PISSN 2508-1640 EISSN 2508-1667 an open access journal
East Asian Economic Review vol. 30, no. 1 (March 2026) 59-89
https://dx.doi.org/10.11644/KIEP.EAER.2026.30.1.461

Impact of Trade Policy Uncertainty on Firms' Innovation*

Kexin Zhan
Korea University
kxzhan413@gmail.com

Hongshik Lee
Korea University
honglee@korea.ac.kr

Shu-Yang Gan
Korea University
sygam103@korea.ac.kr

This study examines how rising trade policy uncertainty (TPU) mainly from the US–China trade war affected innovation at Chinese listed firms between 2015 and 2023. Using an industry level TPU index, we measure innovation quantity by patent applications and innovation quality by citation counts. Our results show that rising TPU is positively associated with both the number and the impact of patents, suggesting that uncertainty tends to drive firms toward more and higher-quality innovation. The heterogeneity analysis further indicates that higher TPU exposure is associated with greater innovation activity among small and medium-sized companies, non-state-owned enterprises, and inland companies. By combining firm-level panel data with a novel TPU measure and distinguishing between innovation quantity and quality, this research offers actionable insights for managers allocating R&D resources under uncertainty and for policymakers aiming to stimulate technological progress in volatile trade environments.

Keywords: Trade Policy Uncertainty, Innovation Quantity, Innovation Quality, Patent

JEL Classification: F13, F14, O31

I. Introduction

Over the past decade, global trade protectionism has intensified, particularly under the Trump administration. Since 2017, the United States has escalated its offensive in global technological competition, increasingly relying on extraterritorial enforcement and tariff measures to restrict transactions between

*All remaining errors are our own.

Chinese semiconductor firms and their non-US suppliers and partners.

International trade facilitates the diffusion of technological knowledge, as embodied technologies in exported goods can be partially adopted by the importing country (Keller, 2004). Conversely, an exporting country can impede such transfers by imposing export controls. Citing national security, the Trump administration initiated a trade conflict with China in early 2018, raising tariffs and adding selected Chinese firms to the Entity List to restrict imports.[1] For example, US authorities prohibited semiconductor suppliers from exporting key infrastructure components to Huawei, deemed a leading competitor in 5G technology. Although Huawei initially circumvented these restrictions by sourcing equipment from Taiwan and South Korea, both the Trump and Biden administrations have continued to employ tariffs as a tool of export control against Chinese technology firms, reflecting the ongoing US–China technology rivalry. These measures have substantially heightened uncertainty surrounding US trade policy.

Specifically, trade policy uncertainty (TPU) manifests through frequent tariff adjustments and the renegotiation of trade agreements. Such shifts impose persistent shocks on firms dependent on global supply chains and international markets. Consequently, long-term planning entails higher costs and resource allocation decisions become more challenging. The theoretical framework of Li et al. (2025) suggests that, in a populous country such as China, heightened uncertainty arising from measures like technology sanctions may produce counterintuitive outcomes. In particular, it may stimulate the emergence of highly productive domestic firms capable of outperforming international competitors, thereby enhancing aggregate productivity. Despite extensive research on the effects of TPU on investment, exports and market entry, few studies have systematically examined its impact on firm-level innovation. Moreover, both the quantity and the quality of innovation have received limited attention in this context.

Innovation is widely recognized as a key driver of firm performance, competitive advantage, and long-term success in global markets. Over the past decade, China's

[1] Since the Trump administration began imposing tariffs on steel and aluminum products from China in March 2018, until the phase one trade agreement was reached at the end of 2019, the average US tariff on Chinese products had actually risen from 3.6% to 26.3%, greatly increasing the uncertainty of trade policy due to the significant export controls in this area.

innovation index has steadily increased, rising from 53.1 in 2018 to 56.6 in 2025.[2] Simultaneously, the number of patent applications, a key indicator of innovation, surged from 2,798,500 in 2015 to 5,561,990 pieces in 2023.[3] However, due to trade uncertainties, including US export controls mentioned before, China's information technology exports are projected to account for 22.64% of total exports, up from 26.6% in 2015. So, understanding how external policy uncertainty affects both the quantity and quality of innovation is essential for evaluating firms' strategic responses to such uncertainty. Unlike previous studies that primarily focus on export-oriented firms, this study examines publicly listed firms, which offer access to more recent and reliable data. Although these firms are typically larger and better resourced, they remain susceptible to TPU through market volatility, regulatory shifts, and disruptions in global supply chains.

In this study, the TPU index is constructed based on the approach developed by Handley and Limão (2017), which is calculated based on the changes in the post-war tariff and the MFN (most- favored-nation) tariff. In addition, while many studies measure innovation only by the number of patent applications, this study introduces innovation quality as a key variable, measured by the count of citations to patents. By considering both quantity and quality, the analysis provides a more comprehensive view of how TPU influences firms' innovation. Hence, this paper aims to address the following two key questions: whether and how elevated TPU significantly affects firm innovation and whether this effect differs in terms of innovation quantity and innovation quality. Furthermore, whether different firm characteristics respond to the improvement of their own innovation level.

To address these questions, this study utilizes panel data from 2015 to 2023 for Chinese listed firms, constructs two indicators of innovation performance, and develops an industry-level TPU index. A fixed effects model is employed for empirical estimation. The results show that increases in TPU following the US–China trade war are significantly associated with improvements in both the quantity and quality of innovation among listed Chinese firms, by approximately 0.09%. Moreover, firm-level economic characteristics such as firm size, R&D

[2] Cornell University, INSEAD, and the WIPO.

[3] *Intellectual Property Statistical Yearbooks for 2015 and 2023* from the China National Intellectual Property Administration, https://www.cnipa.gov.cn/

investment, and leverage show positive correlations with innovation. In contrast, excessive employment appears to hinder innovation performance.[4] Robustness checks confirm the consistency of these findings but we also find that China's industrial policies have a significant stimulating effect on innovation activities, but they are not substitutes for TPU. Notably, sub-period analyses reveal that innovation levels were significantly higher during the trade war compared to the pre- and post-war periods, supporting the conclusions of Li et al. (2025).

Second, our heterogeneity analysis reveals several important firm-level patterns. In terms of labor size, small and medium-sized enterprises (SMEs) exhibit significantly stronger positive associations between rising TPU and both the quantity and quality of innovation compared to large firms. Regarding ownership type, non-state-owned enterprises show stronger innovation responses than state-owned enterprises, likely due to their higher sensitivity to policy fluctuations and more intense market competition. Geographically, while firms in both coastal and inland regions respond positively to TPU, the effect is more pronounced for inland firms. This may be because inland firms face greater difficulty in finding alternative trading partners—similar to the case of Huawei—thus prompting them to accelerate technological self-reliance and innovation.

These findings offer practical value for both firms and policymakers. For corporate managers, the findings provide strategic guidance on how to allocate innovation resources in an uncertain trade environment. For policymakers, the study offers empirical evidence to help coordinate innovation policy with trade policy. Moreover, while most studies measure innovation solely by patent application counts, such a one-dimensional approach may overlook the true economic and technological impact of firms' R&D efforts. To address this, Section IV.3 introduces patent citation counts as a complementary measure of innovation quality. It also provides a detailed explanation for why citation-based metrics better

[4] The opposite signs on asset-based firm size and employment-based size reflect different dimensions of firm scale. Asset size captures capital intensity and financial capacity, which facilitate R&D investment and patenting, whereas a larger workforce may proxy for organizational complexity and coordination costs that dampen innovative efficiency. Consistent with this interpretation, the heterogeneity results show that TPU-induced innovation is concentrated among small and medium labor-intensive firms, while large employers exhibit weaker responses, likely due to higher adjustment frictions.

capture high-impact innovations, and highlights the limitations of using application counts alone.

