

Does Trade Policy Uncertainty Undermine Sustainable Competitiveness? A Nonlinear Green Growth Analysis for China

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Abstract

Trade policy uncertainty (TPU) can affect both economic performance and environmental outcomes, thereby shaping sustainable competitiveness. This study examines the nonlinear relationship between TPU and green growth in China from 2000Q1 to 2021Q4. Green growth is treated as the empirical channel through which sustainable competitiveness is assessed, because it links economic performance with environmental quality. Using quantile autoregressive distributed lag (QARDL) and nonlinear QARDL models, the study estimates heterogeneous short-run and long-run effects across the green-growth distribution. The linear results show that TPU has a negative and statistically significant effect on green growth at several quantiles, especially at the lower and upper parts of the distribution. The nonlinear results indicate that positive TPU shocks reduce green growth, whereas reductions in TPU improve green growth, particularly at higher quantiles. Green investment, human capital, and environmental technology also emerge as important determinants of green growth. The findings suggest that stable trade policy, stronger green investment, human-capital upgrading, and environmental technology development can strengthen China's sustainable competitiveness.

Keywords: Trade policy uncertainty; Sustainable competitiveness; Green growth; China; QARDL; Nonlinear analysis.

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1. Introduction

Trade debates and proposals for a new trade policy framework have increasingly captured the attention of businesses, trade advisors, politicians, and other stakeholders. Such initiatives create uncertainty about the outlook for world trade (Caldara et al., 2020). TPU has been identified as an important source of economic policy uncertainty. The United States and the United Kingdom have reduced their support for low trade protection and firm trade agreements following the Brexit referendum and Trump's election, respectively. The eventual renegotiations and ultimate withdrawal from long-lasting trade treaties and the 2018 trade war spread such uncertainty across developed and developing economies while underpinning new global concerns (Handley & Limão, 2022).

Trade policy determines the extent of the market for a firm's production and therefore potentially influences both national and foreign investments. With the passage of time, the effects of trade policy on investments have been growing (OECD, 2012). Growing TPU and its associated effects are attracting the attention of policy managers across the globe. The World Bank (2019) notes that a sudden increase in policy uncertainty, such as the introduction of significant new trade barriers between major economies, could severely affect confidence and investment. For instance, the United States and China followed a retaliating tariff policy for about three years, creating a huge loss of global income. The studies such as Handley and Limão (2022) and Caldara et al. (2020) underpin the potential negative effects of TPU on investment and economic performance.

TPU can influence short-term decisions of firms such as pricing and inventories. While in the long-term TPU influences investment decisions like market entry (Dixit, 1989). The empirical literature provides robust evidence of the trade-dampening effect of TPU (see, for details, Handley & Limão, 2022). Such an outcome has economic and environmental implications. If trade dampens in those sectors which are supporting green and environmentally friendly technologies, then environmental degradation will increase and vice versa (Tahir et al., 2021). The potential shocks to TPU are helpful in identifying the comprehensive effects of trade. The existing research suggests that TPU leads to broader effects in an open economy. For example, China's accession to WTO, Brexit, and the 2018 trade war have impacted TPU which, in turn, exerted potential impacts on consumption, investment, profits, and many other macroeconomic outcomes (Gebre Borojo et al., 2023). The existing empirical studies have mainly focused on

economic performance (Majeed & Noreen, 2018), inflation (Jones & Olson, 2013), and investment (Ebeke & Siminitz, 2018).

The role of China's exports is critical in shaping global TPU. China joined the WTO in 2001 and afterward its composition and volume of exports increased substantially. According to the estimates of the National Bureau of Statistics, exports in China have reached up to 2.5 trillion (US Dollars), which is tenfold that of total exports in 2000 (Sui et al., 2022). Meanwhile, with increasing TPU and changing population growth models, conventional population dividends are disappearing (Cai, 2020). Since China's WTO accession, Liu and Ma (2020) demonstrate that firms filed more patent applications. In another study, Sui et al. (2022) provided empirical evidence on TPU and export quality nexus in China. Their study suggested that a decline in TPU leads to an increase in export quality. These studies provided evidence on economic indicators and the TPU nexus, ignoring the sustainability repercussions of TPU. Recently, Sun et al. (2022) reported a decline in the PM2.5 concentration in Chinese cities having a lower level of TPU.

Theoretically, TPU can lead to diverse environmental effects. Growing TPU can harm environmental quality if the trade for clean and environmentally friendly technologies is discouraged. On the flip side, if TPU discourages the trade of conventional energy sources and technologies, then it can have a favorable environmental impact. Thus, it remains an empirical question to estimate the actual impact of TPU on the environment and sustainable development. However, analyzing the TPU and environmental quality nexus provides an incomplete picture of sustainable development goals. Particularly, when emissions are coupled with growth rates. In such a situation reducing emissions will also compromise economic growth prospects. Hence, it remains imperative to decouple emissions and growth. Managing green growth and decarbonizing economies have become central goals of sustainable development. Ozturk et al. (2021) highlighted that for Pakistan, India, and China, decoupling economic growth from carbon emissions is essential for effectively managing green growth in these economies.

