

## Dual and Synergistic Roles of Environmental Regulation and Industrial Upgrading on Green Finance-GTFP Nexus in China

Zewen Song

Faculty of Economics, Chiang Mai University, Chiang Mai, 50200, Thailand

Author Email: [zewens1027@gmail.com](mailto:zewens1027@gmail.com)

**Abstract**— Green finance (GF) is pivotal for driving China's green transition, yet the complex interaction between environmental regulation (ER) and industrial upgrading (IU) in this process remains underexplored. Using balanced panel data from 232 Chinese cities (2010–2022), this study empirically investigates the impact of GF on Green Total Factor Productivity (GTFP) employing a two-way fixed model. The baseline results demonstrate that GF exerts a significant and robust positive impact on GTFP. Crucially, the mechanism analysis reveals a structural asymmetry in moderation: Industrial upgrading acts as a robust positive moderator, serving as a prerequisite for unlocking financial efficacy, whereas the linear moderating effect of environmental regulation is conditional and less pronounced. Further threshold analysis confirms a non-linear synergistic mechanism, indicating that the efficacy of environmental regulation is contingent upon specific matching intervals of industrial structure rather than simple linear superposition. These findings provide empirical evidence for coordinating "policy–finance–structure" mechanisms through non-linear threshold effects to optimize urban green productivity.

**Keywords:** Environmental Regulation, Green Finance, GTFP, Industrial Upgrading, Moderation Effect

---

### I. INTRODUCTION

Since initiating market-oriented reforms in 1978, China has experienced unprecedented economic expansion, transforming from an agrarian economy into the world's second-largest economy. However, this development trajectory, largely driven by energy-intensive industries and carbon-heavy production systems, has generated substantial ecological pressures, manifested in atmospheric pollution, declining ecosystem integrity, soil quality deterioration, and accelerating greenhouse gas emissions alongside mounting resource constraints (Liu, 2021). By 2012, China's energy consumption per unit of GDP was 1.8 times the global average, and emissions of major pollutants like sulfur dioxide and nitrogen oxides remained persistently high. These challenges have pushed environmental carrying capacity to its limits, rendering the traditional growth model unsustainable and underscoring the urgent need for a green economic transition. In 2020, China established "dual carbon" goals, targeting a peak in carbon emissions before 2030 and achieving carbon-neutral status by 2060 (Office of the National Climate Change Coordination Group, 2021). This reflects China's close attention to environmental protection and green transformation development.

Green Total Factor Productivity (GTFP) has emerged as a core indicator for assessing the quality of green growth, as it incorporates energy use and pollutant emissions as "undesirable outputs alongside economic outputs, offering a more comprehensive measure of sustainable economic performance (Development Research Center of the State Council, 2021). Green finance serves as a critical mechanism to direct capital toward environmentally sustainable projects and enterprises. By the end of 2024, China's green credit balance exceeded 36.6 trillion yuan (People's Bank of China, 2025). However, green finance faces an inner contradiction in driving the improvement of GTFP: the green transition urgently requires many green projects, yet these projects typically feature substantial investment scales, long return cycles, and low short-term economic benefits (Wang, 2023). This conflicts with the inherent nature of market capital, which pursues short-term returns and avoids risk. This mismatch creates a significant "green financing gap" and market failure (Sachs et al., 2019; Jing, 2024), rendering private capital insufficient to meet the massive funding demands of the transition (Polzin, 2017). Consequently, it may constrain the pace and effectiveness of GTFP improvement (Lee, 2022).

Therefore, exploring how to alleviate this contradiction through well-designed policy and market mechanisms has become crucial. In this context, environmental regulation and industrial upgrading are widely recognized as key drivers of green transformation (Sun, 2022; You, 2023; Shan, 2025). On the one hand, environmental regulation acts as a critical policy push, setting rules and standards that can compel capital to flow towards greener projects and compel firms to adopt cleaner

technologies and practices (Porter, 1995). On the other hand, industrial upgrading represents a market-driven pull, creating a more advanced economic structure that naturally absorbs and utilizes green finance more efficiently. However, these two factors do not always produce positive outcomes. Strict environmental rules can burden companies with high compliance costs, particularly hurting productivity in heavy-industry regions where firms struggle to meet new standards. Similarly, industrial upgrading can backfire when the economy shifts too quickly away from manufacturing without the service sector being ready to absorb displaced workers and resources, sometimes actually harming green productivity (Dai, 2022). These mixed results highlight why we need to look more carefully at how environmental regulation and industrial upgrading individually and jointly shape the effectiveness of green finance.

The transition toward green manufacturing is a structurally contingent process rather than a uniform pathway. First, the efficacy of green finance is not monolithic; the latest literature highlights its highly heterogeneous impacts under varying regional resource endowments and industrial structures (Zhang, 2023). Green financial instruments often yield divergent productivity outcomes depending on the existing industrial foundation. Yue et al. (2024) find that green finance significantly promotes industrial green total factor productivity, with the effect strengthening as city size and industrial upgrading level increase. Second, from the perspective of economic complexity, a region's capacity for industrial upgrading is fundamentally dictated by its accumulated productive knowledge and technological sophistication (Wang et al., 2023; IMF, 2024; Ruan, 2025). Regions with higher economic complexity possess superior absorptive capacities, enabling them to better internalize environmental regulations and convert green finance into substantive technological progress.

Building on these cutting-edge insights, this paper argues that the synergy between green finance, environmental regulation, and industrial upgrading cannot be accurately captured through simple linear assumptions. Instead, it must be evaluated through a non-linear threshold framework that accounts for economic complexity and structural heterogeneity.

This study introduces the concepts of dual moderation and threshold effects, using prefecture-level city data from 2010 to 2022 to enable a more granular and robust analysis. Furthermore, by placing green finance, environmental regulation, and industrial upgrading within a unified framework, this study seeks to uncover not only their individual moderating roles but also their dual and synergistic potential, providing policymakers with scientific evidence to design coordinated, regionally tailored policy packages.

In summary, this research is motivated by China's urgent need for a green transition, the regional imbalances in green finance and GTFP, and the underexplored synergistic roles of environmental regulation and industrial upgrading. It aims to answer the following questions: How does green finance affect GTFP at the city level? How do environmental regulations and industrial upgrading individually and jointly moderate this relationship? In addition, can the synergy among these three elements further amplify the promotional effect of green finance on GTFP?

## II. LITERATURE REVIEW

Empirical studies widely employ panel and spatial econometric methods to examine the effect of green finance on GTFP. Using panel data from 30 Chinese provinces (2006–2018), Zhang (2024) applied a two-way fixed effects (TWFE) model and found that green finance significantly enhances GTFP by stimulating green technological innovation, with stronger effects in more developed eastern regions. Yue (2024) also used TWFE, focusing on the industrial sector, and showed that green finance improves industrial GTFP, particularly in large cities. Therefore, we propose the following assumptions  $H_1$ : Green finance exerts a direct and persistent impact on GTFP, with higher levels of green finance correlating with higher GTFP.

Existing literature offers divergent views on the transmission mechanism of environmental regulation. Supporting the "Porter Hypothesis," studies generally agree that environmental regulation drives GTFP by accelerating industrial upgrading and fostering green innovation. Chen (2023) found that environmental regulation positively moderates the efficacy of green finance, strengthening the flow of funds toward industrial transformation and green technology adoption. However, the "Cost-Compliance Hypothesis" suggests potential trade-offs. Some scholars noted that while regulation offers long-term benefits, it inevitably raises compliance costs, which may crowd out productive investments and reduce efficiency in the short run. This implies that the moderating effect of environmental regulation is not monotonic; while moderate regulation incentivizes the efficient allocation of green finance, excessive regulatory burdens might dampen these benefits due to rising compliance costs.

There is no unified standard for measuring environmental regulation in the existing literature, and a variety of proxy indicators have been employed. Previous studies have approached this issue from different perspectives. Some scholars use pollution control investment per unit of output as a proxy to capture the intensity of environmental regulation (Cole, 2005; Gong, 2020;

Feng, 2021). Others measure environmental regulation based on the frequency of pollutant emissions reported by firms to regulatory authorities (Brunnermeier and Cohen, 2003). In addition, certain studies adopt the level of regulated pollutant emissions as an alternative indicator (Domazlicky, 2004).