The remainder of this paper is organized as follows. Section II reviews the existing literature on trade policy uncertainty, firm behavior, and innovation, identifying the gaps that this study aims to fill. Section III develops the conceptual framework and hypotheses regarding the relationship between TPU and firm innovation. Section IV outlines the methodology, focusing on the fixed effects model used to examine the panel data of listed firms. In Section IV.2, we explain why patent citation counts are chosen to measure innovation quality and discuss the shortcomings of relying only on application counts. Section V estimates the baseline regression, Section VI discusses robustness checks and Section VII shows the results of heterogeneity analysis. Section VIII shows the conclusion.

II. Literature Review with Contributions

Uncertainty has always been a central topic in both theoretical and empirical economic research. Especially at the firm level, many studies have shown that economic policy uncertainty has the potential to significantly affect decisions related to investment, financing and strategy. Since investment decisions are often irreversible and long-term, once the future policy environment become unpredictable, firms tend to delay or even cancel planned investments (Dixit and Pindyck, 1994). Empirical findings also support this idea. According to Bloom et al. (2007), uncertainty increases real option values, thereby inducing firms to behave more cautiously in investment or disinvestment decisions.

Among various types of uncertainty, TPU has become a growing academic focus amid increasing global political and economic turbulence. TPU typically stems from unpredictable changes in policy expectations, such as trade disputes, tariff adjustments, and agreement renegotiation. A large body of literature explores the impact of TPU on firm behavior. Handley and Limão (2017) develop a dynamic heterogeneous firm model, showing that high TPU discourages firms from entering export markets. Empirically, they estimate that the decline in U.S. trade policy uncertainty after China joined the WTO explains about one-third of China's export growth to the U.S. between 2000 and 2005. Feng et al. (2017) further find that lower TPU encourages entry of high-quality, low- price exporters while driving out inefficient firms. These findings highlight TPU's critical role in shaping firm decisions. As TPU intensifies, its effects on firm innovation have drawn increasing scholarly attention.

Another strand of literature examines the impact of TPU on innovation, with most studies suggesting a significant inhibitory effect. Theoretical foundations include the irreversible investment theory (Dixit and Pindyck, 1994) and the "wait-and-see" approach, where uncertainty leads firms to postpone or abandon risky and long-term innovation projects. Liu and Ma (2020) exploit China's WTO accession as a quasi-natural experiment and find that reduced TPU significantly increased invention patent applications, especially among high-productivity, export-oriented, and private firms. This effect was attributed not only to market expansion, but also to improved policy stability expectations. Similarly, Li and Shi (2016) show that higher TPU reduces R&D spending and firms' willingness to innovate, with many opting to hoard cash during uncertain periods. Si et al. (2022) construct a TPU index using panel data of Chinese A-share listed firms from 2003 to 2018, and find that rising TPU significantly decreases patent applications and R&D intensity, particularly in high-tech industries.

While most literature emphasizes the inhibiting effect of trade policy uncertainty (TPU) on innovation, recent studies highlight its potential to stimulate firm innovation as a strategic response to external shocks. Shen and Hou (2021) use panel data of Chinese new energy vehicle firms from 2007 to 2018 and find that TPU significantly boosts R&D investment and patent applications, indicating that firms in policy-sensitive sectors may innovate more to cope with uncertainty. Similarly, Zheng et al. (2025) analyze A-share listed firms from 2012 to 2021 and demonstrate that rising TPU increases innovation input and output, especially among non-state-owned enterprises. This effect mainly operates through capital reallocation, with R&D units facing fewer financing constraints, and reflects ownership-based differences in flexibility and innovation incentives.

In summary, these studies show that TPU does not necessarily inhibit innovation, but may become a source of pressure to stimulate innovation in high uncertainty and high sensitivity situations. In an uncertain market environment, companies may actively seek technological breakthroughs and innovation upgrades to cope with policy fluctuations and competitive pressures. This finding offers important inspiration for understanding the dual role of TPU on innovation, and also provides theoretical support for the research.

Overall, existing research offers no consensus on the impact of TPU on firm innovation. The effects vary significantly by industry and firm characteristics. High-tech firms tend to increase innovation in response to TPU, while labor-intensive firms may scale back due to resource constraints. Large firms, with more resources, are less negatively affected and may even be incentivized to innovate. Both theoretical and empirical evidence suggest a complex relationship between TPU and innovation. Understanding its underlying mechanisms is crucial for offering targeted strategies to firms and policymakers. This study makes several important contributions to the existing studies on how TPU affects firm innovation. By filling key gaps in existing research, this study deepens the understanding of how trade uncertainty affects firms' innovation activities.

First, this study focuses on listed firms rather than export firms, which are commonly examined in prior literature. While export firms are directly exposed to TPU, data limitations—particularly in obtaining key variables such as patent citations (a proxy for innovation quality) and R&D investment—pose significant challenges. In contrast, listed firms are subject to strict information disclosure requirements, enabling access to more comprehensive and timely data on innovation and financial activities. As a result, using listed firms enhances the reliability of the analysis and allows for more policy-relevant and managerial insights. This approach fills an important gap in the literature by offering a more data-rich and robust assessment of the innovation impact of TPU. Second, while most existing studies focus solely on patent counts, this study incorporates both innovation quantity (measured by patent applications) and innovation quality (measured by patent citations) to provide a more comprehensive assessment of firm innovation. Patent application counts may not fully capture the economic value or technological significance of innovations. By including patent citations, this study examines whether TPU encourages firms to pursue high-impact technological breakthroughs or leads them to adopt low-risk, incremental innovation strategies under heightened uncertainty.

Through the above research, this study not only provides new theoretical and empirical evidence for the impact of TPU on innovation, but also provides a reference for enterprises and policymakers to formulate response strategies in an uncertain environment. This paper enriches the research on the relationship between TPU and innovation. It helps to fill the gap in research concerning the link between TPU and innovation and provides a theoretical basis and empirical support for promoting enterprise innovation.

III. Conceptual Framework and Hypotheses

The impact of TPU on the innovation of firms has been an important topic in the fields of economics and management research in recent years. TPU affects the stability and predictability of the external market environment. This forces firms to adjust their resource allocation and strategic decisions, which in turn has a profound impact on their innovation activities. Most previous studies focus on export firms. However, this study examines publicly listed firms, as they offer more complete and up-to-date data on innovation and financial performance. TPU can affect not only the quantity but also the quality of innovation. When faced with greater TPU, firms often change their R&D investment strategies to manage risks. Some firms may reduce innovation efforts due to financial constraints and short-term concerns, while others may respond by enhancing the quality of their innovation to stay competitive. Based on theoretical analysis and literature review, this study proposes two core hypotheses to investigate the effect of TPU on firms' innovation behavior, considering both the quantity of innovation (patent applications) and the quality of innovation (patent citations).

Hypothesis 1: Trade policy uncertainty has a significant impact on the innovation quantity of listed firms.

