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The Impact of Trump's Trade Policies on Corporate Green Total Factor Productivity

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Abstract. This study investigates the impact of Trump's trade policies, particularly the tariffs imposed on Chinese imports during 2018-2019, on corporate green total factor productivity (GTFP). Utilizing a multi-period difference-in-differences (DID) model and mediation analysis, combined with FactSet Revere global supply chain data and Chinese listed company financial data, we find that U.S. tariffs significantly restrain corporate GTFP by exacerbating external financing constraints, suppressing green innovation, and reducing outward foreign direct investment (OFDI). Heterogeneity analysis reveals that state-owned enterprises (SOEs) and private enterprises are significantly impacted, with private enterprises experiencing the largest GTFP losses, whereas foreign-owned enterprises (FOEs) exhibit resilience due to their globalized operations. Our findings highlight the short-term and persistent negative effects of tariff shocks on GTFP and provide insights into designing adaptive policies to mitigate these impacts.

Keywords: Trump's trade policies, green total factor productivity (GTFP), financing constraints, green innovation, outward foreign direct investment (OFDI)

1. Introduction

In the context of deeply integrated global value chains, trade policy shocks have emerged as significant drivers reshaping the global supply chain landscape. Recent trade protectionist measures, exemplified by the United States' imposition of tariffs on Chinese imports during 2018-2019, have not only exacerbated international trade frictions but also posed severe challenges to the stability of multinational firms' production networks and resource allocation efficiency [1]. Most existing research focuses on the macroeconomic effects of trade policies, such as impacts on employment, trade flows, and welfare levels[2-3], or examines changes in import-export adjustments and employment decisions at the firm level [4-5]. However, there is a scarcity of studies that delve into the micro-perspective of "inter-firm supply chain relationships" to systematically analyze the impact of trade policy shocks on supply chain dynamics and their mechanisms on corporates' green Total Factor Productivity (GTFP).

Recent literature has begun to explore supply chain resilience under external shocks, such as the transmission effects of natural disasters [6] and public health events [7] on supply chain disruptions. However, the complexity and uncertainty of trade policy shocks may influence firm behavior

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through unique channels, such as increased tariff costs directly squeezing profit margins, reducing cash flow, and impacting firm investments. Additionally, post-supply chain disruption reconstruction involves regional transfers and industrial adjustments [5]. Amidst the transition to a low-carbon economy, green technological innovation [8] is considered a crucial strategy for firms to cope with such shocks, yet the role of these mechanisms in trade policy research remains under-explored.

Employing the 2018-2019 U.S. tariffs on China as a natural experiment, this study combines FactSet Revere global supply chain data with corporate financial data, utilizing a multi-period difference-in-differences (DID) model and mediation analysis to systematically investigate the impact of trade policy shocks on corporate Green Total Factor Productivity (GTFP) and its transmission mechanisms. The findings reveal three key insights: firstly, U.S. tariff shocks significantly inhibit GTFP by exacerbating external financing constraints, suppressing green innovation, and reducing outward foreign direct investment (OFDI). Specifically, tariffs led to a significant increase in the financing constraint index (SA) (+0.081), forcing firms to cut R&D expenditures (-0.823) and green innovation (-0.186), while OFDI also contracted (-0.229). Secondly, heterogeneity analysis shows that state-owned enterprises (SOEs) and private enterprises are significantly impacted, with private enterprises experiencing the largest GTFP losses (-0.108), whereas foreign-owned enterprises (FOEs) exhibit resilience due to their globalized operations. Thirdly, robustness tests excluding the COVID-19 pandemic, adjusting policy timing, and winsorizing extreme values indicate that the negative effects of tariff shocks on GTFP are concentrated in the short term (1-2 years post-policy implementation),but diminish over time ,suggesting that firms may gradually mitigate the impact through long-term strategies. This study provides new evidence for understanding the micro-transmission mechanisms of trade policies: financial intermediation mechanisms (exacerbated financing constraints, delayed green innovation, and contracted OFDI) are the core pathways through which tariff shocks inhibit GTFP. Furthermore, the findings offer insights for policymakers to design adaptive measures, including alleviating firm financing constraints, providing targeted support for green technology research and development, and optimizing global supply chain layouts through international cooperation. These insights also provide a theoretical basis and implications for firms affected by Trump's trade policies to enhance and optimize their supply chain resilience, as well as for policymakers to design hedging mechanisms..

