The Impact of Green Finance Reform and Innovation Pilot Zone Policy on Firm-Level Total Factor Productivity

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Abstract. Against global climate change and China's "Dual Carbon" targets, green finance has evolved from pilot to institutionalized frameworks. While China leads in green finance market size via policy innovation, the micro-mechanisms driving firm transformation and policy efficacy remain under-researched. Using the green finance reform and innovation pilot zone policy as a quasi-natural experiment, this research employs a multi-time point difference in difference model with 2010–2022 A-share listed firm data to examine its impact on total factor productivity. Results show the policy significantly suppresses firm total factor productivity, with robustness confirmed via parallel trends and multiple robustness tests. Structural heterogeneity exists: larger firms and those with higher institutional ownership experience stronger total factor productivity declines, reflecting asymmetric transition costs. Firms partially offset these effects through adaptive strategies like increased R&D and improved carbon performance, revealing a "constraint-innovation" dynamic. Finally, based on the empirical results, this research puts forward relevant policy suggestions.

Keywords: Green finance, Total factor productivity, R&D investment, Carbon performance.

1. Introduction

The industrial revolution-driven global industrialization has exacerbated greenhouse gas emissions and climate risks. From 2010 to 2020, extreme natural disasters quadrupled in frequency and caused 5.5 times greater economic losses than in the 1970s. In response, the Paris Agreement has spurred global climate governance, yet green growth policies yield paradoxical outcomes: while fostering green technological innovation, near-term compliance costs suppress firm efficiency through rising operational burdens [1].

As the world's largest carbon emitter, China faces dual challenges of diminishing factor productivity and tightening ecological constraints, rendering its extensive growth model unsustainable. To reconcile these tensions, China launched the green finance reform and innovation pilot zones (GFRIPZ) in 2017, leveraging financial instruments to restructure resource allocation. The GFRIPZ initiative targets a triple objective—enhancing environmental regulation, boosting production efficiency, and achieving decarbonization—embodying China's strategy to institutionalize low-carbon transitions through policy innovation.

The evolution of green finance has transitioned from early pollution mitigation interventions to a systemic driver of sustainable development. Recent studies emphasize its role in optimizing capital allocation and fostering green innovation, particularly through policy instruments like China's GFRIPZ. Empirical evidence demonstrates that green finance policies enhance regional economic quality through industrial upgrading while imposing financing constraints that compel polluting firms to adopt cleaner technologies [2-3]. However, such policies risk triggering symbolic environmental actions in the short term before catalyzing substantive innovation in the long run [4].

Total factor productivity (TFP), as a comprehensive efficiency metric, increasingly integrates environmental and regulatory dimensions. Recent work highlights ESG performance as a critical TFP enhancer, particularly in state-owned and pollution-intensive industries, by alleviating financing constraints and curbing inefficient investments [5]. Concurrently, environmental credit policies are shown to boost TFP via capital reallocation and green innovation incentives, with heterogeneous effects across enforcement regimes and market structures [6].

The dual impact of green finance on TFP emerges through environmental regulation and financial allocation pathways. Stringent regulations initially suppress productivity by diverting resources to pollution control but ultimately drive innovation through risk transmission mechanisms [7]. Financially, green policies promote TFP by channeling capital to clean industries, yet risk stagnation when non-polluting firms engage in greenwashing or polluters face prohibitive transition costs [8-9]. These insights underscore the need to reconcile short-term compliance burdens with long-term adaptive capacities—a gap this study addresses through dynamic policy-effect analyses.

This research makes three key contributions. First, by applying a multi-time point difference in difference (DID) model, it analyzes the time-varying effects of the GFRIPZ policy through dynamic mechanism identification. Second, the research demonstrates both theoretically and empirically the two-way interaction between policy constraints and firm adaptive behavior, offering fresh evidence on the dialectical relationship between policy rigidity and market elasticity in transitional economies. Third, methodologically, it enhances causal inference by combining multi-time point DID with event study analysis, capturing both cumulative policy effects and immediate impacts, thus overcoming limitations of traditional single period DID methods.