There are two main ways in which TPU can influence firms' innovation behaviors. On the one hand, TPU may restrict innovation activities, because uncertainty will raise operating costs and market risks. Firms may tend to reduce investment in innovation activities with uncertain long-term returns. On the other hand, TPU may encourage innovation to cope with changes in the international market. This helps firms to enhance their technological capabilities and market competitiveness.

For most firms, innovation is usually an important means to cope with the uncertainty of the external environment. When TPU increases, firms may need to develop new products or improve existing products by increasing innovation activities such as patent applications to adapt to uncertain market demand or reduce dependence on external supply chains. In addition, the innovation activities of firms may also serve as a signal to investors and the market to show their ability to cope with uncertainty and long-term development potential.

On the other hand, although TPU may motivate some firms to increase innovation activities, uncertainty may also inhibit the innovation behavior with limited resources or greater market pressure. In an uncertain environment, firms face problems such as tight funds, rising costs and increased operating pressure. They may prioritize short-term survival rather than long-term investment and reduce investment in R&D and innovation.

Especially in labor-intensive or traditional manufacturing industries, enterprises have low profit margins and weak support for innovation activities. When TPU increases, such enterprises may be more inclined to adopt a "wait-and-see strategy" and postpone or cancel innovation plans.

Hypothesis 2: Trade policy uncertainty has a significant impact on the innovation quality of firms.

TPU not only affects the number of innovations of enterprises, but may also change the innovation model and quality of enterprises. When enterprises face policy uncertainty, they may adjust their innovation strategies to better adapt to changes in the external environment.

On the one hand, TPU may reduce the quality of innovation. Since high-quality innovation often requires longer R&D cycles and more financial support, TPU may cause firms to reduce high-quality innovation projects and turn to short-term, low-cost R&D activities. Limited external financing for technological R&D: Enterprises may prefer low-quality innovation projects with faster returns on investment rather than high-impact innovations due to the capital constraints resulting from TPU.

On the other hand, TPU may also prompt enterprises to improve the quality of innovation. Firms may increase investment in high-quality innovation to get rid of dependence on external markets and improve technological barriers, thereby reducing the risks brought about by future policy changes. To attract investor, firms may show their long-term development capabilities to investors and the market by increasing the technical content and influence of patents to reduce the impact of uncertainty caused by TPU. Especially for technology-intensive enterprises, they may choose to improve the quality of innovation to enhance competitiveness rather than simply increase the number of patents.

IV. Methodology

1. Model

A fixed effect model is constructed in order to explore the relationship between trade policy uncertainty and innovations of firms:

$$InnoQty_{it} = \alpha + \beta TPU_{(j)i} + \gamma X_{it} + \lambda_t + \varepsilon_{it} \tag{1}$$

$$InnoQual_{it} = \alpha + \beta TPU_{(j)i} + \gamma X_{it} + \lambda_t + \varepsilon_{it} \tag{2}$$

where $\mathrm{InnoQty}_{it}$ and $\mathrm{InnoQual}_{it}$ represent the innovation quantity and innovation quality measure for firm *i* in year *t*, respectively. $TPU_{(j)i}$ is the industry-level TPU for the industry *j* to which firm *i* belongs. In the following Section IV.3 we will elaborate on how to measure the above two key variables. To isolate the effect of TPU, $\boldsymbol{X_{it}}$ are a set of time-varying firm-level variables, including such as Firm age (Age_{it}) which is the natural logarithm of the current year minus the establishment year plus one; Firm size (Size_{it}) which takes the logarithm of total assets plus one; R&D with logarithm, including $\mathrm{RDExpense}_{it}$ and $\mathrm{RDStaff}_{it}$ which represent R&D expenditure and the number of R&D personnel, respectively; Leverage ratio (Lev_{it}) which is the total liabilities divided by total assets; Return on assets (ROA_{it}) which is the net income divided by total assets; Labor size ($\mathrm{LaborSize}_{it}$) which is the natural logarithm of total number of employees. We also control the year fixed effects (λ_t) such as macro-level time shocks. By introducing year fixed effects, this model can effectively control the impact of unobservable differences and time trends on the dependent variable, thereby improving the robustness of the estimation results. ε_{it} is the error term.

2. Samples and Data Sources

This study utilizes firm-level data from 2015 to 2023, based on China's A-share listed firms. The sample is carefully selected to ensure data quality and consistency, especially for variables related to innovation and financial performance.[5]

Firm-level financial data are sourced from the China Stock Market & Accounting Research (CSMAR) Database, while patent data, including the number of applications and citations, are sourced from the Chinese Research Data Services (CNRDS) Database.

TPU Index is constructed using the MFN tariff in 2017 and the applied tariff rate during the trade war in 2019 at the HS6 level. Tariff data are obtained from United States International Trade Commission (USITC) database. Since these data are recorded at the product level, we use the HS–CIC concordance constructed by Brandt et al. (2017) to map each HS code to its corresponding 4-digit Chinese Industrial Classification (CIC) industry code.

3. Variable Definition and Measurement

(1) Dependent variable

The research measures firms' innovation levels using two dimensions: innovation quantity ($InnoQty_{it}$) and innovation quality ($InnoQual_{it}$). $InnoQty_{it}$ is measured by the annual number of invention patent applications at the firm level. To mitigate data skewness, we apply a log transformation after adding 1 to the count:

$$InnoQty_{it} = ln(\text{number of patent applications}_{it} + 1) \tag{3}$$

while $InnoQty_{it}$ is measured by the cumulative citations to invention patents filed in a given year, accumulated from the application year through 2023. Specifically,

[5] We acknowledge that focusing on publicly traded companies may limit the external validity of the results, as these companies are typically larger, more regulated, and more resourceful than private companies, and therefore may react differently to TPU. Therefore, we subsequently conducted robustness checks by removing top patenting firms as much as possible.

for a given year *t*, the $InnoQual_{it}$ variable is calculated as the cumulative citations to patents applied for in year *t* from the application year until 2023, plus one, and then takes the natural logarithm

$$InnoQual_{it} = ln(\text{number of patent citations}_{it} + 1) \quad (4)$$

(2) Innovation measures: Quantity vs. Quality

Table 1 reports the 25th, 50th, and 75th percentiles as well as the maximum values for *PatentApp* and *PatentCitation*. It is worth noting that the Pearson correlation between *PatentApp* and *PatentCitation* is 0.7868, indicating a strong positive association between innovation quantity and its measured impact.

Table 1. Descriptive Statistics and Correlation of Patent Measures

	P25	P50	P75	Maximum
PatentApp	2	8	24	6,924
PatentCitation	0	4	23	32,933

Note: Pearson correlation between PatentApp and PatentCitation: 0.7868

Figure 1 and Figure 2 plot the marginal distributions of the logged variables. Figure 1 shows histograms of *ln*(*PatentApp*+1) and *ln*(*PatentCitation*+1) side by side, both of which are highly right-skewed; the citation distribution exhibits an even longer right tail, reflecting the rarity of high-impact patents. Figure 2 presents a scatter plot of *ln*(*PatentApp*+1) vs. *ln*(*PatentCitation*+ 1). While there is a clear upward trend, many firm-year observations have positive patent counts but zero citations, underscoring that relying solely on application counts may overlook the quality dimension of innovation.