2. Literature review

The frequent changes in trade policies have transformed trade relations among countries, profoundly impacting the global economic landscape, and academic attention to this issue has been increasing, gradually forming a multi-level research framework from the macro to the micro level. From a macro perspective, existing studies have found that changes in trade policies not only affect trade flows but also have complex impacts on employment, output, and welfare levels [2][3]. From a micro perspective, research has revealed that trade policy shocks influence firm behavior by increasing trade costs, raising market entry barriers, and enhancing trade policy uncertainty, leading to reductions in firm imports and exports [4], adjustments in hiring decisions [5], and deteriorating financial market performance. Although existing research has shed light on the impact of trade policies at the firm level, analyses from the "inter-firm" perspective are limited. Bellora, C., & Fontagné, L., from an "inter-industry" perspective, found that U.S. trade policy shocks weakened its competitiveness through global value chains, resulting in decreased value-added, job losses, and capital reallocation across most industries [9].

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In addressing various external shocks, the vulnerability of supply chains and firms' coping strategies have become key topics in academic research. Existing literature extensively discusses the destructive impacts of external shocks on supply chains, encompassing a wide range of shocks such as international trade, outward foreign direct investment [17], natural disasters [6], and public health events [7]. It is argued that external shocks not only cause supply chain disruptions but may also generate knock-on effects through supply chain networks. Notably, recent research has begun to focus on the role of financial intermediation mechanisms in the transmission of trade policy shocks. For instance, trade policy shocks can directly squeeze firm cash flow by raising the costs of imported intermediate goods and increasing market demand uncertainty [1]. The "financial accelerator" theory proposed by Bernanke et al. suggests that external shocks amplify firm financing constraints through credit markets [10]. Specifically, financial institutions increase risk premiums due to policy uncertainty [11], forcing firms to cut long-term productive investments (such as R&D expenditures), forming a transmission chain of "consumption downgrade—cash flow contraction—investment reduction" [12]. Recent research further validates that supply chain financial instruments (such as ABS) can mitigate financing constraints by optimizing capital turnover efficiency [13], but their regulatory role in trade policy scenarios requires further exploration.

Green technological innovation [8] and green bond financing can serve as important mediating variables: tariff shocks compel firms to seek low-cost green financing channels. Flammer found that green bonds can reduce financing costs through ESG premiums, providing funding support for clean technology research and development [14]. Dechezleprêtre et al. emphasized that the rising procurement costs of environmental protection technologies are a key driver for firms to shift towards green innovation [15]. Tang & Zhang empirically showed that green bond-issuing firms reduced their financing costs by an average of 12%-15% and increased their annual R&D investments by USD 2.1 million [16]. This "green innovation—reduced financing costs—stable cash flow" pathway offers a new explanation for technological substitution under trade shocks. In response to trade barriers, firms restructure their supply chains through near-shoring or outward foreign direct investment (FDI) [5]. Yu et al. pointed out that FDI can enhance parent firm productivity through technology spillovers and cost optimization [17]. Bellora & Fontagné demonstrated that location adjustments can reduce intermediate goods procurement costs, but their effectiveness depends on the host country's financial market efficiency [9]. Additionally, the securitization of logistics assets (such as REITs) further enhances supply chain resilience by improving capital turnover rates [13]. Such research provides a theoretical basis for the "FDI—reduced procurement costs—mitigated financing constraints" mechanism but lacks empirical validation based on high-frequency supply chain data.

Despite the abundant discussions on supply chain vulnerability and coping strategies under external shocks, research on the impact of trade policy shocks on corporate GTFP remains insufficient, particularly lacking in-depth analysis of specific impact mechanisms, such as transmission effects through financial market-related variables. For example, trade policy uncertainty may inhibit firm investments through the "consumption downgrade—cash flow contraction" pathway [12], or promote technological upgrading through the "green innovation—reduced financing costs" pathway [16], or mitigate financing constraints and impact corporate GTFP through the "location adjustment—increased FDI" pathway. Moreover, enhancing firms' resilience to trade shocks through these mechanisms has not been fully explored in existing literature.

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3. Data description and key variable construction

3.1. Data description

This study focuses on the supply chain relationships between Chinese suppliers and overseas customers from January 2017 to December 2019, constructing a research sample based on multiple datasets: (1) Global supply chain data sourced from the FactSet Revere database. This database systematically monitors and collects information on inter-firm supply chain relationships through company annual and quarterly reports (including U.S. SEC Forms 10-K, 8-K, and 10-Q), investor reports, company websites, and news reports. It records over 2 million "customer-supplier" relationships involving approximately 30,000 listed companies in more than 180 countries worldwide since 2003. Critically, the database logs the start and end dates of each supply chain relationship and tracks them on a daily frequency, providing a sufficiently high-frequency data basis for this study to investigate changes in inter-firm supply chain relationships under trade policy shocks. This study selects all cross-border supply chain relationship data for Chinese listed companies from this database. (2) Trade policy data sourced from the four rounds of tariff lists imposed by the U.S. Trade Representative's Office (USTR) on Chinese exports during 2018-2019. This study matches the 8-digit HS customs codes used in the tariff lists with the 4-digit SIC industry codes used to identify the industries of affected Chinese listed companies. (3) Financial variables and other economic characteristic data for Chinese and overseas firms sourced from the Worldscope and CSMAR databases. (4) Panel data for Chinese listed companies from 2000 to 2022.