The existing studies highlighted the importance of TPU for exports, investment, and enterprise behavior. However, the existing studies primarily focused on the economic dimensions of growth overlooking the environmental sustainability perspectives. Few studies focused on the sustainability dimension; however, they explored the association of TPU with CO₂ emissions, overlooking the green growth perspective. In effect, the empirical literature on TPU and

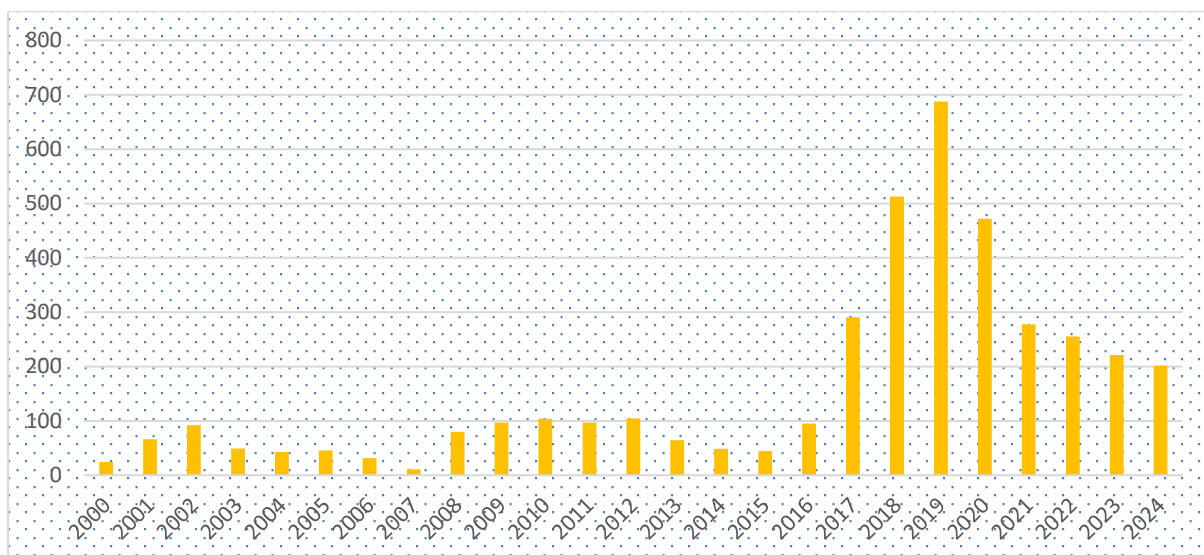
sustainability is quite limited. Instead of continuing to study exports and investment behavior, we combine TPU with green growth, which widens the prospects for novel research in this area. Furthermore, prior research on trade and environmental concerns tended to emphasize the perspectives of trade openness and liberalization; however, this study focuses on changes in TPU, which offers a fresh viewpoint for the analysis of environmental issues. In light of the current context, this research embarks on a new empirical test, delving into the influence of TPU on fostering green growth in China.

As one of the leading economies, China grapples with the challenge of high pollution levels. Numerous studies have highlighted that the rapid economic expansion in China has been a primary driver of environmental degradation (Aslam et al., 2021). Against this backdrop, prioritizing the management of green growth has become a crucial imperative for modern-day China. Recent research endeavors have shed light on the factors influencing green growth within the country. For instance, Qian et al. (2022) attribute China's progress in green growth to financial agglomerations, energy-saving practices, and technological advancements. Similarly, Yu (2022) emphasizes the role of information technology in supporting green growth, showcasing its positive impact through an analysis of data from 30 provinces. While these studies have explored the influence of financial agglomeration, technology, and information technology on green growth, their scope has largely been limited to the city, regional, and province-level contexts. Geng and Zhang (2026) emphasize that high-quality economic development in China depends on stable institutional and policy environments that support innovation and productivity upgrading. Strong institutional quality can mitigate the adverse effects of uncertainty on sustainable development (Zhang et al., 2026). Moreover, these studies have overlooked the potential significance of TPU as a determinant of green growth in China.

To the best of the authors' knowledge, prior research has not sufficiently examined the dynamic and asymmetric linkages between trade policy uncertainty and green growth in China. Although a few studies have explored the impact of TPU on carbon emissions, they have not fully addressed green growth as a broader indicator of sustainable competitiveness. This distinction is important because green growth captures the ability to improve environmental performance without sacrificing economic development.