Furthermore, among all firm-year observations with positive patent applications, 19.21% have zero patent citations. This pattern suggests that the actual impact (measured by citation count) of a significant portion of patent applications was quite limited during our observation period. It is worth noting that we acknowledge this concentration of zero-citation patents may partly reflect citation lag, as newly granted patents typically require time to accumulate citations. However, even

Figure 1. Distributions of Logged Patent Measures

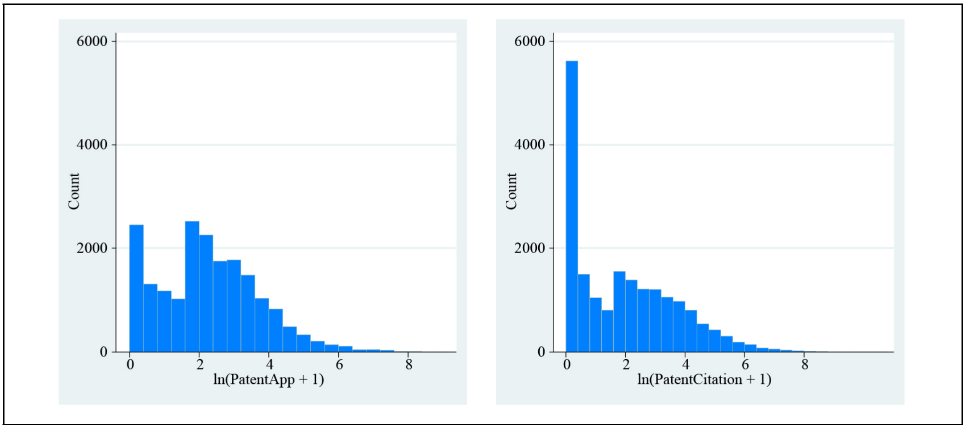
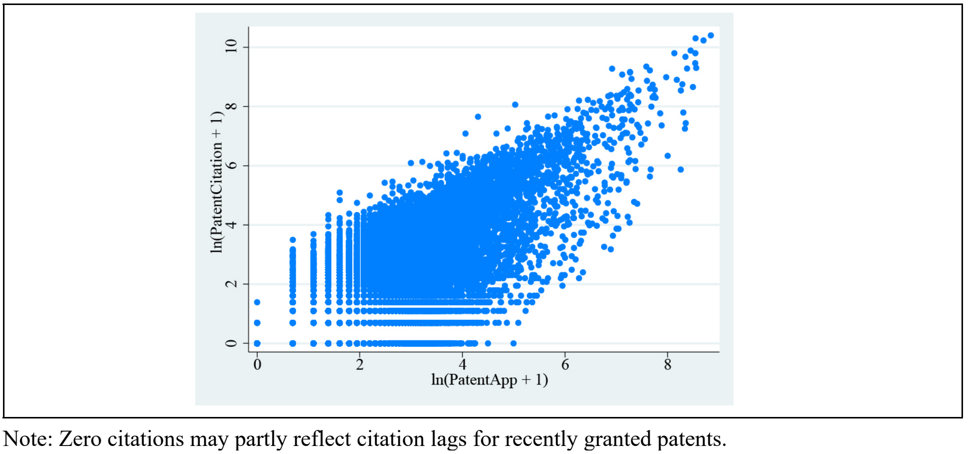


Figure 2. Scatter Plot of *ln*(*PatentApp* + 1) vs. *ln*(*PatentCitation* + 1)



Note: Zero citations may partly reflect citation lags for recently granted patents.

considering this time factor, the data still highlights a key limitation of using only the number of patent applications as a measure of innovation performance. A measure based on the number of applications fails to distinguish between inventions that ultimately produce significant technical impact and those whose impact is limited or unobservable over a meaningful timeframe. By incorporating citation information, our analysis captures not only the quantity of inventive activity but also its actual technical impact, thus providing a more nuanced and policy-relevant assessment of innovation outcomes.

(3) Independent variable

The product-level TPU index is constructed, following the methodology of Handley and Limão (2017), using both the post-war tariff and the MFN tariff at the HS6 level. Specifically, the TPU for product p is defined as:

$$TPU_p = 1 - \left(\frac{\tau_p^{war}}{\tau_p^{MFN}}\right)^{-\sigma} \tag{5}$$

where τ_p^{war} denotes the applied tariff rate during the trade war in 2019, τ_p^{MFN} is the MFN tariff in 2017, and σ is the elasticity of substitution. This approach is based on a key assumption that makes TPU constant over time. We assume that, from the time President Trump assumed office in 2017, there has been a significant rise in the uncertainty of U.S. economic policies toward China, especially after the start of trade war. As a result, we treat affected products as already reflecting this uncertainty prior to the imposition of extra tariffs, thereby making TPU time-invariant in product-level.

To make the product-level TPU applicable to firm-level analysis over the period 2015-2023, we construct industry-level TPU indices by aggregating the TPU values of all products belonging to the same industry:

$$TPU_j = \sum_{p \in j} TPU_p \tag{6}$$

where TPU_j denotes the TPU level for industry j, and TPU_p represents the product-level TPU for product p. The mapping from products to industries is based on a concordance table that links 6-digit HS codes to industry classifications. This approach assumes that all product-level uncertainty signals within an industry contribute equally to the overall uncertainty faced by firms operating in that industry. Based on the industry distribution in our sample, a staggering 98.1% belong to the manufacturing industry, encompassing 28 sub-sectors including specialized equipment manufacturing, automobile manufacturing, textiles, and metal products, as well as one sub-sector: electricity, heat, gas, and water production and supply.[6] The largest segment is computer, communication, and other electronic equipment manufacturing (17.31%). Due to the relatively low heterogeneity among these manufacturing industries, our TPU assumption is a reasonable approximation in our setting. However, this specification implies that identification relies mainly on cross-industry variation rather than within-industry temporal changes.[7]

V. Empirical Results

1. Descriptive Statistical Analysis

Before empirical analysis, this study conducted descriptive statistics on the main variables to better understand the basic characteristics of the data. As shown in Table 2, the means of innovation quantity ($InnoQty_{it}$) and innovation quality ($InnoQual_{it}$) are relatively low, and the standard deviation is large. This suggests a

Table 2. Statistical Analysis

Variables	Obs.	Mean	SD	Min	Max
$InnoQty_{it}$	19,033	2.2661	1.487	0	8.8429
$InnoQual_{it}$	19,033	1.93	1.7883	0	10.4023
$TPU_{j(i)}$	19,033	84.9615	78.2565	0	301.1363
Age_{it}	19,033	2.9946	0.2984	1.3863	4.2195
$Size_{it}$	19,033	22.1093	1.2258	17.81	27.64
$RDExpense_{it}$	19,033	18.5082	1.6578	0	25.1106
$RDStaff_{it}$	19,033	5.4835	1.188	0	11.541
Lev_{it}	19,033	0.3737	0.1903	0.0143	1.5454
ROA_{it}	19,033	0.0483	0.0794	-1.333	1.2848
$LaborSize_{it}$	19,033	7.5953	1.1663	3.4012	13.4638

[6] The industry classification standards refer to the 2012 Guidelines for Industry Classification of Listed Companies and are consistent with the China National Industrial Classification of Economic Activities (GB T4754-2011).