3.2. Calculation of the GTFP

The GTFP, an evaluation method that simultaneously increases productivity and improves the environmental performance, takes both economic growth and environmental pollution factors into consideration (Jin et al., 2018; Li and Lin, 2015). Therefore, we use the GTFP as a measurement index to document China's green economy and green growth. Extending the concept of the slack based model (SBM), Tone (2003) developed the concept of the SBM-undesirable to measure efficiency with undesirable outputs. We employ the SBM-undesirable to estimate the green efficiency. Suppose that there are N companies, each of which is an independent and efficient decision-making unit (DMU),1 with three vectors in each DMU: m input factors $X=[x_{1,\ldots}x_n]$, s_1 desirable outputs $Y^g=[y_1^g,\ldots,y_N^g]$, and s_2 undesirable outputs $Y^b=[y_1^b,\ldots,y_N^b]$. The production possibility is set as below:

$$P=\left\{(x,y^g,y^b)\middle|x\geq X\lambda,y^g\geq Y^g\lambda,y^g\geq Y^g\lambda,\lambda\geq 0\right\}$$

Where $X>0,Y^g>0,Y^b>0$ and λ is the weight vector.
Tone (2003) showed that a non-radial SBM-undesirable can be defined as.

$$\rho^*=min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{s_i}}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\sum_{r=1}^{s_2}\frac{s_t^b}{y_{r0}^b}\right)}$$

$$s.t.$$

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$$x_0^b - \sum_{j=1}^{n} \lambda_j x_j - s^- = 0$$

$$\sum_{j=1}^{n} \lambda_j y_j^g - y_0^g - s^g = 0$$

$$y_0^g - \sum_{j=1}^{n} \lambda_j y_0^b - s^b = 0$$

$$\lambda, s^-, s^g, s^b > 0, \sum_{j=1}^{N} \lambda_j = 1$$

Where $s^b(s^g)$ presents the undesirable (desirable) output slack vector and s^- presents the input slack vector. The model follows the variable return to scale (VRS) assumption. The SBM-directional distance function (SBM-DDF) introduces to the SBM model a directional distance function, which measures the efficiency of input and output in a non-proportional manner. The DDF is defined in the global technology set $P^G(x)$ below:

$$D^G(x, y^g, y)^b = max\{\beta | (y^g + \beta y^g, y^b - \beta y^b \in P^G(x)\}$$

However, the SBM-DDF, a non-radial directional distance model, is a statistical analysis method that cannot reflect the change in the position of each city relative to the technology frontier and the movement toward the meta-frontier in the panel data. Therefore, the Global Malmquist-Luenberer (GML) index (Oh, 2010) is used to measure changes in the GTFP. The GML index and its decomposition are below:

$$GML^{t,t+1}(x_t, y_t^g, y_t^b, x_{t+1}, y_{t+1}^g, y_{t+1}^b)$$

$$= \frac{1+D^G(x_t, y_t^g, y_t^b)}{1+D^G(x_{t+1}, x_{t+1}^g, y_{t+1}^b)}$$

$$= \frac{1+D^t(x_t, y_t^g, y_t^b)}{1+D^{t+1}(x_{t+1}, y_{t+1}^g, y_{t+1}^b)} \times \left[\frac{\frac{1+D^G(x_t, y_t^g, y_t^b)}{1+D^t(x_t, y_t^g, y_t^b)}}{\frac{1+D^G(x_{t+1}, x_{t+1}^g, y_{t+1}^b)}{1+D^{t+1}(x_{t+1}, y_{t+1}^g, y_{t+1}^b)}} \right]$$

$$= \frac{TE^{t+1}}{TE^t} \times \left[\frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}} \right]$$

$$= EC^{t+1} \times BPC^{t,t+1}$$

$GML^{t,t+1}$ reflects the rate of change in the green production efficiency during t to t+1, where EC^{t+1} and $BPC^{t,t+1}$ represent the green technical efficiency change and green technical progress, respectively.

3.3. Empirical model

We investigate the impact of trump trade construction on total factor productivity of enterprises using the DID model. The second group of pilots consists mainly of cities and is supplemented by

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provinces. The first group of cities contains few samples, and the third group of pilot policies has been implemented for only a short time. To estimate accurate results, this paper chooses the second group, comprising 28 companies, to evaluate the level of green growth. This paper uses the data of prefecture-level cities that are processed for the treatment and control groups as follows. First, in the second group of pilots, Jiyuan and the Greater Higgan Range are not prefecture-level cities and lack statistics. Therefore, these two areas are excluded from the treatment group. Second, to calculate the net effect of trade policies, the data of the first group of pilot cities in the control group were excluded.