Building on this literature, this study measures environmental regulation as the ratio of government pollution control investment to regional GDP. Although this indicator may not fully capture regulatory stringency, it effectively reflects the intensity of government intervention in environmental governance, particularly in the context of China's policy-driven environmental system. A higher ratio indicates greater financial resources allocated to pollution control and emission reduction during the process of industrial development, which is expected to play a more significant role in promoting regional green economic growth. Based on this theoretical tension, we propose the following hypothesis  $H_2$ : Environmental regulation positively moderates the impact of green finance on GTFP, but this moderating effect exhibits heterogeneity and may be constrained by compliance costs in highly regulated regions.

Industrial upgrading is a dynamic process centered on industrial structure transformation, specifically referring to the shift from low-value-added, low-tech, resource-intensive industries to high-value-added, high-tech, resource-efficient industries. This refers to the process of transformation from primary industry to secondary industry and ultimately to tertiary industry (Clark, 1940). Industrial upgrading plays a crucial role in enhancing GTFP, whether directly or indirectly. Sun (2022) showed that restructuring in the Yangtze River Economic Belt redirected resources from energy-intensive sectors toward technology-intensive and service-based industries, improving green efficiency. Qi (2025) emphasized industrial upgrading as a moderating variable. Optimized resource allocation and technology diffusion amplify green finance's impact on GTFP, with evidence of a threshold effect: once the tertiary sector's share surpasses a critical level, its marginal contribution to GTFP rises significantly. Referring to previous research (Jiang, 2023; Xie, 2025). This study measures industrial upgrading using the tertiary sector's value-added share of GDP, a concept aligned with China's national conditions. Therefore, we propose the following assumptions:  $H_3$ : Industrial upgrading positively moderates the effect of green finance on GTFP; specifically, the enhancing effect of green finance is more pronounced in regions with advanced industrial upgrading.

Human capital is often regarded as one of the key influencing factors (Cheng, 2022; Xiao, 2021). By enhancing educational attainment, workers' knowledge, skills, and productivity can be directly improved, thereby optimizing the allocation of labour resources and directly promoting GTFP growth. Urbanization rates also have effects on GTFP. The focus of new urbanization is on low-carbon, circular, and green urban development. Through policy guidance, it efficiently aggregates population, industries, and resources within cities (Wang, 2025). The effect on GTFP of opening is equally dual in nature, with its mechanism primarily manifested through technology spillover effects and scale effects. Theoretically, the impact of FDI on GTFP is theoretically contested between the "Pollution Haven Hypothesis," where relocating polluting operations suppresses green growth (Xiao, 2021), and the "Pollution Halo Hypothesis," where technology spillovers promote efficiency. Technological innovation promotes GTFP by applying more advanced clean technologies to directly reduce pollutant emissions and energy consumption during production processes (Wan, 2025). Given that the aforementioned variables exert direct influences on GTFP, we incorporate these five factors as control variables. This approach allows us to mitigate potential confounding effects and isolate the specific impact of green finance on GTFP.

Environmental regulations not only directly improve GTFP but also indirectly foster growth by catalyzing industrial upgrading and green innovation. Ye (2024) demonstrated that green finance and public environmental awareness can further amplify these effects, particularly in non-resource-based cities. Similarly, Xie et al. (2022) found that environmental regulation strengthens the pathway by which green finance drives clean industrial upgrading, highlighting the theoretical existence of a synergistic role among finance, regulation, and industrial transformation.

Although few studies have explicitly examined the joint effects of green finance, environmental regulation, and industrial upgrading on GTFP, existing evidence points to a "Policy-Finance-Structure" nexus. However, recent research emphasizes that this synergy rarely manifests as a simple linear interaction. Instead, it is predominantly revealed through non-linear threshold effects, where the moderating role of environmental regulation becomes significant only within specific intervals of industrial structure upgrading (Cui et al., 2025; Suo Luoman et al., 2025). For instance, Zheng et al. (2025) demonstrate that the coupling of technological and regulatory factors produces dynamic synergistic pathways that linear models often fail to detect. Therefore, this study conceptualizes synergy as threshold-dependent rather than linearly additive, and will test  $H_5$  accordingly through both triple interaction and threshold regression models.

Based on the theoretical framework above, we propose  $H_4$ : Environmental regulations and industrial upgrading can jointly moderate the effect of GF on GTFP, and the strength of this effect is greater than when they act individually, and  $H_5$ : Green

finance, environmental regulations, and industrial upgrading exhibit synergistic effects but are not characterized by a simple linear superposition, which can further amplify the promotion of GTFP.

### III. METHODOLOGY AND DATA

#### III.I. DATA SOURCE AND CALCULATION

This study investigates the impact of GF on GTFP and explores the moderating mechanisms of environmental regulation and industrial upgrading, using balanced panel data from 232 Chinese cities spanning the period 2010 to 2022. Table 1 systematically summarizes the definitions, calculation methods, and data sources for all variables employed in the empirical models, encompassing the dependent, core independent, moderating, and control variables. For conciseness and clarity, the specific abbreviations introduced in this table will be consistently used to represent their respective variables throughout the remainder of this paper.

**Table 1.** Variable Definitions and Calculating Method

Type	Name	Abbreviation	Calculation	Unit	Source of Data
Dependent Variable	Green Total Factor Productivity	GTFP	Super-SBM model	Index	China Environmental Statistical Yearbook, China City Statistical Yearbook
Core Independent Variable	Green Finance	GF	A comprehensive index constructed by the entropy method	Index	China Financial Yearbook, Province and Municipal Finance Statistics, Wind
Moderator Variable	Environmental Regulation	ER	Pollution control investment/GDP (both in 100 million yuan)	%	China Environmental Statistical Yearbook, China City Statistical Yearbook
Moderator Variable	Industrial Upgrading	IU	Tertiary industry value-added amount/ GDP (both in 100 million yuan)	%	China City Statistical Yearbook
Interaction Term	Green Finance × Environmental Regulation	GF×ER	Product of two variables	-	Calculated based on the above variables
	Green Finance × Industrial Upgrading	GF×IU		-	
	Environmental Regulation × Industrial Upgrading	ER×IU		-	
Three Interaction Terms	Three-way Synergistic Effect	GF×ER×IU	Product of three variables	-	
Control Variable	Human Capital	HC	Average years of education per capita	year	China Population and Employment Statistical Yearbook
	Urbanization Rate	UR	Urban population /total population (both in 10,000 persons)	%	China City Statistical Yearbook
	Openness	OP	Total import and export volume /GDP (both in 100 million yuan)	%	China Foreign Economic Statistical Yearbook
	Foreign Direct Investment	FDI	The actual foreign investment's natural logarithm	Ln (100 million yuan)	China Foreign Economic Statistical Yearbook
	Technology Innovation Level	TECH	R&D expenditure/ GDP (both in 100 million yuan)	%	China Science and Technology Statistical Yearbook

In this study, GF is measured by a comprehensive indicator constructed through the entropy method. Following the existing literature (Xu, 2022), we select six key indicators: green credit, green insurance, green bonds, green supports (fiscal environmental expenditure), green funds, and green rights (carbon trading and emission rights trading). To construct the Green

Finance (GF) index, the entropy weight method is employed. Before the weight calculation, all six sub-indicators are treated as positive variables and standardized using the Min-Max normalization method to eliminate dimensional discrepancies, expressed as  $X_{ij} = [x_{ij} - \min(x_{ij})] / [\max(x_{ij}) - \min(x_{ij})]$ . The entropy method is selected because it is a highly objective weighting technique that does not reduce the number of variables or lose underlying data information. Due to its objectivity and accuracy, this method has been widely applied in evaluating China's development level of GF. The calculation of indicators is detailed in Table 2. The entropy method is then applied as a highly objective weighting technique that assigns weights based on data dispersion, effectively capturing the comprehensive development level of green finance without subjective bias.