[7] We addressed this issue as much as possible by adding an industry-year fixed effect; please refer to columns 3 and 4 of Table A1 in Appendix for details.

great heterogeneity in innovation capabilities across firms. TPU has great volatility, showing the instability of the global trade environment during the study period, such volatility is basically driven by the US-China trade war. In terms of control variables, the R&D related variables ($RDExpense_{it}$, $RDStaff_{it}$) are logarithmically transformed to reduce the impact of the skewness of the data on the estimation. The distribution of indicators such as firm size ($Size_{it}$), leverage ratio (Lev_{it}), and profitability (ROA_{it}) is relatively reasonable, and broadly consistent with firm characteristics reported in existing literature.

2. Baseline Results

Using the FE model with Equation (1) and Equation (2) we mentioned earlier, Table 3 examine how trade policy uncertainty impacts corporate innovation and presents the estimated coefficients and significance levels.

Table 3. The Effects of TPU on Firm Innovation: Baseline Results

	$InnoQty_{it}$	$InnoQual_{it}$
$TPU_{j(i)}$	0.0009***	0.0009***
	(0.0002)	(0.0002)
Age_{it}	-0.0739	-0.1319**
	(0.0536)	(0.0572)
$Size_{it}$	0.2536***	0.2702***
	(0.0269)	(0.0285)
$RDExpense_{it}$	0.1918***	0.1898***
	(0.0173)	(0.0176)
$RDStaff_{it}$	0.5675***	0.5548***
	(0.0276)	(0.0301)
Lev_{it}	0.3091***	0.4205***
	(0.0991)	(0.1007)
ROA_{it}	0.0040	-0.0498
	(0.1806)	(0.1842)
$LaborSize_{it}$	-0.2180***	-0.2959***
	(0.0306)	(0.0324)
Time FE	Yes	Yes
R^2	0.4486	0.5320
Observations	19,033	19,033

Note: Robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

First, the TPU coefficient is positive and statistically significant in both regressions. The magnitude indicates that for every unit increase in TPU, the logarithm of patent applications rises by approximately 0.09%, and the quality of innovation based on patent citations also improves accordingly.[8] Although the marginal effect may seem small, its economic significance is nontrivial given the substantial fluctuations in TPU during the trade war. During periods of elevated uncertainty, these associations correspond to noticeably higher levels of firm innovation output and influence. This finding suggests that the uncertainty induced by the Trump administration's trade war was not negatively correlated with China's technological progress but instead associated with greater independent innovation activity among Chinese firms. In fact, despite the Trump administration's control over technology exports, materials including chips can still be obtained by Chinese companies. For other third-party trading partners of Chinese companies, the greater the United States' decoupling ambitions, the more severe the technological restrictions will be, but a few countries are interested in shutting out China.[9]

Second, among the firm-level controls, firm size exhibits a large and economically significant effect: a one-unit increase in firm size is associated with roughly a 25-27 percent increase in both innovation quantity and quality, consistent with their greater resource capacity. R&D investment is positively and significantly associated with both dimensions of innovation, underscoring its critical role. Leverage also shows a positive and significant effect, implying that moderate debt levels may enable firms to undertake higher-impact innovation under uncertainty. Firm age has no significant effect on patent counts but is negatively related to patent impact, suggesting that older firms produce more patents but struggle to generate high-impact inventions. Labor size negatively affects innovation activity, indicating that excessive workforce size may impair managerial efficiency and innovation performance. Finally, return on assets is insignificant, suggesting that short-term

[8] Regarding the potential citation truncation bias in the Innovation Quality setting, we refer to the relevant design in Liu and Ma (2020) and set a fixed time window, namely 5-years after the start date of the patent application, rather than from the application date until 2023. Although this will result in the loss of a large portion of the sample, as shown in Appendix Table 1, our results remain robust.

[9] https://sc.mp/i8pf?utm_source=copy-link&utm_campaign=3236517&utm_medium=share_widget

profitability does not clearly influence firms' innovation activities.

VI. Robustness Checks

1. Non-zero Sample Robustness Check

To further assess the robustness of our baseline findings, we drop all observations with zero patent applications or zero patent citations—retaining 13,402 observations with non-zero values in both patent counts and citation counts—and re-estimate the fixed effects models. Results are presented in Table 4. The positive and significant coefficient on TPU remains, supporting the robustness of our core result. All key control variables retain their expected signs and significance: firm age remain negatively related with both dimensions, firm size, R&D expenditure

Table 4. Robustness Check: Excluding Zero-patent Observations

	$InnoQty_{it}$	$InnoQual_{it}$
$TPU_{j(i)}$	0.0006***	0.0007***
	(0.0002)	(0.0002)
Age_{it}	-0.1089**	-0.1541**
	(0.0533)	(0.0606)
$Size_{it}$	0.2423***	0.2676***
	(0.0267)	(0.0299)
$RDExpense_{it}$	0.1767***	0.1837***
	(0.0168)	(0.0180)
$RDStaff_{it}$	0.4869***	0.5156***
	(0.0283)	(0.0321)
Lev_{it}	0.2826***	0.3666***
	(0.1001)	(0.1084)
ROA_{it}	-0.1934	-0.2152
	(0.1696)	(0.1911)
$LaborSize_{it}$	-0.1862***	-0.2907***
	(0.0312)	(0.0341)
Time FE	Yes	Yes
R^2	0.4486	0.532
Observations	13,402	13,402

Note: Robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

and R&D staff remain positively and significantly related to innovation, leverage continues to have a positive and significant effect, labor size remains significantly negative, and ROA is insignificant. Together, these results show that our findings on TPU's effect on both the quantity and quality of innovation hold firmly.

2. Sub-period Analysis

Since our TPU index is based on the difference of tariff before and after the US-China trade war, we would expect the strongest innovation response in the Trade-war period (2017-2020), little to no effect in the Pre-war period (2015-2016), and a still positive but attenuated response in the Post-war period (2021-2023). Such a pattern would reinforce the causal link between TPU and firm innovation. To test this, we estimate our models for each sub-period respectively.

Table 5 reports the period-specific influence of TPU on innovation outcomes. During the Trade War period (2017-2020), TPU had the strongest positive and statistically significant impact on both innovation quantity and quality. In contrast, the Pre-War period (2015-2016) shows no statistically significant effect. In the Post-War period (2021-2023), the effect of TPU remained positive and significant but weakened compared to the Trade War peak. These results indicate that heightened TPU during the trade war is associated with more active innovation-related behavior among firms. This finding is consistent with the theoretical basis constructed by Li et al. (2025) focusing on the influence of the tech sanctions.

Table 5. Robustness Check: Sub-period Analysis

Period	β(TPU)	Std. Error	P-value	Obs.
InnoQty Pre-war (2015-2016)	0.000488	0.000292	0.0953	2,411
Trade-war (2017-2020)	0.001225	0.000162	0	7,826
Post-war (2021-2023)	0.000687	0.000156	0	8,796
InnoQual Pre-war (2015-2016)	0.000593	0.000391	0.1297	2,411
Trade-war (2017-2020)	0.001478	0.000198	0	7,826
Post-war (2021-2023)	0.000441	0.000152	0.0037	8,796

3. Concentration of Innovation and Robustness to Top Patenting Firms

To address concerns that the results may be driven by a small subset of highly innovative firms, we conduct robustness checks that exclude firms in the top 5% of patenting activity over the sample period. As shown in Table 6, trade policy uncertainty remains significantly associated with higher innovation levels, both in terms of innovation quality and quantity.