To obtain the net effects of policies, the DID model identifies the impact of other factors (excluding the trade pilot status) on the GTFP. The premise of DID is to satisfy the common trend assumption that all cities do not have systematic differences before policy implementation. The heterogeneity of urban development makes it impossible to satisfy this assumption. Then, we adopt PSM-DID (Heckman et al.,1998,1997), which controls the companies 'scale differences and economic growth over time and solves sample-self-selection to evaluate the effects of trump trade policies more effectively and accurately.

The DID baseline model used to investigate the impacts of trade policies on green growth of enterprises defined as:

$$GTFP_{it} = \alpha_0 + \alpha_1 Treated \times Time + \sum_{k=1}^{K} \alpha_k X_{kit} + \delta_i + \sigma_t + \varepsilon_{it}$$

$GTFP_{it}$ is the GTFP for company i at time t. $Time$ is the dummy variable, which equals 1 during the post-policy period and zero otherwise. $Treated$ is the dummy variable that equals one if the city is classified into the second group of pilots and zero otherwise. X_{kit} is the k th control variable affecting the GTFP for company i at time t ,which includes the economic development level, urbanization rate, infrastructure, openness level and labor force aggregation. δ_i refers to the fixed effect of company i. σ_t indicates the fixed effect of year t. The error term ε_{it}, is assumed to be $i.i.d$.

3.4. Mechanism test model setting

In order to find out how the trump trade policies influence the GTFP,we set the mediating variables totest the mechanism.

$$GTFP_{it} = \alpha_0 + \alpha_1 Treated \times Time + \sum_{k=1}^{K} \alpha_k X_{kit} + \delta_i + \sigma_t + \varepsilon_{it} \quad (1)$$

$$M_{it} = \alpha_0 + \alpha_1 Treated \times Time + \sum_{k=1}^{K} \alpha_k X_{kit} + \delta_i + \sigma_t + \varepsilon_{it} \quad (2)$$

When (1) the core explanatory variable $Treated \times Time$ and X_{kit} have a significant effect on the explanatory variable .(2) The core explanatory variable $Treated \times Time$ $and\ X_{kit}$ have a significant effect on the mediating variable M_{it}. (3) The core explanatory variable $Treated \times Time$ and the mediating variable M_{it} have significant effects on the explanatory variable $GTFP_{it}$. it can be concluded that the core explanatory variable $Treated \times Time$ and X_{kit} finally significantly affects the explanatory variable $GTFP_{it}$ through the path of significantly affecting the mediating variable M_{it}.

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3.5. Explanatory variable

The core explanatory variable in this paper is whether the company is reflected by trump trade polices i.e., the dummy variable $Treated \times Time$ in this paper. $Treated$ is a regional dummy variable. A value of 1 indicates that the company is a pilot company for policies, while a value of 0 indicates that the company is not a pilot company for policies. $Time$ is a time dummy variable that takes the value of 0 before the year of policy implementation and 1 after the year of implementation.

In 2016,the dummy variable $Treated \times Time$ of enterprises on trump's tax increase list which are affected by trade policies took the value of 1.

3.6. Control variables

To explore the net impact of the trump trade policy on the total factor productivity of enterprises, it is necessary to control for a series of other factors that may affect the upgrading of total factor productivity of enterprises. The control variables in this paper are selected as follows. (1) Firm Size (Size): Measured by the natural logarithm of total assets, reflecting the overall operational scale and resource base of the enterprise.(2)Leverage Ratio (Lev): Calculated as the ratio of total liabilities to total assets, used to assess the capital structure and financial risk exposure.(3)Return on Assets (ROA): Defined as net profit divided by total assets, characterizing the overall profitability of corporate assets.(4)Total Asset Turnover (ATO): Computed as operating revenue divided by total assets, indicating the operational efficiency and capital utilization capacity of enterprise assets. (5)Revenue Growth Rate (Growth): Measured by the percentage increase in current-period operating revenue relative to the previous period, demonstrating market expansion momentum and growth potential.

3.7. Mechanism variables hypothesis

In conjunction with the previous analysis, the mechanism variables of this paper are selected as follows:

(1) Financial Constraint Aggravation Path: Consumption Downgrade–Cash Flow Contraction Mechanism

Trade policy shocks, such as tariff hikes on intermediate imports (Autor et al., 2016), significantly increase production costs and amplify market uncertainty regarding future demand (Bernanke et al., 1999). Such uncertainty induces financial institutions to tighten credit standards (Whited & Wu, 2006), manifesting as elevated external financing premiums (Huang et al., 2023). To quantify this mechanism, we employ the following variables:

Financing Constraint Index:

① Constructed based on the SA index (Hadlock & Pierce, 2010) to reflect external financing difficulties.

