

ICT-Based Digital Trade and Green Growth in China: Nonlinear Dynamics and Structural Breaks

*Tingting Sun**

Abstract

This study investigates the impact of ICT-based digital trade on green growth in China over the period 1985–2021. To capture nonlinear dynamics and regime-dependent effects, the analysis applies a Smooth Transition Regression (STR) framework and identifies structural break points around 2003, 2010, and 2011. The study also constructs a green gross national income indicator to reflect the environmental cost of economic expansion more explicitly. The findings reveal that the relationship between ICT trade and green growth is nonlinear rather than constant over time. ICT-based digital trade exerts a positive and approximately unit-elastic effect on green growth, while labor and capital also contribute positively, with evidence of increasing returns to scale in the presence of ICT. The results further suggest that technological progress associated with ICT can support green growth by improving energy efficiency, strengthening productive capacity, and facilitating the use of less energy-intensive inputs. These findings imply that the growth and environmental benefits of ICT are conditional on the stage of green development and the broader economic structure. Accordingly, policies that promote ICT trade, technological innovation, capital formation, and skilled labor development may strengthen China's transition toward sustainable and greener growth.

Keywords: ICT trade, green growth, smooth transition regression, nonlinear dynamics, structural breaks, China

JEL Classification: F14, O33, O44, C22, Q56

Article history: Received: December 2025; Accepted: April 2026; Published: October 2026

1 INTRODUCTION

Sustainable growth has become a central objective of the global development agenda, especially in an environment shaped by rapid technological change (X. Li et al., 2022; Chen et al., 2023). Information and communication technology (ICT) can influence green production through both direct and indirect channels. Directly, ICT improves information processing, coordination, and decision-making, thereby enhancing production efficiency (Chen et al., 2023). Indirectly, ICT facilitates knowledge diffusion, innovation, and closer collaboration among firms, workers, and researchers, which can strengthen green production and environmental management (Sulisworo et al., 2012; Tzeremes et al., 2023). ICT also helps firms respond more efficiently to market conditions and adopt cleaner production and pollution-treatment technologies (Evangelista & Hallikas, 2022; Usman et al., 2023).

Over the past three decades, China's digital economy has expanded rapidly and now ranks among the largest in the world. At the same time, the country's growth model has generated

substantial environmental and ecological costs (Shkvarya & Hailing, 2021). Long-standing challenges—including regional imbalance, inequality, and environmental degradation—have intensified the policy relevance of inclusive and green growth (Zhang et al., 2020). In response, China has increasingly integrated ecological objectives into its national development strategy. Recent research suggests that the digital economy can support high-quality green development, with industrial upgrading and green innovation acting as important transmission channels (Ma & Zhu, 2022). Other studies also indicate that the internet may affect green production nonlinearly, with stronger effects emerging once digital development passes critical thresholds and interacts with R&D investment and structural transformation (Li & Zhao, 2021).

1.1 CHINESE ICT SNAPSHOT

Against this backdrop, China provides a particularly relevant setting for examining the green-growth effects of ICT-based trade. China is one of the world's largest producers and exporters of ICT goods and services, and the expansion of ICT trade has become an important component of its broader trade dynamics. At the same time, the country has pursued a green-growth agenda through renewable energy deployment, energy-efficiency improvements, pollution control, and sustainable urbanization. The central empirical question is therefore not whether ICT matters for China's development, but whether ICT trade affects green growth in a linear or nonlinear manner. Table 1 summarizes selected ICT-related rankings for China and comparator countries, highlighting China's scale of digital connectivity and its relatively strong position in innovation and technological capability.

Tab. 1 – Some ranks on ICT-related items. Source: (https://rankingroyals.com) & (https://worldpopulationreview.com)					
S. No	Nation	Internet Users	Mobile Phone Connections	GII Rank	Technological Expertise
1	China	1.05 billion	1.6 billion	3	3
2	US	311.3 million	327 million	1	4
3	Indonesia	212.9 million	386 million	75	60
4	Brazil	181.8 million	284 million	54	51
5	Japan	103 million	147 Million	8	1

China's ICT trade model combines large-scale manufacturing capacity, export orientation, growing R&D intensity, and an increasingly sophisticated digital economy. This creates both opportunities and tensions. On the one hand, ICT can support green growth through smart systems, cleaner production, environmental monitoring, and better resource allocation. On the other hand, the scale of production and trade creates adjustment pressures and raises the need to balance competitiveness with environmental sustainability. Understanding the nonlinear interaction between ICT trade and green growth is therefore important for both academic analysis and policy design.

Accordingly, this paper examines the impact of ICT trade on green growth in China using a smooth transition regression (STR) framework. The STR approach is well suited to this question because it allows the effect of ICT trade to vary across regimes and accommodates structural change more flexibly than a purely linear specification. In doing so, the study moves

beyond descriptive discussions of the digital economy and provides a macro-level assessment of how ICT trade, labour, and capital interact with green growth across different phases of China's development.

The study contributes to the literature in three ways. First, it develops a green income measure that adjusts output for pollution damage. Second, it evaluates whether the ICT–green growth relationship is regime dependent rather than constant over time. Third, it identifies structural shifts around 2003, 2010, and 2011 that help explain the changing contribution of ICT trade to green growth in China. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the model, methodology, and data. Section 4 discusses the empirical findings. Section 5 concludes and outlines policy implications.

2 LITERATURE REVIEW

Green growth has become an important concept in the literature because it links economic expansion with environmental sustainability. A large body of research measures green performance from the perspective of production efficiency, environmental quality, or green total factor productivity (e.g., Lin et al., 2013; Xie et al., 2018; Wu et al., 2020; Lin & Zhou, 2022). In general, the concept refers to growth that preserves natural capital, reduces pollution intensity, and supports long-run welfare rather than simply maximizing conventional output.

Despite this growing literature, there is no single universally accepted measure of green growth. Some studies use green GDP-type measures that deduct the environmental costs of production from standard income aggregates (Kunanuntakij et al., 2017; Li & Fang, 2014). Others emphasize broader indicators that incorporate energy use, labour, environmental quality, or carbon intensity (Reilly, 2012; Jouvet & Perthuis, 2013; Lin & Zhou, 2022). For China, recent evidence suggests that green trade and green energy can improve green growth, but the magnitude of the effect varies across regions and development levels (J. Li et al., 2022).

The macroeconomic literature on ICT and growth has traditionally focused on productivity, capital deepening, and innovation. Studies for advanced economies generally report a positive contribution of ICT to growth and productivity, particularly after the mid-1990s (Jorgenson & Stiroh, 2000; Oliner & Sichel, 2000; Inklaar et al., 2005). Similar evidence is reported for Finland and other countries, where ICT appears to influence growth directly through productivity gains and indirectly through innovation and human capital formation (Jalava & Pohjola, 2008; Bayraktar Sağlam, 2018; Edquist & Henrekson, 2017).

