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Does Sino–U.S. Trade Friction Promote Corporate Innovation Quality? The Mediating Role of Artificial Intelligence

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Abstract

Sino–U.S. trade friction (SUTF) has imposed significant shocks on economic systems and firm operations, attracting growing scholarly attention. This study investigates the impact of SUTF on corporate innovation quality and its underlying mechanism. Using the U.S. Section 301 investigation as a quasi-natural experiment, we adopt a difference-in-differences (DID) research design. The results indicate that SUTF significantly enhances corporate innovation quality, and this positive effect is partially mediated by the adoption of artificial intelligence (AI)—a general-purpose technology that reshapes traditional organizational and management systems. Moreover, the innovation-enhancing effect of SUTF is more pronounced among firms with a higher proportion of executives with IT experience and those with stronger corporate governance. These findings contribute to the literature on the economic consequences of SUTF by revealing AI adoption as a novel mechanism. This study also offers practical insights for firms navigating an era of heightened trade tensions and can inform policies aimed at fostering high-quality innovation.

Keywords: Sino–U.S. trade friction; corporate innovation quality; artificial intelligence adoption; escaping-competition effect

JEL Classification: F14; O31; O33

1. Introduction

Sino–U.S. trade friction (SUTF) in the 21st century was initiated by the U.S. Section 301 investigation against China, an action announced by then-President Donald Trump on 18 August 2017. This protectionist policy, characterized by the imposition of substantial tariffs, aimed to restrict China's trade and technological advancement, particularly within the manufacturing sector. According to the data from the Peterson Institute for International Economics (PIIE), the average tariff rate imposed on Chinese exports to the U.S. increased more than sixfold following the onset of SUTF relative to the pre-SUTF period (available at https://www.piie.com/research/piie-charts/2019/us-china-trade-war-tariffs-date-chart, accessed on 14 November 2025). SUTF has thus disrupted corporate operational systems, undermined the efficiency of global intermediate goods trade, reconfigured supply chains, and fractured global industrial networks [1–5]. This turbulence casts a shadow over the high-quality development of leading Chinese manufacturers, such as Huawei, ZTE, and DJI.

The academic literature, primarily grounded in traditional trade theories, emphasizes that SUTF increases trade policy uncertainty, thereby elevating export costs and opera-

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tional burdens [6–8]. Scholars argue that these adverse effects ultimately deter corporate investment [9], constrain R&D expenditures [10], and lower patent applications [11–13].

However, a growing body of recent studies, informed by the escaping-competition effect, offers a contrasting view. This literature suggests that SUTF can compel firms to enhance their innovation efforts to gain a competitive advantage amid policy-induced uncertainties, thereby exerting a positive effect on corporate innovation [14–17]. Meanwhile, artificial intelligence (AI), a general-purpose technology characterized by powerful information processing capabilities, has significantly reshaped traditional organizational and management systems [18,19]. Scholars argue that corporate AI adoption can help mitigate financial risks [20], reduce corporate misconduct [21], improve investment efficiency [22], and promote sustainable business practices [23], ultimately enhancing corporate innovation quality [24].

Although a nascent literature has begun to examine the relationship between trade frictions and corporate innovation, dedicated research on the causal effect of SUTF on corporate innovation quality in the digital era remains scarce and is subject to several limitations. First, existing studies tend to overemphasize changes in innovation quantity, relying on indicators such as R&D expenditures and patent counts [11,16,17], while largely overlooking the assessment of genuine innovation quality. Second, regarding the measurement of SUTF, extant studies predominantly employ identification strategies that rely either on industry-level tariff shocks [8,17] or on firm-level historical export patterns [12,25]. These approaches, however, fail to jointly account for both cross-sectional variation in firm-level exposure intensity and the temporal evolution of tariff increases. Third, discussions regarding the transmission channels linking SUTF to corporate innovation remain anchored in traditional business frameworks, focusing predominantly on cost pressures and competitive dynamics [10,15]. Despite AI's role as a transformative general-purpose technology that has fundamentally reshaped organizational and managerial systems, this critical contextual factor remains largely absent from current analytical frameworks.

Motivated by these practical concerns and research gaps, this study aims to investigate the following three research questions:

RQ1: What is the causal effect of SUTF on corporate innovation quality?

RQ2: Through which mechanism does SUTF influence corporate innovation quality?

RQ3: Does the effect of SUTF on corporate innovation quality vary with executive IT background and corporate governance structures?

This study investigates the systematic consequences of SUTF from the perspective of corporate innovation quality, with a particular focus on the novel channel of AI adoption. Leveraging the quasi-natural experiment provided by the U.S. Section 301 investigation, we find that SUTF stimulates textually measured corporate AI adoption, which in turn promotes corporate innovation quality. Moreover, this positive effect is more pronounced for firms with more IT-experienced executives and those with superior corporate governance.

Our study contributes to the extant literature in several ways. First, it establishes a causal link between SUTF and corporate innovation quality, thereby helping to reconcile the mixed findings in prior literature on the innovation effects of trade frictions. Second, it identifies a novel mediating mechanism—AI adoption—thereby integrating a critical contemporary business practice into the analysis of trade friction. Third, it systematically advances the understanding of the contingent effects of SUTF by examining boundary conditions related to executive technological background and firms' internal governance structures.

Beyond its theoretical contributions, this study offers practical implications. For practitioners, our findings suggest that advancing AI adoption can serve as a strategic response to SUTF, helping firms systematically reshape organizational structures and processes to

enhance innovation quality. For policymakers, the results highlight the value of refining innovation evaluation frameworks and incentive schemes to foster high-quality innovation in an era of global trade tensions.

2. Background and Literature Review

2.1. Background

The U.S. Section 301 investigation represents a landmark event in SUTF. Following the findings of the investigation, the U.S. government officially imposed substantial tariffs on a wide range of Chinese exports in March 2018, marking the onset of sustained bilateral trade friction. The first formal round of these tariffs took effect on 6 July 2018. Over the subsequent 18 months, the U.S. implemented four successive rounds of escalating tariffs, covering Chinese exports with a cumulative value of approximately $550 billion. As summarized in Table 1, the scope of sectors subject to these additional tariffs expanded progressively. By the fourth round, the tariffs encompassed products classified under 1097 distinct Harmonized System (HS) four-digit codes, accounting for 94.325% of all HS-4 categories. The academic literature has documented the profound negative effects of the SUTF from multiple perspectives, including its impact on globalization initiatives [26], the international financial system [27], the global trading system [1,2], and supply chains [4]. Notably, relative to firms in the U.S., Chinese firms have been identified as suffering more severe adverse consequences in this trade dispute [28].

Table 1. Timeline of major tariff rounds in Sino–U.S. trade friction.

Round	Date	Object	HS 8-Digit Codes Involved (Number)	HS 4-Digit Codes Involved (Number)	Initial Additional Tariff Rate	Updated Additional Tariff Rate in 2020
1st	6 July 2018	US $34 billion Chinese export products	818	134	25%	25%
2nd	23 August 2018	US $16 billion Chinese export products	279	70	25%	25%
3rd	24 September 2018	US $200 billion Chinese export products	5772	812	10%	25%
4th	1 September 2019	US $300 billion Chinese export products	3771	487	15%	15%

Note: This table summarizes the four major rounds of additional tariffs imposed by the U.S. on imports from China pursuant to the Section 301 investigation. The USTR product lists are used for identification.

To assess the magnitude of SUTF, we follow the approach of Benguria et al. [10] to construct industry-level tariff rates faced by Chinese exporters to the U.S. market. The detailed procedure is outlined below.