(2) Green Innovation Acceleration Path: Technological Substitution—Financing Optimization Mechanism

Tariff shocks compress corporate profit margins (Amiti et al., 2019), compelling firms to enhance research and development (R&D) expenditures and green patent outputs (GREENINV) to counter cost pressures, thereby improving technological efficiency. Specific variables include:

① R&D Expenditure: The proportion of annual R&D spending to total assets (Jiao et al., 2022);

② Green Innovation Intensity (GREENINV): The logarithm of the number of green patent applications (Cheng et al., 2019).

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(3) Supply Chain Restructuring Path: Geographical Adjustment—FDI Spillover Mechanism

Firms restructure their supply chains through outward foreign direct investment (OFDI) to navigate trade barriers (Ding et al., 2023). The quantitative indicator is:

① OFDI Intensity: The ratio of annual outward OFDI stock to total assets (CSMAR Outbound Investment Database).

3.8. Descriptive statistics

Table 1 presents descriptive statistics for the full sample and subgroup comparisons from 2000 to 2022. The dataset comprises 51,925 observations, with 37,670 (72.6%) in the treatment group (affected by trade policies) and 14,255 (27.4%) in the control group. While GTFP shows marginal treatment-group advantages (1.004 vs. 1.001), decomposition indicates policy-driven technological upgrading (TC=1.005 vs. 1.000) despite slight TEC declines (0.999 vs. 1.001). Financial metrics exhibit extreme volatility in treated firms: ROA (SD=121.559 vs. 0.380) and NETPROFIT (SD=1608.725 vs. 6.792) demonstrate amplified risk exposure, while Tobin's Q (SD=79.232 vs. 2.372) reflects valuation instability. Firm size differences (21.941 vs. 21.788) and matched age distributions (≈15.6 years) suggest the need for PSM-DID modeling with winsorized financial variables to address selection bias and outlier effects.

Table 1: Descriptive statistics

	Full sample			Treatment group			Control group		
	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.
GTFP	51,925	1.001	0.010	37,670	1.004	0.009	14,255	1.001	0.010
TEC	51,925	1.001	0.011	37,670	0.999	0.006	14,255	1.001	0.011
TC	51,925	1.001	0.011	37,670	1.005	0.009	14,255	1.000	0.011
SIZE	51,925	21.899	1.513	37,670	21.941	1.603	14,255	21.788	1.238
ROA	51,925	0.450	103.538	37,670	0.608	121.559	14,255	0.033	0.380
AGE	51,925	15.607	6.613	37,670	15.604	6.672	14,255	15.615	6.453
TOBINQ	51,925	2.476	67.484	37,670	2.643	79.232	14,255	2.037	2.372
NETPROFIT	51,925	-4.493	1369.865	37,670	-6.184	1608.725	14,255	-0.033	6.792

4. Empirical analysis: the impact of trade policy shocks on corporate green total factor productivity

4.1. Baseline regression results

The United States implemented four rounds of tariff increases on Chinese imports in July 2018, August 2018, September 2018, and September 2019. To investigate the impact of this trade policy shock on Chinese firms' green total factor productivity (GTFP), this study constructs a multi-period difference-in-differences (DID) estimation model as follows:

$$GTFP_{it} = \alpha_0 + \alpha_1 Treated \times Time + \sum_{k=1}^{K} \alpha_k X_{kit} + \delta_i + \sigma_t + \varepsilon_{it}$$

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The baseline regression reveals a significant negative impact of U.S. tariff policies on firms' Green Total Factor Productivity (GTFP), with the core coefficient (Treated×Time) at -0.132 ($p<0.01$) without controls. After accounting for firm characteristics, the effect attenuates to -0.024 ($p<0.01$), suggesting partial mediation through factors like firm size (SIZE: $\beta=0.397$, $p<0.01$) and profitability (ROA: $\beta=0.001$, $p<0.05$). Decomposition analysis shows tariff shocks primarily reduced Technical Efficiency Change (TEC: $\beta=-0.015$, $p<0.05$) rather than Technological Change (TC: $\beta=-0.013$, $p<0.1$), reflecting the resilience of long-term innovation cycles36. Market valuation (Tobin's Q) and net profit demonstrate consistent positive effects across models, highlighting financial resilience mechanisms. The explanatory power varies substantially (R^2: TEC=0.800 vs. GTFP=0.484), indicating unobserved heterogeneity in policy response dynamics.