Several mechanisms explain this positive effect. ICT reduces information frictions, lowers coordination costs, and can improve investment efficiency and resource allocation (Levine, 1997; Mahyideen et al., 2012). It also strengthens research capability, supports education and knowledge diffusion, and can improve public-service delivery through e-government and related digital reforms (Saidi & Chebli, 2018; Majeed & Malik, 2016). However, the literature is not uniformly positive. Some studies report weak or even negative effects when economies lack complementary skills, institutions, or investment depth (Stiroh, 2002; O'Mahony & Vecchi, 2005).

A related strand of research examines the environmental effects of ICT. Some studies show that ICT adoption can reduce emissions by improving efficiency, reducing energy intensity,

and facilitating environmental monitoring (Zhang & Liu, 2015; Lee & Brahmasrene, 2014; Asongu, 2018). Other work finds weaker or context-dependent effects, especially in developing regions (Asongu et al., 2018). More recently, nonlinear analyses suggest that the ICT–environment nexus may follow threshold or inverted-U patterns, implying that the environmental contribution of ICT depends on development stage, institutional conditions, and the quality of complementary policies (Añón Higón et al., 2017; Tang et al., 2023).

For China, studies on the digital economy and green development increasingly point to strong linkages between digitalization, innovation, and environmental upgrading (Ma & Zhu, 2022; Li & Zhao, 2021). However, research that focuses specifically on ICT trade rather than broad digitalization remains limited. Even fewer studies examine whether ICT trade affects green growth through nonlinear or regime-dependent mechanisms.

This gap matters for two reasons. First, China’s ICT trade expanded rapidly only after 2000, suggesting that its macroeconomic and environmental effects may not be stable across the full sample period. Second, structural breaks associated with trade integration, technological upgrading, and policy shifts may alter the size and direction of the ICT effect over time. A nonlinear framework is therefore more appropriate than a constant-parameter model for assessing the ICT trade–green growth nexus.

Against this background, the present study develops a macro-level measure of green growth for China and evaluates whether ICT trade, labour, and capital affect that measure in a nonlinear manner. By applying a smooth transition regression framework, the paper contributes to the literature on green growth, digital trade, and structural change in China.

3 MODEL AND METHODOLOGY

To align the empirical model with the paper’s objective, we begin from an augmented Cobb–Douglas production framework in which green output depends on conventional inputs as well as environmental damage.

$$Y_t = A_t K_t^\alpha L_t^\beta \quad (1)$$

CO2 emissions are assumed to affect the economy through environmental damage that reduces the effective services of capital and labour. Let γ denote the per-ton damage cost of CO2 emissions.

$$Y_t = A_t K_t^\alpha L_t^\beta P_t^\gamma \quad \therefore \quad \alpha, \beta > 0; \gamma < 0 \quad (2)$$

Taking logarithms and rearranging yields a green-growth specification in which output is adjusted for pollution damage.

$$\ln Y_t = \ln A_t + \alpha \ln K_t + \beta \ln L_t + \gamma \ln P_t \quad (3)$$

$$\ln Y_t - \gamma \ln P_t = \ln A_t + \alpha \ln K_t + \beta \ln L_t \quad (4)$$

Defining green output as adjusted income net of pollution costs yields the measure used in the empirical analysis.

$$Y_t^G = \ln A_t + \alpha \ln K_t + \beta \ln L_t \quad (5)$$

The standard production relationship is then augmented by incorporating ICT trade as the technology-related state variable. The resulting reduced-form equation links green growth to ICT trade, labour, and capital.

$$Y_t^G = \ln t b I C T_t + \alpha \ln K_t + \beta \ln L_t + \epsilon_t \quad (6)$$

Although the reduced-form equation is log-linear, the effect of ICT trade on green growth need not be constant over time. Trade shocks can operate asymmetrically, and the influence of ICT may vary once the economy crosses certain development thresholds. Because China's ICT trade expanded rapidly after 2000, structural changes are especially likely. A nonlinear specification is therefore appropriate.

- (1) Smooth transition regression (STR) provides a flexible way to model this nonlinearity. Following Teräsvirta (1994) and van Dijk et al. (2002), the STR framework allows coefficients to change smoothly across regimes as the threshold variable moves between lower and higher states.
- (2) Compared with a purely linear model, STR can capture gradual regime shifts rather than imposing abrupt breaks. This is useful in the present setting because the influence of ICT trade on green growth is likely to evolve progressively as digital trade deepens, technology diffuses, and complementary inputs adjust.

Accordingly, the empirical analysis employs an STR specification to test whether the ICT trade–green growth nexus in China is regime dependent. Recent applications of similar nonlinear frameworks in sustainability and environmental economics include Xu et al. (2021), Ullah et al. (2021), and Tong et al. (2021).

$$\ln Y_t^G = \sum_{j=0}^{m-1} \mathbf{1}_j(s_t; c, \pi) \cdot \mathbf{Z}_t' \delta_j + \mathbf{X}_t \alpha + \mu_t \quad (7)$$

In the general STR specification, π denotes the slope parameter governing the speed of transition, c denotes the threshold value, q_t is the transition variable, Z contains variables whose coefficients vary across regimes, and X contains variables whose coefficients remain invariant across regimes.

$$\ln Y_t^G = \mathbf{1}_0(\ln t b i c t_t; c, \pi) \cdot \mathbf{Z}_t' \delta_0 + \mathbf{1}_1(\ln t b i c t_t; c, \pi) \cdot \mathbf{Z}_t' \delta_1 + \mathbf{X}_t \alpha + \mu_t \quad (8)$$

For the two-regime case considered here, the model can be written in a compact form in which the transition function scales the regime-dependent component of the equation.

To obtain a two-regime STR model, the indicator function is replaced by a continuous transition function G that takes values between 0 and 1.

$$\ln Y_t^G = \mathbf{1} - G(\ln t b i c t_t; c, \pi) \cdot \mathbf{Z}_t' \delta_0 + G(\ln t b i c t_t; c, \pi) \cdot \mathbf{Z}_t' \delta_1 + \mathbf{X}_t \alpha + \mu_t \quad (9)$$

Given a candidate transition variable and threshold value, the parameters of the STR model can be estimated by nonlinear least squares. Model selection is based on the fit of alternative specifications, the plausibility of threshold behavior, and the remaining nonlinearity diagnostics.

3.1 DATA

The empirical analysis uses annual data for China from 1985 to 2021, drawn primarily from the World Development Indicators (WDI) and the National Bureau of Statistics of China (NBS). Table 2 summarizes the variables and their construction. Green gross national income (GGNI) is calculated by adjusting output for the estimated monetary damage associated with CO₂ emissions. ICT trade balance (TBICT) is measured as the log difference between ICT exports and ICT imports to avoid undefined logarithms for negative trade balances. Gross fixed capital formation (GFCF) proxies capital accumulation, while labour force captures labour input.

