ISSN: 2029-4913 / eISSN: 2029-4921

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

2026
Volume 32
Issue 2
Pages 662–697
https://doi.org/10.3846/tede.2026.25671

A STUDY ON THE IMPACT OF GLOBAL DIGITAL ECONOMY DEVELOPMENT ON CHINA'S EXPORT TRADE

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Article History:
- received 25 November 2024
- accepted 02 December 2025

Abstract. The rapid development of the global Digital Economy (DE) is profoundly affecting international trade and has emerged as a crucial engine sustaining the steady expansion of China's export trade (CE). Drawing on panel data covering 146 countries from 2003 to 2023, this study investigates in depth how the development of the global DE influences CE by integrating the level of DE development into an extended gravity model framework, and further examines the threshold effect arising from the DE gap between importing countries and China in this process. The study finds that the development of the global DE has significantly increased CE. The results of heterogeneity analysis indicate that this promoting effect is heterogeneous across countries with different levels of economic development and internet regulation, as well as across different industries. Mechanism analysis shows that this impact is mainly achieved through two channels: reducing trade costs and increasing production capacity. Finally, the empirical results reveal that when the DE gap between China and importing countries is introduced as a threshold variable, the influence of DE development in the importing country on China's exports exhibits a single-threshold effect. Once the DE gap surpasses this critical point, the positive effect diminishes.

Keywords: digital economy, gravity model, export trade, digital economy gap, threshold effect.

JEL Classification: F14, F41, O32, O35.

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1. Introduction

Foreign trade is a crucial driving force for national economic growth, and its importance to any country is self-evident. Since its accession to the WTO in 2001, China has witnessed remarkable expansion in its export trade. In 2023, CE reached 3.38 trillion US dollars. China has established trade partnerships with over 200 countries worldwide. However, in recent decades, while CE has experienced rapid development, it has also faced numerous challenges. Affected by factors such as the global pandemic, the Russia-Ukraine conflict, the Middle East disputes, foreign inflation, and the tense international political situation, foreign demand has shown a weak contraction. Given the complex international environment, it is crucial to find new sources of momentum for China's export growth.

Currently, with the global wave of digital technological innovation, products and services emerging from AI, big data, cloud computing, and blockchain have become deeply integrated into various facets of life, greatly facilitating and enriching our daily lives. As the primary scenario for the application and development of digital technology, the DE refers to a series of economic activities that use digital knowledge and information as production factors, modern information networks as the main carrier, and information and communication technology as the key driving force for improving efficiency and optimizing the economic structure (Liu et al., 2024c). As reported in the White Paper on the Global Digital Economy (2023), the total DE of the five countries – the United States, China, Germany, Japan, and South Korea – amounted to 31 trillion US dollars in 2022, representing 58% of their combined GDP (China Academy of Information and Communications Technology, 2023). Countries are competing to develop their digital economies and capture a share of the international DE market. The DE is increasingly playing a pivotal role in the reallocation of global resources, the transformation of the world's economic structure, and the evolution of the global competitive landscape. Of particular importance is the rise of the DE, which is profoundly reshaping traditional trade models. Through digital platforms, it directly connects producers and consumers, thereby reducing information search and matching costs. At the same time, it optimizes cross-border logistics and payment processes, effectively lowering trade barriers and fostering trade among countries.

Although the importance of the DE as a new driver of foreign trade has been widely recognized, the majority of previous research has centered on exporting countries' perspectives, generally neglecting the critical role of DE in importing countries. In particular, for major exporting countries such as China, there is still limited empirical evidence on how the DE in importing countries affects export performance. This research gap constrains a comprehensive demand-side understanding of the driving mechanisms behind CE. Therefore, clarifying this effect not only deepens the theoretical comprehension of the relationship between the DE and international trade but also provides essential practical guidance for China in stabilizing and expanding its export markets within a complex global environment. It further enables policymakers to design more targeted trade policies and better adapt to the new digital-driven international trade landscape. To bridge this critical gap, the study offers notable contributions, which can be summarized in the following key points: First, concerning perspective, we innovatively focus on the level of DE development in importing countries and empirically examine its independent impact on CE. Second, concerning content, this study not only investigates the impact mechanisms through the dual channels of reducing trade costs and increasing production capacity, but also conducts multi-level heterogeneity analyses, uncovering variations in impact and rendering the findings more policy-relevant. Third, concerning dimension, this study pioneers the introduction and empirical examination of the potential nonlinear threshold effect of the DE gap between importing countries and China, offering theoretical insights into how the digital divide shapes international trade.

Building on the preceding analysis, this study adopts it as a foundation and selects 146 countries worldwide from 2003 to 2023 as the empirical sample. Employing both theoretical analysis and rigorous empirical methodologies grounded in an extended gravity model, the study examines the influence of global DE development on CE. The subsequent sections of the paper are structured as follows: Section 2 presents a systematic review of the relevant literature. Section 3 clarifies the theoretical framework and proposes the research hypotheses. Section 4 introduces the model specification, defines the variables, and details the process of sample selection and data acquisition, offering a comprehensive explanation of the research design. Section 5 analyzes the spatiotemporal evolution of the global DE development level and CE volume, and reports our empirical research results. Section 6 discusses the research findings in detail, summarizes the key conclusions, proposes corresponding policy implications, and identifies the main limitations of the study while suggesting directions for future inquiry.

2. Literature review

So far, numerous studies have examined the factors influencing CE, producing a range of important insights. The existing literature can be broadly classified into three categories. The first category focuses on the structural factors of trade as an entry point to examine their impact on CE. For example, Liu et al. (2024a) empirically studied the impact of geopolitical risks on CE. Their results suggest that geopolitical risks encountered by China's trading partners substantially hinder the country's export performance. Similarly, Liu et al. (2021) investigated the impact of variations in trade facilitation among partner countries on China's agricultural exports. They found that improvements in trade facilitation in importing countries are closely linked to higher export volumes of Chinese agricultural goods. Furthermore, the second category of literature emphasizes the impact of economic policies on CE. For instance, Görg and Mao (2022) demonstrate the pivotal role of the Belt and Road Initiative in stimulating CE. Empirical evidence from Liu et al. (2022) underscores the substantial and positive effect of China's partner diplomacy policy on its exports. Similarly, Zhang et al. (2018) highlight the contribution of China's free trade zone policy in boosting the exports of Chinese enterprises.

The third category of literature directly relates to this research, focusing on how digitalization affects international trade. In recent years, this body of work has grown rapidly and generated substantial research findings. The recent proliferation of studies in this area can be primarily ascribed to the swift development of global digital technologies, especially the extensive deployment of new-generation digital information technologies, including 5G, WLAN, satellite networks, optical fibers, and submarine cables. These technologies have established robust channels for international communication, thereby strengthening economic and trade linkages among countries. Within this context, the DE, as a product of digital technological progress, has become increasingly integrated with the international trade system. The DE has propelled the shift of conventional trade models toward digital and platform-based formats, fostering the emergence of sectors such as cross-border e-commerce, digital services trade, and overseas warehousing. As a result, it has become a pivotal force in reshaping the structure and dynamics of the global trade system. The profound influence of digital technologies and the DE on international trade has garnered growing attention from the academic community. For example, Nham et al. (2023) empirically analyzed the effects of digital transformation on exports using data from 23 European countries, finding a positive linear relationship between digitalization and export volume. Rodriguez-Crespo et al. (2021) examined the influence of internet usage, mobile phone penetration, and broadband access on bilateral trade flows, revealing that each type of ICT is significantly and positively associated with bilateral exports. Similarly, Abeliansky and Hilbert (2017) assessed the differential effects of telecommunication quantity and quality of fixed and mobile telephony and internet services on countries' bilateral exports of goods. Their findings indicate that improvements in both dimensions of telecommunications substantially contribute to the expansion of exports. In addition, regarding the DE, the research results of Xiao and Abula (2024) highlighted the pivotal role of the DE in enhancing agricultural trade efficiency and demonstrated its significant positive impact on exports. Liu et al. (2024c) confirmed the positive effect of the agricultural DE in promoting China's agricultural products exports.

In summary, although numerous studies have explored CE and the implications of digitalization, the existing literature still exhibits several notable limitations. First, most of the literature focuses either on the digitalization process of exporting countries or on their general digital infrastructure, while relatively neglecting the independent impact of the DE development level in importing countries as a key external market condition on CE. This results in a lack of perspective in explaining the dynamics of cross-border trade in the digital era. Second, existing studies generally rely on linear assumptions and fail to fully account for the nonlinear characteristics of DE disparities. In particular, when the DE of importing countries reaches different stages of development or when there exists a significant digital divide with China, the marginal effects may undergo structural changes. However, the current literature shows a clear lack of exploration of such stage-specific differences. Third, previous studies have predominantly employed basic econometric approaches, such as traditional OLS and panel fixed-effects models. Although these methods satisfy the minimal requirements for causal identification, they are often ill-suited to the complex nature of trade data. For instance, trade flow datasets are frequently characterized by a high prevalence of zero values and substantial heteroskedasticity. Traditional approaches exhibit limited capacity to adequately address these challenges, thereby potentially undermining the accuracy and robustness of the resulting estimates.

Specifically, the unique academic contributions of this study relative to prior research can be summarized as follows: First, regarding perspective, this paper takes the DE development level of the importing country as the research perspective and innovatively uses empirical methods to examine the impact of its DE development level on CE, which provides a reference for the problem of weak exports currently faced by China and effectively supplements the deficiencies in the existing literature. Second, regarding content, this paper provides several important extensions to the existing literature. On the one hand, it conducts a heterogeneity analysis based on different levels of economic development and internet regulation, as well as across different industries, thereby uncovering the differential effects of DE in importing countries on CE. On the other hand, this paper enriches the internal impact mechanisms by examining two aspects: reducing trade costs and increasing production capacity. Third, in terms of the research dimension, previous studies have largely overlooked the DE gap between importing countries and China. This paper is the first to investigate the nonlinear effects of DE in importing countries on CE under different DE gaps. This analysis offers both theoretical insights and practical implications for bridging the digital divide and promoting balanced development within the global DE. Finally, in terms of research methods, most related studies still use traditional panel empirical methods such as pooled OLS, fixed effects models, and GMM. However, these methods do not perform as robustly as the PPML model in addressing models with relatively large heteroscedasticity and variable dispersion (Weidner & Zylkin, 2021; Martínez-Zarzoso, 2013; Guo et al., 2025). The use of the PPML model also constitutes a major methodological advantage of this study.