First, we establish baseline tariffs using the U.S. Most-Favored-Nation (MFN) applied tariff rates, which reflect the pre-SUTF bilateral tariff level. Second, we measure the additional tariffs based on the product lists issued by the U.S. Trade Representative Office (USTR) under Section 301. Specifically, we compile the complete list of products subject to Section 301 tariffs against China, along with their corresponding additional tariff rates announced throughout the investigation. The total tariff rate at the HS 4-digit product level during the SUTF period is then calculated as the sum of the baseline MFN tariff and the applicable Section 301 additional tariff. Third, we map HS four-digit product codes to the industry classification codes of the China Securities Regulatory Commission (CSRC) based on product descriptions from the World Trade Organization's Integrated Database (IDB). Finally, we compute a weighted-average industry-level tariff, where the weight for each product is its mean export value from China to the U.S. over our sample period.

Figure 1 presents the changes in average industry-level tariff rates before and after the onset of the U.S. Section 301 investigation. The figure shows that the investigation substantially increased tariff burdens on Chinese exporters, with an average increase

of 16.670 percentage points. This magnitude aligns closely with estimates published by the PIIE.

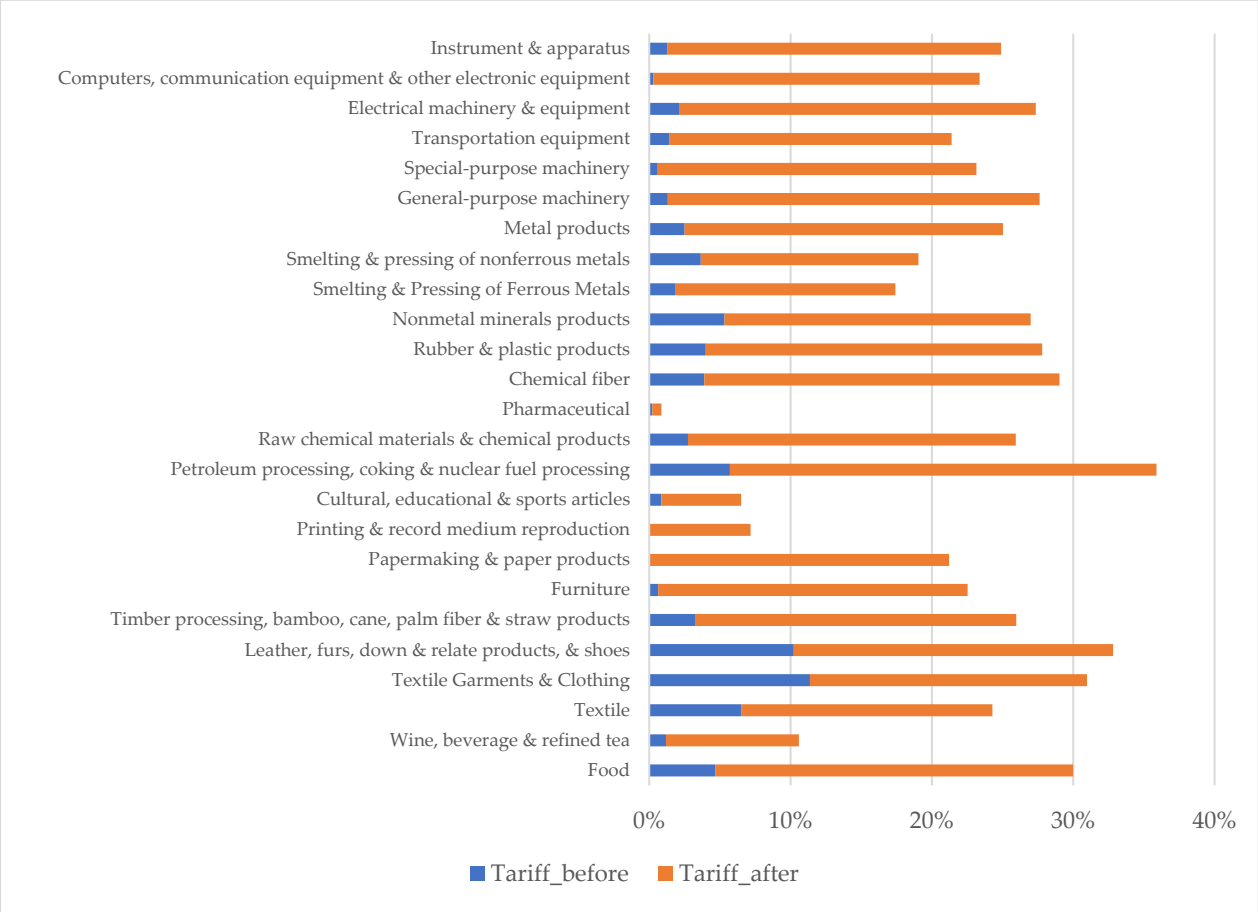


Figure 1. Changes in industry-level tariff rates before and after the U.S. Section 301 investigation. Note: The blue bars indicate the average tariff rates prior to the onset of SUTF, while the orange bars represent the rates following its onset.

2.2. Literature Review

Existing studies examining the innovation effects of SUTF have produced mixed findings. One strand of literature, grounded in traditional trade theory, highlights a negative effect of SUTF on corporate innovation [9–13]. According to this theoretical perspective, higher tariffs—a common tool of trade protection—impose additional trade and compliance costs on firms in the targeted country, intensifying their operational burdens and worsening financing conditions [29–31]. This, in turn, crowds out firms' investment in innovation activities, which require substantial and sustained financial support [32].

However, the heterogeneous-firms trade model introduced by Melitz [33] shifted the theoretical focus to firms' differential investment decisions in dynamic environments. Building on this, Gorodnichenko et al. [34] argue that intensifying competitive pressure in global markets diminishes firms' pre-innovation rents, thereby stimulating an escaping-competition motivation that can foster innovation. Hombert and Matray [35] further attribute this mechanism to the profitability of differentiated products. Subsequently, a burgeoning literature has focused on firms' motivation to escape the heightened competition triggered by SUTF, documenting a positive effect on innovation [14–17]. For example, Li et al. [15] find that the high tariffs triggered by SUTF prompted Chinese exporters to divert sales to domestic or alternative markets, thereby intensifying competition within the domestic industry. This intensified competition motivates firms to increase innovation in-

vestment to escape competitive pressure. Zheng et al. [16] and Tian et al. [17] explore the positive effect of SUTF on innovation outcomes, highlighting firms' motivation to create differentiated products and secure a more competitive market position.

These conflicting arguments regarding the innovation effect of SUTF may stem from a focus on innovation quantity rather than innovation quality. For Chinese firms, quantitative innovation outcomes, such as R&D expenditures and patent counts, are often tied to policy incentives like government subsidies [36], which can encourage rent-seeking behavior and a strategic reallocation of resources toward low-productivity innovations [37]. According to Schumpeter's theory of innovation [38] and the escaping-competition view, firms facing substantial uncertainty can only escape intense competition by enhancing genuine innovation quality that generates sustained economic profits. Therefore, we hypothesize that SUTF will promote corporate innovation quality.

Meanwhile, the rise of the digital economy has created new pathways for firms' high-quality development [39,40]. In the digital era, rapidly advancing AI technologies have become vital tools for enhancing corporate resilience in highly uncertain business environments [41,42]. Confronted with heightened policy uncertainty, firms tend to adopt precautionary and forward-looking strategies by reallocating resources toward digital investments. Such initiatives can generate competitive advantages by lowering operational costs and improving business efficiency [43,44], which, in turn, accelerate digital transformation and facilitate AI adoption.