Tab. 2 – Description of the variables. Source: own research		
Variable Name	Unit	Calculation Method (if any other than available)
GGNI: Green gross national Income	Log taken on the constant USD (2015)	The variable is calculated after adjusted cost incurred by pollution (damage) with WDI definition of \$ 40 per metric ton of CO ₂ emissions. Thus the value of γ in equation 5 above to get green output is 40, i.e., $Y^G = Y - 40P$ Here P is metric tons of pollution.
TBICT: Balance of trade of ICT China	Log taken on the million constant USD (2015) of ICT exports and ICT imports.	To avoid undefined log of negative values, the difference between log values of ICT exports and imports is used.
GFCF: Gross fixed capital formation	Taken as proxy for capital flow Constant USD (2015). Log taken	
Labor Force	Log of total labor force.	

Figure 1 shows that China's ICT exports rose sharply after the beginning of the 21st century. Figure 2 compares the ICT trade balance with the overall goods trade balance and suggests that ICT became an increasingly important contributor to China's external position after the early 2000s. Figure 3 plots GGNI, GFCF, and labour force, indicating broad co-movement between green income and capital formation, alongside relatively slower labour-force growth.

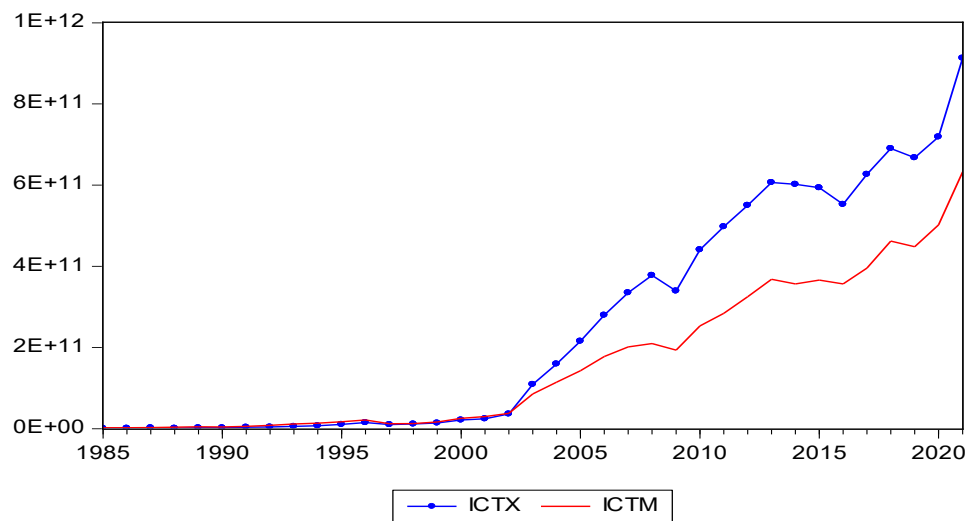


Fig. 1 – ICT exports and imports of China. Source: authors' calculations based on WDI and NBS China.

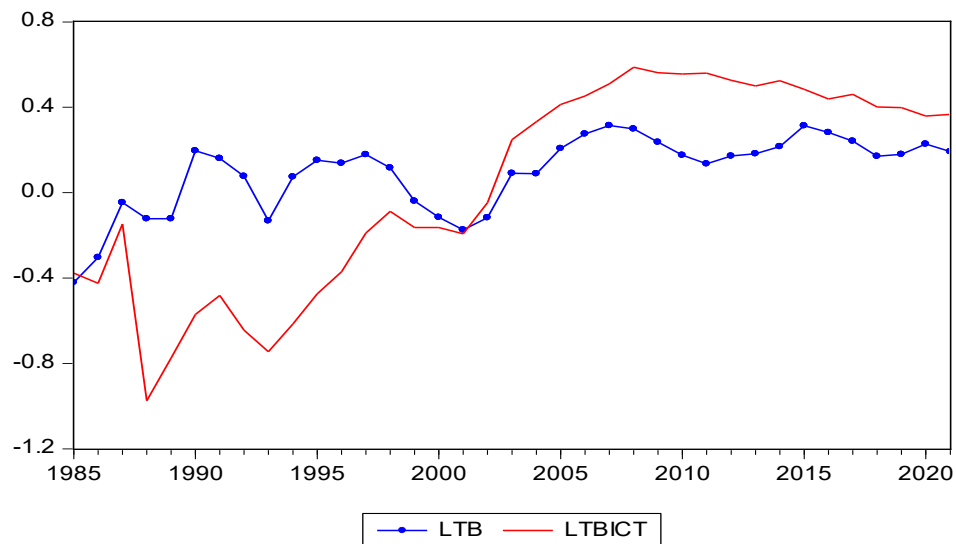


Fig. 2 – ICT trade balance versus overall goods trade balance. Source: authors' calculations based on WDI and NBS China.

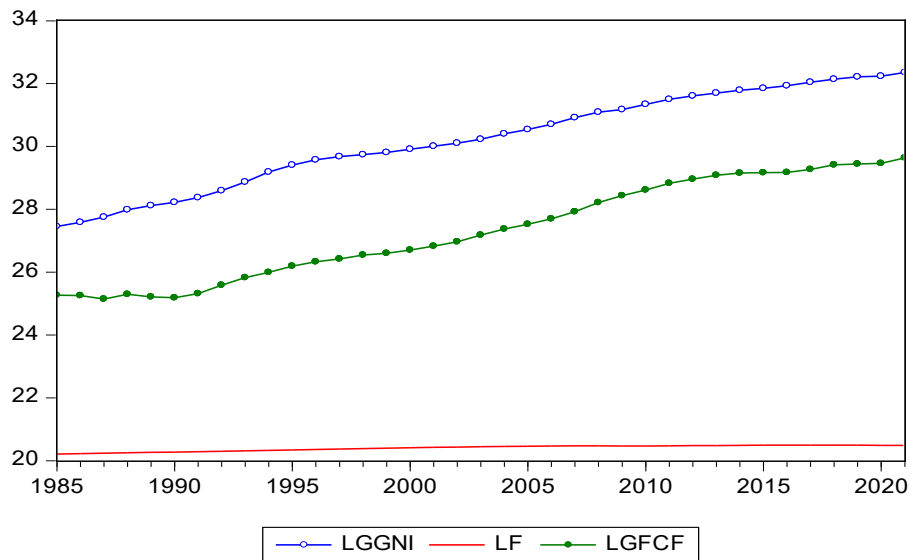


Fig. 3 – GGNI, GFCF, and labour force. Source: authors' calculations based on WDI and NBS China.

4 RESULTS AND DISCUSSION

Table 3 reports the stationarity diagnostics. All variables appear to be integrated of order one, which indicates the presence of persistent long-run movements in the data. Given the paper's emphasis on structural change and regime dependence, the empirical analysis proceeds with the STR specification rather than relying on a constant-parameter linear model.

ab. 3 – Stationarity diagnostics. Source: own research		
Variable Name	ADF Stat	Order
LGGNI	-2.9918	I(1)
LTBICT	-4.92461	I(1)
LGFCF	-3.4197	I(1)
LF	-1.97033	I(1)

To identify plausible threshold points, alternative lag structures for GGNI were examined using model-specification tests. The choice of threshold is based on fit criteria, especially the sum of squared residuals and the standard error of regression. Figure 4 suggests that lag 10 (2011), lag 11 (2010), and lag 18 (2003) provide the most relevant candidates. Table 4 reports the corresponding threshold estimates together with the linear OLS benchmark.