3. Theoretical analyses and research hypotheses

3.1. DE development in importing countries and CE

First, the expansion of the DE has fundamentally changed traditional trade operations by facilitating the growth and diffusion of e-commerce and online retail activities (Xiao & Abula, 2024). These emerging trade modalities not only make trade more convenient and efficient, but also generate expanded market access and competitive advantages for Chinese enterprises. By leveraging cross-border e-commerce platforms, Chinese firms can sell products directly to consumers in importing countries, thereby minimizing intermediary steps and significantly improving trade efficiency. Second, the DE has effectively overcome the temporal and spatial constraints traditionally associated with commodity transactions (Bartelsman et al., 2013). Traditional trade is often hindered by factors such as geographical distance and limited business hours, which significantly restrict the scope and efficiency of transactions. However, empowered by digital technologies, trade activities are no longer confined by time or location, allowing parties to engage in transactions seamlessly, at any time and from any place. This transformation has substantially reduced uncertainties in the trading process and mitigated transaction risks arising from time lags, policy fluctuations, and other external disruptions. Against this backdrop, the internationalization of enterprises has accelerated, with an increasing volume of goods and services transcending local boundaries to be traded across borders and delivered remotely (Li et al., 2023). Finally, the development of the DE has fostered the digitalization and intelligent transformation of global supply chains. By leveraging technologies including the IoT, big data, and AI, firms in importing countries can monitor goods transportation and inventory in real-time, optimize supply chain operations, and enhance logistics efficiency. This helps Chinese products reach consumer markets in importing countries more rapidly and accurately, thereby improving consumer convenience and strengthening bilateral trade (Cui & Yang, 2025). In light of the preceding analysis, we propose Hypothesis 1:

H1: *The development of the DE in importing countries significantly promotes CE.*

3.2. Mechanisms for the impact of DE development in importing countries on CE

This paper further explores the impact mechanism of DE in importing countries on CE, and mainly examines it from the two aspects of reducing trade costs and increasing production capacity.

Regarding trade costs, following the new-new trade theory, enterprises make export participation decisions based on productivity disparities, with more productive enterprises being better equipped to engage in export trade (Zhang et al., 2023). The development of the DE in importing countries can lower the "threshold" for Chinese enterprises to enter the international market, making it possible for Chinese enterprises with low productivity and weak financial strength, especially Small and Medium-Sized Enterprises (SMEs), to engage in exports, and more and more SMEs are beginning to enter the international market (Nham et al., 2023; Melitz, 2003). First, the DE significantly reduces information search costs. In the past, the flow of information between countries and industries faced numerous barriers, requiring firms to devote considerable human, material, and time resources to obtain essential cross-border information. Today, the convenient channels built by digital technology allow information to be transmitted quickly and accurately (Zhou et al., 2022). With the advancement of the DE, the presence of robust internet infrastructure, widely used social media platforms, and dynamic e-commerce systems in importing countries has significantly enhanced the ability of Chinese firms to access and analyze consumer-related information. By leveraging data from social media activities, search engine queries, and online purchasing behaviors, Chinese firms can efficiently identify consumer preferences, purchasing habits, and market trends at lower costs, thereby adjusting production and export decisions based on this information and promoting export growth. Simultaneously, consumers are able to publish demand information online, enabling a two-way flow of information. This connectivity reduces information search costs, mitigates information asymmetry, and accelerates the efficiency of export supply matching (Yaprak et al., 2018). Second, the DE has markedly lowered the communication costs involved in conducting international trade. the DE has also reduced the communication costs associated with trade. Under traditional trade practices, negotiations often required multiple international flights between the two parties, and discussions regarding product details and contract terms typically necessitated face-to-face meetings, resulting in substantially high communication costs (Herman & Oliver, 2023). In contrast, the widespread adoption of digital applications and e-commerce platforms by firms and distributors in importing countries has simplified communication with Chinese exporters regarding product specifications and transaction procedures. This has significantly lowered cross-border communication costs and facilitated the digital signing and execution of trade contracts (Liu et al., 2024c). Finally, the DE also contributes to reducing exporters' compliance costs. Advances in digital technology have accelerated the development of information-based customs clearance platforms across countries. Chinese firms can now submit compliance documentation directly to importing countries via these digital platforms or automatically execute contract terms using smart contracts. These advances minimize the risk of human error and contractual disputes, streamline the customs clearance process, enhance processing efficiency, and shorten waiting times. As a result, compliance costs are lowered, encouraging greater participation in export activities by a broader range of firms (Liu et al., 2024b). Therefore, improvements in the DE of importing countries can substantially reduce various trade-related costs that are otherwise difficult to overlook in bilateral trade (Tang et al., 2025). As trade costs decline, Chinese exporters are able to scale up their export activities, while previously non-exporting domestic firms gain access to international markets (He et al., 2020). This, in turn, facilitates the overall growth of CE. In light of the preceding analysis, we propose Hypothesis 2a:

H2a: *The development of DE in importing countries promotes CE by reducing trade costs.*

From the perspective of production capacity, it denotes a country's capability to generate goods and services and enable their sustainable growth and development (The United Nations). On the one hand, the rapid advancement of the DE has substantially enhanced this capacity. First, the DE treats digital knowledge and information as essential inputs in the production process, fundamentally transforming traditional production relations, enhancing coordination among production elements, reducing production costs, and integrating all stages of the "production-distribution-exchange-consumption" process to achieve interconnection and interoperability, thereby significantly increasing overall production capacity (Zhang et al., 2024). Specifically, digital technology can optimize production processes by minimizing errors and reducing delays (Porter & Heppelmann, 2014). For instance, firms can leverage big data and AI to digitally manage the entire production chain, enabling intelligent decision-making and the timely resolution of production-related issues. In addition, digital tools enable companies to establish transparent supply chains and monitor key operations such as logistics, warehousing, and distribution in a timely manner. Their application can substantially reduce logistics and production cycle costs, thereby enhancing overall production efficiency and capacity (Lan et al., 2025). Second, the DE inherently operates under the principle of "survival of the fittest". In the course of industrial upgrading, enterprises with low production capacity struggle to sustain development, thereby compelling them to pursue comprehensive improvements across production processes and enhance their capabilities to achieve long-term growth (Mao & Zhang, 2021). On the other hand, the increase in production capacity in the importing country can significantly stimulate its demand for imports from China. As domestic production expands, firms increasingly require raw materials, components, and other intermediate goods to support production. When domestic supply is insufficient, the resulting shortfall drives higher demand for these products from China. As the "world factory", China serves as a critical supplier of these goods (Yu & Luo, 2018). Second, within the global industrial chain, countries often occupy different stages of production. A country's production capacity may be concentrated in specific product categories, such as high-end components, while China holds comparative advantages in downstream assembly and supporting sectors (Chen & Wang, 2024; Gereffi et al., 2005). For example, if German automakers expand their production capacity, they may increase imports of Chinese-made automotive interiors, tires, and other complementary products. Finally, as domestic output and economic growth accelerate, consumers' income levels will also increase, which may lead to an increase in consumer demand for imported goods. Moreover, consumers may seek higher-quality, more diverse, or more distinctive imported products to satisfy their needs (Hottman et al., 2016), and China's diversified product production system provides the possibility to meet their consumption needs (Zhan et al., 2025; Liu et al., 2023). In light of the preceding analysis, we propose Hypothesis 2b:

H2b: *The development of DE in importing countries promotes CE by increasing production capacity.*

3.3. Threshold effect of DE gap

Since the rise of information technology, the digital divide has remained a persistent issue. With the accelerated development of the DE, its impact on everyday life has grown increasingly significant, becoming a central concern for organizations, policymakers, and scholars across diverse fields (Lythreatis et al., 2022). The digital divide reflects the inequality in digital use, encompassing multiple dimensions such as access to ICT infrastructure and users' ability to leverage digital technologies to obtain essential goods, information, or services necessary for effective societal participation (Liao et al., 2022). In the context of cross-border trade, this inequality is most prominently reflected in information barriers and asymmetries in the integration capacity of digital business networks, which have become an important problem that must be addressed to achieve trade globalization.

Specifically, a small gap in DE development level between two countries effectively reduces information barriers, indicating the establishment of a relatively smooth channel for communication and data exchange. This facilitates more efficient information collection and processing, helps bridge the gap between consumers and producers, mitigates information asymmetry, and promotes mutual matching between buyers and sellers (Chai &Wang, 2024). During the online search and matching process, consumers can rapidly and efficiently identify potential trading partners via the Internet, thereby broadening the range of available options and increasing the likelihood of successful transactions (Liu et al., 2024b). In addition, a deeper manifestation of the digital divide lies in the pronounced asymmetry among countries in their ability to integrate into the global digital business network. This asymmetry arises from systemic differences in infrastructure, technological adoption, digital literacy, and institutional environment. For example, some scholars argue that the digital divide constrains the development of business applications based on standardized platforms, limits connectivity between countries, and becomes an important obstacle to participating in global trade (Mignamissi & Bio, 2025; Freund & Weinhold, 2002; Nath & Liu, 2017). When the levels of DE development between two countries are similar, asymmetries are significantly reduced. Firms on both sides can connect more efficiently through compatible digital platforms, substantially lowering transaction frictions and thereby enhancing the DE's role in promoting bilateral trade.

On the contrary, the huge gap in DE development level between two countries creates substantial information barriers, impedes the smooth flow of information, increases information costs, limits opportunities for enterprises to access new markets, and ultimately hinders international trade. Market information such as consumer preferences and product market prices in the destination market is essential for exporting countries. A huge gap in DE development level between two countries increases the cost of accessing such critical information (Chai & Wang, 2024), thereby weakening the effectiveness of the DE in facilitating bilateral trade. In addition, a huge gap in DE development level between two countries often reflects significant asymmetries in their capacity to integrate into digital business networks, making it difficult for the two sides to efficiently exchange market information such as consumer preferences, price data, and logistics tracking through digital platforms, leading to higher transaction costs and lower matching efficiency, which ultimately weakens the DE's role in facilitating exports.