The study contributes to the literature in four main ways. First, it links TPU with sustainable competitiveness by using green growth as the operational outcome. Second, it examines China over the quarterly period from 2000Q1 to 2021Q4, allowing the analysis to capture major trade-policy events and changing uncertainty conditions. Third, it applies both QARDL and nonlinear QARDL approaches to determine whether the effects of TPU vary across quantiles of green growth and differ between positive and negative TPU shocks. Fourth, it includes green investment, environmental technology, and human capital as control variables, thereby providing policy-relevant evidence on the conditions that support green growth and sustainable competitiveness in China. Figure 1 illustrates the evolution of trade policy uncertainty in China over the relevant period.

Figure 1. Trend of trade policy uncertainty in China. Source: Davis, Liu, and Sheng.



2. Theoretical framework, model, and methods

Trade policy uncertainty can influence sustainable competitiveness through its effects on trade flows, investment decisions, technology diffusion, and environmental performance. In this study, green growth is used as the observable channel through which sustainable competitiveness is assessed. A stable trade-policy environment can encourage firms to invest in cleaner technologies, improve production efficiency, and participate in environmentally friendly trade. By contrast, higher TPU may delay investment, reduce market-entry incentives,

disrupt green technology imports, and weaken long-term planning. Therefore, TPU may undermine green growth and, by extension, sustainable competitiveness.

The theoretical mechanism is linked to the technique, scale, and composition effects of trade. When trade policy is stable, firms can access cleaner imported technologies and improve production methods, generating a positive technique effect (Gale & Mendez, 1998). When trade-policy conditions are uncertain, firms may postpone investment, reduce innovation activity, and rely on existing production technologies. This can weaken environmental upgrading and slow the transition toward green growth. The direction and size of the effect may also depend on the existing level of green growth, which motivates the use of a quantile-based model.

The baseline long-run relationship is specified as follows:

$$GG_t = \alpha_0 + \alpha_1 TPU_t + \alpha_2 GI_t + \alpha_3 ET_t + \alpha_4 HC_t + \varepsilon_t \quad (1)$$

In Equation (1), GG denotes green growth, TPU denotes trade policy uncertainty, GI denotes green investment, ET denotes environmental technology, HC denotes human capital, and ε denotes the error term. The expected sign of α_1 is negative because higher TPU may discourage green investment, technology adoption, and sustainable production. The coefficients α_2 , α_3 , and α_4 are expected to be positive because green investment, environmental technology, and human capital can support green growth.

Following Cho et al. (2015), the linear QARDL error-correction specification is written as:

$$\Delta GG_t = \mu(\tau) + \rho(\tau)ECM_{t-1}(\tau) + SR_t(\tau) + \varepsilon_t(\tau) \quad (2a)$$

$$ECM_{t-1}(\tau) = GG_{t-1} - \theta_1(\tau)TPU_{t-1} - \theta_2(\tau)GI_{t-1} - \theta_3(\tau)ET_{t-1} - \theta_4(\tau)HC_{t-1} \quad (2b)$$

In Equations (2a) and (2b), τ represents the quantile, where $0 < \tau < 1$. The coefficient $\rho(\tau)$ is the error-correction parameter and is expected to be negative and statistically significant when adjustment toward the long-run equilibrium exists. The term $SR_t(\tau)$ contains the short-run lagged first differences of GG, TPU, GI, ET, and HC. This structure allows both the short-run and long-run effects to vary across the green-growth distribution.

Because the effects of increases and decreases in TPU may differ, the study further applies a nonlinear QARDL specification. Following Shin et al. (2014), TPU is decomposed into positive and negative partial-sum components:

$$TPU_t^+ = \sum_{s=1}^t \Delta TPU_s^+ = \sum_{s=1}^t \max(\Delta TPU_s, 0) \quad (3a)$$

$$TPU_t^- = \sum_{s=1}^t \Delta TPU_s^- = \sum_{s=1}^t \min(\Delta TPU_s, 0) \quad (3b)$$

The positive component captures increases in TPU, while the negative component captures decreases in TPU. This decomposition makes it possible to test whether rising and declining uncertainty have different effects on green growth.