According to Socio-Technical Systems (STS) theory, organizational development is driven by the joint optimization of technical and social subsystems, highlighting the importance of integrating advanced technologies with organizational structures and processes [45–47]. The growing adoption of AI reshapes firms' production, decision-making, and innovation processes [48,49]. These AI technologies, such as intelligent computing, large-scale data analytics, and generative AI, enable firms to access cross-domain knowledge, identify technological opportunities, and achieve more significant technological breakthroughs [50]. Thus, we posit that SUTF enhances firms' AI adoption, thereby promoting innovation quality.

3. Research Design

3.1. Empirical Model Settings

Following the identification strategies of Lu and Yu [51], Bai and Jia [52], and Tang et al. [53], we employ a DID design with a continuous treatment to estimate the causal effect of SUTF on corporate innovation quality. The baseline regression model is specified as follows:

$$CIQ_{i,j,t} = \alpha_0 + \alpha_1 TF_{i,j,t-1} + \sum \alpha_n Controls_{i,j,t-1} + \mu_i + \mu_j + \mu_t + \varepsilon_{i,j,t} \quad (1)$$

In Equation (1), the dependent variable, *CIQ*, denotes corporate innovation quality. The key independent variable, *TF*, measures a firm's exposure intensity to SUTF. The vector *Controls* represents a series of control variables that may influence innovation quality, including firm size (*Size*), firm age (*Age*), governmental subsidies (*Subsidy*), fixed assets (*Capital*), employee compensation (*Salary*), financial leverage (*Leverage*), return on assets (*ROA*), state ownership (*SOE*), ownership concentration (*Top1*), and provincial GDP (*GDP*). Detailed definitions and data sources for all variables are provided in Appendix A. To mitigate potential reverse causality, all firm-level independent variables are lagged by one period. We further include firm, industry, and year fixed effects to absorb time-invariant firm heterogeneity, industry-specific trends, and common time shocks, respectively. Standard errors are clustered at the firm level to account for serial correlation within firms. All

continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

3.2. Variable Construction

3.2.1. Dependent Variable: Corporate Innovation Quality

To measure corporate innovation quality, we follow prior literature [54–58] and employ the patent breadth measure developed by Aghion et al. [59]. Compared with other measures such as invention patent counts and citation counts, patent breadth provides a more comprehensive characterization of innovation quality. Patent breadth is defined as one minus the Herfindahl index of the patent's 4-digit International Patent Classification (IPC) subclasses. A higher patent breadth value indicates that the patent's technological claims are distributed across a more diverse set of technological domains. Such dispersion reflects greater patent complexity, a wider application domain, and a broader scope of patent protection, all of which collectively signal a higher degree of innovation quality [55,56,60,61]. Our firm-level measure of innovation quality, *CIQ*, is calculated as the annual median of patent breadth across all patents applied for by a firm in a given year.

In subsequent robustness analysis (Section 4.3.3), we employ two alternative proxies for corporate innovation quality. The first, *CIQ2*, is the ratio of invention patent applications to total patent applications, capturing innovation quality from the perspective of patent composition. The second, *CIQ3*, is the number of forward citations received by a firm's invention patents, which reflects the technological impact and significance of the innovation.

3.2.2. Key Independent Variable: Trade Friction Exposure

Our key independent variable, *TF*, is the core interaction term in the DID regression model. It is constructed as the product of a continuous treatment intensity measure, *TariffIntensity*, and a post-SUTF indicator, *Post*.

Prevailing approaches to measuring a firm's exposure to SUTF are inconsistent and can be categorized into two strands. The first strand leverages the U.S. Section 301 investigation, employing an industry-level identification strategy, where industries subject to higher tariff increases are designated as the treatment group [8,17]. A key limitation of this approach is its inability to capture heterogeneous exposure across firms within the same industry. The second strand refines the analysis to the firm level by defining treatment groups based on a firm's pre-SUTF export dependence, measured by its historical export share [11,12,25]. While this approach accounts for firm-level heterogeneity, a significant drawback is that it does not directly incorporate the specific tariff increases imposed under the U.S. Section 301 investigation.

To address the limitations of both approaches, we construct a continuous treatment variable (*TariffIntensity*) that integrates industry-level tariff shocks with firm-level export dependence. Specifically, it is calculated as follows:

$$TariffIntensity_{i,j} = DeltaIndTariff_j \times ExportDependence2017_i \quad (2)$$

In Equation (2), $DeltaIndTariff_j$ captures the changes in industry-level tariffs, measured as the difference between the post-SUTF and pre-SUTF average tariff rates for industry j (as detailed in Section 2.1 and illustrated in Figure 1). $ExportDependence2017_i$ represents firm i's export dependence. Following Lu and Yu [51] and Chen et al. [11], we measure it as a firm's export-to-sales ratio in 2017, the year immediately preceding the onset of SUTF.

The interaction term, *TF*, is then constructed as the product of *TariffIntensity* and the post-SUTF indicator, *Post*. The dummy variable *Post* equals one for fiscal years 2018 and onward, and zero otherwise. This specification follows the standard DID design [8,14].

3.3. Sample Construction and Data Sources

Our initial sample comprises Chinese A-share listed manufacturing firms from 2014 to 2022. Data on industry-level tariff changes are compiled from multiple sources. Product-level tariff schedules are obtained from the UN Comtrade database and the IDB. The list of products specifically targeted under the U.S. Section 301 investigation is sourced from official announcements by the office of the USTR. Patent data, which we use to construct our measure of innovation quality, are obtained from the China National Intellectual Property Administration (CNIPA). We match patents to listed firms based on firm names, including full names, former names, and common abbreviations. Firm-level financial and corporate governance variables are sourced from the China Stock Market and Accounting Research (CSMAR) Database, a standard and reliable source for empirical research on the Chinese capital market.

We refine the sample by applying the following filters: (1) firms under Special Treatment (ST) or Particular Transfer (PT) status, which indicate financial distress or other irregularities; (2) firms that went public after the onset of SUTF (i.e., after 2018); (3) firms with negative book equity (i.e., liabilities exceeding assets); (4) firms that changed their primary industry classification during the sample period; and (5) firms with missing or abnormal values for key financial variables, such as negative government subsidies or employee compensation. After applying these filters, our final sample consists of 14,722 firm-year observations, representing 2074 unique manufacturing enterprises.

4. Results

4.1. Summary Statistics and Correlations

Table 2 presents the descriptive statistics for the main variables. The mean of corporate innovation quality (*CIQ*) is 0.245, with a standard deviation of 0.276 and a maximum of 0.934. These statistics indicate substantial cross-sectional variation in innovation quality. The correlation matrix is provided in Table 3. The pairwise Pearson correlation coefficients among the independent variables are all below 0.6, mitigating concerns regarding severe multicollinearity in the regression analyses.

Table 2. Descriptive statistics.

Variables	Observations	Mean	SD	Min	Median	Max
CIQ	14,722	0.245	0.276	0.000	0.000	0.934
TF	14,722	0.017	0.037	0.000	0.000	0.246
Size	14,722	22.078	1.171	19.918	21.922	25.972
Age	14,722	2.912	0.296	1.792	2.944	3.584
Subsidy	14,722	0.007	0.007	0.000	0.005	0.043
Capital	14,722	0.224	0.130	0.015	0.200	0.657
Salary	14,722	17.217	1.493	9.874	17.201	21.718
Leverage	14,722	0.391	0.186	0.048	0.384	0.865
ROA	14,722	0.050	0.069	−0.407	0.047	0.255
SOE	14,722	0.260	0.439	0.000	0.000	1.000
Top1	14,722	0.333	0.138	0.081	0.312	0.750
GDP	14,722	11.305	0.405	10.183	11.362	12.156

Table 3. Correlation matrix.