Therefore, the role of DE in importing countries in promoting CE may be affected by the DE gap between the two countries and have nonlinear characteristics. When this gap widens beyond a certain threshold, a pronounced digital divide can emerge, thereby weakening the export-promoting effect of the DE. At the same time, the linear assumption of the traditional gravity model is insufficient to capture this complex relationship. The threshold model proposed by Hansen (1999) provides a methodological basis for identifying nonlinear effects of an explanatory variable on the explained variable across different ranges of a threshold variable. By employing this model, threshold values can be estimated endogenously, enabling the examination of whether the impact of DE in importing countries on CE changes on either side of the threshold. Building on the analysis presented above, this paper proposes Hypothesis 3:

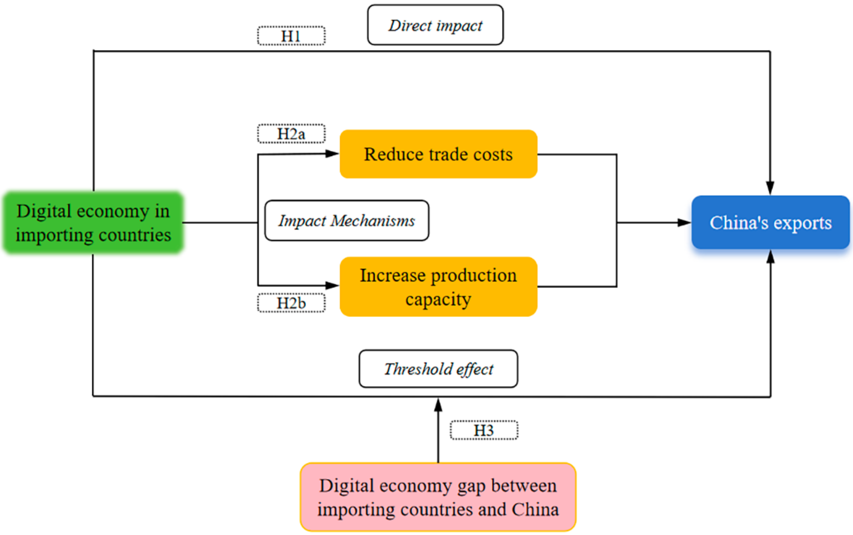


Figure 1. Research framework diagram

H3: *The DE gap shows a threshold effect in the impact of DE development in importing countries on CE. When the DE gap between the two countries exceeds a certain threshold, the promoting effect weakens.*

The research idea framework is illustrated in Figure 1.

4. Research design

4.1. Econometric model

The gravity model is a widely used research method in international trade research. This paper integrates the level of DE development in importing countries into the gravity model framework to examine its impact on CE. Santos Silva and Tenreyro (2006) demonstrated that traditional OLS estimation is biased in the presence of the common heteroskedasticity found in trade flow data. They also provided robust evidence supporting the effectiveness of the PPML estimator in addressing this problem. In addition, the PPML estimator is capable of handling zero trade flows effectively, thereby addressing key limitations of traditional methods and enhancing estimation robustness. Accordingly, this paper adopts the PPML method, and the formula is as follows:

$$EX_{it} = \exp\{\alpha_0 + \alpha_1 LNDIG_{it} + \alpha_2 CONTROL_{it} + \eta_i + \lambda_t\} + \varepsilon_{it}. \tag{1}$$

In the model, i denotes the importing country, t denotes the year, and EX_{it} represents CE to each importing country. exp{ } denotes the exponential function, DIG_{it} represents the level of DE development in the importing country,η_i and λ_t represent country and year fixed effects, respectively, and ε_{it} denotes the random error term. Furthermore, a set of control variables is incorporated into the model.

4.2. Variables selection

4.2.1. Explained variable (EX)

The explained variable is China's export value to each importing country.

4.2.2. Core explanatory variable (DIG)

The core explanatory variable is the level of DE development in the importing country, which is logarithmically transformed in the empirical study. At present, there is no standardized indicator system or practice for measuring the DE's development level. Therefore, this study draws on existing literature and adopts a DE-related indicator system at the national level (Pan et al., 2022; Wu et al., 2021; Wang et al., 2022). Following the approach of Shahbaz et al. (2022), the entropy method is employed to construct a comprehensive measure of the level of DE development in importing countries, covering four dimensions: digital infrastructure, digital trade, social impact, and social support. Among them, infrastructure includes the development of infrastructure related to the DE, such as fixed broadband, fixed telephone, and mobile cellular. Together, these form the foundation of the information society, providing essential channels for data transmission and information exchange, and serving as the cornerstone of DE activity. Digital trade refers to the import and export of ICT products. ICT trade's share directly reflects a country's standing within the global digital industry chain and can be used to assess the depth of its DE involvement in the global division of labor. Social impact primarily reflects changes in social life induced by the DE, such as the popularization of the Internet and electronic devices, online services and electronic participation. The penetration of the Internet and electronic devices reflects the extent of digital technology coverage among the population. A high proportion means that more people and more families can participate in digital activities. Online services are based on digital technology to transform traditional service models into digital services, becoming an important manifestation of the implementation of the DE. E-participation reflects the extent to which citizens engage in policymaking and social oversight through digital platforms, representing a positive impact of the DE on social governance. Social support primarily refers to the per capita value added of the service industry. Digital technologies are reshaping operating models within the service industry; thus, a higher per capita value added typically indicates greater national investment intensity in the DE and a deeper level of technological application. The specific indicator system of the DE is presented in Table 1.

4.2.2.1. Data standardization

Let v_{ij} denote the original value of the j-th indicator for the i-th evaluation object (I = 1, 2, 3,…, n; j = 1, 2, 3,…, m). To ensure comparability across indicators of different scales and to eliminate dimensional disparities, the raw data are standardized using the following Equation:

$$x_{ij} = \frac{v_{ij} - \min\left(v_j\right)}{\max\left(v_j\right) - \min\left(v_j\right)}, \tag{2}$$

where x_{ij} is a dimensionless value after standardization.

Table 1. The specific indicator system of the DE

Primary indexes	Secondary indexes	Units	Data sources
digital infrastructure	Fixed broadband subscriptions	per 100 people	ITU
	Fixed telephone subscriptions	per 100 people	ITU
	Mobile cellular subscriptions	per 100 people	ITU
Digital trade	ICT goods exports	% of total goods exports	World Bank
	ICT goods imports	% of total goods imports	World Bank
Social impact	Individuals using the Internet	%	ITU
	Households with a computer	%	ITU
	Households with Internet access	%	ITU
	Online Service Index	–	UN E-Government Survey
	E-Participation Index	–	UN E-Government Survey
Social support	Per capita value added of service industry	$US/person	World Bank

4.2.2.2. Calculate the entropy value and weight

Let y_{ij} denote the weight of the j-th indicator for the i-th evaluation object, e_j denote the entropy value of the j-th indicator, g_j denote the variation coefficient of the j-th indicator, w_j denote the weight of the j-th evaluation index (j = 1, 2, 3,..., m).

$$y_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}}; \tag{3}$$

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} y_{ij} \ln y_{ij}; \tag{4}$$

$$g_i = 1 - e_j; \tag{5}$$

$$w_j = \frac{g_j}{\sum_{i=1}^{m} g_j}. \tag{6}$$

4.2.2.3. Calculate the development level of the DE

$$DIG_{ij} = \sum_{j=1}^{m} w_j x_{ij}. \tag{7}$$

According to the above Equation, the level of DE development can be calculated by standardized data and entropy weight, where *dig* is the development level of the DE.

Notably, since the DE gap between importing countries and China will be employed as a threshold variable in the subsequent analysis, the DE development levels of 147 countries (including China) are measured in this study.

4.2.3. Mediating variables

This study adopts the methodology proposed by Novy (2013) to estimate trade costs. Trade costs are calculated as follows:

$$TC_{china,i} = 1 - \left\{ \frac{EXP_{china,i} EXP_{i,china}}{\left(GDP_{china} - EXP_{china}\right)\left(GDP_i - EXP_i\right) s^2} \right\}^{\frac{1}{2\rho - 2}}. \tag{8}$$

In the above Equation, $TC_{china,i}$ represents the trade costs between China and importing country i; $EXP_{china,i}$ and $EXP_{i,china}$ represent CE to importing country i and importing country i's exports to China, respectively; GDP_{china} and GDP_i represent the GDP of China and importing country i; EXP_{china} and EXP_i represent the total exports of China and importing country i; The parameter s is set to 0.8; ρ is the elasticity of substitution and takes the value 8. *TC* is logarithmically transformed in the empirical study.

Production capacity (PC_{it}) is measured using the Productive Capacities Index, with data sourced from the UNCTAD database. *PC* is logarithmically transformed in the empirical study.

4.2.4. Control variables

Based on related literature, this study introduces the following control variables:

(1) Distance-related costs between the importing country and China (D_{it}). Previous research indicates that distance-related costs have a notable adverse effect on exports (Cao & Hsu, 2025; Wang et al., 2021; Wilson et al., 2003). However, while many scholars have traditionally used geographical distance as a proxy for distance-related costs, existing studies have shown that distance is not a good proxy for distance-related costs (Martínez-Zarzoso & Nowak-Lehmann, 2007). In fact, distance-related costs are dynamic, implying that using static geographical distance as a proxy has inherent limitations. In order to resolve this issue, this study adjusts the geographical distance to better reflect the actual distance-related costs. First, in line with the methodology proposed by Wang et al. (2024b) and Guo et al. (2025), this paper provides a preliminary estimate of distance-related costs by multiplying bilateral geographical distance by the international crude oil price. Second, as demonstrated in existing studies, the quality of transportation infrastructure is an important factor influencing distance-related costs and bilateral trade (Limão & Venables, 2001). A well-developed transportation network can enhance efficiency, mitigate risks and uncertainties during transit, and thereby effectively reduce distance-related costs and promote bilateral trade. Therefore, this paper employs the Trade and Transport Infrastructure Quality Index, a component of the World Bank's Logistics Performance Index, which measures the quality of a country's trade and transport-related infrastructure, including ports, railways, and roads. Accordingly, the actual distance-related costs are then calculated as the ratio of the preliminarily estimated distance-related costs to this index, as specified in the following Equation:

$$D_{it} = \frac{dist_{it} * oilprice_t}{lpi_{it}}. \tag{9}$$

where D_{it} denotes the distance-related costs; i denotes the importing country; $dist_{it}$ denotes the distance between the most populous cities of the two countries, sourced from the CEPII database, $oilprice_t$ refers to the international crude oil price, calculated as the average of Dated Brent, West Texas Intermediate and Dubai Fateh crude oil prices, with data obtained from the International Monetary Fund; lpi_{it} denotes the quality index of trade and transport-related infrastructure, with corresponding data obtained from the World Bank. The estimated coefficient of D_{it} is expected to be negative.

(2) Population size of importing countries (POP_{it}). The population size of the importing country may influence CE through two primary channels (Guo et al., 2025). First, a larger population typically indicates a greater number of consumers and stronger demand for foreign goods, which can lead to an increase in CE to the country. Second, a large population is often associated with diverse consumer demands, which enables Chinese exporters to provide correspondingly diversified products to meet these needs, thereby contributing to an increase in exports. The estimated coefficient of POP_{it} is expected to be positive.