The nonlinear long-run model is specified as follows:

$$GG_t = \alpha_0 + \alpha_1^+ TPU_t^+ + \alpha_1^- TPU_t^- + \alpha_2 GI_t + \alpha_3 ET_t + \alpha_4 HC_t + \varepsilon_t \quad (4)$$

The corresponding nonlinear QARDL error-correction model is expressed as:

$$\Delta GG_t = \mu(\tau) + \rho(\tau) NECM_{t-1}(\tau) + NSR_t(\tau) + \varepsilon_t(\tau) \quad (5a)$$

$$NECM_{t-1}(\tau) = GG_{t-1} - \theta_1^+(\tau) TPU_{t-1}^+ - \theta_1^-(\tau) TPU_{t-1}^- - \theta_2(\tau) GI_{t-1} - \theta_3(\tau) ET_{t-1} - \theta_4(\tau) HC_{t-1} \quad (5b)$$

The term $NSR_t(\tau)$ contains the short-run lagged first differences of TPU^+ , TPU^- , GI , ET , and HC . Equation (5) allows the short-run and long-run responses of green growth to positive and negative TPU shocks to vary across quantiles. Long-run asymmetry exists if $\theta_1^+(\tau)$ differs from $\theta_1^-(\tau)$, while short-run asymmetry exists if the short-run coefficients attached to ΔTPU^+ and ΔTPU^- differ.

The Wald tests for asymmetry are stated as follows:

$$H_0^{LR}: \theta_1^+(\tau) = \theta_1^-(\tau) \quad (6a)$$

$$H_0^{SR}: \sum \pi_j^+(\tau) = \sum \pi_j^-(\tau) \quad (6b)$$

Rejection of these null hypotheses indicates asymmetric effects in the corresponding time horizon. The QARDL and nonlinear QARDL approaches are therefore suitable for examining whether TPU undermines green growth and sustainable competitiveness differently across the green-growth distribution.

3. Data and variable description

Quarterly data for China from 2000Q1 to 2021Q4 are assembled for the empirical analysis. Following Sohail et al. (2022), green growth (GG) is used as the dependent variable and is measured as pollution-adjusted GDP growth (%), with the data obtained from the OECD. Because green growth combines economic expansion with environmental performance, it

serves as the empirical indicator of sustainable competitiveness in this study. Trade policy uncertainty (TPU) is included as the main explanatory variable. The China Trade Policy Uncertainty index is obtained from the PolicyUncertainty database. The index was developed by Davis, Liu, and Sheng (2019) using newspaper-based measures from the Renmin Daily and Guangming Daily. Green investment (GI) is included as a control variable because previous evidence suggests that it supports green growth (Mo et al., 2023). Electricity production from renewable sources, excluding hydroelectricity, is used as a proxy for green investment. Environmental technology (ET) is included because environment-related technologies can promote green growth (Ahmed et al., 2023). Human capital (HC), proxied by tertiary school enrolment, is also included because it can strengthen innovation capacity and sustainable development (Li et al., 2022). Data for GI and HC are obtained from the WDI, while ET is obtained from the OECD (Table A1).

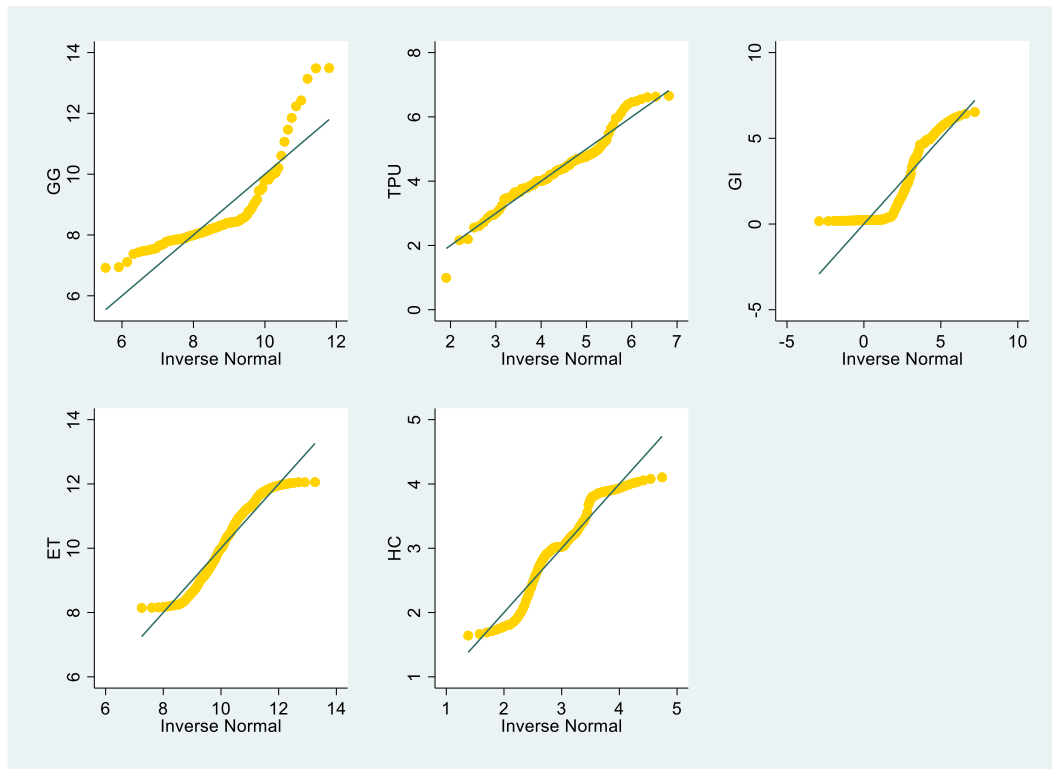
Table 1. Descriptive statistics. Source: authors' calculations.