**Table 2.** GF Indicator System

Indicator	Calculation Method
Green Credits	Environmental Project Credit / Total Credits (both in 100 million yuan)
Green Insurance	Environmental Pollution Liability Insurance Revenue / Total Premium Income (both in 100 million yuan)
Green Bonds	Issuance Volume of Green Bond / Issuance Volume of Total Bond (both in 100 million yuan)
Green Support	Fiscal Expenditure of Environmental Protection / Total Fiscal Budget Expenditure (both in 100 million yuan)
Green Funds	Green Funds Market Value / Total Funds Market Value (both in 100 million yuan)
Green Rights	(Energy Consumption Rights Trading + Carbon Trading + Pollutant Emission Rights Trading) / Equity Market's Total Transactions. (both in 100 million yuan)

GTFP is an innovative efficiency indicator developed based on traditional TFP theory to meet the demands of global green development. It incorporates "undesirable inputs" (e.g., energy and resource consumption) and "undesirable outputs" (e.g., industrial pollutant emissions) into its evaluation framework. This study adopts the Super-SBM (Slacks-Based Measure) model, incorporating undesirable outputs, initially proposed by Tone (2001, 2002). The Super-SBM model utilizes a non-radial, non-oriented approach that accounts for slack and allows efficiency scores to exceed 1, thereby providing a more precise and comparable evaluation of green productivity. By integrating these input-output indicators into the Super-SBM model, we calculate the annual GTFP index for the 232 sample cities. The secondary indicators are detailed in Table 3.

**Table 3.** GTFP Index System

Type	Indicator	Indicator Definition	Unit
Input	Labor Input	Number of Employed Persons	persons
	Capital Input	Capital Stock	100 million yuan
	Energy and Resource Input	Energy Consumption	10,000 tons of standard coal
Industrial Water Use		100 million tons	
Desired Output	Economic Benefit	Industrial Added Value	100 million yuan
Undesired Output	Environmental Pollution	Industrial SO <sub>2</sub> Emissions	ton
		Industrial Wastewater Discharge	10,000 tons
		Industrial dust emissions	ton

### III.II. MODEL DESIGN

To empirically test the impact of GF on GTFP ( $H_1$ ), we construct a panel data regression model. Based on the results of the Hausman test, which strongly rejects the null hypothesis of random effects, we select the TWFE model as our baseline empirical specification. This approach effectively controls for unobserved, time-invariant city-specific characteristics as well as macroeconomic shocks common to all cities over time, thereby mitigating potential omitted variable bias. The baseline econometric model is specified as follows:

$$GTFP_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where the subscripts  $i$  and  $t$  denote the city and the year, respectively. GTFP represents the Green Total Factor Productivity of city  $i$  in year  $t$ . It  $GF_{it}$  is the core explanatory variable, denoting the development level of green finance.  $X_{it}$  represents the vector of control variables, including  $HC$ ,  $UR$ ,  $OP$ ,  $LnFDI$ , and  $TECH$ .  $\beta_0$  is the constant term,  $\mu_i$  denotes the city fixed effects,  $\lambda_t$  denotes the year fixed effects,  $\varepsilon_{it}$  represents the random error term.

To further investigate the moderating mechanisms and empirically test Hypotheses  $H_2$  through  $H_5$ , we extend the baseline model to construct four moderation models. These models are designed to sequentially examine how ER and IU individually moderate the GF-GTFP relationship, how they jointly operate (to test for potential asymmetry), and whether a synergistic effect exists among the three variables.

First, to test the individual moderating effects of ER ( $H_2$ ) and IU ( $H_3$ ), we introduce their respective interaction terms with GF into the baseline equation:

$$GTFP_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 ER_{it} + \beta_3 (GF_{it} \times ER_{it}) + \beta_4 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$GTFP_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 IU_{it} + \beta_3 (GF_{it} \times IU_{it}) + \beta_4 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Second, to explore the dual moderating mechanism and verify the asymmetrical effects posited in Hypothesis  $H_4$ , we incorporate both interaction terms simultaneously into a comprehensive model:

$$GTFP_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 ER_{it} + \beta_3 IU_{it} + \beta_4 (GF_{it} \times ER_{it}) + \beta_5 (GF_{it} \times IU_{it}) + \beta_6 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

Finally, to test the potential synergistic mechanism among green finance, environmental regulation, and industrial upgrading ( $H_5$ ), we construct a triple interaction model. This includes the three-way interaction term alongside all necessary lower-order interactions:

$$GTFP_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 ER_{it} + \beta_3 IU_{it} + \beta_4 (GF_{it} \times ER_{it}) + \beta_5 (GF_{it} \times IU_{it}) + \beta_6 (ER_{it} \times IU_{it}) + \beta_7 (GF_{it} \times ER_{it} \times IU_{it}) + \beta_8 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

The research path of this paper is shown in Figure 1.

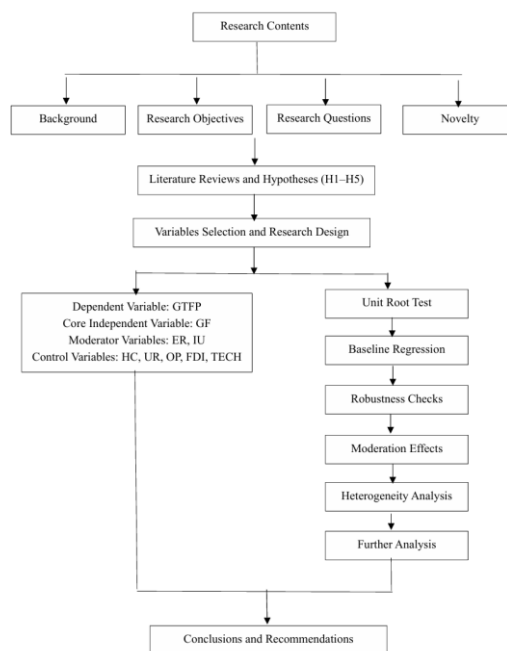


Figure1. Conceptual Framework

## IV. EMPIRICAL RESULTS AND ANALYSIS

### IV.I. DESCRIPTIVE STATISTICS

Table 4. Descriptive Statistics

	Observations	Mean	Std.Dev	Min	Max	Median
GTFP	3016	0.3491	0.1416	0.1086	1.177	0.3206
GF	3016	0.3357	0.1064	0.0608	0.6575	0.3545
ER	3016	0.9676	0.3939	0	11	0.9131
IU	3016	2.3081	0.1448	1.8312	2.8359	2.3016
HC	3016	9.1787	0.8319	6.55	12.31	9.0545
UR	3016	0.5639	0.1543	0.1806	1	0.544
OP	3016	0.2220	0.3562	0	3.6587	0.1009
LnFDI	3016	11.8815	2.0783	3.0084	16.8347	12.0595
TECH	3016	0.018	0.0184	0.0006	0.2068	0.0121

Table 4 presents the descriptive statistics of the main variables. The sample comprises a total of 3,016 city-year observations. The mean value of GTFP is 0.349, with a standard deviation of 0.142, indicating a certain degree of variation in GTFP levels across different cities and time periods. The average value of GF is 0.336, reflecting noticeable disparities in the development level of green finance across cities. ER spans a wide range, with a minimum of 0 and a maximum of 11, illustrating significant heterogeneity in the intensity of environmental regulations among different regions. In contrast, the IU index exhibits relatively low volatility, suggesting that the transformation of China's urban industrial structure is a long-term and steady evolutionary process. Regarding the control variables, HC, UR, OP, FDI, and TECH all demonstrate reasonable distributions without significant outliers. Overall, the variables exhibit sufficient variation, supplying a strong database for the economic regression analysis that follows.

### IV.II. UNIT ROOT TEST

Table 5. Unit Root Test

	CADF (Level)	CADF (1st Diff)	CIPS (Level)	CIPS (1st Diff)
GTFP	-0.409	-5.773***	-1.739	-2.123***
GF	-8.926***	-14.815***	-2.349***	-2.77***
ER	-3.728***	-10.748***	-1.977***	-2.479***
IU	-3.305***	-5.089***	-1.947***	-2.074***
HC	52.947	-27.227***	1.609	-3.658***
UR	11.170	-11.438***	-1.436	-2.529***
OP	3.671	-16.308***	-1.447	-2.877***
LnFDI	-6.442***	-11.306***	-2.171***	-2.519***
TECH	3.161	-4.830***	-1.484	-2.056***

Notes: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively. A linear trend and adjusted lag lengths are applied to demographic variables (HC, UR) to control for their monotonic growth.