(3) Gross domestic product of importing countries (GDP_{it}). A higher GDP in an importing country indicates a larger economic scale and market size, which tends to drive greater demand for a wide range of goods. This expanded demand creates huge sales space for commodities in exporting countries, including China, thereby contributing to an increase in CE to that country. Wang and Zhu (2024) and Liu et al. (2024a) both used the GDP of the importing country as a control variable and demonstrated that it significantly promotes CE. The estimated coefficient of GDP_{it} is expected to be positive.

(4) Exchange rate of the Renminbi against the currency of the importing country (ER_{it}). Studies have demonstrated that the exchange rate is a critical factor influencing bilateral trade (Xing, 2018; Chen et al., 2023; Thorbecke, 2015). A higher exchange rate indicates an appreciation of the RMB, which raises the relative price of Chinese goods, reduces their international competitiveness, and dampens demand from consumers and enterprises in importing countries. Consequently, the importing countries will reduce imports from China. The estimated coefficient of ER_{it} is expected to be negative.

(5) Institutional distance between importing countries and China (ID_{it}). Existing studies have demonstrated that institutional distance negatively affects bilateral trade (Xing et al., 2023; Liu et al., 2020). First, the divergent institutions of the two countries will lead to the unfamiliarity of business processes and difficulty in building trust, thereby increasing search costs and adjustment costs (Liu et al., 2020; De Groot et al., 2004; De Mendonça et al., 2014). Second, institutions reflect the business and contractual environment. Significant institutional differences can undermine effective contract enforcement and transactional mechanisms, ultimately impeding trade flows (Liu et al., 2020). The estimated coefficient of ID_{it} is expected to be negative. Institutional distance is measured based on the Worldwide Governance Indicators (WGI) provided by the World Bank, which comprise six dimensions: voice and accountability, political stability and absence of violence, government effectiveness, control of corruption, regulatory quality, and rule of law. The calculation Equation is presented as follows (Heavilin & Songur, 2020):

$$ID_{it} = \frac{1}{6}\sum_{c=1}^{6}\left[\frac{\left(I_{cit} - I_{ct,china}\right)^2}{V_c}\right]. \tag{10}$$

where c denotes the six indicators of institutional distance, $I_{cit}–I_{ct,china}$ represents the difference between importing country i and China for institutional indicator c, and V_c is the variance of the -th indicator. The introduction of V_c addresses potential comparability issues across different indicators. The larger the *ID* value, the greater the institutional distance between the two countries and the worse the institutional consistency.

(6) Trade openness of importing countries (TO_{it}). Trade openness helps reduce tariffs and trade barriers. A higher degree of trade openness in a country facilitates the freer flow of goods and resources across borders, thereby expanding the scale of bilateral te ratio of total imports and exports of goods and services to GDP as a measure of trade openness. The estimated coefficient of TO_{it} is expected to be positive.

(7) Whether the importing country has a free trade agreement with China (FTA_{it}). The signing and implementation of free trade agreements facilitate the reduction of trade barriers, such as tariffs and non-tariff barriers, thereby enabling more seamless trade (Guo et al., 2025). Therefore, it is expected that the signing of a free trade agreement between an importing country and China will considerably raise CE to that country. Data on free trade agreements are sourced from the China Free Trade Zone Service Network.

(8) Whether the importing country is imposing anti-dumping on China (FC_{it}). Anti-dumping measures tend to exert a trade-destroying effect (Lin & Liu, 2025). Specifically, when importing countries impose anti-dumping on CE, they increase the export costs for Chinese enterprises, erode their price competitiveness, and consequently reduce export volumes (Cheng et al., 2021; Chandra, 2017). Therefore, the estimated coefficient of *FC* is expected to be negative. Data on anti-dumping measures are obtained from the China Trade Remedy Information Network.

(9) Whether the importing country shares a common official language with China (CL_{it}). First, when the importing country shares a common official language with China, translation time is minimized, substantially reducing communication costs in trade activities and thereby facilitating bilateral trade (Yang et al., 2017). Second, the common language often reflects shared cultural and historical ties, which help foster trust and make individuals more inclined to engage in trade with counterparts who speak the same language (Lohmann, 2011). Therefore, the estimated coefficient of *CL* is expected to be positive.

(10) Whether the importing country shares a common border with China (CT_{it}). Sharing a common border implies shorter transportation distances, greater logistical convenience, and reduced time and risk associated with transit, all of which are conducive to promoting bilateral trade (Wang & Zhu, 2024). Therefore, the estimated coefficient of *CT* is expected to be positive.

4.3. Data sources and descriptive statistics

With regard to the completeness and accessibility of the data, this paper selects 146 countries from 2003 to 2023 as research samples. China's export data are sourced from the UN Comtrade and the WITS database. Except for the special instructions above, all other data are obtained from the World Bank. Missing values are supplemented using interpolation. Descriptive statistics of the variables are shown in Table 2.

Table 2. Descriptive statistics of variables

Variable	N	Mean	SD	Min	Max
EXP	3066	1.130E+10	3.603E+10	0	5.830E+11
LNDIG	3066	–1.9700	1.0638	–5.8619	–0.3840
LND	3066	12.2625	0.7968	9.0569	16.2039
LNPOP	3066	16.2155	1.5851	11.9435	21.0866
LNGDP	3066	24.7961	2.0038	18.4413	30.9532
LNER	3066	1.1743	2.9454	–3.6976	16.2134
LNID	3066	1.2315	0.3359	–0.1179	1.7612
TO	3066	84.4764	51.4225	2.4737	437.3270
FTA	3066	0.1148	0.3188	0	1
FC	3066	0.3343	0.4718	0	1

Note: LN( ) denotes the natural logarithm of the variable.

5. Empirical results and discussion

5.1. Spatiotemporal analysis of global DE development level and CE

Before conducting the formal empirical analysis, this study selects four observation years at approximately equal intervals (2003, 2009, 2016, and 2023) and presents spatial distribution maps of the explained and core explanatory variables to analyze their development dynamics, as shown in Figures 2–3.

5.1.1. Spatiotemporal analysis of global DE development level

As shown in Figure 2, from a spatial perspective, regions with relatively high levels of DE development are primarily concentrated in Europe, North America, East Asia, and Oceania, which are predominantly developed countries. This is mainly because developed countries have deep technological foundations and strong innovation capacities in the field of information technology. These technologies have strongly supported the fast growth of the DE. Regions with underdeveloped digital economies are primarily situated in Africa and South Asia. This is mainly due to underdeveloped network infrastructure, low Internet penetration rates, and limited digital usage, all of which have significantly constrained the growth of the DE in these regions. Many African countries, in particular, remain on the periphery of global DE development. From a temporal perspective, the level of global DE development exhibits an upward trend, indicating that countries are accelerating their digital transformation and that the global DE is undergoing rapid development.

5.1.2. Spatiotemporal analysis of CE

As shown in Figure 3, from a spatial perspective, China's major export destinations are widely distributed across the Americas, Asia, Europe, and Oceania. These regions have a strong consumer market demand, providing broader market space for Chinese goods. However, many African countries are unable to effectively participate in the international market due to low levels of economic development, a single market demand structure, and inadequate trade facilitation, resulting in relatively low import value from China. In addition, from a temporal perspective, CE have exhibited an increasing trend. This paper argues that the development of the modern global DE is a key driver behind this growth.