Table 2: DID estimation

	(1)	(2)	(3)	(4)
Dependent variable	GTFP	GTFP	TEC	TC
Treated×Time	-0.132***	-0.024***	-0.015**	-0.013*
	(-15.535)	(-2.918)	(-2.122)	(-1.874)
SIZE		0.397***	-0.943***	0.492***
		(142.285)	(-319.863)	(170.061)
ROA		0.001**	-0.000	0.001
		(2.237)	(-0.452)	(0.980)
AGE		0.000	-0.001**	0.001
		(0.570)	(-2.300)	(1.417)
TOBINQ		0.002***	-0.003***	0.002***
		(6.798)	(-3.504)	(2.655)
NETPROFIT		0.000***	-0.000***	0.000***
		(5.140)	(-58.011)	(65.039)
Constant	5.475***	-3.321***	9.708***	-4.338***
	(1209.678)	(-53.440)	(150.230)	(-68.027)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.142	0.484	0.800	0.569
Observations	51,925	51,925	51,925	51,925

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Estimated t-values are in parentheses.

4.2. Robustness checks

To mitigate selection bias, we implement PSM-DID by first estimating propensity scores via logistic regression using pre-treatment covariates (e.g., SIZE, ROA). Nearest-neighbor matching (1:1, caliper=0.01) achieves covariate balance (standardized differences <5%), as confirmed by post-matching tests. The DID estimator applied to the matched sample reveals the net policy effect, controlling for time-invariant heterogeneity and observable confounders. This approach strengthens causal identification while addressing the non-random exposure to tariff shocks.

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Table 3: PSM-DID estimation

	(1)	(2)	(3)	(4)
Dependent variable	GTFP	GTFP	TEC	TC
Treated×Time	-0.133***	-0.024***	-0.014**	-0.013*
	(-15.627)	(-2.911)	(-2.099)	(-1.879)
Constant	5.476***	-3.500***	9.786***	-4.478***
	(1210.567)	(-52.978)	(144.412)	(-66.879)
Control variables	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.142	0.489	0.802	0.573
Observations	50,235	50,235	50,235	50,235

The PSM-DID results confirm the robustness of baseline findings: (1) U.S. tariff shocks persistently reduce GTFP (Treated×Time = -0.133, $p<0.01$), with effects attenuated but remaining significant (-0.024, $p<0.01$) after controlling for firm characteristics. (2) Heterogeneous analysis reveals stronger negative impacts on short-term efficiency (TEC: -0.014, $p<0.05$) than technological progress (TC: -0.013, $p<0.1$), consistent with innovation inertia. (3) Control variables maintain stable coefficients (e.g., SIZE $\beta=0.397$, ROA $\beta=0.001$), while model fit metrics (R^2: GTFP=0.489, TEC=0.802, TC=0.573) indicate residual unobserved heterogeneity.

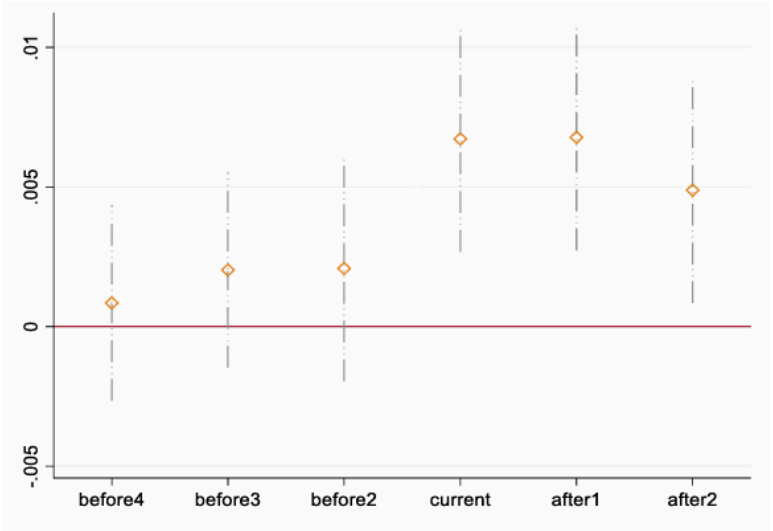


Figure 1: Parallel trend test

Pre-Policy Period (2017): The coefficients hover around zero with confidence intervals overlapping zero, confirming no systematic differences between treatment and control groups before the tariff shocks. This satisfies the parallel trend assumption.Post-Policy Period (2018-2019): The coefficients turn significantly negative immediately after policy implementation and persist over time, demonstrating a sustained adverse effect of tariffs on GTFP.