Table 6. Robustness Check: Excluding Top-patenting Firms

	(1) $InnoQty_{it}$	(2) $InnoQual_{it}$
$TPU_{j(i)}$	0.0009***	0.0009***
	(0.0002)	(0.0002)
Age_{it}	-0.0995*	-0.1506***
	(0.0510)	(0.0542)
$Size_{it}$	0.1543***	0.1724***
	(0.0251)	(0.0266)
$RDExpense_{it}$	0.1719***	0.1696***
	(0.0158)	(0.0163)
$RDStaff_{it}$	0.4813***	0.4521***
	(0.0251)	(0.0272)
Lev_{it}	0.3580***	0.4768***
	(0.0921)	(0.0935)
ROA_{it}	0.1795	0.1129
	(0.1659)	(0.1692)
$LaborSize_{it}$	-0.1794***	-0.2577***
	(0.0285)	(0.0303)
Time FE	Yes	Yes
Observations	18,073	18,073

4. Alternative TPU Measurement

To address the issue of the baseline TPU metric remaining unchanged over time, we use an alternative, time-varying TPU metric for robustness testing. Specifically, we consider an interaction design based on the timing of the trade war's outbreak, and a time-varying TPU index constructed based on textual analysis.

Table 7. Robustness Checks: Alternative TPU Measurement

	(1)	(2)	(3)	(4)
	$InnoQty_{it}$	$InnoQual_{it}$	$InnoQty_{it}$	$InnoQual_{it}$
$TPU_{j(i)} \times Post2018_t$	0.0014***	0.0038***		
	(0.0002)	(0.0003)		
TPU_t			0.0006***	0.0018***
			(0.0004)	(0.0001)
Firm-level Control	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	Yes
Observations	19,033	19,033	19,033	19,033

Note: We still control firm-level variables, but we focus on the robustness of the results for key coefficients, so we do not report the specific results of firm-level controls in this table. Detailed information will be provided upon request.

First, we introduce time variation into the baseline industry-level TPU measure by interacting it with an indicator for the post-trade war period. Specifically, we construct an interaction term between industry-level TPU and a post-2018 dummy, $TPU_{j(i)} \times Post2018_t$ where the latter equals 1 for years from 2018 onward. This specification allows the effect of TPU to differ before and after the trade war, thereby partially exploiting temporal variation in TPU while retaining the cross-industry differences in baseline exposure. In columns 1 and 2 of Table 7, we find a consistent result with the baseline estimates.[10] While this design does not fully exploit within-industry variation over time, it alleviates concerns that our findings are driven solely by time-invariant industry characteristics and supports an interpretation linked to heightened uncertainty after the onset of the trade war.

Second, following the approach of Wu et al. (2025), we replaced TPU with a time-varying textual analysis-based index, namely the TPU index in China constructed by Davis et al. (2019) to replace our original TPU. This index measures TPU over time by utilizing the frequency of words related to trade and uncertainty appearing in mainland Chinese newspapers. We then converted their

[10] In the appendix Figure A1, we present the corresponding figure of the parallel trend test. With -1 period as the base period and omitted, the coefficients of the two periods before the event intersect the 0 axis but not after the event. The overall trend shows a significant upward trend, which to some extent passes the pre-trend test.

monthly index to an annual one. As shown in columns 3 and 4 of Table 7, our baseline regression results remain significant and robust.[11]

5. Industrial Policy Targeting: Evidence from "Made in China 2025"

One possible explanation is that the estimated TPU effect after 2018 may reflect China's industrial policy objectives rather than uncertainty. To this end, we used "Made in China 2025 (*MDC2025*)" as a proxy variable for policy impact, setting MDC=1 if the firm's industry belongs to one of the key industries listed in MDC2025, and 0 otherwise, for robustness analysis. "Made in China 2025," launched in 2015, aims to enhance China's manufacturing capabilities and provides unprecedented support to ten key industries.[12] We interacted industry-level TPU with indicators after 2018 and the MIC2025 industry classification to assess whether the relationship between TPU and innovation is systematically more significant in policy-supported industries. The results in Table 8 show that the coefficients of the double interaction term remain robust, while the triple interaction term is also significantly positive for both measurements of innovation, indicating that the TPU effect is more pronounced in the relevant industries of MDC2025 after 2018. Overall, these results suggest that national industrial policies do indeed promote innovation, but this effect is complementary to that of TPU, rather than a substitute for it.[13] In other words, our estimates reflect the uncertainty-driven effects and policy amplification, rather than a pure industrial policy channel.

[11] Since TPU is time-varying, we did not control for time-fixed effects in this estimate, as Wu et al. (2025) did.

[12] Specifically, they are Information Technology; Robotics; Green Energy and Green Vehicles; Aerospace Equipment; Marine Engineering and High-Tech Shipbuilding; Railway Equipment; Electrical Equipment; New Materials; Pharmaceuticals and Medical Devices; Agricultural Machinery.

[13] We also report the results of the grouped regression in Table A2 of the Appendix, and the results are consistent.

Table 8. Robustness Check: Made in China 2025 Industry Policy

	(1)	(2)
	$InnoQty_{it}$	$InnoQual_{it}$
$TPU_{j(i)} \times Post2018_t$	0.0009***	0.0033***
	(0.0002)	(0.0003)
$TPU_{j(i)} \times Post2018_t \times MDC2025_j$	0.0022***	0.0019***
	(0.0004)	(0.0005)
Firm-level Controls	Yes	Yes
Industry-Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	19,033	19,033

VII. Heterogeneity Analysis

1. Labor Size

To explore how the impact of TPU varies with firm scale, we classify firms into small, medium, and large groups based on the 33rd and 66th percentiles of employee counts. The results of Table 9 show that, for small and medium firms, TPU shows a significant positive association with innovation quantity and quality, while for large firms, the effect is not significant.

This indicates that small and medium firms tend to enhance patent application and impact under greater TPU. Large firms show a positive but insignificant response. A possible reason is differences in decision-making speed. Small and medium firms typically have fewer management layers and shorter approval processes, so they can quickly redirect efforts into innovation activities when TPU rises. In contrast, large firms face layers of review and complex budgeting procedures. Each new project must pass more gates, which weakens their marginal response to uncertainty. Therefore, although the coefficient on TPU remains positive for large firms, it is not statistically significant due to their slower decision-making chain.