2. Theoretical Mechanisms and Research Hypotheses

2.1. Impact of Green Finance Policies on Firm TFP

Total factor productivity, as a pivotal metric of resource allocation efficiency, encapsulates the dual effects of green finance policies: incentivizing innovation through structural reforms while imposing transitional costs.

Green finance policies reshape financing constraints by ameliorating capital accessibility for clean-tech firms and coercing high-pollution firms toward green innovation, thereby strengthening R&D-productivity linkages [10-11]. Within the Porter Hypothesis framework, these policies internalize environmental costs into technological upgrading, substituting carbon-intensive assets with clean alternatives to enhance resource productivity [12].

Conversely, rigid compliance mandates divert resources from productive R&D to end-of-pipe pollution control, inducing temporary innovation-output decoupling [13]. Tightened credit constraints exacerbate liquidity stress in industries with protracted technology substitution cycles, where transition friction suppresses short-term TFP. Structural rigidities such as information asymmetrical and agency problems further distort outcomes.

Synthesizing these mechanisms, this research posits that green finance policies exhibit a net inhibitory effect on TFP in their nascent phase, dominated by capital reallocation costs and structural inertia. Thus, the hypothesis is advanced:

H1: The establishment of the GFRIPZ inhibits firm TFP.

2.2. Heterogeneous Effects of Green Finance Policies on Firm TFP

The GFRIPZ policy’s TFP impacts diverge across firm size and governance structures. Large-scale firms face structural rigidities: heavy-asset models entrench carbon-intensive technologies via sunk costs and low reversibility, necessitating capital-intensive retrofits that crowd out R&D and suppress productivity. In contrast, SMEs leverage organizational agility and light-asset flexibility to adopt incremental green upgrades at lower costs, achieving policy-innovation synergies through targeted subsidies[14]. Financing constraint heterogeneity amplifies disparities—large firms endure liquidity stress from rigid green investment demands, while SMEs adaptively reallocate resources.

Institutional investor ownership introduces governance-driven heterogeneity. Firms with high institutional ownership prioritize short-term metrics under quarterly performance pressures, diverting capital from high-risk green innovations to compliance-focused projects. This short-termism dilutes R&D efficiency despite enhanced oversight[15]. Green investment uncertainties further skew resource allocation toward “quick-win” initiatives over productivity-enhancing breakthroughs. These mechanisms yield two hypotheses:

H2: The GFRIPZ exerts stronger TFP suppression on large-scale firms than SMEs.

H3: The GFRIPZ imposes more pronounced TFP suppression on firms with high institutional ownership.

3. Research Design

3.1. Model setting

To examine the causal effects of the GFRIPZ policy on firm TFP, this research leverages the staggered implementation of GFRIPZ in China as an exogenous policy shock. Using a multi-time point DID framework, this research divides the sample into pilot and non-pilot cities, effectively addressing endogeneity issues and enabling precise identification of the policy's impact.

$$lnTFP_{it} = \beta_0 + \beta_1 Policy_{it} + \gamma X_{it} + v_i + f_t + \varepsilon_{it} \quad (1)$$

Where $lnTFP_{it}$ denotes the natural logarithm of TFP for firm *i* in year t. $Policy_{it}$ is a binary variable equal to 1 if firm i is located in a green finance pilot zone during the policy implementation period, and 0 otherwise. X_{it} includes firm-level control variables. v_i captures time-invariant firm fixed effects. f_t controls for year fixed effects. ε_{it} represents idiosyncratic errors.

3.2. Sample Selection

The analysis employs a panel dataset of Chinese A-share listed firms spanning from 2010 to 2022, with financial and firm-level data sourced from the Wind and CSMAR databases. To ensure empirical robustness, this research excluded firms under special treatment (ST), delisting risk alert (*ST), or particular transfer (PT) due to abnormal financial conditions that may bias estimation results and deleted the observations of the financial industry to avoid the characteristics of specific industries. Furthermore, firms with a debt-to-asset ratio exceeding 1 were excluded.