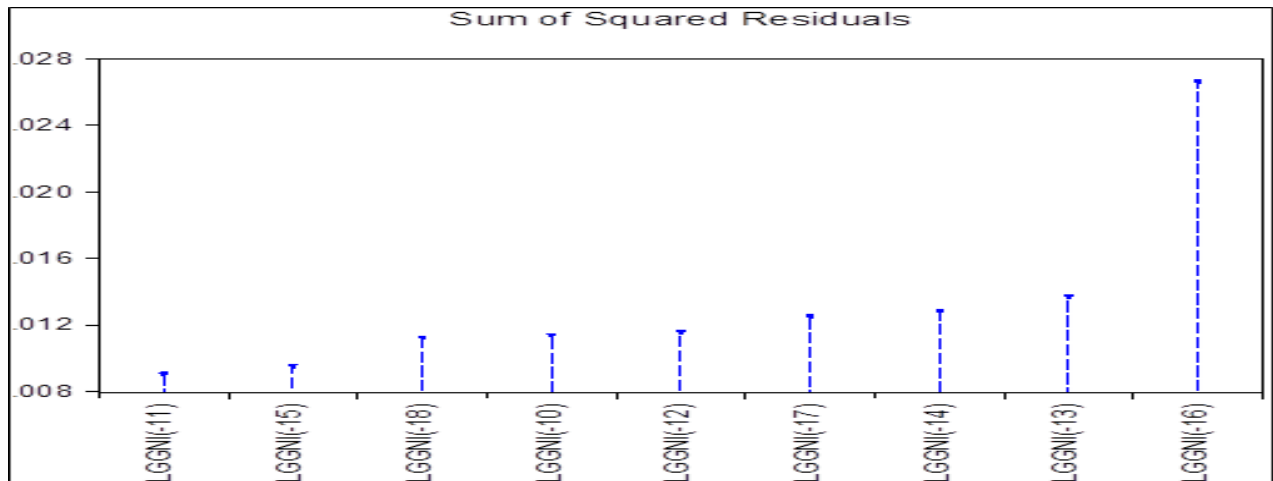


Fig. 4 – Model specification diagnostics. Source: authors' calculations based on WDI and NBS China.

The threshold estimates indicate that ICT trade has a positive association with green growth, and that the nonlinear component is economically large. Across the preferred threshold specifications, the nonlinear elasticity of ICT trade is close to unity, implying that improvements in ICT trade are associated with a near-proportional response of green growth within the transition regime. Labour and capital also enter with positive and statistically significant coefficients, and their combined magnitudes suggest increasing returns in the presence of ICT-related technological change.

Tab. 4 – Nonlinear threshold estimation vs OLS. Dependent variable: Green growth. Source: own research				
Threshold Variables (linear part)				
Variable/Coefficients	Threshold LGGNI(-10)	Threshold LGGNI(-11)	Threshold LGGNI(-18)	OLS Estimates
LTBICT: δ_0	0.1283* (0.066)	0.1331* (0.0598)	0.3540* (0.153)	-0.0745* (0.0254)
Threshold Variables (nonlinear part)				
LTBICT: δ_1	1.0672* (0.4626)	1.404* (0.5633)	1.047528* (0.2095)	
Non-Threshold Variables				
LF: α_1	0.5665* (0.0611)	0.6109* (0.0692)	0.5672* (0.0358)	-0.1608 (1.2159)
LGFCF: α_2	0.6868* (0.046)	0.6532* (0.0527)	0.6830* (0.0282)	0.3746* (0.0817)
Slopes				
SLOPE: π	3.3714* (1.531)	2.6552* (0.8809)	7.599* (1.805)	--
Thresholds				

Tab. 4 – Nonlinear threshold estimation vs OLS. Dependent variable: Green growth. Source: own research				
Threshold Variables (linear part)				
Variable/Coefficients	Threshold LGGNI(-10)	Threshold LGGNI(-11)	Threshold LGGNI(-18)	OLS Estimates
THRESHOLD: c	30.815* (0.1133)	30.658* (0.121)	29.782* (0.0338)	--
Fitness and Diagnostics				
R-squared	0.9991	0.9992	0.9985	0.5275
S.E. of regression	0.0311	0.0297	0.0294	0.0456
Durbin-Watson stat	1.4786	1.5460	1.7214	1.1273
BG Serial Correlation LM Test:	1.2465	1.3264	0.3766	7.159 ⁹

Note: Standard Errors in parenthesis. * indicates statistically significant parameters at least at 10% or below. ⁹ indicates presence of serial-correlation at lag 1.

Compared with the STR results, the OLS benchmark performs poorly. The linear specification yields less stable coefficients, lower explanatory power, and evidence of serial correlation. By contrast, the threshold models deliver much better fit statistics and more plausible coefficient estimates. The estimated threshold values cluster around the period from 2010 to 2011, while the longer-lag specification also captures an earlier structural shift around 2003. Taken together, these results support the presence of regime-dependent dynamics in the ICT trade–green growth relationship.

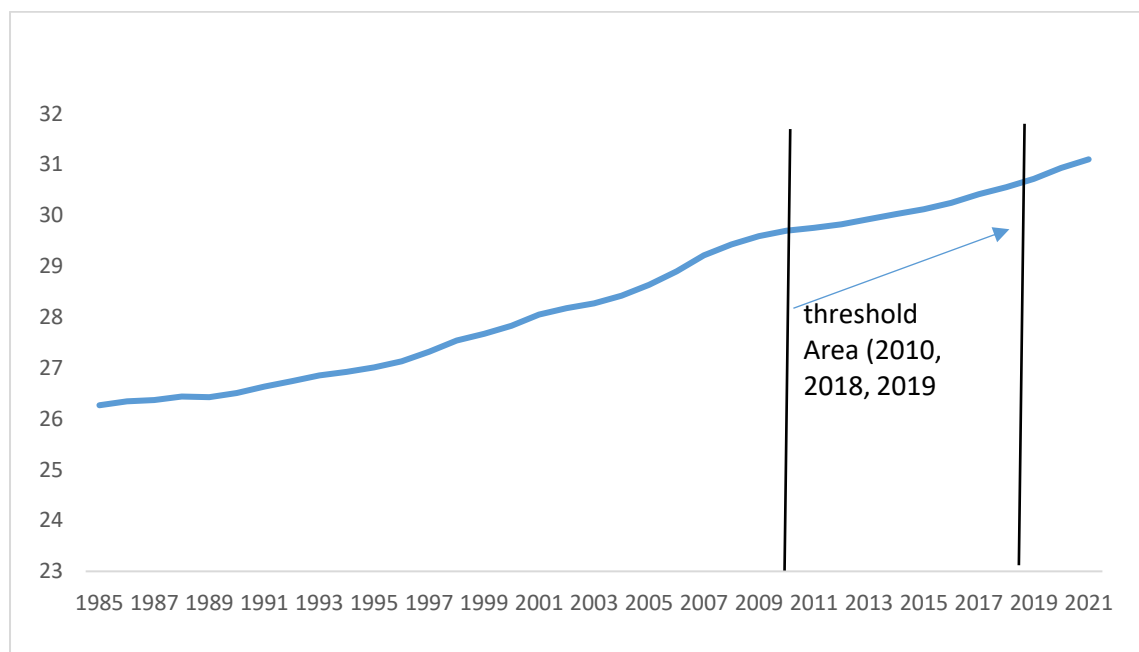


Fig. 5 – Log GNI with estimated threshold values. Source: authors' calculations based on WDI and NBS China.