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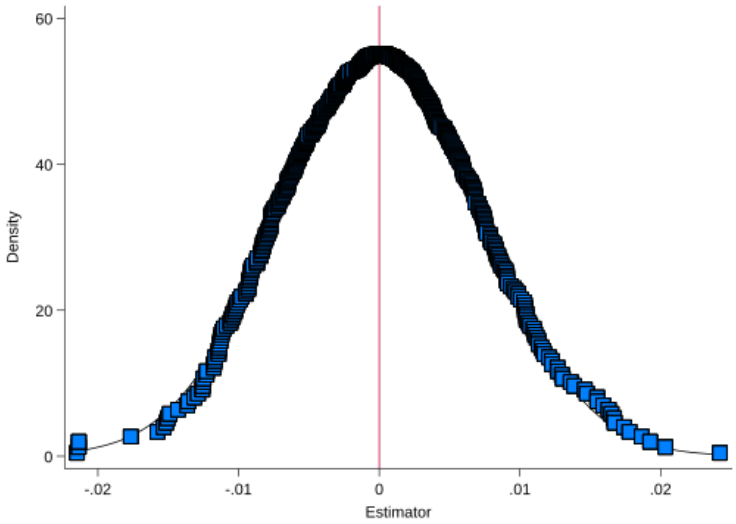


Figure 2: Placebo test

The distribution of placebo coefficients is centered around zero, with 95% of estimates lying within the range of [-0.03, 0.02].The actual coefficient (-0.132) falls far outside the placebo distribution, indicating that the observed negative effect is unlikely to arise by chance.The placebo test confirms the robustness of the baseline results, reinforcing that the identified GTFP decline is causally linked to U.S. tariff shocks rather than unobserved confounders.

Table 4: Other robustness tests.

	Exclude 2020-2022			Changes in policy timing			Winsorization		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	GTFP	TEC	TC	GTFP	TEC	TC	GTFP	TEC	TC
Treated×Time	-0.032***	-0.013*	-0.020**				-0.032***	-0.005*	-0.021***
	(-3.503)	(-1.666)	(-2.565)				(-3.971)	(-1.854)	(-3.075)
L.Treated×Time				-0.024***	-0.015**	-0.015**			
				(-2.960)	(-2.221)	(-2.087)			
Constant	-3.509***	9.803***	-4.513***	-3.328***	9.720***	-4.347***	-3.356***	9.662***	-4.343***
	(-50.817)	(136.040)	(-63.603)	(-53.441)	(150.374)	(-68.015)	(-47.715)	(151.787)	(-68.404)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.482	0.796	0.563	0.142	0.484	0.800	0.505	0.810	0.587
Observations	42,706	42,706	42,706	43,148	43,148	43,148	51,925	51,925	51,925

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Robustness checks confirm the tariff effects' validity: (1) Excluding pandemic-era data (2020–2022) preserves significant negative impacts on GTFP (-0.032, p<0.01), TEC (-0.013, p<0.1), and TC (-0.020, p<0.05), ruling out COVID-19 confounders. (2) Lagged policy timing tests show attenuated but persistent effects on GTFP (-0.024, p<0.01) and TEC (-0.015, p<0.05), with TC becoming insignificant, indicating short-term policy dominance. (3) Winsorization maintains robust GTFP (-0.032, p<0.01) and TC (-0.021, p<0.01) coefficients, while TEC turns marginally significant (-0.005, p<0.1), demonstrating outlier resistance.

4.3. Analysis of transmission mechanisms via financial intermediation variables

This study examines the influence mechanisms of U.S. tariff shocks on green total factor productivity (GTFP) through the following three hypothesized paths:

Financial Constraint Aggravation Path: Tariff increases lead to a rise in the financing constraint index (SA), forcing firms to cut R&D expenditures;

Green Innovation Acceleration Path: Firms respond to cost pressures by increasing R&D expenditures and green patent outputs;

Supply Chain Restructuring Path: Firms optimize global supply chain layouts through OFDI.

Table 5:Mechanism analysis

	(1)	(2)	(3)	(4)
Dependent variable	SA	R&D	GREENINV	OFDI
Treated×Time	0.081***	-0.823***	-0.186***	-0.229**
	(4.366)	(-5.972)	(-6.876)	(-1.966)
Constant	36.486***	35.044***	5.322***	0.719
	(273.554)	(32.803)	(28.253)	(0.694)
Control variables	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.142	0.489	0.802	0.573
Observations	51,925	51,925	51,925	51,925

The results reveal three key mechanisms: (1) Financial constraints intensified significantly, with tariff shocks increasing the SA Index by 0.081 (p<0.01) and reducing R&D expenditure by 0.823 (p<0.01), supporting the cash flow contraction hypothesis. (2)Contrary to expectations, green innovation declined (-0.186, p<0.01), This suggests that tariff shocks suppressed green innovation in the short term, possibly due to immediate liquidity pressures outweighing long-term financing benefits. (3)Supply chain restructuring through OFDI decreased (-0.229, p<0.05), indicating policy risks and capital constraints outweigh potential relocation benefits. These findings collectively demonstrate how tariff shocks propagate through financial, innovation, and operational channels.