3.3. Variable Definitions

TFP, as the dependent variable, is commonly estimated using methods such as the OP (Olley-Pakes) and LP (Levinsohn-Petrin) approaches. Compared to OP, the LP method introduces critical methodological improvements: by using intermediate inputs rather than physical investment as proxies for unobserved productivity shocks, LP avoids OP’s restrictive assumption of strictly positive investment, thereby minimizing sample attrition and enhancing estimator reliability. Additionally, LP partially addresses endogeneity concerns in production function estimation through strategic use of intermediate inputs, yielding more accurate TFP measures.

This research employs the LP semi-parametric estimator to measure TFP. Building on the Cobb-Douglas production function, LP incorporates intermediate inputs as proxies for unobserved productivity shocks.

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \omega_{it} + \varepsilon_{it} \quad (2)$$

Where y_{it} is the logarithm of total output, k_{it} represents capital input, l_{it} denotes labor input, m_{it} captures intermediate inputs, ε_{it} is the random error term, and ω_{it} reflects time-varying productivity shocks influencing contemporaneous factor allocation decisions. Following Levinsohn and Petrin’s two-step estimation procedure, TFP is calculated as:

$$TFP_{it} = y_{it} - \beta_0 - \beta_1 k_{it} - \beta_2 l_{it} - \beta_3 m_{it} \quad (3)$$

The core explanatory variable $Policy_{it}$ is a binary indicator equal to 1 if firm *i* operates in a green finance pilot zone during policy implementation year *t*, and 0 otherwise.

Control variables include Return on Assets (ROA), Revenue Growth Rate (Growth), Tobin’s Q (TobinQ), Total Assets (lnSize), Employees (lnEmployee), Firm Age (lnFirmAge), Listing Age (lnListAge), Fixed Asset Ratio (Fixed), Tangible Asset Ratio (TAR), Intangible Asset Ratio (IAR), and Price-to-Book Ratio (lnPB). Table 1 presents the descriptive statistics of variables included in the baseline model following preprocessing.

Table 1. Descriptive statistics for the main variables

Variable	Count	Mean	SD	Min	Max
lnTFP	32869	2.12	0.13	1.30	2.58
$Policy_{it}$	32869	0.03	0.17	0.00	1.00
ROA	32869	0.04	0.08	-3.99	0.97
Growth	32869	1.24	58.98	-29.48	9290.91
TobinQ	32869	2.11	2.03	0.64	122.19
lnSize	32869	3.10	0.06	2.87	3.35
lnEmployee	32869	2.03	0.17	0.79	2.58
lnFirmAge	32869	1.07	0.12	-0.37	1.46
lnListAge	32869	0.69	0.45	-0.37	1.25
lnPB	32869	0.99	0.73	-2.23	7.25
Fixed	32869	0.21	0.16	0.00	0.97
TAR	32869	0.93	0.09	0.11	1.00
IAR	32869	0.05	0.06	0.00	0.89

4. Empirical Results

4.1. Benchmark Results

Table 2 presents the effects of the GFRIPZ policy on firm TFP, with group (1) displaying the baseline regression. All specifications control firm fixed effects and year fixed effects. Group (1) excludes control variables, while Group (2) includes them. The policy variable $Policy_{it}$ yields a statistically significant negative coefficient in both specifications, with minor magnitude variations, indicating that the establishment of GFRIPZ significantly suppresses firm TFP.

Table 2. Benchmark results.

Variable	(1) *lnTFP*	(2) *lnTFP*
$Policy_{it}$	-0.0078*** (0.0030)	-0.0111*** (0.0023)
Controls	NO	YES
Year FE	YES	YES
Firm FE	YES	YES
N	32869	32869
R^2	0.234	0.551

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.2. Parallel Trends Test

A critical condition for valid DID estimation is the parallel trends assumption, which requires treatment and control groups to exhibit similar pre-policy TFP trajectories. To validate this, this research employs an event study approach by constructing relative-year dummy variables centered on the first pilot zone establishment year (2017). The model is specified as:

$$lnTFP_{it} = \alpha + \sum_{k=-9}^{5} \beta_k Policy_{it}^{k} + \gamma X_{it} + v_i + f_t + \varepsilon_{it} \tag{4}$$

Where $Policy_{it}^{k}$ represents year-specific dummies relative to 2017, and β_k captures dynamic policy effects.