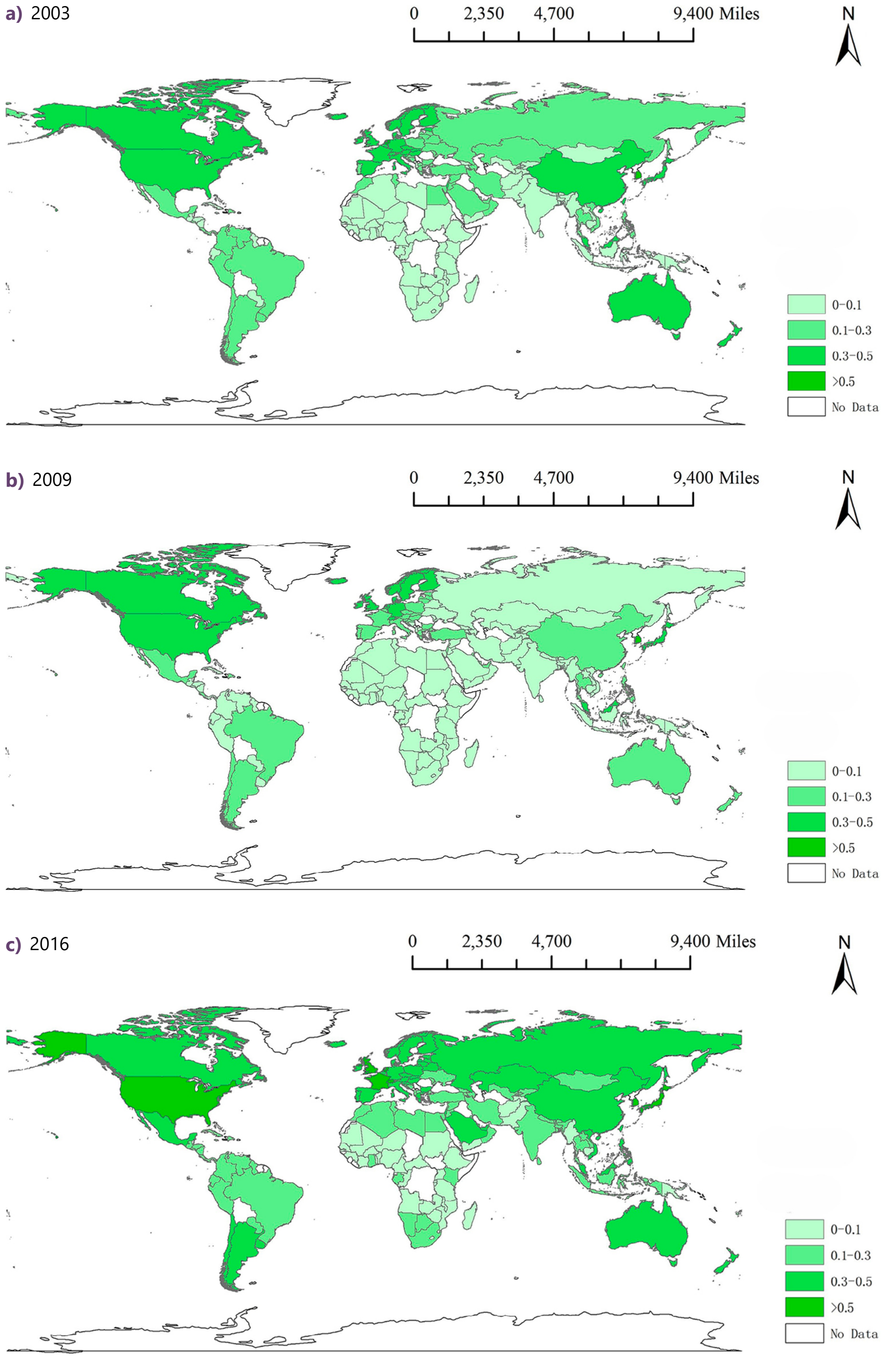


Figure 2. *Continued on next page*

d) 2023

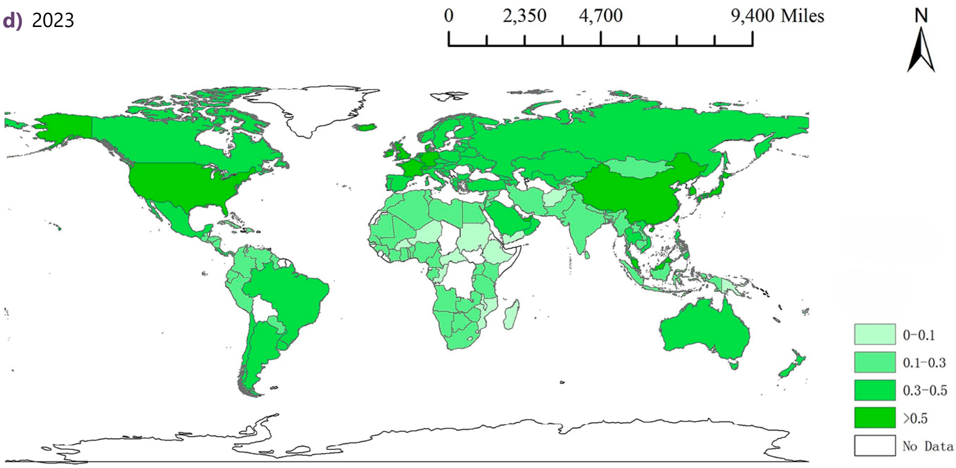
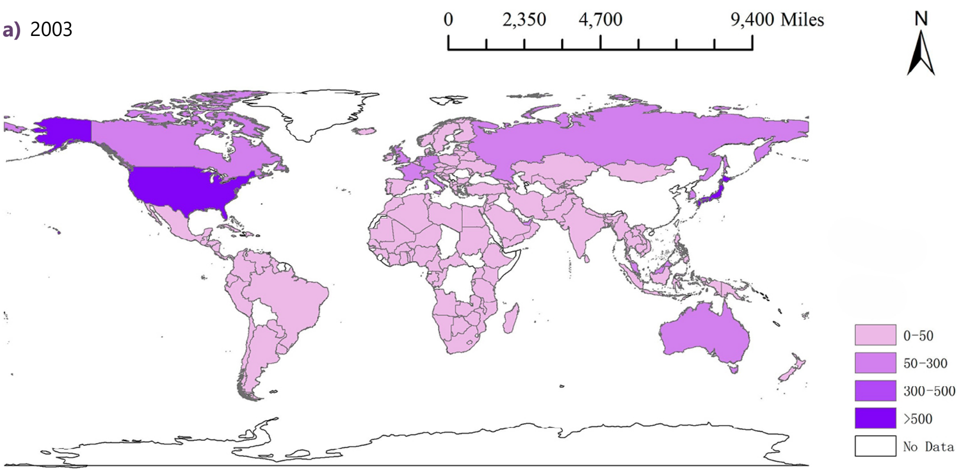


Figure 2. Spatiotemporal evolution of global DE development

a) 2003



b) 2009

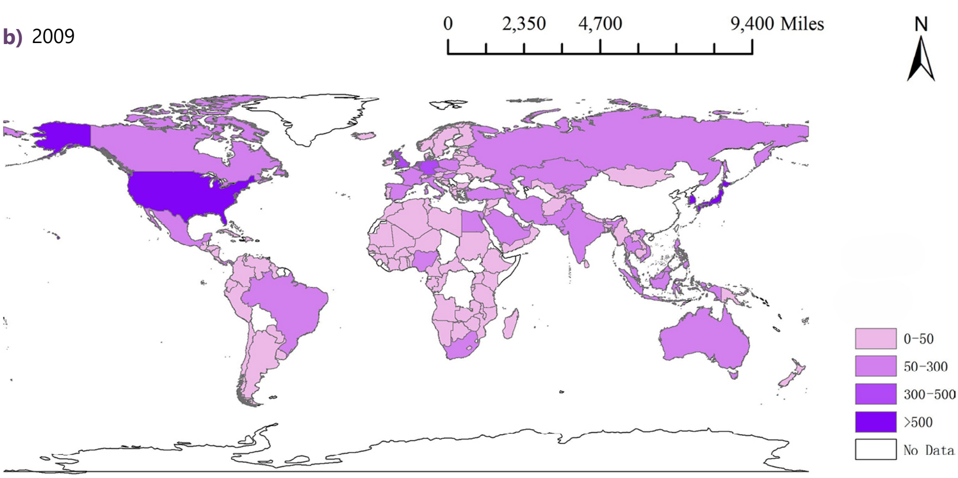


Figure 3. *Continued on next page*

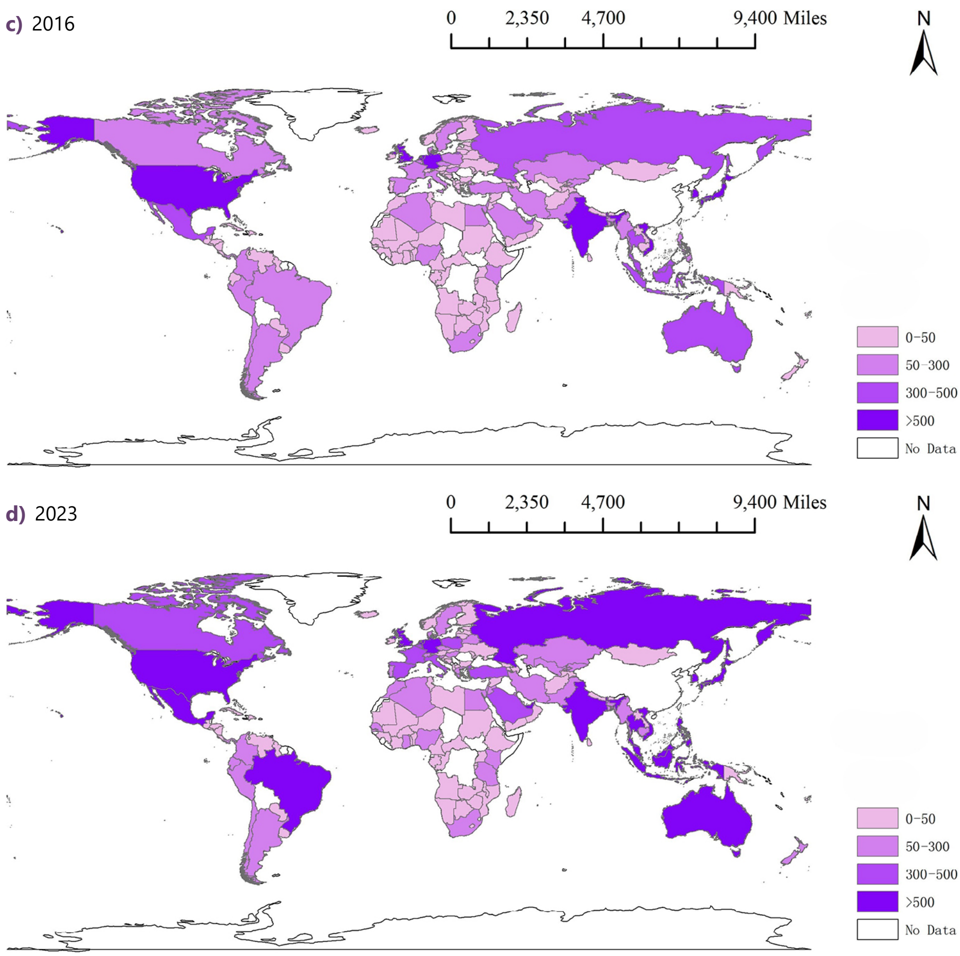


Figure 3. Spatiotemporal evolution of CE

5.2. Benchmark regression

Ensuring that the data are stationary is a crucial prerequisite for regression modeling, as non-stationary data may produce spurious regression outcomes, thereby undermining the validity of empirical analysis (Fan et al., 2022). Therefore, we conducted unit root tests, including the LLC and IPS tests. The results in Table 3 indicate that all variables reject the null hypothesis of a unit root, confirming that the panel data used in this study are stationary.

Second, considering the possible multicollinearity between the explanatory variables, this paper calculates the VIF for the main explanatory variables prior to the formal regression analysis, with the results shown in Table 4.

The VIF results in Table 4 show that all major explanatory variables are below the critical value of 10, indicating no multicollinearity among them.

Finally, the Hausman test is carried out to determine the suitable model specification. With a chi2(9) value of 98.84 and a p-value of 0.0000, the Hausman test rejects the null hypothesis of random effects, and thus a fixed effects model is employed.

Table 3. Unit root test results

Variable	LLC test	IPS test	Result
TEX	−18.7729***	−13.1771***	smooth
LNDIG	−19.7091***	−8.3544***	
LND	−14.0691***	−13.5349***	
LNPOP	−19.7267***	−10.2564***	
LNGDP	−15.2568***	−9.7843***	
LNER	−14.2356***	−10.5628***	
LNID	−7.8796***	−7.3020***	
TO	−7.2183***	−3.7770***	

Table 4. VIF of main explanatory variables

Variable	VIF
LNDIG	2.35
LND	1.36
LNPOP	3.23
LNGDP	4.40
LNER	1.62
LNID	1.03
TO	1.58
FTA	1.16
FC	1.76

In summary, this paper employs PPML estimator with two-way fixed effects to estimate equation (1). However, a major limitation of the fixed effects method is that time-invariant control variables are absorbed by the country-pair fixed effects, rendering their effects unidentifiable. Therefore, the random effects model is employed as a robustness test to control for the effects of time-invariant control variables such as language and border relations (Oum et al., 2024). Table 5 displays the fixed effects regression results for the benchmark model.