Variables	*TF*	*Size*	*Age*	*Subsidy*	*Capital*	*Salary*	*Leverage*	*ROA*	*SOE*	*Top1*	*GDP*
TF	1										
Size	0.035 ***	1									
Age	0.121 ***	0.200 ***	1								
Subsidy	0.008	−0.124 ***	−0.051 ***	1							
Capital	−0.017 **	0.108 ***	0.051 ***	−0.085 ***	1						
Salary	0.149 ***	0.727 ***	0.179 ***	−0.010	0.030 ***	1					
Leverage	0.022 ***	0.502 ***	0.132 ***	−0.067 ***	0.158 ***	0.340 ***	1				
ROA	0.011	0.007	−0.051 ***	0.068 ***	−0.123 ***	0.118 ***	−0.379 ***	1			
SOE	−0.093 ***	0.346 ***	0.211 ***	−0.046 ***	0.127 ***	0.243 ***	0.273 ***	−0.106 ***	1		
Top1	−0.037 ***	0.099 ***	−0.092 ***	−0.034 ***	0.036 ***	0.097 ***	−0.008	0.148 ***	0.131 ***	1	
GDP	0.235 ***	−0.021 **	0.095 ***	0.006	−0.176 ***	0.094 ***	−0.066 ***	0.034 ***	−0.179 ***	−0.033 ***	1

Note: This table reports the Pearson correlation coefficients for the independent variables. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

4.2. Baseline Regression Results

Table 4 presents the baseline regression results. Column (1) reports a positive and statistically significant coefficient for the variable of interest, *TF*, suggesting a positive association between SUTF and corporate innovation quality. In Column (2), after incorporating control variables, the coefficient on *TF* remains positive and statistically significant. The coefficient estimate of 0.288 implies that, following the policy shock, a one-standard-deviation increase in a firm's exposure to SUTF leads to a 0.011 (=0.288 × 0.037) increase in corporate innovation quality for the treatment group relative to the control group. Given the sample mean of *CIQ* is 0.245, this effect translates to an approximately 4.349% (=0.288 × 0.037/0.245) improvement. We regard this as economically meaningful, especially considering that the average annual growth rate of manufacturing value added—a broad indicator of productivity—was only about 6% during our sample period (National Bureau of Statistics of China, 2014–2022). Collectively, these baseline results provide preliminary evidence consistent with the hypothesis that SUTF enhances corporate innovation quality.

Table 4. Baseline results: the effect of SUTF on corporate innovation quality.

Variables	**(1)** ***CIQ***	**(2)** ***CIQ***
TF	0.305 ***	0.288 ***
	(0.094)	(0.095)
Size		0.033 ***
		(0.009)
Age		0.131 **
		(0.062)
Subsidy		−0.168
		(0.414)
Capital		0.103 ***
		(0.040)
Salary		−0.006
		(0.004)
Leverage		−0.030
		(0.031)
ROA		0.104 **
		(0.041)
SOE		−0.006
		(0.019)
Top1		−0.003
		(0.051)
GDP		0.057 *
		(0.032)
Constant	0.240 ***	−1.424 ***
	(0.002)	(0.453)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Firm FE	Yes	Yes
Observations	14,722	14,722
Adjusted R^2	0.443	0.445

Note: The dependent variable is corporate innovation quality (*CIQ*). Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.3. Robustness Checks

4.3.1. Parallel Trend Test

The validity of the DID approach rests on the parallel trends assumption. This assumption posits that, absent the treatment, the outcomes of the treatment and control groups would have followed similar trajectories. To test this assumption, we employ an event-study framework following Beck et al. [62], spanning an estimation window from four periods before to three periods after the onset of SUTF. Because our dependent variable, corporate innovation quality (*CIQ*), is measured with a one-year lead in the baseline specification, the event-time indicators in this analysis effectively cover the period from five years before to three years after the shock. We omit the event-time dummy for the year five years prior to the shock to avoid perfect multicollinearity, thus establishing it as the reference period. As reported in Table 5, the coefficients on the pre-treatment period dummies are individually insignificant. Moreover, an F-test fails to reject the null hypothesis that all pre-treatment coefficients are jointly zero. These results suggest that the pre-treatment trends in innovation quality between the treatment and control groups are not statistically distinguishable, supporting the parallel trends assumption.

Table 5. Parallel trend: event-study estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Pre-Treatment Period				**Post-Treatment Period**		
Relative Period	**t − 4**	**t − 3**	**t − 2**	**t − 1**	**t**	**t + 1**	**t + 2**	**t + 3**
coefficients	−0.007	−0.110	0.088	0.076	0.174	0.273	0.376 **	0.433 **
t-statistics	−0.043	−0.666	0.515	0.453	1.019	1.583	2.069	2.352
F-statistics			0.01				4.08 **	

Note: This table reports the coefficients from an event-study regression. The dependent variable is *CIQ*. The estimation window spans four years before to three years after the onset of SUTF. The omitted baseline year is t = −5. All regressions include the full set of control variables and fixed effects as in Column (2) of Table 4. ** denotes statistical significance at the 5% level.

Figure 2 plots the dynamic treatment effects. The point estimates for the pre-treatment periods are close to zero, and their 95% confidence intervals encompass zero. In contrast, the coefficients for the post-treatment period are predominantly positive and statistically significant, exhibiting a gradually increasing pattern over time. Overall, the results from the event-study analysis lend support to the validity of our DID identification strategy and illustrate a sustained, positive effect of SUTF on corporate innovation quality.

4.3.2. Placebo Test

We conduct a placebo test to assess whether our baseline results are driven by the actual effect of SUTF, or alternatively, by random chance or unobservable confounding trends. Following Ferrara et al. [63], we perform a simulation in which we randomly assign treatment status and its corresponding shock years to construct a placebo treatment indicator. This procedure is replicated 2000 times. Figure 3 plots the kernel density distribution of the estimated coefficients on the placebo treatment variable from these 2000 replications. The distribution is tightly centered around zero, in stark contrast to the statistically significant coefficient from the actual baseline estimation. This discrepancy provides evidence that our main finding is unlikely to be spurious, thereby strengthening the credibility of our causal inference regarding the effect of SUTF.

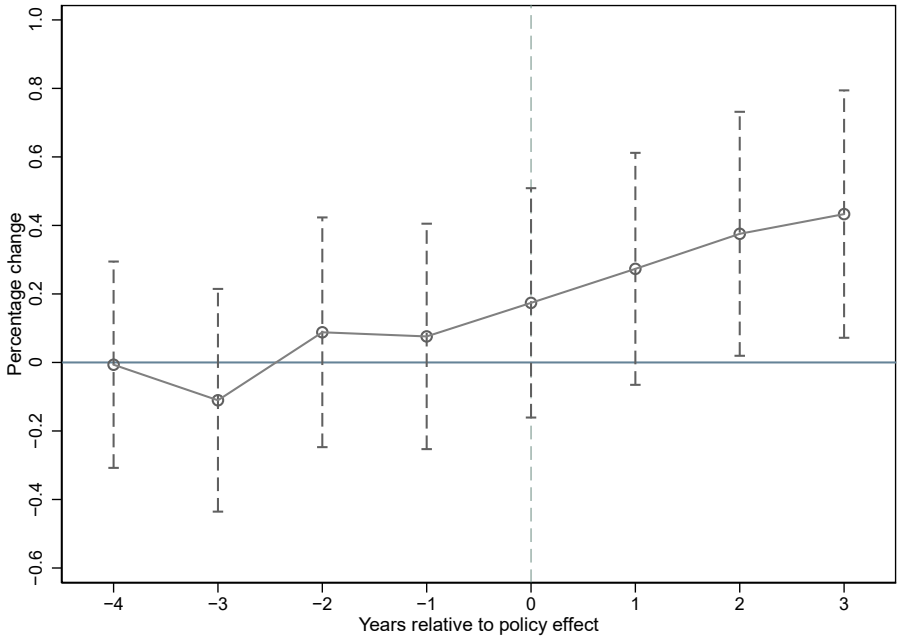


Figure 2. Dynamic effects of SUTF on corporate innovation quality (*CIQ*). Note: The solid dots represent the estimated coefficients for each relative year, with the vertical bars indicating the corresponding 95% confidence intervals. The dashed vertical line marks the shock year (t = 0). The omitted reference period is five years prior to the onset of SUTF.