The results of the dynamic effects test are presented in Figure 1. Prior to policy implementation, no significant differences were observed in the trends of TFP between the treatment and control groups. Specifically, point estimates fluctuated slightly around zero, and 95% confidence intervals consistently included zero, meeting the parallel trends assumption of the DID model. In the policy implementation year (2017), the point estimate remained close to zero but did not attain statistical significance, indicating the lack of immediate policy effects. Two years after policy implementation, significant dynamic effects emerged: estimated coefficients demonstrated a sustained decline, with 95% confidence intervals fully excluding zero. This evidence confirms that the inhibitory effect of the GFRIPZ policy on firm TFP gradually intensified. From the fourth to the fifth year after policy implementation, the negative effect coefficients stabilized, indicating that the inhibitory effect of the GFRIPZ policy on firm TFP has stabilized.

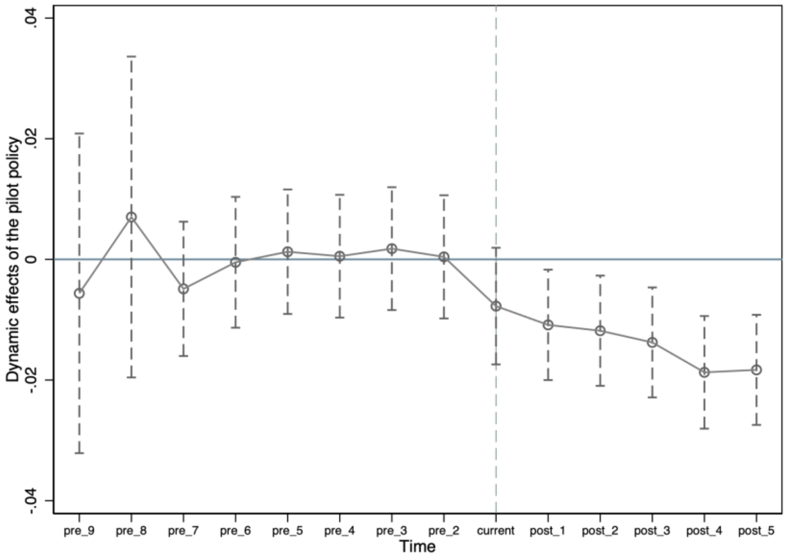

Fig 1. The diagram of parallel trend test.

4.3. Robustness Checks

4.3.1. Goodman-Bacon Decomposition

The multi-time point implementation of the GFRIPZ policy may introduce estimation bias in the DID model. To validate the reliability of model specification, this research applies to the Goodman-Bacon decomposition method to decompose the multi-time point DID estimators. As shown in Table 3, the core comparison group “treated vs. untreated” contributes the dominant weight, with its estimated coefficient directionally consistent with the baseline regression and constituting the primary source of the net policy effect. The bad weights are only 0.002, indicating that the actual impact of bias issues remains limited.

Given the dominant contribution of core groups and the uniform directional consistency of all group effects with the policy's inhibitory effect in the baseline regression, the estimation results of the multi-time point DID model remain free from significant interference by implementation timing differences. Consequently, the baseline regression conclusions exhibit robust reliability, affirming the methodological validity of the DID framework employed.

Table 3. Decomposition results.