Table 5 reports the smooth-threshold linearity tests for three candidate threshold variables: LGGNI(-10), LGGNI(-11), and LGGNI(-18). The Taylor-series tests provide evidence against linearity for LGGNI(-10) and LGGNI(-18) at the 10% level, with p-values of 0.083 and 0.092, respectively. By contrast, the null of linearity is clearly not rejected for LGGNI(-11), where the p-value is 0.86. The Teräsvirta sequential tests lead to the same conclusion because, in the reported specification, the H1 statistic mirrors the basic linearity test.

Tab. 5 – Smooth threshold linearity tests. Source: own research									
Sample: 1985 2021									
Test for nonlinearity	LGGNI(-10) as the threshold			LGGNI(-11) as the threshold			LGGNI(-18) as Threshold		
Taylor series options: $c_0 + c_1*s [+ c_2*s^2 + c_3*s^3 + c_4*s^4]$									
Linearity Tests									
Null Hypothesis	F-stat	d.f.	p-value	F-stat	d.f.	p-value	F-stat	d.f.	p-value
H04: $c_1=c_2=c_3=c_4=0$	2.781	(1, 23)	0.083	0.03	(1, 22)	0.86	2.614	(1, 15)	0.092
H03: $c_1=c_2=c_3=0$	2.781	(1, 23)	0.083	0.03	(1, 22)	0.86	2.614	(1, 15)	0.092
H02: $c_1=c_2=0$	2.781	(1, 23)	0.083	0.03	(1, 22)	0.86	2.614	(1, 15)	0.092
H01: $c_1=0$	2.781	(1, 23)	0.083	0.03	(1, 22)	0.86	2.614	(1, 15)	0.092
The H0i test uses i-th order Taylor expansion ($c_j=0$ for all $j>i$).									
Terasvirta Sequ. Tests	LGGNI(-10) as threshold			LGGNI(-11) as threshold			LGGNI(-18) as threshold		
Null Hypothesis	F-stat	d.f.	p-value	F-stat	d.f.	p-value	F-stat	d.f.	p-value
H3: $c_3=0$	NA	(0, 23)	NA	NA	(0, 22)	NA	NA	(0, 15)	NA
H2: $c_2=0 \mid c_3=0$	NA	(0, 23)	NA	NA	(0, 22)	NA	NA	(0, 15)	NA
H1: $c_1=0 \mid c_2=c_3=0$	2.781	(1, 23)	0.083	0.03	(1, 22)	0.86	2.614	(1, 15)	0.092
Third-order Taylor expansion is basis of all tests ($c_4=0$).									
Linear model is statistically not rejected at 5% level via H03.									
Escribano-Jorda Tests	LGGNI(-10) as the threshold			LGGNI(-11) as the threshold			LGGNI(-18) as the threshold		
Null Hypothesis	F-stat	d.f.	p-value	F-stat	d.f.	p-value	F-stat	d.f.	p-value
H0L: $c_2=c_4=0$	82.899	(1, 22)	0	63.384	(1, 21)	0	12.43	(1, 14)	0.003
H0E: $c_1=c_3=0$	83.816	(1, 22)	0	63.288	(1, 21)	0	12.71	(1, 14)	0.003
All tests are based on the fourth-order Taylor expansion.									
Linear model is statistically not rejected at the 5% level with H04.									

The Escribano–Jordá tests (Escribano & Jordá, 1999) provide stronger evidence of nonlinearity. For all three candidate lags, both H0L and H0E are rejected at conventional significance levels, suggesting that the relationship is not well represented by a purely linear model. This pattern

indicates that support for nonlinearity is stronger when higher-order dynamics are taken into account.

Accordingly, the linearity tests should be interpreted as mixed but overall supportive of a nonlinear specification. The evidence is not equally strong across all candidate thresholds, yet the combined test results—especially the Escribano-Jorda statistics—suggest that a smooth-threshold model is preferable to a purely linear alternative. This implies that the effect of ICT trade on green growth depends on the level of green income and changes across regimes rather than remaining constant over time.

Table 6 presents the remaining-nonlinearity tests, which assess whether the selected STR specification leaves substantial nonlinear structure unmodeled.

Tab. 6 – Smooth threshold remaining nonlinearity tests. Source: own research									
Sample: 1985 2021									
Additive nonlinearity tests	LGGNI(-10) as threshold			LGGNI(-11) as threshold			LGGNI(-18) as threshold		
Taylor series options: $c_0 + c_1*s [+ c_2*s^2 + c_3*s^3 + c_4*s^4]$									
Null Hypothesis	F-stat	d.f.	p-value	F-stat	d.f.	p-value	F-stat	d.f.	p-value
H04: $c_1=c_2=c_3=c_4=0$	0.472	(1, 20)	0.499	0.207	(1, 19)	0.654	1.281	(1, 12)	0.28
H03: $c_1=c_2=c_3=0$	0.472	(1, 20)	0.499	0.207	(1, 19)	0.654	1.281	(1, 12)	0.28
H02: $c_1=c_2=0$	0.472	(1, 20)	0.499	0.207	(1, 19)	0.654	1.281	(1, 12)	0.28
H01: $c_1=0$	0.472	(1, 20)	0.499	0.207	(1, 19)	0.654	1.281	(1, 12)	0.28
The H0i test uses the i-th order Taylor expansion ($c_j=0$ for all $j>i$).									
Terasvirta Sequential Tests	LGGNI(-10) as the threshold			LGGNI(-11) as the threshold			LGGNI(-18) as the threshold		
Null Hypothesis	F-stat	d.f.	p-value	F-stat	d.f.	p-value	F-stat	d.f.	p-value
H3: $c_3=0$	NA	(0, 20)	NA	NA	(0, 19)	NA	NA	(0, 12)	NA
H2: $c_2=0 \mid c_3=0$	NA	(0, 20)	NA	NA	(0, 19)	NA	NA	(0, 12)	NA
H1: $c_1=0 \mid c_2=c_3=0$	0.4723	(1, 20)	0.499	0.207	(1, 19)	0.654	1.281	(1, 12)	0.28
All tests are based on the 3rd-order Taylor expansion ($c_4=0$).									
Original model is statistically not rejected at the 5% level with H03.									
Escribano-Jorda Tests	LGGNI(-10) as the threshold			LGGNI(-11) as the threshold			LGGNI(-18) as the threshold		
Null Hypothesis	F-stat	d.f.	p-value	F-stat	d.f.	p-value	F-stat	d.f.	p-value
H0L: $c_2=c_4=0$	5.461	(1, 19)	0.0305	5.424	(1, 18)	0.0317	0.073	(1, 11)	0.79
H0E: $c_1=c_3=0$	5.494	(1, 19)	0.0301	5.396	(1, 18)	0.0321	0.084	(1, 11)	0.77
All tests are based on 4 th -order Taylor expansion.									
Original model is statistically not rejected at the 5% level with H04.									