Table 9. Heterogeneity Analysis by Firm Labor Size (Small / Medium / Large)

	$InnoQty_{it}$			$InnoQual_{it}$		
	Small	Medium	Large	Small	Medium	Large
$TPU_{j(i)}$	0.0008***	0.0012***	0.0007	0.0008***	0.0013***	0.0006
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Age_{it}	-0.1894**	-0.1629*	0.1361	-0.2178**	-0.2352**	0.1150
	(0.0680)	(0.0894)	(0.1072)	(0.0702)	(0.0969)	(0.1161)
$Size_{it}$	0.1743***	0.1617***	0.3039***	0.1837***	0.1789***	0.3118***
	(0.0392)	(0.0451)	(0.0299)	(0.0428)	(0.0467)	(0.0510)
$RDExpense_{it}$	0.1610***	0.1889***	0.2212***	0.1480***	0.1926***	0.2373***
	(0.0255)	(0.0316)	(0.0294)	(0.0281)	(0.0318)	(0.0302)
$RDStaff_{it}$	0.4921***	0.5468***	0.5973***	0.4590***	0.5227***	0.6018***
	(0.0461)	(0.0422)	(0.0446)	(0.0495)	(0.0462)	(0.0484)
Lev_{it}	0.1825	0.4747***	0.2988	0.3617***	0.5735***	0.3746*
	(0.1259)	(0.1529)	(0.2178)	(0.1239)	(0.1593)	(0.2190)
ROA_{it}	0.3888*	0.1305	-0.7191	0.3824*	0.2350	-0.8713*
	(0.2290)	(0.2449)	(0.4754)	(0.2295)	(0.2725)	(0.4511)
$LaborSize_{it}$	-0.2382***	-0.1697**	-0.2000**	-0.3540***	-0.1951**	-0.2445***
	(0.0578)	(0.0849)	(0.0727)	(0.0591)	(0.0921)	(0.0761)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2319	0.2821	0.4505	0.4076	0.4399	0.5738
Observations	6,350	6,339	6,344	6,350	6,339	6,344

Note: Robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

2. Ownership

Table 10 presents the heterogeneity analysis of TPU's influence on innovation across firms with different ownership types. We divide the sample into two groups–State and Non-State (Private, Foreign and Mixed)–and estimate the fixed effects models for both innovation quantity and quality.

For non-state-owned firms, TPU positively and significantly contributes to both innovation quantity and innovation quality, suggesting that rising TPU stimulates these firms to increase not only the number but also the impact of their patents. Regarding state-owned firms, while the effect of TPU is both positive, it is not statistically significant, showing that these firms may be less responsive to TPU.

Table 10. Heterogeneity Analysis by Firm's Ownership Type (State vs. Non-State)

	$InnoQty_{it}$		$InnoQual_{it}$	
	Non-State	State	Non-State	State
$TPU_{j(i)}$	0.0009***	0.0008	0.0010***	0.0006
	(0.0002)	(0.0005)	(0.0002)	(0.0005)
Age_{it}	-0.1104*	-0.2734*	-0.1532**	-0.2578
	(0.0583)	(0.1395)	(0.0612)	(0.1571)
$Size_{it}$	0.1465***	0.3028***	0.1832***	0.3134***
	(0.0339)	(0.0537)	(0.0364)	(0.0581)
$RDExpense_{it}$	0.1969***	0.2237***	0.1886***	0.2320***
	(0.0240)	(0.0288)	(0.0237)	(0.0295)
$RDStaff_{it}$	0.5776***	0.5285***	0.5612***	0.5226***
	(0.0334)	(0.0494)	(0.0360)	(0.0548)
Lev_{it}	0.3740***	0.0263	0.4697***	0.2172
	(0.1053)	(0.2294)	(0.1056)	(0.2452)
ROA_{it}	0.3132	-1.3959***	0.2309	-1.2354**
	(0.1915)	(0.4602)	(0.1934)	(0.4986)
$LaborSize_{it}$	-0.2189***	-0.1494**	-0.3020***	-0.2240***
	(0.0335)	(0.0729)	(0.0353)	(0.0796)
Time FE	Yes	Yes	Yes	Yes
R^2	0.3794	0.5481	0.4962	0.5875
Observations	14,701	4,332	14,701	4,332

Note: Robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

These results indicate that that non-state-owned firms are more sensitive to policy shocks. This possibly due to stronger market incentives. These firms often face intense competition and greater performance pressure. When TPU rises, they need to respond quickly to maintain their market position, which leads to a significant rise in the count and impact of patents. In contrast, state-owned firms tend to receive more policy support and enjoy greater internal stability. Therefore, they are generally less affected and response to TPU weaker.

3. Geographic Region

To explore the heterogeneous impact of TPU across different geographic regions, we divide the sample into "Coastal" and "Inland" firms based on their registered addresses.

Table 11 shows the fixed effects regression results for each subsample. The findings indicate that, in both the innovation-quantity and innovation-quality model, the positive incentive effect of TPU on inland firms is stronger than that on coastal firms. This suggests that while all firms boost innovation under greater TPU, inland firms respond more aggressively. One possible explanation is that when TPU rises, coastal firms can rely on existing export channels and logistics networks; while inland firms with fewer direct trade channels may turn to enhance innovation as a strategy to open new market, demonstrate competitiveness and offset external shocks.[14]

Table 11. Heterogeneity Analysis by Region (Coastal vs. Inland)

	$InnoQty_{it}$		$InnoQual_{it}$	
	Coastal	Inland	Coastal	Inland
$TPU_{j(i)}$	0.0006**	0.0014***	0.0008***	0.0010**
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Age_{it}	-0.0432	-0.1340	-0.0904	-0.2209**
	(0.0628)	(0.1006)	(0.0678)	(0.1052)
$Size_{it}$	0.2134***	0.2808***	0.2252***	0.2984***
	(0.0362)	(0.0436)	(0.0378)	(0.0472)
$RDExpense_{it}$	0.2230***	0.1731***	0.2280***	0.1651***
	(0.0274)	(0.0232)	(0.0277)	(0.0237)
$RDStaff_{it}$	0.5552***	0.5717***	0.5315***	0.5733***
	(0.0383)	(0.0407)	(0.0418)	(0.0444)
Lev_{it}	0.2882**	0.3550**	0.4084***	0.4593**
	(0.1201)	(0.1735)	(0.1209)	(0.1790)
ROA_{it}	0.1590	-0.2753	0.0241	-0.1934
	(0.2177)	(0.3312)	(0.2218)	(0.3346)
$LaborSize_{it}$	-0.2157***	-0.2141***	-0.2847***	-0.3023***
	(0.0382)	(0.0513)	(0.0403)	(0.0551)
Time FE	Yes	Yes	Yes	Yes
R^2	0.4342	0.4742	0.5272	0.5405
Observations	12,518	6,515	12,518	6,515

Note: Robust standard errors in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

[14] In Appendix Table A3, we introduce region as a dummy variable. The significantly negative coefficient of the interaction term indicates that inland companies do indeed respond more strongly to TPU innovation activities than coastal companies.

VIII. Conclusion and Policy Implications

1. Conclusion

This study provides empirical evidence how increasing TPU brought by the US-China trade war affects the innovation activities of Chinese listed firms. Using data from 2015 to 2023, we constructed an industry-level TPU index and examined both innovation quantity and innovation quality to explore their relationship. Our research indicates that TPU has a positive correlation with the innovation activities of Chinese listed firms. Specifically, when faced with rising TPU, firms tend not only to increase the number of patent applications, but also to pursue more impactful, high-quality innovations. This finding supports the view that TPU associated with the trade war can serve as an external factor linked to higher levels of firm innovation. What's more, China's industrial policies also encourage innovation, but they are not a substitute or a purely unilateral channel.

In the analysis of heterogeneity across different firm types, the results indicate that a positive and statistically significant association between TPU and innovation is observed for small and medium-sized firms, whereas no statistically significant association is found for firms with a larger labor force. Regarding ownership types, this significant positive effect is significant only for non-state-owned firms, while it is not statistically significant for state-owned firms. In addition, when examining geographic regions, the association between TPU and innovation is stronger for inland firms than for coastal firms.