Treated group vs Control group	Weight	Coefficient
Treated group vs Never-treated group	0.985	-0.009
Treated group vs Already-treated group	0.010	-0.011
Early treated group vs Late treated group	0.003	-0.025
Late treated group vs Early treated group	0.002	-0.007

4.3.2. Two-Stage DID Model Estimation

In the context of heterogeneous treatment effects, the two-way fixed effects model (TWFE) estimator may produce estimation bias. To address this challenge, a two-stage DID approach is adopted: first identifying group and time effects and then removing these effects before parameter estimation. Based on this framework, this study employs heterogeneity-robust estimators to further analyze dynamic treatment effects and constructs event study plots, as shown in Figure 2. Empirically, no treatment effects are observed prior to policy implementation, whereas firm TFP exhibits a significant downward trend in the years following policy implementation. These results validate the inhibitory effect of GFRIPZ policy on TFP, with heterogeneous treatment effects demonstrating no substantial interference with the reliability of this core conclusion.

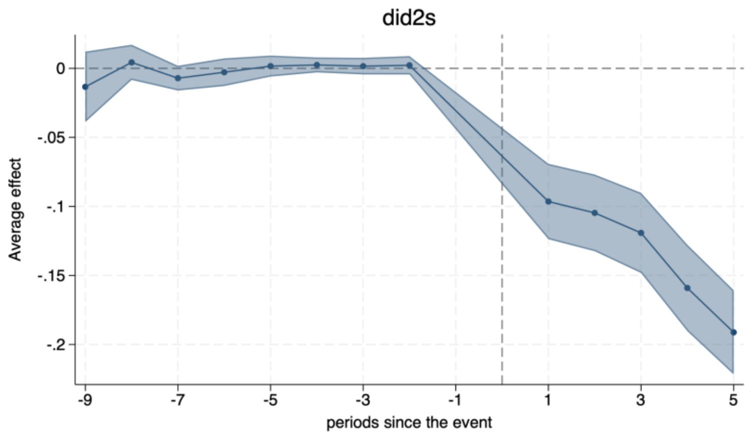

Fig 2. Robust estimators under heterogeneous treatment effect.

4.3.3. Placebo test

In order to exclude the influence of unobserved omitted variables and ensure that the change in firm TFP is attributable to the green finance policy, this research conducts a placebo test to determine whether this effect is spurious. As shown in Figure 3, the average of the estimated coefficients is close to zero, and this average is substantially larger in magnitude than the benchmark coefficient of -0.0111. The distribution of the coefficients is closer to a normal distribution. The above analysis indicates that the placebo test in this paper has passed, verifying the robustness of the benchmark regression results.

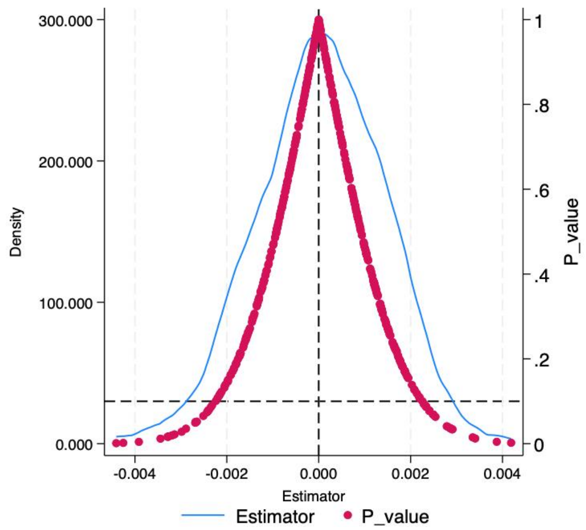

Fig 3. The diagram of placebo test.

4.4. Heterogeneity Analysis

4.4.1. Firm size

This research classifies firms into “large-scale” (total assets above the median) and “small-scale” (total assets below or equal to the median) groups using the sample median. Group (1)-(2) of Table 4 show that $Policy_{it}$ significantly suppresses TFP for large-scale firms at the 1% level but not for small-scale firms. A Fisher test confirms significant inter-group differences at the 10% level. This divergence arises from large firms' asset specificity and adjustment cost rigidity. Dynamically, small firms take advantage of organizational agility to cushion the blow through business pivots or technology substitution, while larger companies face severe short-term cost pressures due to asset illiquidity. These findings validate the "scale-vulnerability" hypothesis in environmental regulation contexts.