	Mean	Median	Max	Min	S.D	Skewness	Kurtosis	J-B	Prob.
GG	8.670	8.270	13.49	6.923	1.352	1.981	6.749	119.0	0.000
TPU	4.364	4.333	6.656	0.993	1.061	0.059	3.634	1.664	0.435
GI	2.151	1.076	6.534	0.163	2.187	0.659	1.836	12.36	0.002
ET	10.25	10.39	12.05	8.143	1.298	-0.203	1.682	7.613	0.022
HC	3.061	3.065	4.104	1.642	0.726	-0.432	2.159	5.810	0.055

Table 1 displays descriptive statistics. The mean values are reported as: 8.670 for GG, 4.364 for TPU, 2.151 for GI, 10.25 for ET, and 3.061 for HC. The J-B statistics for GG, GI, ET, and HC are highly significant, indicating non-normality, with some series being negatively skewed

and others positively skewed. Both the Q-Q plots (Figure 2) and the J-B test yield consistent results regarding normality.

Figure 2. Q-Q plots for normality. Source: authors' calculations.



4. Results and discussion

Before evaluating the QARDL estimates, we carried out unit root tests on the chosen time series using the DF-GLS and Zivot-Andrews (ZA) structural-break tests. The results of these tests are presented in Table 2. The DF-GLS test indicates that all series, with the exception of environment-related technologies (ET), exhibit stationarity at the first difference. On the other hand, the outcomes of the ZA test suggest that the green growth (GG) and green investment (GI) series are stationary at the first difference, while TPU, ET, and HC series exhibit level stationarity. Thus, the findings show a mixed order of integration. These test results provide support for the use of the QARDL model.

Table 2. Unit root tests. Source: computed from dataset.

	DF-GLS		ZA			
	I(0)	I(1)	I(0)	Break date	I(1)	Break date

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	DF-GLS		ZA			
GG	-1.254	-1.785*	-3.257	2010 Q2	-7.658***	2007 Q1
TPU	-1.587	-13.21***	-4.658**	2016 Q3		
GI	-0.231	-1.875*	-3.645	2017 Q2	-4.521**	2000 Q2
ET	-2.452**		-6.654***	1999 Q4		
HC	-0.154	-2.321**	-5.658***	1999 Q4		

Table 3 displays the estimates attained from the QARDL model. The findings show that the ρ^* is statistically significant at all quantiles. Moreover, the negative sign indicates a tendency to revert to the LR equilibrium. Regarding TPU, the empirical findings reveal a negative relationship between β_{TPU} (τ) and GG across all quantiles. However, this relationship is not statistically significant in the lower and middle quantiles (0.20-0.60). It becomes significant at the 1% from quantiles 0.70 to 0.95. Additionally, the negative effect is significant at the lowest quantiles (0.05-0.10). Thus, TPU influences GG growth only in the lowest or higher quantiles. This finding is consistent with the studies (Gebre Borojo et al., 2023; Caldara et al., 2020; Sun et al., 2022) which consider the negative role of TPU in economic growth or green sustainability. A reduction in TPU can enhance quality exports, green technologies, and production efficiency, therefore, improving GG prospects.

The results for GI are positive and statistically significant across most quantiles, except at the 0.20 quantile. This positive association between green investment and green growth suggests that greater investment in environmentally sustainable activities can support green-growth performance in China. This finding is consistent with Chen and Ma (2021), who show that green investment can improve long-term firm performance, reduce environmental violations, and strengthen environmental performance in Chinese energy firms. They used the data of energy-listed firms over the period 2008-2017. Their findings suggested that green investment contributes to the reduction of environmental breaches and the promotion of sustainable practices and that environmental sustainability can increase the influence of green investment on enhancing long-run firm performance. ET is positively associated with GG, but the coefficient is not statistically significant. The positive sign is consistent with the view that an increase in environmental technologies supports green growth by increasing green technologies

(Ahmed et al., 2023). The likely reason for the insignificant impact could be the level of these technologies which is perhaps lower than the threshold level required for significant effects.

The results for HC are not statistically significant at the highest quantiles (0.90 and 0.95). At the remaining quantiles, however, the coefficients are positive and significant, indicating that improvements in human capital can support green growth in China. Human capital can contribute to green growth by strengthening knowledge accumulation, innovation capability, technological adoption, and the development of environmentally sustainable production practices. This result is consistent with Liu et al. (2022), who provide empirical evidence that human capital is an important driver of green growth in China.