The Additive Nonlinearity Tests do not reject the null of no remaining nonlinearity for any of the three threshold candidates. The corresponding Teräsvirta sequential tests lead to the same result, indicating that the main STR specification captures most of the nonlinear behavior identified in the data. The Escribano-Jorda remaining-nonlinearity tests provide a more nuanced picture. For LGGNI(-10) and LGGNI(-11), the p-values around 0.03 suggest some residual nonlinear structure. For LGGNI(-18), however, the null of no remaining nonlinearity is not rejected. This indicates that the adequacy of the STR model depends on the threshold choice, with the longer-lag specification appearing more complete in absorbing the nonlinear pattern.

Overall, the diagnostics suggest that the STR framework captures the principal nonlinear dynamics linking ICT trade and green growth in China, although some higher-order effects may remain for particular thresholds. The results therefore support a nonlinear interpretation of the ICT trade–green growth nexus, while also indicating that threshold selection matters for model adequacy. Appendix Figures A1–A3 present the estimated threshold weight functions associated with the selected STR specifications.

4.1 DISCUSSION

The empirical results indicate that ICT trade is positively associated with green growth in China, but the strength of this relationship varies across regimes. This finding is consistent with the view that ICT supports sustainable development by improving efficiency, facilitating knowledge spillovers, and strengthening technological capability (Oláh et al., 2020; Chen et al., 2019). The positive coefficients on labour and capital further suggest that human and physical capital remain essential complements to digital trade in the transition toward greener growth, which aligns with evidence reported by Ouyang et al. (2018) and Fujii and Managi (2016).

The threshold results also imply that the contribution of ICT trade is not immediate and uniform across time. Specifications based on GGNI(-10) and GGNI(-18) perform better in the linearity tests than the lag-11 alternative, pointing to delayed and regime-dependent responses. This pattern is plausible for China, where the environmental benefits of ICT trade may emerge only after complementary investments in infrastructure, innovation, and industrial upgrading have accumulated.

From a policy perspective, the results suggest that ICT trade can support green growth, but its payoff depends on the stage of green development and on the availability of supporting factors such as skilled labour, capital formation, and green innovation. Policies that deepen ICT capabilities, strengthen technological diffusion, and support clean production are therefore likely to be more effective when combined with broader investments in human capital and environmental governance.

5 CONCLUSIONS AND POLICY IMPLICATIONS

This paper investigates whether ICT trade affects green growth in China in a nonlinear manner. Using annual data for 1985–2021, it constructs a green gross national income measure and compares a linear benchmark with smooth-threshold specifications. The empirical evidence identifies structural changes around 2003, 2010, and 2011 and shows that a threshold model describes the ICT trade–green growth relationship better than a constant-parameter OLS model.

The results indicate that ICT trade has a positive and economically meaningful effect on green growth once regime dependence is taken into account. Labour and capital also make positive contributions, and the estimated coefficients are consistent with increasing returns in the presence of ICT-related technological change. At the same time, the nonlinearity diagnostics show that the strength of the evidence varies across thresholds, which means that policy conclusions should be drawn with some caution rather than on the assumption of a single invariant effect.

Overall, the findings suggest that technological progress linked to ICT trade can contribute to greener growth by improving efficiency, supporting more skilled labour, and encouraging less energy-intensive capital formation. For policymakers, the key implication is that digital trade policy should be coordinated with investment in innovation, human capital, and environmental management. Future research could extend the analysis using higher-frequency data, alternative measures of green growth, or richer nonlinear specifications to test whether the identified threshold effects remain stable over time.

REFERENCES

1. Añón Higón, D., Gholami, R., & Shirazi, F. (2017). ICT and environmental sustainability: A global perspective. *Telematics and Informatics*, 34(4), 85–95. <http://doi.org/10.1016/j.tele.2017.01.001>
2. Asongu, S. A. (2018). ICT, openness and CO2 emissions in Africa. *Environmental Science and Pollution Research*, 25(10), 9351–9359. <http://doi.org/10.1007/s11356-018-1239-4>
3. Asongu, S. A., Le Roux, S., & Biekpe, N. (2018). Enhancing ICT for environmental sustainability in sub-Saharan Africa. *Technological Forecasting and Social Change*, 127, 209–216. <http://doi.org/10.1016/j.techfore.2017.09.022>
4. Bayraktar Sağlam, B. (2018). ICT diffusion, R&D intensity, and economic growth: A dynamic panel data approach. *Journal of the Knowledge Economy*, 9(2), 636–648. <http://doi.org/10.1007/s13132-016-0353-0>
5. Chen, R., Ramzan, M., Hafeez, M., & Ullah, S. (2023). Green innovation-green growth nexus in BRICS: Does financial globalization matter? *Journal of Innovation & Knowledge*, 8(1), 100286. <http://doi.org/10.1016/j.jik.2022.100286>
6. Chen, X., Gong, X., Li, D., & Zhang, J. (2019). Can information and communication technology reduce CO2 emission? A quantile regression analysis. *Environmental Science and Pollution Research*, 26(32), 32977–32992. <http://doi.org/10.1007/s11356-019-06380-8>
7. Edquist, H., & Henrekson, M. (2017). Swedish lessons: How important are ICT and R&D to economic growth? *Structural Change and Economic Dynamics*, 42, 1–12. <http://doi.org/10.1016/j.strueco.2017.05.004>
8. Escribano, Á., & Jordá, Ó. (1999). Improved testing and specification of smooth transition regression models. In P. Rothman (Ed.), *Nonlinear Time Series Analysis of Economic and Financial Data* (pp. 289–319). Springer. http://doi.org/10.1007/978-1-4615-5129-4_14
9. Evangelista, P., & Hallikas, J. (2022). Exploring the influence of ICT on sustainability in supply management: Evidence and directions for research. *Cleaner Logistics and Supply Chain*, 4, 100051. <http://doi.org/10.1016/j.clscn.2022.100051>
10. Fujii, H., & Managi, S. (2016). Economic development and multiple air pollutant emissions from the industrial sector. *Environmental Science and Pollution Research*, 23(3), 2802–2812. <http://doi.org/10.1007/s11356-015-5523-2>
11. Inklaar, R., O'Mahony, M., & Timmer, M. P. (2005). ICT and Europe's productivity performance: Industry-level growth account comparisons with the United States. *Review of Income and Wealth*, 51(4), 505–536. <http://doi.org/10.1111/j.1475-4991.2005.00166.x>
12. Jalava, J., & Pohjola, M. (2008). The roles of electricity and ICT in economic growth: Case Finland. *Explorations in Economic History*, 45(3), 270–287. <http://doi.org/10.1016/j.eeh.2007.11.001>