Table 4. Heterogeneity Analysis.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Policy_{it}$	-0.0116***	-0.0038	-0.0129***	-0.0032	-0.0063**	-0.0099***
	(0.0028)	(0.0039)	(0.0030)	(0.0035)	(0.0030)	(0.0033)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N	16438	16431	16434	16435	12120	20749
R^2	0.490	0.415	0.516	0.525	0.527	0.570
p-value	0.072*		0.008***		0.397	

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; Bootstrap p-values (1000 replications) test the significance of inter-group coefficient differences for $Policy_{it}$.

4.4.2. Governance structure

This research divides firms into "high institutional ownership" (above the median) and "low institutional ownership" (below or equal to the median) groups based on institutional investor ownership. Group (3)-(4) in Table 4 show that at the 1% level, TFP of high-ownership firms is significantly suppressed, while TFP of low-ownership firms is not suppressed, and a Fisher test confirms the difference between groups. This stems from the short-term performance pressure of institutional investors: they prioritize quarterly returns and incentivize risk-averse behavior over long-term green investments, forcing companies to spend less on innovation. As a result, institutional governance is a "double-edged sword" in the face of increased regulatory compliance oversight, while also impeding strategic innovation commitments.

4.4.3. Ownership type

This research constructs a binary variable *SOE* (1 = state-owned enterprise, 0 otherwise). Group (5)-(6) of Table 4 show that the GFRIPZ policy significantly suppresses TFP for both state-owned and non-state-owned enterprises, with no statistically significant difference between the two ownership groups (Fisher test p-value > 0.1). This uniform effect arises from two interacting mechanisms. First, the GFRIPZ policy imposes standardized compliance costs through environmental regulation and financing constraints channels, necessitating costly equipment upgrades and technological transitions regardless of ownership structure. Second, offsetting dynamics emerge: while state-owned enterprises benefit from preferential financing access, however, these advantages are counterbalanced by mandatory social obligations such as employment guarantees and public service provision. In contrast, non-state-owned enterprises partially mitigate policy shocks through operational agility and market-responsive strategies, despite facing tighter credit constraints.

5. Further Analysis

Building on the finding that GFRIPZ policy initially suppresses TFP, this research delves into the temporal dynamics of this effect through Porter's Hypothesis, which argues that regulatory pressure induces adaptive innovation. While the early-stage compliance costs divert resources to end-of-pipe pollution control and crowd out productive R&D, a critical question arises: The tension between regulatory compliance and productivity sustainability emerges as a challenge.

This research proposes a "constraint-compensation" pathway: as firms adapt to policy pressures, they increasingly reallocate resources toward low-carbon technology innovation and carbon performance improvement, potentially mitigating the initial TFP decline. To empirically reveal this mechanism, this research focuses on two key mediating channels: R&D investment and carbon performance, and takes them as mediating variables to test this through a three-step mediating framework: (i) Estimate total policy effects on TFP using the baseline model; (ii) Examine policy impacts on mediating variables; (iii) Decompose direct/indirect effects via integrated models with Sobel tests. The models are specified as:

$$lnTFP_{it} = \beta_0 + \beta_1 M_{it} + \gamma X_{it} + v_i + f_t + \varepsilon_{it} \tag{5}$$

$$M_{it} = \beta_0 + \beta_2 Policy_{it} + \gamma X_{it} + v_i + f_t + \varepsilon_{it} \tag{6}$$

$$lnTFP_{it} = \beta_0 + \beta_3 Policy_{it} + \beta_4 M_{it} + \gamma X_{it} + v_i + f_t + \varepsilon_{it} \tag{7}$$

Where M_{it} denotes the mediator. Partial mediation is confirmed if β_1, β_2, β_3, β_4 are significant and Sobel tests reject the null hypothesis.