To avoid spurious regression, we employ Pesaran's (2007) CIPS and CADF tests to examine variable stationarity, which effectively account for cross-sectional dependence. As shown in Table 5, while some variables (e.g., GF, ER, and IU) are stationary at their levels, others are not. However, after first-differencing, the test statistics for all variables become highly

significant at the 1% level ( $p < 0.01$ ). This confirms that all variables are either  $I(0)$  or  $I(1)$ , fully satisfying the prerequisites for panel estimation.

### IV.III. CORRELATION ANALYSIS

**Table 6.** Correlation Analysis

	GTFP	GF	ER	IU	HC	UR	OP	LnFDI	TECH
GTFP	1								
GF	0.278***	1							
ER	-0.013	-0.004	1						
IU	0.262***	0.330***	0.040**	1					
HC	0.244***	0.267***	-0.030*	0.654***	1				
UR	0.267***	0.280***	-0.013	0.662***	0.784***	1			
OP	0.181***	0.207***	-0.111***	0.323***	0.351***	0.405***	1		
LnFDI	0.272***	0.133***	-0.113***	0.477***	0.534***	0.460***	0.343***	1	
TECH	0.205***	0.179***	-0.065***	0.492***	0.446***	0.512***	0.393***	0.538***	1

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively.

Table 6 presents the pairwise correlation coefficients for the study variables. Notably, the correlation coefficient between GF and GTFP is 0.278, which is statistically significant at the 1% level. This positive association suggests that the development of green finance is linked to improvements in GTFP, providing preliminary empirical evidence to justify subsequent causal inference.

All control variables exhibit significant positive correlations with GTFP, consistent with theoretical expectations, which validates the rationality of the variable selection. Specifically, IU optimizes resource allocation efficiency, thereby exerting a positive influence on GTFP. The weak correlation between ER and GTFP (-0.013) suggests a potential non-linear relationship or indicates that ER may primarily function as a moderator rather than a direct driver.

Although significant correlations exist among some variables, the absolute values of the vast majority of coefficients are below 0.6, with the highest value observed only between Human Capital and Urbanization (0.784). To further rule out potential multicollinearity, we conducted the Variance Inflation Factor (VIF) test. The results shown in Table 7 indicate that the maximum VIF value is 3.13 for UR, and the mean VIF is 1.91. Since all values are well below the threshold of 5, this confirms that there is no serious multicollinearity among the selected variables, ensuring the reliability of the regression results.

**Table 7.** Multicollinearity Test

Variable	VIF	1/VIF
GF	1.15	0.8715024
ER	1.04	0.9650043
IU	2.17	0.4602769
HC	3.06	0.3264049
UR	3.13	0.3198256
OP	1.31	0.7649950
LnFDI	1.72	0.5798612
TECH	1.71	0.5846537
Mean VIF		1.91

## IV.IV. BASELINE REGRESSION

**Table 8.** Baseline Regression Results

Variables	Pooled OLS (1)	FE (without control) (2)	RE (without control) (3)	Pooled OLS (all controls) (4)	FE (twoways) (5)	RE (twoways) (6)
(Intercept)	0.225*** (0.008)		0.233*** (0.017)	-0.011 (0.050)		-0.186* (0.080)
GF	0.369*** (0.023)	0.156* (0.069)	0.347*** (0.045)	0.280*** (0.024)	0.259*** (0.059)	0.307*** (0.044)
ER				0.003 (0.006)	0.007 (0.005)	0.006 (0.005)
IU				0.048* (0.024)	0.059 (0.034)	0.076* (0.031)
HC				-0.006 (0.005)	0.046** (0.015)	0.012 (0.009)
UR				0.102*** (0.027)	0.104** (0.037)	0.114*** (0.034)
OP				0.012 (0.008)	-0.044** (0.014)	-0.033** (0.011)
LnFDI				0.013*** (0.002)	0.006** (0.002)	0.007*** (0.002)
TECH				-0.063 (0.170)	0.240 (0.178)	0.251 (0.169)
Num.Obs.	3016	3016	3016	3016	3016	3016
R <sup>2</sup>	0.077	0.002	0.020	0.146	0.109	0.104

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively.

Table 8 presents the baseline regression results on the impact of GF on GTFP using Pooled OLS, Fixed Effects (FE), and Random Effects (RE) models. Columns (1)-(3) include only GF as the core explanatory variable across the three models. Columns (4)-(6) add control variables to address potential omitted variable bias. The Hausman test (Chi-square = 143.19,  $p < 0.01$ ) strongly rejects the null hypothesis, indicating a correlation between unobserved individual effects and explanatory variables. This confirms that the FE model yields more consistent estimates than the RE model. Accordingly, we adopt the Two-Way Fixed Effects specification (Column 5) as our baseline.

The regression results indicate that GF exerts a significant positive impact across all model specifications. In the Two-Way Fixed Effects model, the coefficient of GF is 0.259, significant at the 1% level, suggesting that the improvement in GF development levels significantly promotes GTFP. This finding remains highly stable across different specifications, confirming the direct and persistent nature of the impact. Green finance enhances resource allocation efficiency and green production efficiency by channeling funds toward green technologies and eco-friendly industries, alleviating financing constraints for green innovation, and reducing corporate green investment costs. Thus, Hypothesis  $H_1$  is supported.

Regarding control variables, HC is significantly positive in the FE model, indicating that a high-quality workforce facilitates the absorption of green technologies and the diffusion of eco-friendly production methods. The coefficient for UR is 0.104 and significantly positive at the 1% level, suggesting that urbanization generates positive agglomeration effects and improves factor mobility efficiency, thereby fostering GTFP growth. FDI also exhibits a significant positive effect, supporting the "Pollution Halo Hypothesis," where foreign investment drives green productivity through technology spillovers and advanced management practices.

Notably, the coefficient for OP is -0.044 and significantly negative. This implies that during the sample period, scale effects exert a suppressing influence (Zhang, 2021), as expanding trade inevitably increases production, potentially leading to higher energy consumption and pollution emissions, and finally inhibiting GTFP growth. The coefficient for TECH did not reach statistical significance, possibly due to the long gestation period characteristic of R&D investments. Current innovation inputs may not immediately translate into concurrent productivity gains, often requiring several years to materialize.

Regarding ER and IU, although their coefficients are positive in the baseline linear model, neither passed the statistical significance test. This suggests that within a singular linear framework, these factors may not constitute independent direct drivers of GTFP. Instead, consistent with existing literature (Qi, 2025; Liu, 2024), they likely function more as mechanism variables or boundary conditions. Consequently, it is necessary to conduct subsequent analyses on moderating effects and heterogeneity.

## IV.V. ROBUSTNESS CHECKS

### IV.V.I. ROBUSTNESS CHECK I: ROBUST STANDARD ERRORS

Table 9. Robust Standard Errors

	Dependent variable: GTFP				
	Baseline	Coefficient test			
		White SE	City Cluster	Two-way	Driscoll-
	(1)	(2)	(3)	(4)	(5)
GF	0.259*** (0.059)	0.259*** (0.090)	0.259*** (0.090)	0.259*** (0.092)	0.259*** (0.065)
CONTROLS	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,016				
R <sup>2</sup>	0.109				
F-Statistic	42.448*** (df = 8; 2776)				

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively; Standard error is in parentheses.

In panel data analysis, issues such as heteroscedasticity, within-city serial correlation, and cross-sectional dependence can lead to biased standard errors, thereby compromising the validity of statistical inference. To address this, we re-estimated the baseline model using four different standard error specifications: White's heteroscedasticity-consistent standard errors, city-level clustered standard errors, two-way (city and year) clustered standard errors, and Driscoll-Kraay standard errors, which account for cross-sectional dependence, as shown in Table 9. Across all specifications, the coefficient of GF remains positive and statistically significant at the 1% level. The consistency of the estimation results indicates that the significance of our core findings is not driven by specific assumptions regarding the error structure. Furthermore, it demonstrates that the baseline results remain robust against potential heteroscedasticity and autocorrelation."

### IV.V.II. ROBUSTNESS CHECK II: BOOTSTRAP ESTIMATION

To further verify that the baseline results are not driven by sampling randomness or specific distributional assumptions, we employed the Bootstrap resampling method. We conducted 500 random replications with replacement. The results indicate that the mean coefficient of GF (0.256) is highly consistent with the baseline estimate, and the 95% confidence interval [0.126, 0.396] does not include zero. This confirms that the positive impact of GF on GTFP represents a systematic relationship rather than a coincidental result of random noise within a specific sample, thereby further validating the stability of the estimation.

