems.

Fourth, green firms should be guided toward stable development while potential risks are mitigated. Information disclosure and market supervision should be strengthened to help green firms avoid potential risks arising from earnings management or shareholder conflicts of interest while improving production efficiency, thereby fostering a transparent and fair market environment.

Fifth, differentiated support should be provided according to firm characteristics. Policy design should fully account for firm heterogeneity and introduce targeted measures to improve green finance policies. For example, green transformation performance evaluation systems should be developed, firms should be encouraged to implement green transformation projects and redeploy absorbed organizational slack, and green financial product innovation should be promoted to activate absorbed slack resources and reduce capital lock-in and path dependence.

7.3. Limitations and Future Research Directions

Although this study yields several important findings, it also has limitations.

First, this study mainly examines the impact, heterogeneity, mechanisms, mitigation measures, and economic consequences of green finance for the total factor productivity of heavily polluting firms and green firms. However, the discussion of heterogeneity across specific green finance instruments remains relatively general. Future research could further distinguish among green finance policy instruments, such as green credit, green bonds, and green insurance, and examine their independent mechanisms.

Second, this study focuses on China, and its conclusions are mainly applicable to the institutional context of a large developing country. Future research could extend the analytical framework to different countries or regions and conduct cross-country comparisons to further examine the specific effects and boundary conditions of green finance policies on firm total factor productivity, thereby enriching the research agenda on how green finance promotes sustainable firm development from a global perspective.

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Appendix A

Table A1. Key Tasks of the Green Finance Reform and Innovation Pilot Zones.

Main Tasks	Specific Tasks
Standard setting	Establish standards for the identification and evaluation of green projects, green enterprises, and green financial products
Project database development	Develop catalogues of green projects and green enterprises and establish dynamic management mechanisms
Platform development	Build integrated green finance service platforms and mechanisms linking financial institutions with enterprises
Trading market development	Promote the development of carbon emission trading and other environmental rights trading platforms
Carbon emission–related system development	Establish carbon accounting systems and explore carbon financial products and trading mechanisms
Other supporting infrastructure	Strengthen industry self-regulation in green finance and improve green finance think tank systems

Appendix B

Appendix B.1. Identification Basis

This study identifies green firms based on the Green Industry Guidance Catalogue (2019 Edition) and the Green and Low-Carbon Transformation Industry Guidance Catalogue (2024 Edition) issued by the National Development and Reform Commission of China and other ministries. The 2019 catalogue mainly covers energy-saving and environmental protection industries, cleaner production industries, clean energy industries, ecological and environmental industries, green upgrading of infrastructure, and green services. The 2024 catalogue further expands the scope to energy-saving and carbon-reduction industries, environmental protection industries, resource recycling industries, green and low-carbon energy transformation, ecological protection, restoration and utilization, green upgrading of infrastructure, and green services.

Appendix B.2. Text Sources and Preprocessing

This study uses the main business descriptions disclosed in firms' annual reports as the identification object. The text is uniformly renamed Mainbusiness. Before identification, the text is standardized and cleaned. First, Unicode normalization is performed and the text is converted to lowercase. Second, spaces, line breaks, tabs, common Chinese and English punctuation marks, and quotation marks are removed. Third, standardized boilerplate expressions without substantive identification value, such as "projects subject to approval according to law", "business activities may be conducted only after approval by relevant departments", "general business items", and "licensed business items", are removed. After these procedures, the cleaned main business text variable Mainbusiness_clean is generated and used as the basis for subsequent identification.

Appendix B.3. Variable Definitions

The program generates four core variables:

(1) green_hit: equals 1 if a firm's main business matches the green business identification rules, and 0 otherwise;
(2) green_review: equals 1 if a firm's main business involves mixed operations or boundary cases requiring manual review, and 0 otherwise;

(3) green_final: the final identification result for green firms. It equals 1 when green_hit = 1 and green_review = 0, and 0 otherwise;
(4) hit_kw: records the first keyword or combined rule matched by the sample, which is used for subsequent manual verification.