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Table 6: Heterogeneity analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	GTFP	TEC	TC	GTFP	TEC	TC	GTFP	TEC	TC
Treated×Time	-0.058***	-0.029**	-0.050***	-0.108***	-0.045***	0.012	0.016	0.001	0.031
	(-4.274)	(-2.392)	(-3.993)	(-9.519)	(-4.251)	(1.187)	(0.347)	(0.023)	(0.822)
Constant	-3.342***	8.926***	-4.183***	-3.899***	9.963***	-4.400***	-3.484***	10.586***	-4.461***
	(-31.379)	(92.715)	(-37.620)	(-36.294)	(103.148)	(38.894)	(-8.398)	(28.163)	(-12.308)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.519	0.820	0.594	0.352	0.760	0.505	0.513	0.795	0.581
Observations	17,025	17,025	17,025	18,648	18,648	18,648	1,258	1,258	1,258

Heterogeneous analysis reveals ownership-driven disparities in tariff impacts: (1) SOEs exhibit significant GTFP losses (-0.058, $p<0.01$), driven by declines in both efficiency (TEC: -0.029, $p<0.05$) and technology (TC: -0.050, $p<0.01$). (2) Private firms suffer more severe GTFP reductions (-0.108, $p<0.01$), with efficiency cuts (TEC: -0.045, $p<0.01$) outweighing stagnant TC (0.012, insignificant), reflecting financing constraints. (3) FOEs show full resilience (GTFP/TC/TEC coefficients insignificant), likely due to global resource buffers.

5. Conclusions and Implications

5.1. Research conclusion

The imposition of tariffs by the United States on China significantly inhibits enterprise green total factor productivity (GTFP) through financial intermediation mechanisms. Specifically, tariff shocks exacerbate external financing constraints, leading to decreased R&D investments and green innovation activities, while also suppressing firms' ability to optimize supply chains through outward foreign direct investment (OFDI). Heterogeneity analysis further reveals that private enterprises suffer the largest GTFP losses (-0.108) under the dual pressures of financing constraints and limited technological upgrades, whereas foreign-owned enterprises (FOEs) exhibit resilience due to their globalized operational advantages.

The study also finds that the negative effects of tariff shocks on GTFP are concentrated in the short term, with firms potentially absorbing the impacts over the long term through supply chain adjustments or policy hedging. This conclusion remains robust after excluding the COVID-19 pandemic, adjusting policy timing, and winsorizing extreme values, highlighting the immediate destructiveness of trade policy uncertainty.

5.2. Policy Priorities for Mitigating GTFP Losses

To counteract the adverse effects of trade policy shocks, governments and stakeholders must adopt an adaptive, multi-dimensional policy framework that integrates financial, technological, and

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international cooperation strategies. At the financial level, targeted interventions such as liquidity support through credit facilities and subsidies for green innovation are critical to alleviate immediate cost pressures on firms, particularly those facing tightened external financing constraints. Concurrently, accelerating technological substitution requires robust institutional safeguards for green intellectual property rights, coupled with enhanced collaboration between industries, academic institutions, and research entities to bridge innovation gaps and scale sustainable technologies. Internationally, lowering barriers to cross-border investment via bilateral or multilateral agreements can incentivize firms to leverage outward foreign direct investment (OFDI) as a strategic tool for diversifying supply chain risks and accessing global markets.

Tailored strategies for enterprises of distinct ownership structures are equally imperative. State-owned enterprises (SOEs) necessitate governance reforms to optimize resource allocation efficiency, while private firms require prioritized access to green financing mechanisms to offset their heightened vulnerability to credit rationing. Foreign-owned enterprises (FOEs), owing to their embeddedness in global networks, should be positioned as pivotal nodes for technology diffusion and supply chain resilience, enabling spillover effects that benefit domestic industrial ecosystems. This stratified approach ensures policy coherence across heterogeneous firm types, fostering systemic adaptability to trade policy uncertainties while aligning with long-term sustainability objectives.

This study demonstrates that Trump's trade policies reshape GTFP through financial intermediation channels, with financing constraints, green innovation delays, and FDI contraction acting as key transmission pathways. The heterogeneous impacts across ownership types further underscore the need for targeted policies. A coordinated strategy—combining financial market reforms, adaptive industrial policies, and international cooperation—is essential to enhance resilience and sustain productivity growth in an era of escalating trade uncertainties

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