### IV.V.III. ROBUSTNESS CHECK III: LAG VARIABLES AND DYNAMIC SPECIFICATIONS

Table 10. Lag Variables and Dynamic Models

Dependent variable: GTFP	
--------------------------	--

	Baseline (1)	Lagged GF (2)	Dynamic Panel (3)
GTFP_lag1			0.403*** (0.014)
GF	0.259*** (0.059)		0.196*** (0.052)
GF_lag1		0.149*** (0.037)	
CONTROLS	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	3,016	3015	3015
$R^2$	0.109	0.107	0.303
F-Statistic	42.448*** ( $df=8; 2776$ )	41.582*** ( $df=8;$	133.888*** ( $df=9; 2774$ )

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively. Standard error is in parentheses.

To further address potential endogeneity concerns arising from reverse causality and to capture the dynamic persistence of productivity, this study employs two alternative specifications: introducing lagged explanatory variables and estimating a dynamic panel model, as shown in Table 10.

First, we replace the current Green Finance variable GF with its one-period lag (GF\_lag1). This approach is commonly used in the literature as a practical solution when valid external instruments are difficult to obtain (Wooldridge, 2010). Since current GTFP levels cannot logically influence past financial investments (GF\_lag1), this temporal precedence helps mitigate potential reverse causality bias. The results in Column (2) show that the coefficient remains significantly positive (0.149 with  $p < 0.01$ ), confirming that the positive impact of green finance is not driven by simultaneity bias.

Second, we augment the baseline model by including the one-period lagged dependent variable (GTFP\_lag1) to construct a dynamic panel specification. The coefficient of GTFP\_lag1 is 0.403 and highly significant, indicating strong path dependence and confirming the dynamic nature of productivity accumulation. Even after controlling for this inertia, the impact of GF remains significantly positive. The results from these dynamic panels and lagged specifications demonstrate that even when accounting for the historical path dependence of GTFP, green finance continues to exert a significant positive influence. Overall, although endogeneity concerns cannot be eliminated, the consistency of results across multiple specifications suggests that the estimated relationship reflects a stable and systematic effect rather than spurious correlation. This evidence reinforces the direct and persistent nature of the relationship initially observed in the baseline regression, providing robust empirical support for Hypothesis  $H_1$ .

## IV.VI. MODERATION EFFECT

To validate the earlier conjecture that ER and IU function not merely as background factors but may actively moderate the efficacy of GF, this section introduces the moderation effect models. We examine the individual and joint moderating effects of ER and IU, and further explore the three-way interaction among GF, ER, and IU.

First, we introduce the interaction term for ER. The coefficient is 0.060 and significant at the 5% level, which indicates: On average, stricter environmental regulation facilitates Green Finance in unlocking greater GTFP dividends, although the magnitude of this effect is relatively modest. Meanwhile, the main effect of ER remains insignificant, suggesting that environmental regulation does not directly drive GTFP but primarily exerts its influence indirectly by reinforcing the impact of GF.

Next, we introduce the interaction term for IU. The results show that the interaction coefficient is positive and highly significant (1.881 with  $p < 0.01$ ). This implies that as the level of industrial upgrading increases, the promotional effect of Green Finance on GTFP is dramatically enhanced. This pattern highlights IU as a powerful enabler that unlocks the potential of green finance.

Subsequently, we include both interaction terms in the same model. The coefficient and significance of  $GF \times IU$  remain virtually unchanged (1.881,  $p < 0.01$ ), whereas the coefficient of  $GF \times ER$  drops substantially and loses statistical significance (0.037,  $p >$

0.10). This suggests that the moderating role of environmental regulation is far less robust than that of industrial upgrading. Once both interaction terms are considered simultaneously, the effect of ER is absorbed by IU, indicating that industrial upgrading dominates the moderating mechanism and renders the contribution of ER fragile and secondary. Therefore, *H4* is not supported. The joint moderating effect does not exceed the sum of individual effects; rather, IU subsumes the role of ER, suggesting a dominance relationship between the two moderators.

Finally, we introduce a triple interaction term to test for potential synergistic effects among GF, IU, and ER. The insignificant triple interaction (0.003) suggests that the coordination mechanism may not follow a simple linear superposition pattern. Given the rejection of the linear synergy, we further investigate whether a non-linear synergistic mechanism exists, which may be unveiled through a threshold model that accounts for structural breaks in the moderating roles.

**Table 11.** Moderation Effects

	Baseline (1)	ER Mod (2)	IU Mod (3)	Dual Mod (4)	Synergistic Effects (5)
GF	0.259*** (0.059)	0.197*** (0.070)	-4.284*** (0.438)	-4.288*** (0.438)	-4.400*** (0.773)
ER	0.007 (0.005)	-0.014 (0.013)	0.007 (0.004)	-0.004 (0.013)	0.142 (0.249)
IU	0.059* (0.034)	0.058* (0.034)	-0.483*** (0.062)	-0.479*** (0.062)	-0.417*** (0.117)
GF × ER		0.060* (0.037)		0.033 (0.036)	0.093 (0.689)
GF × IU			1.881*** (0.180)	1.869*** (0.180)	1.887*** (0.325)
ER × IU					-0.072 (0.109)
GF × ER × IU					0.003 (0.292)
CONTROLS	YES	YES	YES	YES	YES
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,016	3,016	3,016	3,016	3,016
R <sup>2</sup>	0.109	0.110	0.143	0.143	0.144
F-Statistic	42.448*** (df= 8; 2776)	38.058*** (df= 9; 2775)	51.393*** (df= 9; 2775)	46.332*** (df= 10; 2774)	38.980*** (df= 12; 2772)

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively. Standard error is in parentheses.

## IV.VII. HETEROGENEITY ANALYSIS

**Table 12.** Group Regression

	Dependent variable: GTFP			
	Low ER (1)	High ER (2)	Low IU (3)	High IU (4)
GF	0.300*** (0.089)	0.201** (0.083)	0.065 (0.066)	0.253** (0.100)
CONTROLS	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes

	Yes	Yes	Yes	Yes
Year Fixed Effects				
Observations	1,508	1,508	1,508	1,508
$R^2$	0.118	0.093	0.056	0.165
$F$ -Statistic	21.288*** ( $df=8; 1279$ )	16.393*** ( $df=8; 1275$ )	9.839*** ( $df=8; 1320$ )	32.298*** ( $df=8; 1309$ )

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively. Standard error is in parentheses.

In this section, the full sample is divided into high and low subgroups based on the median values of ER and IU to examine how the impact of GF on GTFP varies across different levels of ER and IU, respectively, and group regressions are conducted.

First, regarding IU, the coefficient of Green Finance is significantly positive only in the High-IU group (0.253,  $p < 0.05$ ), whereas it is statistically insignificant in the Low-IU group (0.065). This suggests that industrial upgrading serves as a prerequisite "soil" for green finance to exert its effects. The absorptive capacity of cities with advanced industrial structures is generally higher, which can absorb technology and capital, superior human capital, and well-established innovation systems, enabling them to efficiently translate Green Finance into GTFP gains. Conversely, in cities with lagging industrial structures, the lack of support from high-tech industries may lead to inefficient utilization of funds, thereby will not be able to promote the returns on green investment. Combining this with the moderation effect,  $H_3$  holds.

Second, regarding ER, it is clear to see that GF significantly promotes GTFP in both groups; however, the magnitude of the coefficient is larger in the low-regulation group (0.300,  $p < 0.01$ ) than in the high-regulation group (0.201,  $p < 0.05$ ). This indicates that the productivity-enhancing effect of GF is more pronounced in regions with weaker environmental constraints. Cities with looser regulations often have a lower initial green baseline, implying higher marginal returns from introducing green finance. In contrast, highly regulated regions have already incurred substantial environmental costs and achieved a certain level of efficiency; thus, the marginal productivity gain from additional green investment is relatively smaller. Furthermore, overly stringent environmental regulations may impose high compliance costs, forcing firms to reallocate resources. These high compliance costs can crowd out R&D funds, thereby attenuating the impact of GF on GTFP to some extent. Similarly, combining with the moderation effect discussed earlier, we say  $H_2$  holds.