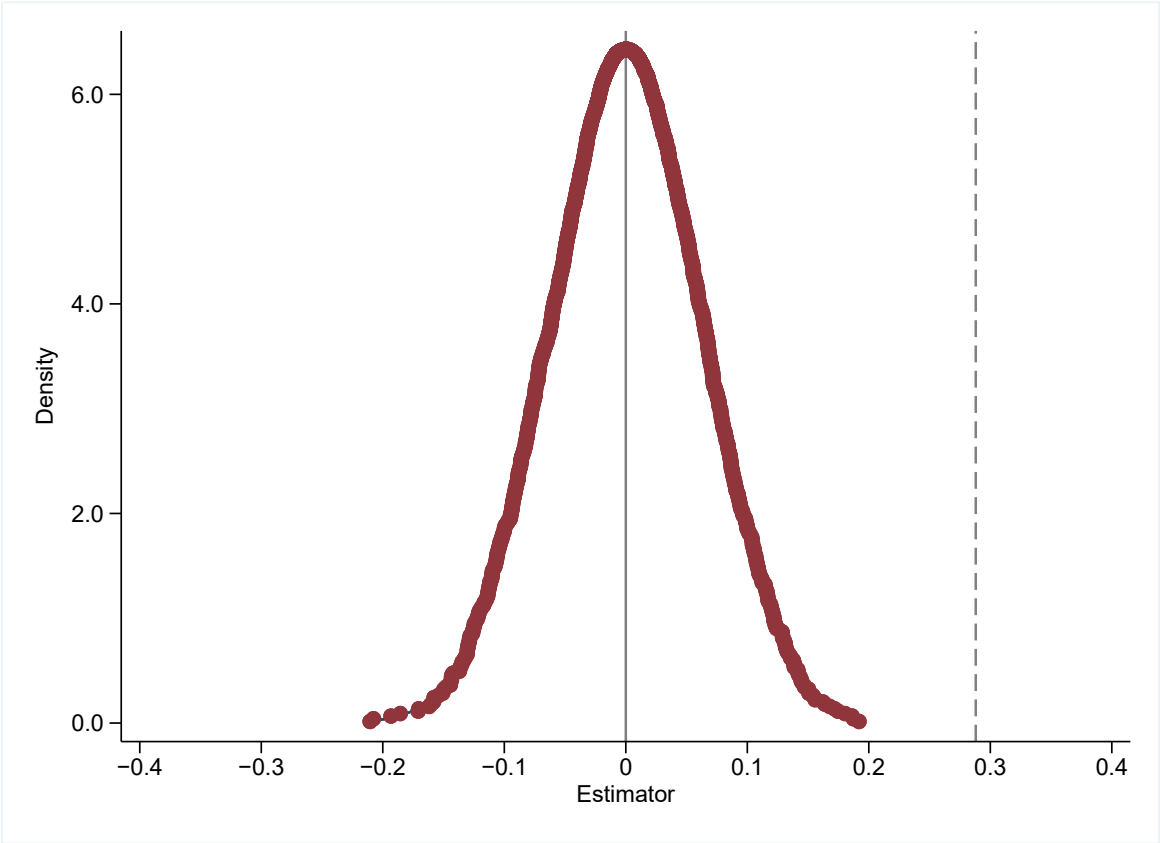


Figure 3. Placebo test. Note: The curve represents the kernel density distribution of the estimated coefficients from 2000 placebo simulations, in which the treatment status and shock years are randomly assigned. The solid vertical line at 0 represents the expected distribution under the null hypothesis of no true policy effect. The dashed vertical line indicates the estimated coefficient on *TF* from the baseline regression.

4.3.3. Alternative Measures for Key Variables

To assess the robustness of our core findings, we conduct a series of tests using alternative measures for the key variables. First, we examine the sensitivity of our results to different specifications of the SUTF shock. We employ three alternative independent variables: (1) Following Bai and Jia [52], we construct an alternative continuous treatment variable, *TariffIntensity2*, by interacting *DeltaIndTariff* with a firm's pre-shock export dependence, where the latter is measured as the firm's average export-to-sales ratio over the three-year period preceding the onset of SUTF (i.e., 2015–2017). The alternative interaction term, *TF2*, is then constructed as the product of *TariffIntensity2* and the post-SUTF indicator, *Post*. (2) Consistent with the industry-level identification strategies in Liu et al. [8] and Tian et al. [17], we implement a standard DID design. The treatment group comprises firms in industries facing above-median tariff increases (where *DeltaIndTariff* exceeds the sample median), and the treatment effect is captured by the interaction term between this treatment dummy and a post-policy indicator (*DIDindustry*). (3) We directly utilize the weighted average industry-level tariff rate (*Tariff*) to measure the intensity of the SUTF shock, as detailed in Section 2.1. Columns (1) through (3) of Table 6 present the regression results using these alternative measures. The coefficients on *TF2*, *DIDindustry*, and *Tariff* are all positive and statistically significant at the 1% level. These results confirm the robustness of our core findings to alternative shock specifications.

Table 6. Robustness checks: alternative variable definitions.

Variables	(1) *CIQ*	(2) *CIQ*	(3) *CIQ*	(4) *CIQ2*	(5) *CIQ3*
TF2	0.274 ***				
	(0.095)				
DIDindustry		0.034 ***			
		(0.011)			
Tariff			0.379 ***		
			(0.065)		
TF				0.294 ***	0.640 **
				(0.091)	(0.314)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	14,722	14,722	14,722	14,158	14,722
Adjusted R^2	0.445	0.445	0.447	0.546	0.911

Note: The dependent variable in Columns (1)–(3) is *CIQ*; in Column (4) it is *CIQ2*; and in Column (5) it is *CIQ3*. Robust standard errors clustered at the firm level are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Second, we evaluate the sensitivity of our results to alternative proxies of corporate innovation quality. (1) Following Yang [64], we use the share of invention patent applications in total applications (*CIQ2*) to capture innovation quality. Invention patents undergo a more stringent and lengthy examination process, making them the most valuable among the three patent types. A higher value of *CIQ2* thus indicates a better innovation structure and higher overall innovation quality. (2) We employ the forward citations of invention patents (*CIQ3*) as an alternative measure of innovation quality. *CIQ3* captures the frequency with which a firm's patents are cited by subsequent patent applications. A higher citation count signifies greater knowledge dissemination and, by implication, higher patent quality [65]. Columns (4) and (5) of Table 6 present the regression results using *CIQ2* and *CIQ3* as the dependent variables, respectively. The coefficients on *TF* re-

main positive and statistically significant in both specifications, reinforcing the robustness of our baseline findings.