As shown in columns (1)–(2) of Table 5, the estimated coefficient of LNDIG remains significantly positive regardless of whether control variables are included. This indicates that the development of the DE in importing countries can promote CE, thereby verifying Hypothesis 1.

The regression results in column (2) indicate that the population size, GDP, trade openness, and bilateral free trade agreements of importing countries significantly promote CE, while distance-related costs, exchange rates, and institutional distance exert a negative impact. The estimation results align with the preceding analysis. In addition, anti-dumping measures do not have a significant effect on CE. A possible explanation is that Chinese firms may adopt strategies such as improving product quality and optimizing product structures, thereby enhancing competitiveness and maintaining stable demand for Chinese products in importing countries.

Table 5. Benchmark regression results

	(1)	(2)
LNDIG	0.5584***	0.2561***
	(0.0361)	(0.0308)
LND		–0.3291***
		(0.0847)
LNPOP		0.3018**
		(0.1420)
LNGDP		0.5805***
		(0.0387)
LNER		–0.0273**
		(0.0134)
LNID		–0.0056**
		(0.0027)
TO		0.0045***
		(0.0005)
FTA		0.2411***
		(0.0310)
FC		–0.0126
		(0.0291)
_cons	25.2464***	6.7448**
	(0.0362)	(3.1010)
Country FE	Yes	Yes
Year FE	Yes	Yes
N	3066	3066
R^2	0.9889	0.9924

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The robust standard errors are in parentheses. The same applies below.

5.3. Robustness tests

In addition, this paper adopts the following methods to conduct robustness tests, and the t results are shown in Table 6. First, the core explanatory variable is replaced. While the prior analysis assessed DE development using the entropy method, the current test utilizes principal component analysis. Second, data winsorization is applied. To reduce the potential bias caused by outliers, continuous variables are winsorized at the 1% level. Third, the core explanatory variables are lagged by one period. Given the potential lagged effect of DE development in importing countries on CE, this paper lags the core explanatory variables by one period. Fourth, time-invariant control variables are added to the model, and the random effects model is adopted for the estimation. Fifth, countries involved in the Belt and Road Initiative (BRI) are removed from the sample. Considering the BRI's substantial influence on CE, excluding these countries helps eliminate potential interference. Sixth, the estimation method is replaced. In the literature related to the gravity model, only a few papers have adopted new methods and empirical progress in trade economics. Many papers still use linear estimation methods, such as OLS. The model is re-estimated using the traditional OLS approach as an alternative estimation method. In addition, the Double Machine Learning (DML) method proposed by Chernozhukov et al. (2018) effectively addresses the limitations of traditional causal inference methods. Specifically, DML is particularly effective in addressing challenges associated with high-dimensional data, nonlinear relationships, and regularization bias. It mitigates the "curse of dimensionality" and multicollinearity issues, reduces model specification bias, and improves the robustness and precision of estimation outcomes (Shen et al., 2024). To enhance the reliability of the research findings, this study further employs the DML method for regression analysis, using a sample split ratio of 1:4 and the random forest algorithm for prediction and solution. The above robustness test results are shown sequentially in columns (1) to (7) of Table 6. The estimated coefficient of LNDIG remains statistically significant and positive across all seven columns of Table 6, further confirming the robustness of the research conclusions.

Table 6. Robustness test results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LNDIG	0.0995***	0.2498***	0.2195***	0.7609***	0.2373***	0.2881***	0.4018***
	(0.0199)	(0.0316)	(0.0293)	(0.0462)	(0.0409)	(0.0333)	(0.0415)
_cons	2.0255	–0.4233	6.4456**	–0.2409	–7.4918*	2.1298	–0.0102
	(3.0824)	(2.7753)	(3.2105)	(0.6959)	(4.0613)	(2.0307)	(0.0086)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	Yes
N	3066	3066	2920	3066	1890	3066	3066
R^2	0.9922	0.9877	0.9924	0.9271	0.9948	0.9687	–

5.4. Endogenous analysis

Endogeneity is a common problem in empirical analysis. First, while the study incorporates numerous control variables related to CE, some unobservable variables may still exist. These variables can affect CE and be correlated with the DE, thereby leading to the endogeneity problem. Second, a potential reverse causality may exist between the DE and CE. Specifically, countries with closer trade ties to China may be more inclined to develop the DE. Consequently, reverse causality may introduce endogeneity into the model. To address this issue, the 2SLS instrumental variable method is first employed.

Regarding the selection of instrumental variables, this study employs two instruments that are strongly associated with the level of DE development in importing countries. The first instrumental variable is the nighttime light brightness (LNLB) of the importing country, derived from NPP-VIIRS nighttime light remote sensing data. Prior research has demonstrated that DE development significantly increases the average brightness of nighttime light (Deng et al., 2022). The DE, as a component of the real economy, depends on supporting infrastructure such as digital equipment, human capital, and distribution centers (Kim, 2006). Such infrastructure is closely associated with nighttime light brightness that can be recorded in the NPP-VIIRS data. Moreover, the development of the DE promotes employment concentration and stimulates market activity, both of which contribute to increased nighttime light brightness (Chen et al., 2022). Nighttime light brightness satisfies the relevance condition for an instrumental variable. Moreover, since it does not directly affect trade volume, it meets the exogeneity requirement for a valid instrumental variable. The second instrumental variable is the tertiary school enrollment rate (LNTE). This variable reflects a country's level of education and is therefore associated with the country's potential for DE development and its capacity to adopt digital technologies, satisfying the relevance condition for an instrumental variable. Moreover, the tertiary school enrollment rate is unlikely to directly affect trade volume, thereby meeting the exogeneity requirement for a valid instrumental variable.

As shown in the first-stage regression results of the 2SLS in Table 7, both instrumental variables exhibit a significantly positive correlation with the level of DE development, consistent with the analysis above. Moreover, the p-values for the Kleibergen-Paap rk LM statistic reject the null hypothesis of under-identification at the 1% significance level, while the Kleibergen-Paap rk Wald F-statistic exceeds the Stock-Yogo critical value of 16.38 for weak instrumental variables at the 10% significance level. These results indicate that there is no weak instrumental variable problem, confirming the appropriateness of the selected instrumental variables. Finally, the second-stage regression results indicate that after addressing the endogeneity problem, the development of the DE in importing countries maintains a significant positive effect on CE.

In addition, this paper employs SYS-GMM and DIF-GMM estimation to address the potential endogeneity problem. Given that the lagged term of the explained variable satisfies the requirements of exogeneity and correlation, it is often used as an instrumental variable (Dong et al., 2024). Accordingly, the first-order lag of the explained variable is employed for re-estimation. The GMM estimation results are presented in Table 8.

Table 7. 2SLS regression results

	(IV-1: LNLB) First stage	(IV-1: LNLB) Second stage	(IV-2: LNTE) First stage	(IV-2: LNTE) Second stage
	(1)	(2)	(3)	(4)
LNDIG		1.3323***		1.5019***
		(0.1790)		(0.2900)
LNLB	0.1207***			
	(0.0175)			
LNTE			0.1959***	
			(0.0301)	
Kleibergen-Paap rk LM statistic		123.771***		61.014***
Kleibergen-Paap rk Wald F statistic		47.525{16.38}		42.235{16.38}
Control variables	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3066	3066	3066	3066

Table 8. GMM estimation results

	(1)	(2)
	SYS-GMM	DIF-GMM
LNDIG	0.3219**	0.3678***
	(0.1401)	(0.1388)
first-order lagged term	0.6033***	0.5282***
	(0.1743)	(0.1581)
AR (1)	0.002	0.003
AR (2)	0.784	0.942
Hansen test	0.688	0.217
Control variables	YES	YES
Country FE	YES	YES
Year FE	YES	YES
N	2920	2774

The GMM estimation results suggest the presence of first-order autocorrelation and the absence of second-order autocorrelation in the random error term, as the p-values for AR (1) and AR (2) are below and above 0.1, respectively. Secondly, the P-values of all Hansen tests are greater than 0.1, suggesting that the instrumental variables used in the GMM are not over-identified. In addition, the coefficient of the lagged one-period term of the explained variable is significantly positive, indicating the persistence of CE and further supporting the appropriateness of using the GMM model. The GMM estimation results indicate that the DE development in importing countries can still significantly promote CE after eliminating the endogeneity problem, which again supports the previous research conclusions.

5.5. Heterogeneity analysis

5.5.1. Heterogeneity analysis based on economic development level

Given that the effect of DE development on CE may differ across countries at varying levels of economic development, this study adopts the World Bank's classification system to categorize the sample into developed and developing countries for separate regression analyses. As shown in columns (1)–(2) of Table 9, DE development in developed countries significantly promotes CE to these countries. This can be attributed to the more advanced digital infrastructure and the availability of efficient, convenient digital services in developed economies, which create a more favorable environment for firms to engage in cross-border e-commerce and international trade. In addition, residents of developed countries have higher income levels, and the development of the DE has expanded both the channels through which consumers purchase goods and the range of available choices. This has stimulated demand for more diversified products, thereby contributing to increased imports from China.

5.5.2. Heterogeneity analysis based on internet regulation level

As concerns over the security of international data flows intensify, regulating cross-border information transmission has become a common practice among countries. Theoretically, the more open an importing country is to international information, meaning the lower its level of internet regulation or the higher its level of internet freedom, the stronger the positive effect of the DE is expected to be (Ma et al., 2024). Given this, this study utilizes internet regulation level rankings from the international technology website Comparitech to classify the sample countries into two groups, namely low regulation and high regulation, based on the median value, and conducts separate regression analyses. The regression results in the last two columns of Table 9 show that in countries with low internet regulation, DE development significantly promotes China's export growth.

Table 9. Heterogeneity analysis I

	(1)	(2)	(3)	(4)
	developed countries	developing countries	low regulation	high regulation
LNDIG	0.6087***	–0.0411	0.2136***	0.0294
	(0.0921)	(0.0357)	(0.0453)	(0.0392)
_cons	–1.0515	12.8680***	8.8704**	17.0285***
	(4.8457)	(3.4303)	(3.8539)	(3.7597)
Control variables	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	756	2310	1533	1533
R^2	0.9958	0.9870	0.9962	0.9854

5.5.3. Heterogeneity analysis based on industry differences

Given that the impact of DE development in importing countries on CE may vary across different industries, this study replaces total export value with the export values of several major industries to conduct a heterogeneity analysis. The regression results are presented in Table 10. The results indicate that DE development in importing countries is more conducive to CE of mechanical and electrical products, as well as iron and steel products, while its promoting effect on chemical and textile products is relatively limited. We argue that the primary reason for industry heterogeneity may lie in the nature of mechanical and electrical products, which, as technology-intensive goods, are highly dependent on the digital infrastructure and the level of information technology application in importing countries, and are therefore most affected. Iron and steel products follow, as digital trade platforms in importing countries integrate supply and demand data, enabling Chinese steel enterprises to more accurately match with overseas orders. Agricultural products overcome trust barriers and reduce constraints on fresh food trade through cross-border e-commerce and digital traceability technologies, making them sensitive to the level of DE development in importing countries. In contrast, chemical products are primarily traded through traditional models and frequently face challenges from environmental regulations and high compliance costs, which limit the effectiveness of the DE. The textile industry is labor-intensive, characterized by a high proportion of SMEs, substantial digital transformation costs, and a low degree of digital adoption, resulting in the least impact. Therefore, China should implement differentiated trade and industrial policies.