In the lowest quantiles, a decrease in TPU does not yield a significant improvement in GG, according to the SR dynamics. However, for the remaining quantiles, a reduction in TPU leads to a statistically significant increase in green growth. The negative impact of TPU on GG remains consistent in both the SR and LR. The impact varies across the lower and middle quantiles. In conclusion, a reduction in TPU significantly contributes to the improvement of GG in China. On the other hand, in the SR, the influence of GI (π_{1GI}) on GG is not significant. However, the effect of HC on GG is positive at higher quantiles. The analysis of the SR suggests that the drivers of GG growth predominantly manifest their positive effects in the LR.

Table 4 displays the estimates derived from the nonlinear model. The results suggest that the ρ^* is insignificant at lower quantiles. However, the coefficient becomes significant at higher quantiles (0.40-0.95) suggesting a reversion to LR equilibrium. The empirical findings show that a positive shock in TPU ($\beta^+_{TPU}(\tau)$) has an insignificant impact on GG at lower quantiles. However, a reduction in TPU at higher quantiles (0.40-0.95) significantly improves GG. This result supports the idea that lowering TPU can improve the prospects for GG by boosting high-quality exports, green technologies, and industrial efficiency (Gebre Borojo et al., 2023; Caldara et al., 2020; Sun et al., 2022).

A negative shock in TPU ($\beta^-_{TPU}(\tau)$) does not exert any significant influence on GG at lower quantiles but significantly improves GG at higher quantiles (0.60-0.95). Thus, a negative shock also underscores the significance of TPU in determining GG. The negative shocks exhibit a comparatively higher magnitude, ranging from 0.36 to 0.78, while for positive shocks, the range is small, from 0.04 to 0.12. Therefore, asymmetry is evident both in terms of magnitudes and quantiles. The results for control variables align closely with those of QARDL.

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The SR dynamics observed in NQARDL indicate that a positive shock to TPU does not significantly enhance GG in the lowest quantiles (0.05-0.30). For quantiles ranging from 0.40 to 0.95, however, a positive shock in TPU significantly reduces GG, suggesting that an increase in TPU discourages GG prospects. This finding aligns with the LR effects of positive TPU shocks on GG, where the effect is even stronger, indicating that GG prospects can more effectively materialize over the long term. Similarly, a negative shock in TPU does not significantly enhance GG in the lowest quantiles (0.05-0.30). Conversely, in higher quantiles (0.40-0.95), a negative shock in TPU significantly increases GG, implying that a decrease in TPU boosts GG prospects. In Table 5, Wald statistics reveal the presence of observed asymmetry.

Table 3. Linear estimates of green growth. Source: computed from dataset.

	Constant	ECM	Long-run				Short-run				
Quantiles	$\mu(\tau)$	$\rho(\tau)$	$\beta_{TPU}(\tau)$	$\beta_{GI}(\tau)$	$\beta_{ET}(\tau)$	$\beta_{HC}(\tau)$	$\pi_{TPU}(\tau)$	$\pi_{0GI}(\tau)$	$\pi_{1GI}(\tau)$	$\pi_{ET}(\tau)$	$\pi_{HC}(\tau)$
0.05	15.20***	-0.798***	-0.280**	1.511*	1.029	2.329***	-0.133	0.050	0.163	0.252	0.319
	(6.663)	(5.982)	(2.104)	(1.883)	(0.938)	(5.042)	(1.341)	(0.437)	(0.337)	(0.101)	(0.132)
0.10	13.49***	-0.850***	-0.215*	1.358*	1.071	2.036***	-0.146	0.029	0.441	0.654	0.479
	(5.129)	(8.116)	(1.865)	(1.716)	(0.808)	(4.027)	(1.451)	(0.244)	(1.074)	(0.254)	(0.184)
0.20	7.039***	-0.862***	-0.084	1.584	0.115	0.992**	-0.114**	0.220**	0.560	0.174	0.225
	(4.006)	(15.76)	(1.054)	(1.074)	(0.396)	(2.169)	(2.264)	(2.411)	(1.155)	(0.064)	(0.085)
0.30	6.659***	-0.875***	-0.090	2.379***	0.076	1.041**	-0.160***	0.257***	0.300	1.768	1.323
	(3.532)	(20.76)	(0.993)	(3.213)	(0.239)	(2.025)	(4.950)	(2.630)	(0.596)	(1.078)	(0.825)
0.40	5.789***	-0.845***	-0.044	1.665***	0.047	0.921*	-0.147***	0.315***	0.782	1.277	0.856
	(2.973)	(8.846)	(0.454)	(2.654)	(0.143)	(1.752)	(4.019)	(3.146)	(1.148)	(1.113)	(0.749)
0.50	5.857***	-0.721***	-0.076	1.214***	0.104	0.759*	-0.130***	0.297***	0.818	1.405	1.019
	(2.934)	(9.033)	(0.809)	(2.955)	(0.309)	(1.946)	(4.684)	(2.937)	(1.148)	(1.659)	(1.198)
0.60	6.514**	-0.679***	-0.021	1.112***	0.043	1.182**	-0.129***	0.453**	0.992	1.697	1.350*
	(2.362)	(8.703)	(0.166)	(2.744)	(0.074)	(1.967)	(4.664)	(2.225)	(1.413)	(1.132)	(1.699)
0.70	6.503**	-0.721***	-0.040*	1.147***	0.252	2.065*	-0.130***	0.689***	0.776	2.083	1.771**
	(1.989)	(8.781)	(1.754)	(3.102)	(0.373)	(1.855)	(4.981)	(3.925)	(1.313)	(1.102)	(2.335)
0.80	7.257*	-0.823***	-0.023**	1.272***	0.364	2.554*	-0.145***	0.851***	0.584	2.525	2.198***
	(1.799)	(9.947)	(2.137)	(3.548)	(0.460)	(1.720)	(5.186)	(4.656)	(0.991)	(1.405)	(3.011)