4.3.4. Addressing Potential Confounding Policies

Although our regression models include a comprehensive set of control variables, the estimated relationship between SUTF and corporate innovation quality may still be confounded by other concurrent policy initiatives. We focus on three prominent concurrent initiatives: the China–Europe Railway Express (CERE), the National AI Innovation Pilot Zone (NAIIPZ) program, and the Made in China 2025 (MIC2025) strategy.

First, the CERE represents a sustained effort to deepen trade partnerships and has substantially reduced overland transportation time. This improvement in logistics may induce trade diversion effects that are independent of SUTF, potentially biasing our estimates. Second, the NAIIPZ aims to foster the digital economy by providing firms in designated zones with AI-related resources and policy support. This place-based industrial policy could independently stimulate innovation within pilot cities, introducing a source of endogeneity if the selection of NAIIPZ cities is correlated with firms' exposure to SUTF. Third, the MIC2025 policy was launched in 2015 to accelerate the transformation of the manufacturing sector toward high-end, intelligent, and green development. Within two years of its inception, more than 30 cities were designated as demonstration pilots. This targeted industrial policy may spur innovation in designated pilot cities, thereby confounding the estimated effect of SUTF.

To mitigate potential bias, we augment our baseline regression model, Equation (1), by including dummy variables for CERE, NAIIPZ, and MIC2025, as well as their respective interaction terms with *TF*. The *CERE* dummy equals one for firms located in cities connected to the railway network following its inauguration and zero otherwise. The *NAIIPZ* dummy equals one for firms headquartered in cities designated as pilot zones after the policy launch, and zero otherwise. The *MIC2025* dummy equals one for firms headquartered in cities selected as demonstration pilots and zero otherwise.

Table 7 reports the estimation results. After incorporating dummy variables for these potential confounding policies and their interaction terms with *TF*, the coefficients on *TF* remain significantly positive across all specifications. The continued significance supports the robustness of our primary finding that SUTF enhances corporate innovation quality.

Table 7. Robustness checks: controlling for concurrent policies.

Variables	(1) *CIQ*	(2) *CIQ*	(3) *CIQ*	(4) *CIQ*	(5) *CIQ*	(6) *CIQ*
TF	0.288 ***	0.216 *	0.287 ***	0.280 ***	0.288 ***	0.291 ***
	(0.095)	(0.120)	(0.095)	(0.096)	(0.095)	(0.111)
CERE	0.000	−0.003				
	(0.009)	(0.009)				
TF × *CERE*		0.156				
		(0.145)				
NAIIPZ			0.007	0.004		
			(0.010)	(0.013)		
TF × *NAIIPZ*				0.080		
				(0.189)		
MIC2025					0.015	0.015
					(0.010)	(0.010)
TF × *MIC2025*						−0.012
						(0.160)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. *Cont.*

Variables	(1) *CIQ*	(2) *CIQ*	(3) *CIQ*	(4) *CIQ*	(5) *CIQ*	(6) *CIQ*
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,722	14,722	14,722	14,722	14,722	14,722
Adjusted R^2	0.445	0.445	0.445	0.445	0.445	0.445

Note: The dependent variable is corporate innovation quality (*CIQ*). All specifications are based on Equation (1). Robust standard errors clustered at the firm level are reported in parentheses. *** and * denote statistical significance at the 1% and 10% levels, respectively.

4.3.5. Alternative Sample Specifications

To address concerns that the baseline results may be driven by a unique sub-sample of firms with consistently superior innovation performance, we exclude firms that rank in the top 10% annually in terms of innovation quality. As reported in Column (1) of Table 8, the coefficient on *TF* remains positive and statistically significant. Furthermore, to mitigate the potential influence of location-specific advantages, we exclude firms headquartered in the four municipalities under the direct administration of the central government (i.e., Beijing, Tianjin, Shanghai, and Chongqing). These regions typically provide greater resource endowments and a more favorable innovation ecosystem. The results, presented in Column (2) of Table 8, show that the coefficient on *TF* continues to be positive and statistically significant. Collectively, these results suggest that our core findings are robust to alternative sample specifications designed to alleviate concerns regarding sample selection bias.

Table 8. Robustness checks: subsample analyses.

Variables	(1) *CIQ*	(2) *CIQ*
TF	0.259 ***	0.287 ***
	(0.088)	(0.099)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Firm FE	Yes	Yes
Observations	12,738	12,649
Adjusted R^2	0.444	0.448

Note: The dependent variable is corporate innovation quality (*CIQ*). Column (1) excludes firms annually ranked in the top 10% in terms of innovation quality. Column (2) excludes firms headquartered in the four direct-controlled municipalities (Beijing, Tianjin, Shanghai, and Chongqing). Robust standard errors clustered at the firm level are reported in parentheses. *** denotes statistical significance at the 1% level.

4.4. Mechanism Analysis

In this section, we explore whether corporate AI adoption serves as a channel through which SUTF affects innovation quality. SUTF substantially increases uncertainty and intensifies competitive pressure, triggering firms' motivation to adopt precautionary and forward-looking strategies, such as AI adoption. As a transformative general-purpose technology, AI can systemically reshape corporate organizational structures and processes, thereby enhancing innovation quality. To investigate this channel, we employ a causal mediation analysis framework. Specifically, we estimate the following two-stage system of equations:

$$AI_{i,j,t} = \beta_0 + \beta_1 TF_{i,j,t} + \sum \beta_n Controls_{i,j,t} + \mu_i + \mu_j + \mu_t + \varepsilon_{i,j,t} \quad (3)$$

$$CIQ_{i,j,t} = \gamma_0 + \gamma_1 TF_{i,j,t-1} + \gamma_2 AI_{i,j,t-1} + \sum \gamma_n Controls_{i,j,t-1} + \mu_i + \mu_j + \mu_t + \varepsilon_{i,j,t} \quad (4)$$

Equation (3) estimates the effect of SUTF on the proposed mediator, AI adoption. Equation (4) then examines the effect of both SUTF and lagged AI adoption on corporate innovation quality, thereby testing the hypothesized mediation path. All other variables and the model structure are consistent with the baseline specification in Equation (1).

Following the recent literature on AI [20,22,23,66], we measure AI adoption using the textual analysis approach proposed by Yao et al. [67]. Their method begins by compiling an initial vocabulary of AI-related terms from multiple sources: the extant literature, documents published by the World Intellectual Property Organization (WIPO), and industry reports from leading Chinese research institutions. This lexicon is then expanded using the Word2Vec model—a word embedding technique that identifies semantically similar words—resulting in a final dictionary of 73 Chinese keywords. The complete list is provided in Appendix B. Our primary proxy, *AIRatio*, is defined as the frequency of AI-related keywords in the Management's Discussion and Analysis (MD&A) section of a firm's annual report. To assess robustness, we construct an alternative measure, *AINum*, defined as the raw count of such keywords in the MD&A.

Panel A of Table 9 presents the estimation results. Column (1) shows that the coefficient on *TF* is positive and statistically significant at the 5% level when *AIRatio* is the dependent variable, indicating that SUTF significantly promotes AI adoption. In Column (2), which includes *AIRatio*, the coefficient on *TF* remains positive and significant for *CIQ*, albeit attenuated in magnitude compared to the baseline estimate. This attenuation, coupled with a significant Sobel test statistic ($p < 0.05$), suggests that AI adoption mediated a portion of SUTF's total effect on innovation quality. Columns (3) and (4) report results using the alternative mediating variable, *AINum*. The findings are qualitatively similar: SUTF positively affects *AINum* (Column 3), and its direct effect on *CIQ* decreases upon controlling for *AINum* (Column 4), with the Sobel test again significant. Collectively, these results support the interpretation that AI adoption serves as a partial mediator in the relationship between SUTF and corporate innovation quality.