2. Policy Implications

The findings of this study offer valuable insight for both corporate managers and policymakers in responding to TPU. For firms, uncertainty should not only be seen as a challenge, but also as an opportunity to drive innovation and enhance core competitiveness. Especially for small- and medium-sized and non-state-owned firms, as they are more sensitive to uncertainty and respond quicker, they should actively adjust their innovation strategies, and utilize their flexibility of decision-making to turn external pressure into internal innovation drivers.

For policymakers, it is important to recognize the impact that uncertainty may have on firm innovation. When designing trade policies, the government should consider introducing supporting incentive measures to guide firms to enhance their innovation capabilities in uncertain environments. In addition, the government should pay attention to the heterogeneity among firms, providing more targeted innovation support for small- and medium-sized and non-state-owned firms to further strengthen their positive response toward uncertainty. At the same time, efforts should be made to help large firms, state-owned firms and coastal firms improve their ability to innovate under uncertainty. This can contribute to promote the balanced innovation development across the country.

REFERENCES

Bloom, N., Bond, S. and J. Van Reenen. 2007. "Uncertainty and investment dynamics." *Review of Economic Studies,* vol. 74, no. 2, pp. 391-415. https://doi.org/10.1111/j.1467-937X.2007.00426.x

Brandt, L., Van Biesebroeck, J., Wang, L. and Y. Zhang. 2017. "WTO accession and performance of Chinese manufacturing firms." *American Economic Review,* vol. 107, no. 9, pp. 2784-2820. https://doi.org/10.1257/aer. 20121266

Davis, S. J., Liu, D. and X. S. Sheng. 2019. "Economic policy uncertainty in China since 1949: The view from mainland newspapers (Preliminary and incomplete)." https://static1.squarespace.com/static/5e2ea3a8097ed30c779bd707/t/5f7f49d054a84229354fe9ab/1602177496854/EPU.in.China,.View.from.Mainland.Newspapers,.August.2019.pdf

Dixit, A. K. and R. S. Pindyck. 1994. *Investment under Uncertainty*. Princeton University Press.

Feng, L., Li, Z. and D. L. Swenson. 2017. "Trade policy uncertainty and exports: Evidence from China's WTO accession." *Journal of International Economics,* vol. 106, pp. 20-36. https://doi.org/10.1016/j.jinteco.2016.12.009

Handley, K. and N. Limão. 2017. "Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States." *American Economic Review,* vol. 107, no. 9, pp. 2731-2783. https://doi.org/10.1257/aer. 20141419

Keller, W. 2004. "International technology diffusion." *Journal of Economic Literature,* vol. 42, no. 3, pp. 752-782. https://doi.org/10.1257/0022051042177685

Li, F.-Y. and Y. Shi. 2016. "Economic policy uncertainty and corporate cash holding strategy: empirical research by using China economic policy uncertainty index." *Journal of Management Sciences in China,* vol. 19, no. 6, pp. 157-170.

Li, Y., Zheng, X. and C.-P. Lo. 2025. "Technological sanctions and their unintended consequences: Theory and evidence." *China Economic Review,* vol. 93. https://doi.org/10.1016/ j.chieco.2025.102458

Liu, Q. and H. Ma. 2020. "Trade policy uncertainty and innovation: Firm level evidence from China's WTO accession." *Journal of International Economics,* vol. 127. https://doi.org/10.1016/j.jinteco.2020.103387

Shen, H. and F. Hou. 2021. "Trade policy uncertainty and corporate innovation evidence from Chinese listed firms in new energy vehicle industry." *Energy Economics,* vol. 97. https://doi.org/10.1016/j.eneco.2021.105217

Si, D., Li, X., Kong, D. and C. Jiang. 2022. "[Trade policy uncertainty, financial marketization and firm's innovative development: The synergy effects of financial marketization]." *Finance and Trade Economics,* vol. 43, no. 4. https://d.wanfangdata.com.cn/periodical/CiBQZXJpb2RpY2FsQ0hJU29scjkyMDI2MDIwMjE0MTYxMhINY21qajIwMjIwNDAwNRoIc2NlaWhpdDg%3D (in Chinese)

Wu, Y.-L., Jian, M., Li, Z. and W. Xu. 2025. "Incentive or inhibition? The impact of trade policy uncertainty on R&D investment." *Emerging Markets Finance and Trade*, vol. 62, no. 2, pp. 439-456. https://doi.org/10.1080/1540496X.2025.2535716

Zheng, F., Chen, X. and Y. Sun. 2025. "The influence of trade policy uncertainty on corporate innovation strategies." *Finance Research Letters,* vol. 75. https://doi.org/10.1016/j.frl.2025.106922

First version received on November 21, 2025
Peer-reviewed version received on January 2, 2026
Final version accepted on January 15, 2026

APPENDIX

Table A1. Additional Robustness Checks

	Fixed-window (5 years)	Exclude 2020-2023 sample	Additional Industry-Year FE	
	(1)	(2)	(3)	(4)
	$InnoQual_{it}$	$InnoQual_{it}$	$InnoQty_{it}$	$InnoQual_{it}$
$TPU_{j(i)}$	0.0008*	0.0013***	0.0011***	0.0011***
	(0.0004)	(0.0004)	(0.0002)	(0.0002)
Age_{it}	-0.1731	-0.0836	-0.0346	-0.0970*
	(0.1221)	(0.0944)	(0.0519)	(0.0554)
$Size_{it}$	0.0782	0.3097***	0.2407***	0.2588***
	(0.0589)	(0.0450)	(0.0255)	(0.0274)
$RDExpense_{it}$	0.2752***	0.2133***	0.1892***	0.1875***
	(0.0401)	(0.0228)	(0.0161)	(0.0166)
$RDStaff_{it}$	0.4638***	0.7070***	0.4434***	0.4448***
	(0.0600)	(0.0407)	(0.0275)	(0.0299)
Lev_{it}	0.7551***	0.6569***	0.1274	0.2593***
	(0.1739)	(0.1727)	(0.0969)	(0.0989)
ROA_{it}	0.4948*	-0.0965	0.1050	0.0398
	(0.2931)	(0.3171)	(0.1692)	(0.1766)
$LaborSize_{it}$	-0.3340***	-0.3204***	-0.0818**	-0.1752***
	(0.0621)	(0.0501)	(0.0317)	(0.0334)
Time FE	Yes	Yes	Yes	Yes
Industry-Year FE	No	No	Yes	Yes
Observations	8,662	7,953	19,033	19,033

Table A2. Industrial Policy Test: Group Regression

	Made in China 2025		No-Made in China 2025	
	(1)	(2)	(3)	(4)
	$InnoQty_{it}$	$InnoQual_{it}$	$InnoQty_{it}$	$InnoQual_{it}$
$TPU_{j(i)} \times Post2018_t$	0.0036***	0.0066***	0.0012***	0.0026***
	(0.0004)	(0.0005)	(0.0002)	(0.0003)
Firm-level Controls	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	10,195	10,195	8,838	8,838

Table A3. Alternative Estimation for Heterogeneity Analysis (Coastal vs. Inland)

	(1) $InnoQty_{it}$	(2) $InnoQual_{it}$
$TPU_{j(i)}$	0.0016***	0.0014***
	(0.0003)	(0.0003)
$TPU_{j(i)} \times Region_i$	-0.0009***	-0.0008**
	(0.0003)	(0.0003)
Firm-level Controls	Yes	Yes
Time FE	Yes	Yes
Observations	19,033	19,033

Figure A1. Parallel Trends