Appendix B.4. Identification Rules

Appendix B.4.1. High-Precision Direct Matching Rules

For main business descriptions that are highly consistent with the meaning of the official catalogue entries and have clear expressions, this study uses direct matching to identify green businesses. Such keywords include, but are not limited to, landscaping and greening, greening maintenance, sponge cities, green data centers, energy performance contracting, water-saving performance contracting, demand-side power management, energy-saving assessment, energy auditing, energy-saving diagnosis, environmental impact assessment, cleaner production audit, carbon accounting, carbon verification, carbon monitoring, carbon trading, green certificate trading, green electricity trading, emissions permit trading, energy-use rights trading, water-use rights trading, waste-to-energy incineration, hazardous waste treatment, solid waste treatment, solid waste disposal, sludge treatment and disposal, renewable resource recycling, comprehensive utilization of industrial solid waste, environmental monitoring systems, environmental monitoring instruments, firm environmental monitoring, pollution source monitoring, SCR denitration catalysts, ultra-low emissions, smart grids, prefabricated buildings, ultra-low-energy buildings, and green building consulting. These expressions are directly derived from official catalogue entries or correspond closely to the business objects listed in the catalogues.

Appendix B.4.2. Identification Based on Combined Rules

For main business descriptions that are ambiguous but whose business orientation can be clarified through contextual information, this study adopts combined identification rules.

First, landscaping and greening. If the main business description contains “landscaping” or “greening” and co-occurs with terms such as “engineering”, “construction”, “design”, “maintenance”, “landscape”, or “seedlings”, it is identified as a green business.

Second, sewage treatment. If the main business description contains “sewage” and co-occurs with terms such as “treatment”, “resource utilization”, “reuse”, “operation”, “facilities”, or “plant”, it is identified as a green business. If specific expressions such as “reclaimed water”, “greywater reuse”, “sludge resource utilization”, or “kitchen waste treatment” appear, it is also identified as a green business.

Third, waste treatment. If the main business description contains “waste” and co-occurs with terms such as “waste-to-energy incineration”, “treatment”, or “leachate”, it is identified as a green business.

Fourth, desulfurization and denitrification. If the main business description contains terms such as “desulfurization”, “denitrification”, “dust removal”, or “flue gas treatment”, and co-occurs with terms such as “equipment”, “catalysts”, “engineering”, “operation”, “construction”, “treatment”, “manufacturing”, or “sales”, it is identified as a green business.

Fifth, photovoltaic and solar energy. If the main business description contains “photovoltaic” or “solar energy” and co-occurs with terms such as “modules”, “batteries”, “silicon wafers”, “power stations”, “power generation”, “equipment”, “inverters”, “glass”, “ribbons”, “brackets”, “frames”, “water heaters”, “heating systems”, “EPC”, “construction”, or “operation”, it is identified as a green business.

Sixth, wind power. If the main business description contains “wind power” or “wind power generation” and co-occurs with terms such as “units”, “equipment”, “main shafts”, “towers”, “blades”, “wind turbines”, “wind farms”, “projects”, “development”, “construction”, “operation”, “services”, or “basic equipment”, it is identified as a green business.

Seventh, energy storage and hydrogen energy. If the main business description contains "energy storage" and co-occurs with terms such as "systems", "products", "batteries", "inverters", "equipment", "power stations", "electrochemical", or "household use", it is identified as a green business. If the main business description contains "hydrogen energy", "hydrogen production", "hydrogen storage", "hydrogen transportation", "hydrogen refueling stations", or "hydrogen refueling equipment", it is identified as a green business. If expressions such as "charging piles", "charging and battery swapping", "battery swapping stations", or "new energy vehicle charging and battery swapping" appear in the main business description, it is also identified as a green business.

Eighth, energy-saving and environmental protection equipment. If the main business description contains "energy saving" and co-occurs with terms such as "boilers", "kilns", "motors", "fans", "transformers", "lighting", "compressors", "air compressors", "blowers", "doors and windows", "equipment", "retrofitting", or "services", it is identified as a green business. If the main business description contains "environmental protection" and co-occurs with terms such as "equipment", "facilities", "treatment", "water services", "monitoring", "processing", "remediation", "power generation", "engineering", or "services", it is identified as a green business.

Ninth, environmental monitoring. If the main business description contains terms such as "environmental monitoring", "ecological environmental monitoring", "pollution source monitoring", or "carbon monitoring", and co-occurs with terms such as "systems", "instruments", "meters", "facilities", "equipment", "operation", "operation and maintenance", or "services", it is identified as a green business.

Appendix B.5. Manual Review Rules

To avoid misclassification caused by broad expressions or mixed operations, this study assigns green_review = 1 to the following samples for manual review:

(1) Samples whose main business descriptions match the green business identification rules but also contain clearly non-green main businesses, such as real estate, property management, hotels, department stores, retail, wholesale, banking, supermarkets, watches, mobile phones, televisions, bicycles, textile printing and dyeing, food and beverages, furniture, port loading and unloading, warehousing, and transportation;
(2) Samples whose main business descriptions contain both "conventional energy" and "new energy";
(3) Samples whose main business descriptions are limited to "rail transit operation and maintenance";
(4) Samples in which green businesses appear together with "thermal power generation";
(5) Samples containing chemical businesses that can be confused with hydrogen energy businesses, such as "benzene hydrogenation" and "coal tar hydrogenation".