Table 10. Heterogeneity analysis II

	(1)	(2)	(3)	(4)	(5)
	Mechanical and electrical products	Iron and steel products	Chemical products	Agricultural products	Textile products
LNDIG	0.4189***	0.3691***	0.1952***	0.3145***	0.1618***
	(0.0441)	(0.0599)	(0.0507)	(0.0493)	(0.0508)
_cons	22.5034***	–4.0927	3.3812	–5.8029	–2.5716
	(3.4679)	(4.5521)	(4.8777)	(3.9088)	(5.1212)
Control variables	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	3066	3066	3066	3066	3066
R^2	0.9918	0.9716	0.9858	0.9893	0.9752

Specifically, China should focus on guiding the mechanical and electrical, as well as iron and steel industries, to deepen the application of digital technologies, supporting the agricultural sector in expanding cross-border e-commerce and establishing blockchain-based traceability and quality certification systems, dismantling barriers to digital transformation in the chemical and textile industries, and enhancing the export competitiveness of various sectors through digital empowerment, ultimately promoting export growth.

5.6. Further analysis

5.6.1. Analysis of impact mechanism

Based on the above assumptions, this study selects trade costs (LNTC) and production capacity (LNPC) as mediating variables and adopts the analytical method proposed by Baron and Kenny (1986) to test the mediating mechanism. The results of the impact mechanism test are presented in Table 11.

Table 11. Results of the impact mechanism test

	(1)	(2)	(3)	(4)
	LNTC	EX	LNPC	EX
LNDIG	–0.0313***	0.2282***	0.0855***	0.2051***
	(0.0053)	(0.0291)	(0.0056)	(0.0355)
LNTC		–0.3760***		
		(0.1076)		
LNPC				0.4960***
				(0.1772)
_cons	–0.9103***	7.0107**	1.1806***	4.9955
	(0.3088)	(3.0452)	(0.3048)	(3.0944)
Control variables	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	3066	3066	3066	3066
R^2	0.9061	0.9926	0.9765	0.9924

As presented in column (1) of Table 11, the DE development in the importing country significantly lowers trade costs. Furthermore, column (2) shows that, after the inclusion of total exports, DE development promotes CE by reducing trade costs, thereby confirming Hypothesis 2a. Additionally, trade cost plays a partial mediating role.

As shown in column (3) of Table 11, the DE development in the importing country significantly increases production capacity. After the inclusion of total exports in column (4), DE development promotes CE by increasing production capacity, thereby confirming Hypothesis 2b. Similarly, production capacity plays a partial mediating role.

5.6.2. Threshold effect analysis

Given that the DE gap between importing countries and China may generate a threshold effect in the process of the DE development of importing countries promoting CE, resulting in a nonlinear influence relationship between the two. Building on Hansen's (1999) panel threshold model, this paper constructs a threshold model using the DE gap between importing countries and China (DIGGAP) as the threshold variable, where DIGGAP is defined as the absolute difference in DE development levels between the two countries. In addition, this study applies the Bootstrap method with 300 replications, and the results are shown in Table 12.

As shown in Table 12, the DE gap passes the single-threshold test but fails the double- and triple-threshold tests, indicating the DE gap has a single threshold effect in the impact of DE development in importing countries on CE. Therefore, a single-threshold model is applied, and the estimation results are presented in Table 13.

The regression results in Table 13 show that the coefficient of LNDIG remains significantly positive on both sides of the threshold, further confirming the research conclusions in the previous study. In addition, when the DE gap exceeds the threshold value of 0.1110, the

Table 12. Threshold effect test results

Threshold variable	Threshold type	F-value	P-value	Critical value		
				10%	5%	1%
DIGGAP	single	29.14	0.0600	24.8853	29.4568	45.8599
	double	10.97	0.4967	21.3414	26.8128	40.4104
	triple	8.18	0.7000	20.1786	25.8141	36.2371

Table 13. Threshold regression estimation results

	Estimated coefficient	Robust standard error	P-value
LNDIG(DIGGAP ≤0.1110)	0.4223***	0.0829	0.000
LNDIG(DIGGAP >0.1110)	0.3007***	0.0626	0.000
Control variables	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	3066	3066	3066

positive effect of DE development in the importing country on CE weakens, thereby supporting Hypothesis 3. When the DE levels of two countries are similar, differences in information technology, infrastructure, digital applications, and related areas are relatively minor. This alignment helps reduce technical barriers and search costs in international information flows, facilitating smoother cross-border data exchange. Under such conditions, the DE plays a stronger role in promoting bilateral trade. As the DE gap widens, the effects of the digital divide begin to manifest. When the DE gap reaches the threshold value, the smoothness of information flow decreases sharply, limiting consumers in importing countries from accessing relevant information. The serious digital divide weakens the export-promoting effect of the DE. This nonlinear relationship indicates that the DE's synergy effectively translates into trade momentum only when the DE gap between the two countries remains at a low level. Based on the above analysis, differentiated policy measures should be adopted according to the magnitude of the DE gap. First, for countries whose DE gap with China is less than 0.1110, China should prioritize advancing mutual recognition of digital standards and the joint development of digital trade platforms to enhance the export-promoting effect of the DE. Second, given China's relatively high level of DE development, countries whose DE gap with China is greater than 0.1110 have a relatively low level of DE development. For these countries, China should focus on implementing a digital infrastructure gap-filling initiative. Through the Belt and Road Initiative for international cooperation in the DE, efforts should be made to build 5G base stations, broadband networks, and mobile payment systems in local areas, improve digital infrastructure, and reduce the gap to below the threshold level.

6. Discussion, research conclusions and policy recommendations

6.1. Discussion

This study reveals that the development of the global DE has a significant impact on CE.

First, this study systematically measures the level of DE development in 147 countries worldwide by constructing a comprehensive indicator framework, and provides an in-depth analysis of global DE development trends. This aligns with the research methods and indicator system of Shahbaz et al. (2022) and Wang et al. (2022).

Second, this study incorporates the level of DE development into the analytical framework of the trade gravity model and employs the PPML estimation to empirically examine the impact of global DE development on CE. In comparison, previous studies have either limited the research area to China, examining the impact of China's domestic DE development on CE (Liang & Tan, 2024; Li & Xiao, 2025; Liu et al., 2024b, 2024c), or used cross-country panel data to explore how national DE levels affect export performance (Li et al., 2023; Yin & Choi, 2024; Chiappini & Gaglio, 2024; Nham et al., 2023). This paper addresses the limitations of previous research perspectives by treating the DE development level of the importing country as an external shock, offering an innovative contribution compared to prior research. This study demonstrates that global DE development significantly promotes CE. The result holds true even after applying various robustness tests and addressing potential endogeneity, supporting the credibility of the finding.

Third, this study examines the heterogeneous impacts of the DE across regions and industries. The findings indicate that in importing countries with higher levels of economic development and lower levels of internet regulation, the DE more effectively facilitates CE. Its impact is particularly pronounced in promoting the export of mechanical and electrical products. In contrast, previous studies have been notably limited in their analysis of heterogeneity. Only Wang et al. (2024a) found that the development of the DE in RCEP member countries with higher levels of economic development significantly boosted CE. However, no existing studies have extended heterogeneity analysis to the level of internet regulation and different industries.

In addition, this study also examines the underlying mechanisms through which the development of the DE in importing countries affects CE. The study finds that reducing trade costs and increasing production capacity are important impact mechanisms, consistent with the findings of Tang et al. (2025). Using data from Belt and Road countries, Tang et al. (2025) also confirmed the positive role of the DE in reducing trade costs. This research finding offers a new practical approach for fully leveraging the export-promoting effects of the DE and effectively addresses the shortcomings of existing research.

Finally, using a threshold model, this study provides novel evidence that the effect of DE development in importing countries on CE performance exhibits a single-threshold effect, with the DE gap between the two serving as the threshold, which is estimated at 0.111. When the DE gap exceeds the threshold value of 0.111, the serious digital divide constrains the information bridge function of digital technologies and platforms, hindering precise alignment between trading partners and thereby weakening the DE's role in promoting CE. A survey of existing literature indicates that research on this topic remains scarce. Chai and Wang (2024) found that the internet gap between countries can obstruct bilateral export activities. However, their analysis overlooked the threshold effect of the digital divide. Drawing on the current global imbalance in DE development, this study extends the research frontier on the relationship between the DE and international trade. It offers new perspectives and empirical evidence for future research, helping policymakers deepen their understanding of the potential impact of the DE development gap and enabling the formulation of more targeted trade promotion policies.