	Constant	ECM	Long-run				Short-run				
0.90	11.92**	-0.795***	-0.786**	0.850*	0.077	1.087	-0.148***	0.384	0.570	1.149	0.750
	(2.270)	(10.49)	(2.186)	(1.824)	(0.088)	(0.689)	(3.220)	(1.166)	(1.099)	(0.689)	(0.447)
0.95	13.81**	-0.754***	-1.085**	0.633**	0.057	0.910	-0.104***	0.246	0.514	0.546	0.443
	(2.402)	(6.375)	(2.425)	(2.063)	(0.063)	(0.301)	(2.776)	(0.632)	(1.105)	(0.391)	(0.326)

Note: T-statistics' absolute values are presented within parentheses.

Table 4. Nonlinear estimates of green growth. Source: computed from dataset.

	Constant	ECM	Long-run					Short-run				
Q	$\mu(\tau)$	$\rho(\tau)$	$\beta^+_{TPU}(\tau)$	$\beta^-_{TPU}(\tau)$	$\beta_{GI}(\tau)$	$\beta_{ET}(\tau)$	$\beta_{HC}(\tau)$	$\pi^+_{TPU}(\tau)$	$\pi^-_{TPU}(\tau)$	$\pi_{GI}(\tau)$	$\pi_{ET}(\tau)$	$\pi_{HC}(\tau)$
0.05	10.76**	-0.693	-0.241	-0.143	0.153	0.908	2.207***	-0.105	0.155	0.097	0.421	0.795***
	(2.277)	(1.071)	(1.134)	(0.706)	(0.613)	(1.601)	(4.262)	(1.126)	(1.438)	(0.176)	(0.338)	(2.579)
0.10	9.860*	-0.609	-0.213	-0.121	0.080	0.775	2.125***	-0.092	0.069	0.329	0.450	0.822***
	(1.667)	(1.087)	(1.150)	(0.472)	(0.252)	(1.107)	(3.524)	(1.271)	(0.894)	(0.760)	(0.971)	(4.131)
0.20	5.921**	-0.585	-0.111	-0.066	0.150	0.071	1.171**	-0.118	0.017	0.514	0.508	0.693***
	(2.129)	(1.372)	(1.422)	(0.453)	(1.121)	(0.199)	(2.336)	(1.218)	(0.181)	(1.000)	(1.146)	(3.143)
0.30	6.376**	-0.561	-0.083	-0.096	0.281***	0.085	0.989**	-0.093	0.000	0.275	0.996	0.774***
	(2.191)	(0.535)	(0.947)	(0.654)	(2.587)	(0.224)	(1.975)	(1.089)	(0.003)	(0.516)	(0.848)	(3.674)
0.40	6.722**	-0.492***	-0.090	-0.148	0.353***	0.059	0.711*	-0.132***	-0.099*	0.902	1.464***	0.753***
	(2.186)	(16.70)	(1.058)	(1.008)	(2.922)	(0.145)	(1.825)	(2.963)	(1.855)	(1.391)	(3.366)	(5.671)
0.50	8.343**	-0.521***	-0.110*	-0.255	0.458**	0.151	0.289*	-0.133***	-0.124***	0.965	1.664***	0.575***
	(2.380)	(8.255)	(1.825)	(1.547)	(2.339)	(0.355)	(1.758)	(3.728)	(3.161)	(1.454)	(4.036)	(3.724)
0.60	10.43***	-0.542***	-0.091**	-0.361**	0.669***	0.285*	0.170*	-0.133***	-0.131***	1.134	1.850***	0.503***
	(2.780)	(7.355)	(2.106)	(1.980)	(2.880)	(1.690)	(1.876)	(3.715)	(3.344)	(1.112)	(3.117)	(3.335)
0.70	11.31**	-0.610***	-0.052**	-0.396*	0.969***	0.491*	0.274**	-0.146***	-0.143***	0.909	1.754***	0.501***
	(2.281)	(6.334)	(2.412)	(1.824)	(4.174)	(1.793)	(2.217)	(3.565)	(3.640)	(1.471)	(2.801)	(2.885)
0.80	16.99*	-0.655***	-0.047**	-0.785**	1.401***	2.275*	0.141*	-0.130***	-0.128***	0.710	1.323***	0.473***
	(1.857)	(9.071)	(2.225)	(2.523)	(3.947)	(1.893)	(2.059)	(3.111)	(3.301)	(1.142)	(2.645)	(2.751)
0.90	18.50*	-0.694***	-0.076**	-0.788***	1.514***	2.318**	0.387*	-0.141*	-0.174***	0.808	1.467***	0.292*
	(1.818)	(4.110)	(2.385)	(3.708)	(4.793)	(2.021)	(1.870)	(1.902)	(3.541)	(1.240)	(2.791)	(1.689)
0.95	15.36***	-0.713***	-0.126*	-0.685***	1.615***	1.989***	0.423**	-0.096***	-0.146***	0.768	1.999***	0.052**
	(5.785)	(4.129)	(1.759)	(3.391)	(5.008)	(2.729)	(2.229)	(3.312)	(3.959)	(1.589)	(3.696)	(2.211)