Table 9. Mechanism analysis: the mediating role of AI adoption. (**Panel A**) Two-stage least squares and Sobel test results. (**Panel B**) Bootstrap test for mediation effects.

(**Panel A**)				
Variables	**(1)** ***AIRatio***	**(2)** ***CIQ***	**(3)** ***AINum***	**(4)** ***CIQ***
TF	3.647 **	0.278 ***	0.812 **	0.281 ***
	(1.646)	(0.094)	(0.330)	(0.094)
AIRatio		0.003 ***		
		(0.001)		
AINum				0.008 **
				(0.004)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	14,722	14,722	14,722	14,722
Adjusted R^2	0.700	0.445	0.708	0.445
Sobel Z	2.310 **		2.051 **	

Table 9. *Cont.*

(Panel B)					
Mediator	**(1) Effect**	**(2) Coefficient**	**(3) Z-Statistics**	**(4) *p*-Value**	**(5) [95% Conf. Interval]**
AIRatio	Indirect	0.009	2.199 **	0.028	[0.001, 0.018]
	Direct	0.278	3.420 ***	0.000	[0.119, 0.438]
AINum	Indirect	0.007	2.162 **	0.031	[0.001, 0.013]
	Direct	0.281	3.046 ***	0.002	[0.100, 0.462]

Note: Panel A reports the result of a two-stage least squares estimation and Sobel test for mediation. Columns (1) and (3) report the first-stage regression results where the dependent variables are the AI adoption measures (*AIRatio* and *AINum*, respectively). Columns (2) and (4) report the second-stage results where the dependent variable is corporate innovation quality (*CIQ*), incorporating the lagged mediator. Robust standard errors clustered at the firm level are reported in parentheses. Panel B reports the bias-corrected bootstrap estimates for the direct and indirect effects. Confidence intervals and *p*-values are based on 1000 bootstrap replications. In both panels, *** and ** denote statistical significance at the 1% and 5% levels, respectively.

To address the potential limitations of the Sobel test, we follow the prior literature [68,69] and implement a nonparametric bootstrap procedure with 1000 replications. As shown in Panel B of Table 9, the 95% bias-corrected confidence intervals for the indirect effects (via AI adoption) exclude zero for both *AIRatio* and *AINum*, while the direct effect of SUTF remains positive and significant. These results reinforce the presence of a significant mediation effect and alleviate concerns regarding the parametric assumptions of the Sobel test.

4.5. Heterogeneity Analysis

We explore the heterogeneous effects of SUTF on innovation quality along two dimensions: the digital competence of executives and the quality of corporate governance.

First, we investigate whether the effect varies with the level of executive digital competence. We measure the presence of IT expertise in the top management team by the proportion of executives with an IT-related professional background to the total number of executives (*ITE*). The sample is then partitioned at the annual median of *ITE*. As reported in Columns (1) and (2) of Table 10, the coefficient on *TF* is positive and statistically significant only for the subsample of firms with above-median *ITE*. This suggests that the innovation-enhancing effect of SUTF is concentrated in firms with greater digital leadership capacity. A plausible explanation is that firms lacking executives with relevant IT expertise may face greater challenges in assimilating AI concepts and implementing related technologies, thereby capturing fewer innovation benefits from policy-induced incentives. This finding aligns with recent studies on the value of executive IT background [70] and underscores the critical role of specialized human capital in the digital transformation era.

Second, we investigate the moderating influence of corporate governance. We use the proportion of independent directors on the board of directors (*CG*) as a proxy for governance quality and, similarly, split the sample at its annual median. Results presented in Columns (3) and (4) of Table 10 show that the coefficient on *TF* is larger in magnitude and exhibits stronger statistical significance for firms with above-median *CG*. This indicates a more pronounced innovation-enhancing effect of SUTF in firms with stronger governance. This result highlights the importance of effective corporate governance in mitigating external challenges. Sound governance structures are likely to improve organizational resilience [71], allowing firms to allocate resources more effectively and formulate more strategic responses to external pressures, such as trade frictions, in highly uncertain environments.

Table 10. Heterogeneity analysis: executive IT background and corporate governance.

Variables	(1) High *ITE* *CIQ*	(2) Low *ITE* *CIQ*	(3) High *CG* *CIQ*	(4) Low *CG* *CIQ*
TF	0.338 **	0.229	0.356 ***	0.219
	(0.142)	(0.147)	(0.133)	(0.134)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	7229	7493	7230	7492
Adjusted R^2	0.453	0.455	0.427	0.470
Permutation test (difference in coefficients)	0.109 ***		0.137 ***	

Note: This table reports regression results for subsamples split by the annual median of executive IT background (*ITE*) and corporate governance quality (*CG*). Columns (1) and (2) compare firms with high vs. low *ITE*. Columns (3) and (4) compare firms with high vs. low *CG*. The permutation test reports the difference in the coefficients of *TF* between the high and low groups. Robust standard errors clustered at the firm level are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

5. Conclusions

5.1. Summary of Findings and Discussion

This study investigates the impact of SUTF on corporate innovation quality. Based on a sample of Chinese listed manufacturing firms from 2014 to 2022 and employing a DID design with a continuous treatment, we find robust evidence that SUTF exerts a positive and statistically significant effect on corporate innovation quality. This finding supports the escaping-competition view, illustrating that beyond imposing cost pressures, external trade shocks can motivate firms to upgrade their innovation strategies and shift toward more quality-oriented technological activities. Our mechanism analysis identifies AI adoption as a significant channel through which SUTF enhances innovation quality. Confronted with heightened uncertainty and intensified competition, firms are incentivized to adopt precautionary and forward-looking strategies, leading to increased AI adoption. This general-purpose technology, in turn, reshapes organizational systems and processes, ultimately fostering innovation quality. Moreover, the positive effect is more pronounced for firms whose executives possess greater digital competence (i.e., a higher proportion of IT-experienced executives) and for those with stronger corporate governance. These heterogeneous effects underscore the complementary roles of specialized human capital and effective monitoring mechanisms in enabling firms to capture the innovation benefits triggered by external policy shocks.

The literature on the effect of SUTF on firm innovation presents mixed findings. One stream of research, grounded in traditional trade theories, documents a negative effect, arguing that trade frictions inhibit corporate innovation by raising costs and operational burdens [6,7,10,11]. In contrast, a growing body of recent studies reports a positive effect, suggesting that trade frictions can stimulate innovation as firms seek to escape intensified competition [15–17]. Our study departs from prior studies that primarily rely on quantitative indicators such as R&D spending or patent counts by shifting the focus to innovation quality. Furthermore, regarding the underlying mechanism, while extant studies highlight factors like incremental costs [11], financing constraints [16], and competitive pressure [15], they pay scant attention to the systematic, transformative role of emerging general-purpose technologies, particularly AI. We address this gap by identifying AI adoption as a novel mediating channel. Moreover, by examining the moderating roles of executive IT background and internal governance structures, we introduce a con-

tingency perspective that elucidates for which firms the innovation-promoting effect of SUTF is strongest. This analysis echoes and extends the traditional corporate finance literature on the role of human capital and governance [70,71].