Appendix B.6. Final Definition of Green Firms

Based on the manual review results, this study includes firms that meet the identification criteria in the sample of green firms.

Appendix C

Table A2. Variable definitions.

Variable	Symbol	Measurement
Dependent variable	TFP	Estimated using the Levinsohn–Petrin (LP) method.

Table A2. *Cont.*

Variable	Symbol	Measurement
Independent variable	Treat × Time × Type	Measured by the interaction of the treatment-group indicator (Treat), the post-treatment indicator (Time), and the firm-type indicator (Type).
Mechanism variables	GreInv	Measured by the number of green invention patent applications, transformed by taking the natural logarithm after adding one.
	Inveff	Measured as the negative absolute value of the residual from the expected-investment model; higher values indicate greater capital allocation efficiency.
Control variables	Age	Measured by the number of years since the firm was established, transformed by taking the natural logarithm after adding one.
	Analyst	Measured by the number of securities analysts following the firm, transformed by taking the natural logarithm after adding one.
	Cash	Measured by the ratio of net cash flow from operating activities to operating revenue.
	Dual	Measured by an indicator equal to 1 if the chairperson and general manager are the same person, and 0 otherwise.
	FixAssIn	Measured by the change in net fixed assets from the beginning to the end of the period, divided by total assets.
	IO	Measured by the ratio of shares held by institutional investors to total shares.
	Lev	Measured by the ratio of total liabilities to total assets.
	RD	Measured by R&D investment, transformed by taking the natural logarithm after adding one.
	ROA	Measured by the ratio of net profit to total assets.
	SA	Measured using the SA index, calculated as SA = −0.737 × FirmSize + 0.043 × FirmSize2 − 0.040 × FirmAge.
	SOE	Measured by an indicator equal to 1 if the firm is state-owned, and 0 otherwise.
	Size	Measured by total assets, transformed by taking the natural logarithm after adding one.
	TopTen	Measured by the ratio of shares held by the top ten shareholders to total shares.
	HHI	Measured by the sum of squared shares of each firm's main business revenue in total industry revenue.
	Income	Measured by the total operating revenue of firms within the industry, transformed by taking the natural logarithm after adding one.
	Number	Measured by the number of firms within the industry, transformed by taking the natural logarithm after adding one.
	Fin	Measured by the year-end balance of loans from financial institutions, transformed by taking the natural logarithm after adding one.
	PerGdp	Measured by per capita gross domestic product, transformed by taking the natural logarithm after adding one.
	Protect	Measured by general public budget expenditure, transformed by taking the natural logarithm after adding one.
	SecGdp	Measured by the ratio of value added in the secondary industry to gross domestic product.
	SciProtect	Measured by science and technology expenditure in the general public budget, transformed by taking the natural logarithm after adding one.

Appendix D

Taking the effect of the green finance pilot policy on firm total factor productivity as an example, this study employs the Double Machine Learning method for empirical analysis. The model is specified as follows:

$$TFP_{it} = \beta_0 D_{it} + g(W_{it}) + U_{it} \quad \text{(A1)}$$

$$E(U_{0it}|D_{it}, W_{it}) = 0 \quad \text{(A2)}$$

In Equation (A1), TFP_{it} denotes the total factor productivity of firm i in year t; D_{it} denotes the treatment variable, measured by $Treat_i \times Time_{it} \times Type_i$. β_0 denotes the treatment

effect coefficient. W_{it} denotes the high-dimensional nuisance-function covariate set, whose effect on firm total factor productivity is estimated using machine learning algorithms and is specifically represented by the fitted function $g(W_{it})$. The expected value of the random error term U_{it} is zero. By estimating Equations (A1) and (A2), the estimate of the treatment effect coefficient $\hat{\beta}_0$ can be obtained:

$$\hat{\beta}_0 = \frac{1}{n}\left(\frac{1}{n}\sum_{i\in I,t\in T} D_{it}^2\right)^{-1} \sum_{i\in I,t\in T} D_{it}(TFP_{it} - \hat{g}(W_{it})) \tag{A3}$$