5.1. R&D Investment

R&D investment is a direct representation of innovation capability and represents capital investment in technological innovation and knowledge accumulation in a firm, which is usually measured by annual R&D expenditure. Group (1)-(3) in Table 5 show significant coefficients and Sobel test results significant at the 5% level, confirming partial mediation. The GFRIPZ policy increases R&D intensity, and resulting technological innovation positively impacts TFP. This validates the adjustment logic where the policy incentivizes R&D-driven compliance cost offsetting via green technology financing facilitation. From the dynamic perspective, the “J-curve effect” of R&D investment explains the late attenuation of policy effects: Although resources are squeezed in the short term, its technological dividends are gradually released in the long term.

5.2. Carbon Performance

Carbon performance refers to the economic value created by the unit carbon emission in the production and operation activities of the firm, which reflects the carbon emission intensity and resource conversion efficiency of firms. Group (4)-(6) in Table 5 show significant coefficients and Sobel test results significant at the 10% level, supporting the theory of a partial mediation effect. This shows that firms can transform short-term compliance costs into long-term efficiency gains through carbon management optimization, confirming the equilibrium mechanism of “compliance cost-innovation compensation”.

Table 5. Mechanism analysis.

Variable	(1) *lnTFP*	(2) *M1*	(3) *lnTFP*	(4) *lnTFP*	(5) *M2*	(6) *lnTFP*
$Policy_{it}$	-0.0113*** (0.0022)	0.537*** (0.1720)	-0.0114*** (0.0022)	-0.0128*** (0.0022)	0.0175* (0.0094)	-0.0129*** (0.0022)
M1			0.0002*** (0.0001)			
M2						0.0059*** (0.0015)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
N	32,244	32,244	32,244	25,281	25,281	25,281
R^2	0.554	0.194	0.554	0.595	0.871	0.595
Sobel Test		P=0.0333**			P=0.0968*	
Proportion		1.12%			1.09%	

Notes: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6. Conclusions

This research leverages the establishment of the GFRIPZ as a quasi-natural experiment, employing a multi-time point DID model and event study methodology to systematically examine the impacts of the GFRIPZ policy on firm total factor productivity. Key findings reveal that the GFRIPZ policy exerts a significant suppressive effect on firm TFP, with robustness validated across multiple sensitivity checks. Furthermore, the effects vary significantly across firm characteristics: large-scale firms and those with high institutional ownership experience disproportionately stronger suppression. These results are further contextualized by the mechanism analysis, which identifies R&D investment and carbon performance as partial mediators, highlighting dynamic interactions between policy constraints and firms' adaptive responses through innovation and carbon management. Based on these findings, this research proposes three policy recommendations:

First of all, differentiated policy designs should address scale and governance heterogeneities by implementing phased compliance transitions for large firms and firms with high institutional ownership. For large firms, this research proposes dedicated green transition funds targeting technological upgrade costs, while high-institutional-ownership firms should face stricter ESG disclosure requirements and pilot green governance credit systems linking carbon performance improvements to investor incentives.

Secondly, it is necessary to adopt fiscal incentive measures linked to carbon performance, including implementing progressive tax credits for enterprises with R&D intensity higher than the industry average and continuously improving carbon efficiency. Incorporating green technology patents into the carbon trading market and establishing regional technology diffusion platforms can further amplify the compensation effect of innovation.

Thirdly, dynamic policy optimization involves dual-dimensional audits for green credit, third-party evaluations for subsidized projects, and adaptive adjustments to balance regulatory stringency with firm adaptive capacities. These measures aim to steer short-term TFP suppression toward long-term innovation dividends by aligning policy design with firms' resource reconfiguration capabilities.

While this study provides empirical evidence on the GFRIPZ policy's productivity effects and adaptive mechanisms, several avenues warrant further exploration. Future research could extend the temporal scope to evaluate long-term innovation dividends beyond the current sample period, particularly as firms transition toward mature decarbonization strategies. Additionally, comparative analyses across heterogeneous policy contexts may refine the generalizability of constraint-compensation dynamics.

Acknowledgements

The author gratefully acknowledges the financial support from Innovation and Entrepreneurship Training Program for College Students of Southwest Minzu University funds.

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