5.2. Theoretical and Practical Implications

Our findings offer important implications for both theory and practice. Theoretically, this study makes two primary contributions. First, by integrating the escape-competition logic into the context of the digital economy, it provides a novel theoretical lens to examine the complex relationship between trade policy shocks and corporate innovation strategies. Second, it extends the application of Schumpeter's theory of innovation and STS theory by demonstrating how external competitive shocks, mediated by technological adoption, can act as a catalyst for creative destruction and quality upgrading at the firm level.

Practically, our results offer actionable insights for policymakers and corporate managers. For policymakers, the findings suggest that proactive industrial and innovation policies—such as subsidies for digital infrastructure or R&D tax credits—could be designed to complement trade policies. This integrated approach can better guide and incentivize enterprises, especially those highly exposed to trade frictions, to embark on a high-quality, innovation-driven transformation path. For corporate managers, the findings underscore a strategic imperative: to actively cultivate in-house AI capabilities and decisively integrate these technologies into core operational and innovation systems. Such a commitment positions firms to achieve high-quality innovation.

5.3. Limitations and Future Research Directions

This study is subject to several limitations that also point to promising avenues for future research. First, our measure of firm-level AI adoption relies on textual analysis of corporate disclosures. Although this method is well established in the literature, it is susceptible to concerns about rhetorical emphasis and may not fully capture the substantive depth or effectiveness of AI implementation. A primary constraint stems from the underdevelopment of Chinese accounting standards regarding the recognition and disclosure of AI-related intangible assets. The absence of clear, mandatory classification for AI-related expenditures makes it challenging to construct more refined indicators, such as the scale of dedicated AI personnel, proprietary algorithms, or firm-specific AI capabilities. We expect that as China's accounting standards evolve to mandate better disclosure of data and intangible assets, future research will be able to employ more direct and comprehensive metrics for AI adoption.

Second, our analysis focuses on the microeconomic effects stemming from the tariff sanctions imposed under the U.S. Section 301 investigation. We do not examine the potential impact of non-tariff barriers, such as entity list designations or technical standards. These instruments constitute an increasingly important dimension of modern trade friction. Future research could fruitfully explore how these alternative forms of trade restriction influence corporate strategy and innovation, thereby providing a more holistic understanding of the multifaceted nature of Sino–U.S. technological competition.

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Appendix A

Table A1. Variable definitions and data sources.

Variables	Definition	Source
Explained Variables		
CIQ	Corporate innovation quality, measured as the annual median patent breadth across all patents applied for by a firm in a given year. Patent breadth is defined as one minus the Herfindahl index of the patent's 4-digit IPC subclasses.	CNIPA
Explanatory Variables		
TF	The core independent variable, constructed as the interaction term between *TariffIntensity* and the post-SUTF indicator *Post*. *TariffIntensity* is defined in Equation (2), and *Post* is a dummy variable equal to one for fiscal years 2018 and onward, and zero otherwise.	Comtrade, IDB, USTR, and CSMAR
Mediating Variables		
AIRatio	The ratio of the count of AI-related keywords in the MD&A section to the total word count of the MD&A section.	CSMAR
AINum	The natural logarithm of one plus the raw count of AI-related keywords in the MD&A section.	CSMAR
Control Variables		
Size	Firm size, measured as the natural logarithm of total assets.	CSMAR
Age	Firm age, measured as the natural logarithm of one plus the number of years since the firm's establishment.	CSMAR
Subsidy	Governmental subsidies, scaled by total assets.	CSMAR
Capital	Capital intensity, measured as net property, plant, and equipment (PPE) scaled by total assets.	CSMAR
Salary	Labor cost intensity, measured as the natural logarithm of total employee compensation.	CSMAR
Leverage	Financial leverage, measured as the ratio of total liabilities to total assets.	CSMAR
ROA	Return on assets (ROA), calculated as net income divided by total assets.	CSMAR
SOE	State ownership, an indicator variable that equals one for state-owned enterprises (SOEs), and zero otherwise.	CSMAR
Top1	Ownership concentration, measured as the shareholding percentage of the largest shareholder.	CSMAR
GDP	Regional economic development, measured as the natural logarithm of provincial per capita gross domestic product (GDP).	CSMAR
Other Variables		
ITE	The proportion of executives with IT experience to the total number of executives.	CSMAR
CG	The proportion of independent directors on the board of directors.	CSMAR

Note: CNIPA denotes the China National Intellectual Property Administration. Comtrade refers to the UN Comtrade Database. IDB denotes the World Trade Organization's Integrated Database, which reports Most-Favored-Nation Treatment (MFN) applied tariff data. USTR denotes the Office of the United States Trade Representative. CSMAR refers to the China Stock Market and Accounting Research Database, a widely used and authoritative database on Chinese listed companies. *CIQ* is constructed from patent data provided by CNIPA. *TF* is constructed using tariff data from Comtrade, IDB, USTR, and firm-level export data from CSMAR. All other variables are sourced from the CSMAR database.

Appendix B

Table A2. Terms of AI-related keywords.

Chinese Term	English Translation	Chinese Term	English Translation
人工智能	Artificial Intelligence	智能家居	Smart Home
计算机视觉	Computer Vision	循环神经网络	Recurrent Neural Network
图像识别	Image Recognition	大数据风控	Big Data Risk Control
知识图谱	Knowledge Graph	机器人流程自动化	Robotic Process Automation
智能教育	Intelligent Education	可穿戴产品	Wearable Devices
增强现实	Augmented Reality	大数据平台	Big Data Platform
智能政务	Smart Government	增强智能	Augmented Intelligence
特征提取	Feature Extraction	大数据运营	Big Data Operations
商业智能	Business Intelligence	机器翻译	Machine Translation
智能养老	Smart Elderly Care	神经网络	Neural Network
支持向量机	Support Vector Machine	语音合成	Speech Synthesis
知识表示	Knowledge Representation	人机协同	Human–Machine Collaboration
模式识别	Pattern Recognition	智能农业	Smart Agriculture
物联网	Internet of Things	智能音箱	Smart Speaker
人机对话	Human–Machine Dialog	卷积神经网络	Convolutional Neural Network
AI 产品	AI Product	问答系统	Question Answering System
人机交互	Human–Computer Interaction	强化学习	Reinforcement Learning
数据挖掘	Data Mining	大数据分析	Big Data Analytics
智慧银行	Smart Banking	自然语言处理	Natural Language Processing
智能客服	Intelligent Customer Service	大数据管理	Big Data Management
虚拟现实	Virtual Reality	智能计算	Intelligent Computing
自动驾驶	Autonomous Driving	语音交互	Voice Interaction
无人驾驶	Unmanned Driving	机器学习	Machine Learning
智慧金融	Smart Finance	生物识别	Biometrics
大数据营销	Big Data Marketing	语音识别	Speech Recognition
长短期记忆	Long Short-Term memory	智能监管	Intelligent Supervision
智能芯片	Intelligent Chip	智能投顾	Robo-Advisor
边缘计算	Edge Computing	智能语音	Intelligent Voice Assistant
云计算	Cloud Computing	声纹识别	Voiceprint Recognition
深度神经网络	Deep Neural Network	人脸识别	Face Recognition
AI 芯片	AI Chip	智能体	Intelligent Agent
深度学习	Deep Learning	大数据处理	Big Data Processing
特征识别	Feature Recognition	分布式计算	Distributed Computing
智能保险	Smart Insurance	智能传感器	Smart Sensor
智能零售	Smart Retail	智能搜索	Intelligent Search
智能医疗	Smart Healthcare	智能环保	Smart Environmental Protection
智能运输	Intelligent Transportation		

Note: This list of AI-related keywords, originally compiled in Chinese, is sourced from Yao et al. [67]. The English translations are provided for reference.

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