13. Jorgenson, D. W., & Stiroh, K. J. (2000). Raising the speed limit: U.S. economic growth in the information age. *Brookings Papers on Economic Activity*, 2000(1), 125–210. <http://doi.org/10.1353/eca.2000.0008>
14. Jouvét, P., & Perthuis, C. (2013). Green growth: From intention to implementation. *International Economics*, 134, 29–55. <http://doi.org/10.1016/j.inteco.2013.05.003>
15. Kunanuntakij, K., Varabuntoonvit, V., Vorayos, N., Panjapornpon, C., & Mungcharoen, T. (2017). Thailand green GDP assessment based on environmentally extended input-output model. *Journal of Cleaner Production*, 167, 970–977. <http://doi.org/10.1016/j.jclepro.2017.02.106>
16. Lee, J. W., & Brahmasrene, T. (2014). ICT, CO₂ emissions and economic growth: Evidence from a panel of ASEAN. *Global Economic Review*, 43(2), 93–109. <http://doi.org/10.1080/1226508X.2014.917803>
17. Levine, R. (1997). Financial development and economic growth: Views and agenda. *Journal of Economic Literature*, 35(2), 688–726.
18. Li, D., & Zhao, Y. (2021). Does internet promote green growth? An empirical test from China. *Polish Journal of Environmental Studies*, 30(6), 5089–5103. <http://doi.org/10.15244/pjoes/134089>
19. Li, G., & Fang, C. (2014). Global mapping and estimation of ecosystem services values and gross domestic product: A spatially explicit integration of national ‘green GDP’ accounting. *Ecological Indicators*, 46, 293–314. <http://doi.org/10.1016/j.ecolind.2014.05.020>
20. Li, J., Dong, X., & Dong, K. (2022). Is China’s green growth possible? The roles of green trade and green energy. *Economic Research-Ekonomska Istraživanja*, 35(1), 7084–7108. <http://doi.org/10.1080/1331677X.2022.2058978>
21. Li, X., Ozturk, I., Majeed, M. T., Hafeez, M., & Ullah, S. (2022). Considering the asymmetric effect of financial deepening on environmental quality in BRICS economies: Policy options for the green economy. *Journal of Cleaner Production*, 331, 129909. <http://doi.org/10.1016/j.jclepro.2021.129909>
22. Lin, B. Q., & Zhou, Y. C. (2022). Measuring the green economic growth in China: Influencing factors and policy perspectives. *Energy*, 241, 122518. <http://doi.org/10.1016/j.energy.2021.122518>
23. Lin, E. Y. Y., Chen, P. Y., & Chen, C. C. (2013). Measuring green productivity of country: A generalized metafrontier Malmquist productivity index approach. *Energy*, 55, 340–353. <http://doi.org/10.1016/j.energy.2013.03.055>
24. Ma, D., & Zhu, Q. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *Journal of Business Research*, 145, 801–813. <http://doi.org/10.1016/j.jbusres.2022.03.041>
25. Mahyideen, J., Ismail, N. W., & Law, S. H. (2012). A pooled mean group estimation on ICT infrastructure and economic growth in ASEAN-5 countries. *International Journal of Economics and Management*, 6(2), 360–378.

26. Majeed, M. T., & Malik, A. (2016). E-government, financial development and economic growth. *Pakistan Journal of Applied Economics*, 26(2), 107–128.
27. O'Mahony, M., & Vecchi, M. (2005). Quantifying the impact of ICT capital on output growth: A heterogeneous dynamic panel approach. *Economica*, 72(288), 615–633. <http://doi.org/10.1111/j.1468-0335.2005.0435.x>
28. Oláh, J., Aburumman, N., Popp, J., Khan, M. A., Haddad, H., & Kitukutha, N. (2020). Impact of Industry 4.0 on environmental sustainability. *Sustainability*, 12(11), 4674. <http://doi.org/10.3390/su12114674>
29. Oliner, S. D., & Sichel, D. E. (2000). The resurgence of growth in the late 1990s: Is information technology the story? *Journal of Economic Perspectives*, 14(4), 3–22. <http://doi.org/10.1257/jep.14.4.3>
30. Ouyang, X., Wei, X., Sun, C., & Du, G. (2018). Impact of factor price distortions on energy efficiency: Evidence from provincial-level panel data in China. *Energy Policy*, 118, 573–583. <http://doi.org/10.1016/j.enpol.2018.04.022>
31. Reilly, J. M. (2012). Green growth and the efficient use of natural resources. *Energy Economics*, 34(S1), S85–S93. <http://doi.org/10.1016/j.eneco.2012.08.033>
32. Saidi, K., & Chebli, M. (2018). The effect of education, R&D and ICT on economic growth in high income countries. *Economics Bulletin*, 38(2), 810–825.
33. Shkvarya, L. V., & Hailing, Y. (2021). Digital economy in China: Modern trends. In *Modern Global Economic System: Evolutional Development vs. Revolutionary Leap* (pp. 1209–1216). Springer. http://doi.org/10.1007/978-3-030-69415-9_131
34. Stiroh, K. J. (2002). Are ICT spillovers driving the New Economy? *Review of Income and Wealth*, 48(1), 33–57. <http://doi.org/10.1111/1475-4991.00039>
35. Sulisworo, D., Tawar, & Ahdiani, U. (2012). ICT based information flows and supply chain in integrating academic business process. *International Journal on Advanced Science, Engineering and Information Technology*, 2(6), 454–458. <http://doi.org/10.18517/ijaseit.2.6.243>
36. Tang, Y., Chen, W., Chen, S., & Sohail, M. T. (2023). Examining the potential role of ICT diffusion on green growth: Does financial development matter in BRICS economies? *Environmental Science and Pollution Research*, 30(13), 38582–38591. <http://doi.org/10.1007/s11356-022-24894-6>
37. Teräsvirta, T. (1994). Specification, estimation, and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association*, 89(425), 208–218. <http://doi.org/10.1080/01621459.1994.10476462>
38. Tong, Y., Zhou, H., & Jiang, L. (2021). Exploring the transition effects of foreign direct investment on the eco-efficiency of Chinese cities: Based on multi-source data and panel smooth transition regression models. *Ecological Indicators*, 121, 107073. <http://doi.org/10.1016/j.ecolind.2020.107073>
39. Tzeremes, P., Dogan, E., & Alavijeh, N. K. (2023). Analyzing the nexus between energy transition, environment and ICT: A step towards COP26 targets. *Journal of Environmental Management*, 326, 116598. <http://doi.org/10.1016/j.jenvman.2022.116598>
40. Ullah, A., Zhang, Q., Raza, S. A., & Ali, S. (2021). Renewable energy: Is it a global challenge or opportunity? Focusing on different income level countries through Panel