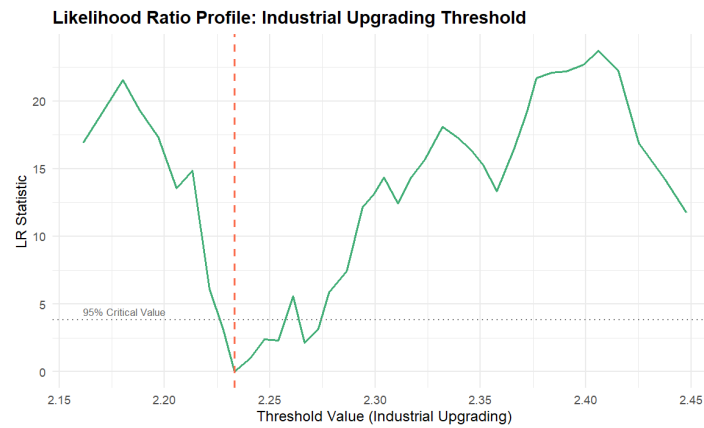
## V. FURTHER ANALYSIS

The insignificant linear triple-interaction term in Section 4.6 suggests that the synergistic effect among GF, ER, and IU is not a simple linear superposition. To definitively verify the non-linear synergistic mechanism proposed in Hypothesis  $H_5$ , this study introduces threshold regression models. Following Cui et al. (2025) and Suo Luoman et al. (2025), we treat industrial upgrading as the threshold variable to examine whether the efficacy of environmental regulation and green finance is contingent upon specific structural intervals.

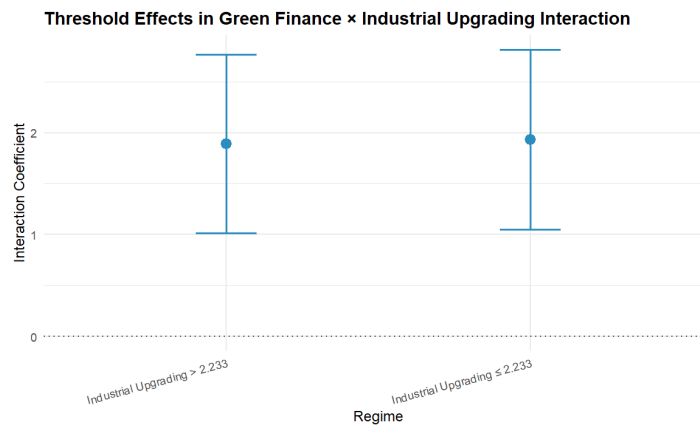
First, to investigate whether the moderating effect of industrial upgrading is contingent upon specific developmental stages, we employ IU as the threshold variable and construct the following single-threshold model:

$$GTFP_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 (GF_{it} \times IU_{it}) \cdot I(IU_{it} \leq \gamma) + \beta_3 (GF_{it} \times IU_{it}) \cdot I(IU_{it} > \gamma) + \beta_4 (GF_{it} \times ER_{it}) + \beta_5 X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

According to Table 12, the interaction coefficients for both the lower regime (1.9306,  $p < 0.01$ ) and the higher regime (1.8907,  $p < 0.01$ ) remain consistently positive and highly significant. This non-linear estimation provides a rigorous statistical rationale for the lack of significance in the low-IU group observed during the prior median-split heterogeneity analysis. As illustrated in the Likelihood Ratio (LR) profile (Figure 2), the LR statistic drops sharply and forms a distinct "V-shape," cleanly piercing the 95% critical value line at the threshold estimate of  $\gamma = 2.233$ . This visual evidence confirms the robust statistical existence of a structural breakpoint in the industrial upgrading process.



**Figure 2.** Likelihood Ratio Profile: Industrial Upgrading Threshold



**Figure 3.** Threshold Effects in Green Finance × Industrial Upgrading Interaction

More importantly, the corresponding threshold coefficient plot (Figure 3) intuitively demonstrates the stability of this moderating effect across different regimes. As shown, the point estimates for the interaction term (GF × IU) in both the lower regime ( $IU \leq 2.233$ ) and the higher regime ( $IU > 2.233$ ) are tightly clustered around 1.9. Furthermore, the 95% confidence intervals for both regimes are situated well above the zero line, indicating persistent and high statistical significance. This combined visual and statistical evidence further clarifies the estimation bias observed in the prior median-split analysis. It proves that by endogenously identifying the optimal structural breakpoint, industrial upgrading is revealed not as a stage-dependent variable, but as a highly robust and consistent driving factor that amplifies green finance efficiency across all developmental stages.

**Table 13.** Estimation Results of the IU Threshold Model

	IU Threshold Model
thresh_IU_low	1.931*** (0.450)
thresh_IU_high	1.891*** (0.447)
GF×ER	0.029 (0.029)
GF	-4.330***

	(1.034)
Control Variables	YES
City Fixed Effects	YES
Year Fixed Effects	YES
Observations	3016

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively. Standard error is in parentheses.

To further encapsulate the "policy-structure" synergy and test the robustness of the asymmetrical effects within a unified framework, we extend the analysis to a Double Threshold Model encompassing both ER and IU simultaneously:

$$GTFP_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 (GF_{it} \times ER_{it}) \cdot I(ER_{it} \leq \gamma_1) + \beta_3 (GF_{it} \times ER_{it}) \cdot I(ER_{it} > \gamma_1) + \beta_4 (GF_{it} \times IU_{it}) \cdot I(IU_{it} \leq \gamma_2) + \beta_5 (GF_{it} \times IU_{it}) \cdot I(IU_{it} > \gamma_2) + \beta_6 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (7)$$

The comprehensive results in Table 14 further corroborate the dual moderation logic. In this unified model, the coefficient for ER in the lower regime is positively significant at the 10% level (0.057), whereas it loses significance in the higher regime (0.034). This structural divergence provides empirical evidence for the "compliance cost" hypothesis, indicating that excessive regulation may crowd out the productive allocation of green capital. Conversely, the IU coefficients remain robustly positive and highly significant (1.931 and 1.891) across both regimes. This continuity suggests that industrial upgrading serves as a universal engine for green finance efficacy. Unlike the state-dependent nature of environmental regulation, the positive moderating role of industrial structure is not restricted by specific developmental intervals. It implies that an advanced industrial base provides a stable absorptive capacity and technical foundation, ensuring that green capital can be consistently converted into productivity gains regardless of the current stage of structural transformation.

**Table 14.** Estimation Results of the Double Threshold Model

	Double Threshold Model
thresh_IU_low	1.931*** (0.450)
thresh_IU_high	1.891*** (0.447)
thresh_ER_low	0.057* (0.033)
thresh_ER_high	0.034 (0.028)
GF×ER	0.029 (0.029)
GF	-4.349*** (1.027)
Control Variables	YES
City Fixed Effects	YES
Year Fixed Effects	YES
Observations	3016

Note: \*\*\*, \*\*, and \* indicate significance at the levels of 1%, 5%, and 10%, respectively. Standard error is in parentheses.

In conclusion, these findings lend empirical support to  $H_5$ . The synergistic mechanism exhibits significant non-linear and structurally asymmetrical characteristics: Green finance achieves its optimal potential only when anchored by the continuous and stable support of industrial upgrading, and calibrated with a moderate, interval-appropriate intensity of environmental regulation. These non-linear results are highly consistent with the practical logic of China's Green Finance Reform and

Innovation Pilot Zones. For instance, Huzhou (Zhejiang Province) established the 'Green Loan Link' digital platform to achieve precise matching between capital and projects. By integrating industrial green transformation (IU) with differentiated environmental supervision (ER), Huzhou effectively directed funds into high-productivity sectors rather than mere end-of-pipe pollution control. This real-world evidence also validates our Hypothesis  $H_5$ , proving that the synergistic effect is not a simple linear addition but a result of precise 'policy–finance–structure' coordination within specific developmental intervals.

## VI. DISCUSSION

The findings of this study provide several important insights into how green finance affects GTFP and why the surrounding policy and structural environment matters.