Note: T-statistics' absolute values are presented within parentheses.

Table 5. Wald test. Source: computed from dataset.

	LR ($H_0: \beta^+ = \beta^-$)	SR ($H_0: \pi^+ = \pi^-$)
0.05	0.278	9.654***
0.10	0.145	9.542***
0.20	0.102	7.785***
0.30	0.021	3.246***
0.40	0.345	3.987**
0.50	2.692*	0.257
0.60	2.725*	0.120
0.70	2.758*	0.015
0.80	5.121***	0.102
0.90	8.657***	2.831*
0.95	10.20***	3.687***

5. Conclusion and policy implications

This study examines whether trade policy uncertainty undermines sustainable competitiveness in China by weakening green growth. Green growth is used as the empirical channel for assessing sustainable competitiveness because it captures the ability to improve environmental performance while maintaining economic progress. Using QARDL and nonlinear QARDL models for the period 2000Q1 to 2021Q4, the analysis evaluates both short-run and long-run effects across different quantiles of the green-growth distribution.

The linear QARDL results indicate that TPU has a negative effect on green growth at several quantiles, particularly at the lower and upper parts of the distribution. The nonlinear results further show that positive TPU shocks reduce green growth, whereas reductions in TPU improve green growth, especially at higher quantiles. These findings confirm that the green-growth effects of TPU are asymmetric and quantile-dependent. The control variables also matter: green investment, human capital, and environmental technology contribute to green growth, although their effects vary across specifications and quantiles.

The findings have important policy implications. First, policymakers should reduce trade-policy uncertainty by maintaining transparent, predictable, and consistent trade-policy frameworks. Greater policy stability can encourage firms to invest in cleaner technologies, improve export quality, and support long-term green transformation. Second, China should strengthen green investment and environmental technology development, since these factors help offset the negative effects of uncertainty and promote sustainable competitiveness. Third, human-capital upgrading should remain a central policy priority because skilled workers and researchers can support green innovation, technology adoption, and productivity improvement.

Because TPU has asymmetric effects, policymakers should treat rising and declining uncertainty differently. Reducing TPU can be especially beneficial for green growth, while increases in TPU may weaken the incentives needed for environmental upgrading. International cooperation is also important because trade-policy uncertainty can generate cross-border spillovers that affect trade, investment, technology diffusion, and environmental sustainability. Clear multilateral trade rules, stable trade agreements, and cooperation on green products can therefore support China's green-growth objectives and strengthen sustainable competitiveness.

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Appendix

Table A1: Definitions and sources Source: own research

Variables	Symbol	Definitions	Sources
Green growth	GG	Pollution-adjusted GDP growth (%)	OECD
Trade policy uncertainty	TPU	Trade policy uncertainty index	Baker, Bloom, and Davis
Green investment	GI	Electricity production from renewable sources, excluding hydroelectric (% of total)	WDI
Environmental technology	ET	Environment-related technologies (total patents)	OECD
Human capital	HC	School enrollment, tertiary (% gross)	WDI

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