- Smooth Transition Regression Model. *Renewable Energy*, 177, 689–699. <http://doi.org/10.1016/j.renene.2021.05.132>
41. Usman, M., Balsalobre-Lorente, D., Jahanger, A., & Ahmad, P. (2023). Are Mercosur economies going green or going away? An empirical investigation of the association between technological innovations, energy use, natural resources and GHG emissions. *Gondwana Research*, 113, 53–70. <http://doi.org/10.1016/j.gr.2022.10.018>
 42. van Dijk, D., Teräsvirta, T., & Franses, P. H. (2002). Smooth transition autoregressive models—A survey of recent developments. *Econometric Reviews*, 21(1), 1–47. <http://doi.org/10.1081/ETC-120008723>
 43. Wu, H. T., Hao, Y., & Ren, S. Y. (2020). How do environmental regulation and environmental decentralization affect green total factor energy efficiency: Evidence from China. *Energy Economics*, 91, 104880. <http://doi.org/10.1016/j.eneco.2020.104880>
 44. Xie, H. L., Chen, Q. R., Wang, W., & He, Y. F. (2018). Analyzing the green efficiency of arable land use in China. *Technological Forecasting and Social Change*, 133, 15–28. <http://doi.org/10.1016/j.techfore.2018.03.015>
 45. Xu, X., Huang, S., An, H., Vigne, S., & Lucey, B. (2021). The influence pathways of financial development on environmental quality: New evidence from smooth transition regression models. *Renewable and Sustainable Energy Reviews*, 151, 111576. <http://doi.org/10.1016/j.rser.2021.111576>
 46. Zhang, C., & Liu, C. (2015). The impact of ICT industry on CO2 emissions: A regional analysis in China. *Renewable and Sustainable Energy Reviews*, 44, 12–19. <http://doi.org/10.1016/j.rser.2014.12.011>
 47. Zhang, K., Shao, S., & Fan, S. (2020). Market integration and environmental quality: Evidence from the Yangtze River Delta region of China. *Journal of Environmental Management*, 261, 110208. <http://doi.org/10.1016/j.jenvman.2020.110208>

Contact information

Tingting Sun (Corresponding author)

School of Economics and Trade,
Shandong Management University
Jinan, Shandong 250357, China
E-mail: 3050871942@qq.com
ORCID: 0000-0002-2267-6701

APPENDIX

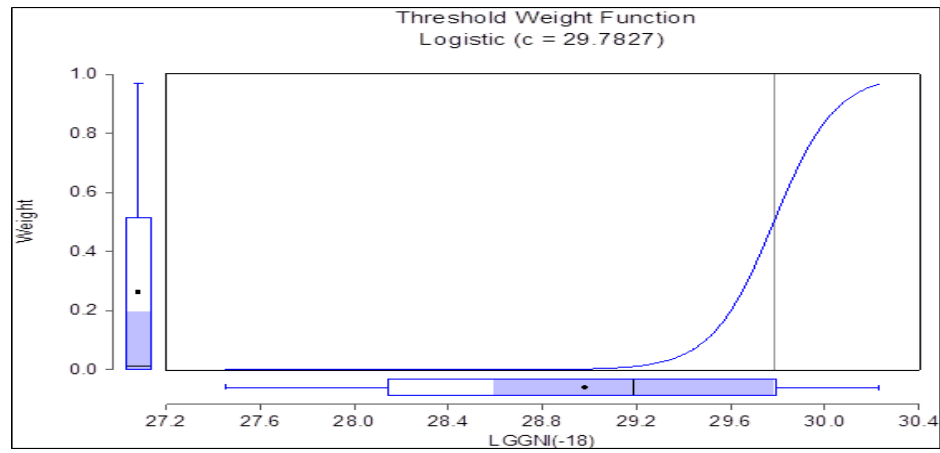


Fig. A1 – Threshold weight function for LGGNI(-18). Source: own research

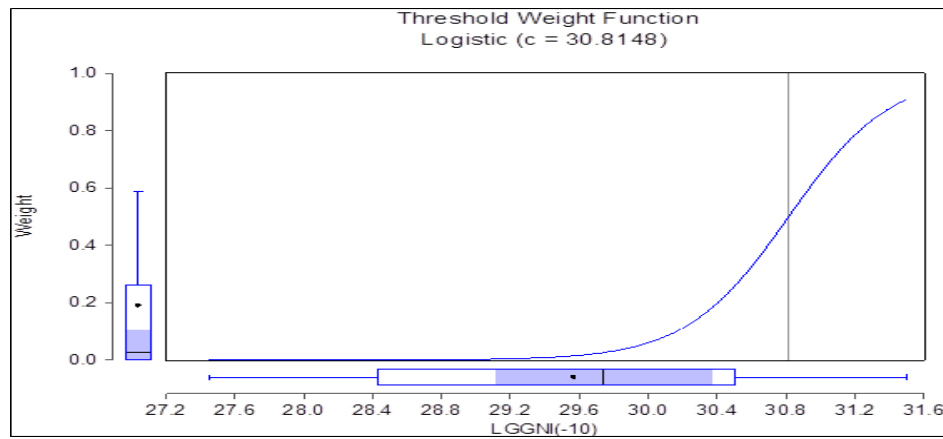


Fig. A2 – Threshold weight function for LGGNI(-10). Source: own research

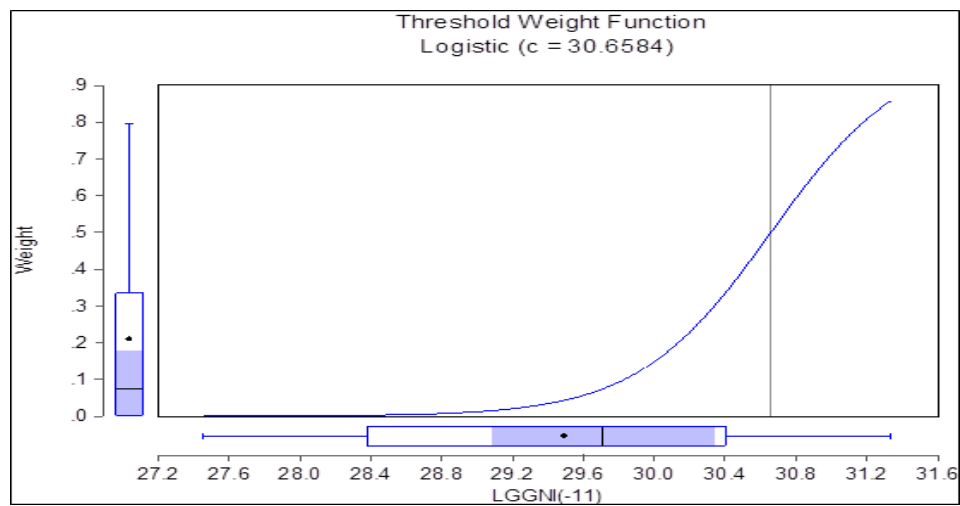


Fig. A3 – Threshold weight function for LGGNI(-11). Source: own research