The positive and persistent effect of green finance on GTFP is consistent with Sustainable Development Theory. Green finance works by directing capital toward clean technologies, renewable energy, and environmentally friendly projects. This process not only supports economic output but also reduces energy consumption and pollutant emissions, which are the "undesirable outputs" penalized in the GTFP framework. As a result, green finance improves productivity from both sides simultaneously. The fact that this effect holds even after accounting for the historical accumulation of productivity further confirms that green finance is a genuine long-run driver of green growth, not simply a short-term policy response.

The moderating role of environmental regulation presents a more complex picture. When regulation is moderate, it supports the Porter Hypothesis: firms facing environmental pressure are pushed to innovate and adopt cleaner technologies, which strengthens the productivity gains that green finance can generate. However, the heterogeneity analysis shows that this positive effect weakens in highly regulated regions. This is consistent with the compliance cost mechanism: when regulatory intensity is too high, firms must spend a large share of their green financial resources on meeting compliance requirements rather than investing in genuine productivity improvements. Chen (2023) found that environmental regulation drives green innovation primarily under moderate intensity, while Ye et al. (2024) observed that compliance burdens can suppress green finance effectiveness in resource-dependent cities. The present findings confirm that this relationship is non-linear and that the optimal regulatory intensity for amplifying green finance impact lies below the threshold of excessive compliance cost.

Industrial upgrading plays a more fundamental role. The results show that green finance is most effective in cities with advanced industrial structures, while its impact is much weaker where resource-intensive industries still dominate. This finding is grounded in Industrial Structure Upgrading Theory. Cities that have already transitioned toward technology-intensive and service-oriented industries have developed the capacity to absorb green capital and convert it into productivity gains, through better-skilled workers, more sophisticated supply chains, and stronger innovation systems. By contrast, cities that remain heavily reliant on traditional manufacturing lack these channels. This explains why industrial upgrading, rather than environmental regulation, is the dominant factor in determining how much productivity benefit a city can extract from green finance.

The relationship between environmental regulation and industrial upgrading is not one of simple complementarity. When both are included in the same model, the moderating effect of environmental regulation disappears, while that of industrial upgrading remains strong and unchanged. This suggests that industrial upgrading absorbs the role that regulation would otherwise play. Where industrial transformation is already underway, firms are naturally moving away from high-emission, low-efficiency production, reducing their dependence on regulatory pressure to drive green behavior. Environmental regulation, therefore, plays a secondary and conditional role—most useful in cities where industrial upgrading has not yet created sufficient endogenous incentives for green transition.

Finally, the synergistic mechanism among green finance, environmental regulation, and industrial upgrading does not manifest in a simple linear triple interaction. Instead, as revealed by the double-threshold model, synergy emerges through non-linear and structurally asymmetrical channels (Cui et al., 2025; Suo Luoman et al., 2025), which is consistent with the logic of the Environmental Kuznets Curve. The EKC suggests that the relationship between economic development and environmental quality is path-dependent and changes across developmental stages. Similarly, the joint effectiveness of these three factors depends on the specific combination of regulatory intensity and industrial development within a city. Green finance achieves its full potential only when industrial upgrading provides a stable structural foundation and when environmental regulation is calibrated to encourage innovation rather than simply impose costs. This explains the success of China's Green Finance Reform and Innovation Pilot Zones, which achieve strong results precisely because they match regulatory design with the industrial conditions of each region.

## VII. CONCLUSION

This study empirically investigates the impact of green finance on Green Total Factor Productivity (GTFP) using balanced panel data from 232 Chinese cities spanning 2010 to 2022, with particular attention to the dual and synergistic moderating roles of environmental regulation and industrial upgrading within a "policy–finance–structure" coordination framework.

### VII.I. CORE FINDINGS

First, the baseline regression confirms that green finance exerts a significant and robust positive impact on GTFP. This result holds consistently across multiple specifications, including pooled OLS, fixed effects, and random effects models. Dynamic panel analysis further reveals that GTFP exhibits strong path dependence, yet green finance continues to exert a persistent promotional effect on urban green productivity even after accounting for this historical accumulation, confirming that its contribution is a durable structural force rather than a transient policy response.

Second, the moderation analysis uncovers a structural asymmetry between the two moderators. Industrial upgrading consistently and strongly amplifies the effectiveness of green finance across all specifications, serving as a dominant structural precondition—effectively the "soil" that enables green capital to translate into productivity gains. Environmental regulation, by contrast, plays a conditional and secondary role: its positive moderating effect is only statistically significant under moderate regulatory intensity, and this effect is fully absorbed by industrial upgrading when both moderators are included simultaneously. This dominance relationship suggests that industrial structure, rather than regulatory pressure, constitutes the binding constraint on green finance efficacy at the city level.

Third, the threshold analysis uncovers a critical non-linear synergistic mechanism. The triple interaction term is statistically insignificant, rejecting simple linear superposition as the channel of synergy. Instead, the double-threshold model reveals that synergy among green finance, environmental regulation, and industrial upgrading is structurally contingent: industrial upgrading functions as a universal and persistent engine across all developmental stages, while environmental regulation acts as an interval-based auxiliary force whose contribution is positive only within a moderate intensity range and diminishes as regulation intensifies. This non-linear, structurally asymmetrical coordination pattern is empirically consistent with the practice of China's Green Finance Reform and Innovation Pilot Zones.

### VII.II. THEORETICAL IMPLICATIONS

This study makes several contributions to the theoretical understanding of green finance and sustainable productivity. First, it extends the green finance–GTFP literature by demonstrating that the efficacy of green finance is not monolithic but fundamentally contingent on structural and regulatory context, consistent with the heterogeneous-impact perspective highlighted in recent complexity-based growth literature (Wang et al., 2023; Ruan, 2025). Second, the study advances the Porter Hypothesis by showing that its applicability is conditional: environmental regulation induces productivity-enhancing innovation only within a moderate intensity range, beyond which compliance costs crowd out the productive deployment of green capital—a finding that bridges and reconciles the Porter and cost-compliance hypotheses within a unified threshold framework. Third, by revealing that industrial upgrading subsumes the moderating role of environmental regulation when both are considered simultaneously, this study reframes the conventional "complementarity" assumption as a "dominance" relationship, contributing new nuance to Industrial Structure Upgrading Theory. Finally, the finding that synergy manifests through non-linear threshold effects—rather than linear additivity—is consistent with the path-dependent logic of the Environmental Kuznets Curve and offers a methodological argument for applying threshold regression frameworks in future green finance research.

### VII.III. POLICY IMPLICATIONS

Based on the empirical findings, three targeted policy recommendations are proposed. First, authorities should prioritize industrial upgrading as the foundational driver of green finance effectiveness. Cities must accelerate the transition from resource-intensive manufacturing toward knowledge-intensive and technology-driven industries to build the absorptive capacity necessary for green capital to generate productivity returns. Strategic investments in digital infrastructure, R&D subsidies for clean technology, and workforce retraining programs are essential to facilitate this structural transformation.

Second, environmental regulation should be calibrated to regional industrial development stages rather than applied uniformly. In cities with lower levels of industrial upgrading, moderate regulation best supports compliance without overwhelming enterprises; in structurally advanced cities, stricter standards are sustainable. Policymakers should resist the temptation to

intensify regulatory pressure beyond what local industrial structures can productively absorb, as doing so risks crowding out green investment rather than catalyzing it.

Third, integrated policy packages that synchronize green finance expansion, industrial upgrading initiatives, and environmental regulation are essential for maximizing green productivity outcomes. Local governments should establish cross-departmental coordination mechanisms to ensure these three elements reinforce rather than contradict one another. The success of pilot zones such as Huzhou demonstrates that precisely matching financial instruments with industrial conditions and regulatory design is key to achieving the "policy–finance–structure" synergy this study identifies.

This study highlights that the effectiveness of green finance is fundamentally shaped by the structural and policy context in which it operates. Future research extending the "policy–finance–structure" framework to other developing and emerging economies, or incorporating spatial econometric methods to account for cross-city spillover effects, would further enrich our understanding of how green finance can be most effectively deployed across diverse institutional and structural settings.

## VIII. ACKNOWLEDGEMENT

This research work was partially supported by Chiang Mai University.