In Equation (A3), n denotes the sample size. However, the estimated parameter $\hat{\beta}_0$ is biased. The fundamental reason is that $\hat{\beta}_0$ has difficulty converging to the true parameter β_0. Therefore, it is necessary to analyze the bias based on the above estimation results:

$$\sqrt{n}\left(\hat{\beta}_0 - \beta_0\right) = \frac{1}{\sqrt{n}}\left(\frac{1}{n}\sum_{i\in I,t\in T} D_{it}^2\right)^{-1} \sum_{i\in I,t\in T} D_{it}U_{it} + \frac{1}{\sqrt{n}}\left(\frac{1}{n}\sum_{i\in I,t\in T} D_{it}^2\right)^{-1} \sum_{i\in I,t\in T} D_{it}(\hat{g}(W_{it}) - g(W_{it})) \tag{A4}$$

Specifically, define $a = \frac{1}{\sqrt{n}}\left(\frac{1}{n}\sum_{i\in I,t\in T} D_{it}^2\right)^{-1} \sum_{i\in I,t\in T} D_{it}U_{it}$, which follows a normal distribution with mean zero. Further define $b = \frac{1}{\sqrt{n}}\left(\frac{1}{n}\sum_{i\in I,t\in T} D_{it}^2\right)^{-1} \sum_{i\in I,t\in T} D_{it}(\hat{g}(W_{it}) - g(W_{it}))$. This definition is important because Double Machine Learning uses various machine learning algorithms and regularization algorithms to derive the specific form of the fitted function $\hat{g}(W_{it})$, and this process inevitably introduces "regularization bias". Although this method can alleviate excessive variance in the estimation process, it also generates bias. This can be reflected in the following phenomenon: $\hat{g}(W_{it})$ converges slowly to the true function $g(W_{it})$, specifically at a rate satisfying $n^{-\varphi_g} > n^{\frac{1}{2}}$. Therefore, as n approaches infinity, the variable b also tends to infinity, which makes it difficult for the estimated parameter $\hat{\beta}_0$ to converge to the true parameter β_0.

To accelerate the convergence rate, an orthogonalization method is required to correct the error, and the following auxiliary regression equation is constructed:

$$D_{it} = m(W_{it}) + V_{it} \tag{A5}$$

$$E(V_{it}|W_{it}) = 0 \tag{A6}$$

In Equation (A5), $m(W_{it})$ denotes the regression function of the treatment effect coefficient with respect to the high-dimensional control variables, and V_{it} is the error term with a conditional mean of zero. Machine learning algorithms are used to estimate $\hat{m}(W_{it})$, and the residual $V_{it} = D_{it} - \hat{m}(W_{it})$ must be calculated. Similarly, $\hat{g}(W_{it})$ must be estimated.

In the subsequent estimation, $\hat{V}_{it}$ is used to construct Neyman-orthogonal moment conditions for the treatment-effect parameter β_0, thereby mitigating the first-order impact of nuisance-function estimation errors on the estimation of the target parameter. Accordingly, the orthogonalized estimator is given by

$$\breve{\beta} = \left(\frac{1}{n}\sum_{i\in I,t\in T} \hat{V}_{it}D_{it}\right)^{-1} \frac{1}{n}\sum_{i\in I,t\in T} \hat{V}_{it}(TFP_{it} - \hat{g}(W_{it})) \tag{A7}$$

The asymptotic bias of $\breve{\beta}_0$ at this stage can be expressed as

$$\sqrt{n}\left(\breve{\beta}_0 - \beta_0\right) = \left[E(V_{it}^2)\right]^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,t\in I} V_{it}U_{it} + \left[E(V_{it}^2)\right]^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} (\hat{m}(W_{it}) - m(W_{it}))(\hat{g}(W_{it}) - g(W_{it})) \tag{A8}$$

Here, $\left(E(V_{it}^2)\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i\in I,t\in T} V_{it}U_{it}$ follows a normal distribution with mean zero. Since machine learning estimation is applied twice, the convergence rate of $\left(E(V_{it}^2)\right)^{-1} \frac{1}{\sqrt{n}}$

$\sum_{i\in I,t\in T}(\hat{m}(W_{it})-m(W_{it}))(\hat{g}(W_{it})-g(W_{it}))$ can be expressed as $n^{-(\phi_g+\phi_m)}$. Consequently, $\sqrt{n}\left(\breve{\beta}_0-\beta_0\right)$ converges to zero at a faster rate, and $\breve{\beta}_0$ becomes an asymptotically unbiased estimator.

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