## REFERENCES

1. Brunnermeier, S. B., & Cohen, M. A. (2003). Determinants of environmental innovation in US manufacturing industries. *Journal of environmental economics and management*, 45(2), 278-293.
2. Chen, D., Hu, H., & Chang, C. P. (2023). Green finance, environment regulation, and industrial green transformation for corporate social responsibility. *Corporate Social Responsibility and Environmental Management*, 30(5), 2166-2181.
3. Cheng, C., Yu, X., Hu, H., Su, Z., & Zhang, S. (2022). Measurement of China's green total factor productivity introducing human capital composition. *International Journal of Environmental Research and Public Health*, 19(20), 13563.
4. Clark, C. (1967). The conditions of economic progress.
5. Cole, M. A., Elliott, R. J., & Shimamoto, K. (2005). Why the grass is not always greener: the competing effects of environmental regulations and factor intensities on US specialization. *Ecological Economics*, 54(1), 95-109.
6. Cui, Z., Li, X., Wang, L., Zhang, Y., & Ni, L. (2025). Effects of environmental regulation on green total factor productivity under different regional synergistic development thresholds. *Journal of Environmental Management*, 394, 127311.
7. Dai, Z., Niu, Y., Zhang, H., & Niu, X. (2022). Impact of the transforming and upgrading of China's labor-intensive manufacturing industry on the labor market. *Sustainability*, 14(21), 13750.
8. Domazlicky, B. R., & Weber, W. L. (2004). Does environmental protection lead to slower productivity growth in the chemical industry?. *Environmental and resource economics*, 28(3), 301-324.
9. Feng, J., Yan, J., & Tao, X. (2021). Exposing the effects of environmental regulations on China's green total factor productivity: Results from econometrics analysis and machine learning methods. *Frontiers in Environmental Science*, 9, 779358.
10. Gong, M., Yi, M., Liu, H., & Jiang, X. (2020). Environmental regulation, hidden economy, and China's outward foreign direct investment. *Chinese Journal of Population, Resources and Environment*, 18(1), 35-41.
11. Jiang, H., Chen, Z., Liang, Y., Zhao, W., Liu, D., & Chen, Z. (2023). The impact of industrial structure upgrading and digital economy integration on China's urban carbon emissions. *Frontiers in Ecology and Evolution*, 11, 1231855.
12. Jing, F., Muhamad, H., Said, R. M., & Daud, Z. M. (2024). Green Credit Policy and Firms' Green Total Factor Productivity: The Mediating Role of Financial Constraints. *Theoretical and Practical Research in Economic Fields*, 15(4), 871-884.
13. Lee, C. C., & Lee, C. C. (2022). How does green finance affect green total factor productivity? Evidence from China. *Energy economics*, 107, 105863.
14. Liu, M., Zhu, Y., & Zhang, J. (2024). Can Environmental Regulation Enhance Green Total Factor Productivity?—Evidence from 107 Cities in the Yangtze River Economic Belt. *Sustainability*, 16(12), 5243.
15. Liu, Y., Lei, J., & Zhang, Y. (2021). A study on the sustainable relationship among the green finance, environment regulation and green-total-factor productivity in China. *Sustainability*, 13(21), 11926.
16. Luoman, S., & GOLAM, H. A. (2025). Threshold Effect of Environmental Regulation in Green Finance-Promoted High-Quality Economic Development—Evidence from 282 Cities in Mainland China. *INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS AND SOCIAL SCIENCES*, 15(2).
17. Polzin, F. (2017). Mobilizing private finance for low-carbon innovation—A systematic review of barriers and solutions. *Renewable and Sustainable Energy Reviews*, 77, 525-535.
18. Porter, M. E., & Linde, C. V. D. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of economic perspectives*, 9(4), 97-118.
19. Qi, Y., Lu, Y., Xu, H., & Sheng, G. (2025). Financial Technology Expenditure and Green Total Factor Productivity: Influencing Mechanisms and Threshold Effects. *Sustainability (2071-1050)*, 17(14).

20. Ruan, X., Lin, S., Huang, J., & Li, C. (2025). The impact of economic complexity on green technology innovation in China. *Scientific Reports*, 15(1), 39979.
21. Sachs, J. D., Woo, W. T., Yoshino, N., & Taghizadeh-Hesary, F. (2019). Importance of green finance for achieving sustainable development goals and energy security. In *Handbook of green finance* (pp. 3-12). Springer, Singapore.
22. Shan, Z., Han, X., & Zhang, Z. (2025). Environmental regulation and firm productivity: evidence from China's new energy industry. *Eurasian Business Review*, 1-36.
23. Sun, J., Tang, D., Kong, H., & Boamah, V. (2022). Impact of industrial structure upgrading on green total factor productivity in the Yangtze river economic belt. *International Journal of Environmental Research and Public Health*, 19(6), 3718.
24. Wan, A. W., & Cui, W. (2025). Has the green total factor productivity increased in the early stage of the establishment of smart city. *PLoS One*, 20(5), e0322922.
25. Wang, F., Wu, M., & Wang, J. (2023). Can increasing economic complexity improve China's green development efficiency?. *Energy Economics*, 117, 106443.
26. Wang, X., & Li, X. (2025). Towards a green world: how new urbanization affects green total factor carbon productivity. *Frontiers in Environmental Science*, 12, 1522259.
27. Wang, X., Li, J., & Wang, N. (2023). Are economic growth pressures inhibiting green total factor productivity growth?. *Sustainability*, 15(6), 5239.
28. Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.
29. Xiao, H., & You, J. (2021). The heterogeneous impacts of human capital on green total factor productivity: Regional diversity perspective. *Frontiers in Environmental Science*, 9, 713562.
30. Xiao, H., & Zhang, X. (2021). FDI, Spillover Effect and Green Total Factor Productivity (GTFP)-Research from the Perspective of Regional Heterogeneity. In *E3S Web of Conferences* (Vol. 292, p. 03051). EDP Sciences.
31. Xie, H., Cheng, J., Tan, X., & Li, J. (2025). Artificial Intelligence Technology Applications and Energy Utilization Efficiency: Empirical Evidence from China. *Sustainability*, 17(14), 6463.
32. Xie, R., & Teo, T. S. (2022). Green technology innovation, environmental externality, and the cleaner upgrading of industrial structure in China—Considering the moderating effect of environmental regulation. *Technological Forecasting and Social Change*, 184, 122020.
33. Yan, G., Jiang, L., & Xu, C. (2022). How environmental regulation affects industrial green total factor productivity in China: The role of internal and external channels. *Sustainability*, 14(20), 13500.
34. Ye, Z., Liu, Y., & Rong, Y. (2024). How Environmental Regulations Affect Green Total Factor Productivity—Evidence from Chinese Cities. *Sustainability*, 16(7), 3010.
35. Yin, J., Ibrahim, S., Mohd, N. N. A., Zhong, C., & Mao, X. (2024). Can green finance and environmental regulations promote carbon emission reduction? Evidence from China. *Environmental Science and Pollution Research*, 31(2), 2836-2850.
36. Yin, Q., Xu, F., Liao, K., Dai, E., & Sun, A. (2024). How does new urbanization affect urban green total factor productivity? A perspective based on coordinated development. *Environmental Science and Pollution Research*, 31(38), 50316-50332.
37. You, X., Li, Z., & Yi, Y. (2023). Carbon constraints, industrial structure upgrading, and green total factor productivity: an empirical study based on the Yangtze River Economic Belt. *Journal of Water and Climate Change*, 14(9), 3010-3026.
38. Yue, H., Zhou, Z., & Liu, H. (2024). How does green finance influence industrial green total factor productivity? Empirical research from China. *Energy Reports*, 11, 914-924.
39. Zhang, G. (2023). The heterogeneous role of green finance on industrial structure upgrading-Based on spatial spillover perspective. *Finance Research Letters*, 58, 104596.
40. Zhang, G., Shi, Y., & Huang, N. (2024). Government Subsidies, Green Innovation, and Firm Total Factor Productivity of Listed Artificial Intelligence Firms in China. *Sustainability*, 16(8), 3369.
41. Zhang, H. (2021). Trade openness and green total factor productivity in China: the role of ICT-based digital trade. *Frontiers in Environmental Science*, 9, 809339.
42. Zheng, S., Zhang, Y., Luo, T., & Gong, Y. (2025). Synergistic effects of digital technology and environmental regulation on the green transformation of China's manufacturing industry. *Scientific Reports*, 15(1), 36092.