6.2. Research conclusions and policy recommendations

Based on panel data from 146 countries spanning the period 2003 to 2023, this study employs an extended trade gravity model to examine the impact of global DE development on CE. The empirical analysis reveals that: First, the development of the global DE significantly increases CE. Second, the results of the heterogeneity analysis indicate that this positive effect is more pronounced in countries with higher levels of economic development and lower levels of internet regulation. Moreover, the impact is particularly strong in the export of mechanical and electrical products, as well as iron and steel products. Third, the mechanism analysis reveals that reducing trade costs and increasing production capacity are important impact channels. Finally, the threshold effect analysis reveals that as the DE gap between importing countries and China widens, the impact of DE development in importing countries on CE displays a nonlinear positive effect, with diminishing marginal effects. Based on the above findings, this paper proposes the following policy recommendations:

For China, first, it is essential to increase investment in 5G networks, data centers, cloud computing, and related areas to develop a digital infrastructure characterized by wide coverage and advanced performance, thereby enabling interconnection and interoperability. At the same time, enterprises should be encouraged to engage in research, development, and application-oriented innovation of digital technologies. These efforts aim to enhance the digitalization and intelligence of products and services, actively promote emerging trade patterns such as cross-border e-commerce and digital trade, and strengthen the international competitiveness of export commodities. Second, China should implement differentiated market development strategies for different partner countries. For high-potential markets such as developed countries and those with low levels of internet regulation, China should, on the one hand, conduct in-depth analyses of local demand for various products in developed countries, use big data analytics to accurately identify consumer preferences, develop appropriate products, and stimulate consumer demand. On the other hand, China should actively integrate into the relatively relaxed digital regulatory environments of countries with low levels of internet regulation. This includes strengthening communication with local governments and enterprises, promoting the coordination and harmonization of cross-border data flows and digital trade rules, reducing trade barriers, creating favorable conditions for Chinese enterprises to expand into overseas markets, and further consolidating and increasing exports to these countries. For countries with relatively low market potential, such as developing countries and those with high levels of internet regulation, China can, on the one hand, provide digital infrastructure assistance through cooperation frameworks such as the Digital Silk Road, in order to help developing countries overcome the bottlenecks that constrain their DE development. On the other hand, when confronting the stringent internet regulatory environments in certain countries, China should implement adaptive digital solutions. These include developing e-commerce platforms and digital payment systems that comply with data sovereignty requirements, as well as simplifying digital trade processes through bilateral agreements, such as mutual recognition of electronic certifications, thereby enhancing trade efficiency and promoting the expansion of CE. Finally, China should also formulate differentiated development strategies tailored to various industries. Priority should be given to deepening the digital empowerment of key sectors, particularly by increasing investment in the digital transformation of the mechanical and electrical industry. This includes promoting the extensive application of technologies such as intelligent manufacturing and AI in production and supply chains, thereby enhancing product added value and service levels, and ultimately consolidating and expanding China's share in the global market. Secondly, steel enterprises should be encouraged to develop digital supply chain management systems and overseas digital marketing platforms, aiming to reduce transaction costs stemming from information asymmetry while enhancing order matching efficiency and market responsiveness. Thirdly, China should prioritize supporting agricultural enterprises in establishing blockchain-based quality traceability systems to ensure the authenticity and reliability of product information, address trust issues in agricultural trade, strengthen the international brand reputation of Chinese agricultural products, and ultimately promote agricultural exports. In contrast, the chemical and textile industries are less affected by the level of DE development in importing countries. For chemical industry, China can pursue a dual transformation of green transition and digitalization, leveraging digital technologies to enhance energy efficiency management, strengthen emission reduction monitoring, and improve compliance cost control, thereby mitigating environmental pressures and gradually boosting the industry's international competitiveness. For the textile industry, it is recommended to assist textile companies, particularly SMEs, in lowering the barriers to digitalization and accelerating their digital empowerment through the development of industrial Internet platforms, support from public digital service platforms, and targeted training subsidies. In summary, these measures will not only strengthen the overall competitiveness of the export sector but also promote the sustainable growth of CE.

For importing countries, first, investment in DE development should also be increased. Based on their stages of development and economic structures, they should formulate and implement national-level strategies and plans for DE development. Financial and policy support should be strengthened in areas such as digital technology research and development, infrastructure construction, and talent cultivation, thereby promoting the development of DE and creating a supportive environment for domestic economic growth and the expansion of foreign trade. Second, given that the impact of DE development in importing countries on CE has a single threshold effect with the DE gap between the two as the threshold, and the entropy method measurements indicate China maintains a relatively high level of DE development, corresponding policy recommendations can be formulated based on the DE development levels of the importing partner countries. Specifically, for countries whose level of DE development is relatively close to that of China, government authorities should actively promote mutual recognition of regulations such as bilateral data flows and product market access, accelerate the establishment of a digital institutional system aligned with international standards, further advance institutional opening, and eliminate barriers related to cross-border data flows and digital service access, thereby supporting the deep application and integration of the DE into the field of trade. For countries with a significant gap in DE development relative to China, government authorities should actively facilitate the involvement of foreign companies in the construction of digital infrastructure. This includes addressing critical gaps in network coverage, data centers, and related areas, thereby creating a favorable environment conducive to the development of the DE. These countries should also actively engage in international digital technology cooperation. By strengthening collaborative efforts in digital technology and joint R&D initiatives, they can accelerate the advancement of their digital economies, narrow the digital divide, expand access to the benefits of technological innovation, and establish a new DE landscape characterized by mutual benefit and win-win outcomes. Thirdly, importing countries should value the role of the DE in reducing costs and increasing production, and smooth the channels through which it promotes foreign trade. On the one hand, as countries promote the rapid development of the DE, they should continually enhance bilateral information linkages, optimize transaction processes, reduce trade barriers, mitigate trade risks, and foster a smoother and more stable international trade environment. These efforts will effectively lower trade costs and promote trade growth. On the other hand, countries should continue to enhance support for enterprises, encouraging increased investment in research and development, accelerating digital transformation, leveraging innovation as a driving force, and improving production efficiency and capacity to better align with the demands of the digital age. Finally, the differences in industrial structures across importing countries should also be considered. For example, countries with a high share of manufacturing should focus on promoting digital trade cooperation with China in capital- and technology-intensive products such as machinery, electronics, and steel. Countries dominated by agriculture and resource-based industries could prioritize cooperation with China in cross-border e-commerce for agricultural products and digital traceability systems. For countries that are highly dependent on chemical imports, entry barriers for Chinese chemical products should be reduced by enhancing green certification, promoting mutual recognition of environmental standards, and developing digital compliance systems. In countries with substantial demand for textile imports, the digital transformation of SMEs should be promoted to facilitate their integration with Chinese cross-border e-commerce platforms. This approach will enable Chinese high-quality textiles to better align with local consumer preferences and foster mutually beneficial trade outcomes.

6.3. Limitations and future research

Last but not least, this paper also has certain limitations, which can be expanded in future related studies. First, the construction of an indicator system using the entropy method inevitably entails a degree of subjectivity. Researchers may select different indicators depending on their specific objectives and priorities. Such subjectivity in indicator selection can influence the weights generated by the entropy method, thereby affecting the measurement of DE development levels. Future research should comprehensively consider the theoretical framework, practical needs, and policy orientation of DE development in order to establish a scientific and comprehensive set of criteria for indicator selection. For example, incorporating indicators of emerging digital technologies such as AI, blockchain, and cloud computing into the evaluation system would enable a more accurate measurement of DE development levels. Second, the heterogeneity analysis could be further expanded. Although this study examines the heterogeneous impacts across countries with different levels of economic development and internet regulation, as well as across different industries, other potential factors such as cultural differences, human capital, and geopolitical conditions remain underexplored. Future research could integrate these factors into the analytical framework to capture deeper heterogeneity in how the DE influences export trade, thereby offering more nuanced insights for countries to design differentiated policy responses. Finally, this study employs macro-level national panel data, which effectively captures the overall relationship between the DE development of importing countries and CE. However, such data are limited in their ability to probe underlying micro-mechanisms and to fully reflect the decision-making logic underlying firms' export behavior. Future research could extend the analysis to the firm level, thereby enriching the hierarchical depth and practical applicability of the findings, while enhancing both their explanatory power and policy relevance.

Funding

This research was supported by the Major Project of the National Social Science Fund of China (Grant No: 2021MZD015) and the Liaoning Provincial Social Science Planning Fund Project (Grant No: L24BJY019).

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abeliansky, A. L., & Hilbert, M. (2017). Digital technology and international trade: Is it the quantity of subscriptions or the quality of data speed that matters? *Telecommunications Policy*, *41*(1), 35–48. https://doi.org/10.1016/j.telpol.2016.11.001

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Bartelsman, E., Haltiwanger, J., & Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review*, *103*(1), 305–334. https://doi.org/10.1257/aer.103.1.305

Cao, T. L., & Hsu, J. (2025). Digitalization and country distance in international trade: An empirical analysis of European countries. *Telecommunications Policy*, *49*(1), Article 102877. https://doi.org/10.1016/j.telpol.2024.102877

Chai, J. W., & Wang, L. H. (2024). The effect of internet gap on bilateral export: evidence from an extended gravity model. *Applied Economics*, *56*(57), 7912–7921. https://doi.org/10.1080/00036846.2023.2289907

Chandra, P. (2017). Trade destruction and trade diversion: Evidence from China. *China* & *World Economy*, *25*(3), 31–59. https://doi.org/10.1111/cwe.12199

Chen, C., Salike, N., & Thorbecke, W. (2023). Exchange rate effects on China's exports: Product sophistication and exchange rate elasticity. *Asian Economic Journal*, *37*(3), 371–400. https://doi.org/10.1111/asej.12309

Chen, H. X., & Wang, S. H. (2024). Can the development of industrial intelligence improve the benefits of China's participation in global value chains? *Environmental Impact Assessment Review*, 105, Article 107445. https://doi.org/10.1016/j.eiar.2024.107445

Chen, Z. Q., Wei, Y., Shi, K. F., Zhao, Z. Y., Wang, C. X., Wu, B., Qiu, B., & Yu, B. L. (2022). The potential of nighttime light remote sensing data to evaluate the development of digital economy: A case study of China at the city level. *Computers Environment and Urban Systems*, *92*, Article 101749. https://doi.org/10.1016/j.compenvurbsys.2021.101749

Cheng, L., Mi, Z., Coffman, D., Meng, J., & Chang, D. (2021). Destruction and deflection: Evidence from American antidumping actions against China. *Structural Change and Economic Dynamics*, *57*, 203–213. https://doi.org/10.1016/j.strueco.2021.03.009

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, *21*(1), C1–C68. https://doi.org/10.1111/ectj.12097

Chiappini, R., & Gaglio, C. (2024). Digital intensity, trade costs and exports' quality upgrading. *The World Economy*, *47*(2), 709–747. https://doi.org/10.1111/twec.13448

China Academy of Information and Communications Technology. (2023). *White paper on global digital economy* (*2023*). https://www.caict.ac.cn/kxyj/qwfb/bps/202401/P020240326601000238100.pdf

Cui, K., & Yang, W. (2025). The digital economy and the resilience of enterprise exports: Supply chain stability as a mediator. *Finance Research Letters*, 73, Article 106650. https://doi.org/10.1016/j.frl.2024.106650

De Groot, H. L. F., Linders, G.-J., Rietveld, P., & Subramanian, U. (2004). The institutional determinants of bilateral trade patterns. *Kyklos*, *57*(1), 103–123. https://doi.org/10.1111/j.0023-5962.2004.00245.x

De Mendonça, T. G., Lirio, V. S., Braga, M. J., & da Silva, O. M. (2014). Institutions and bilateral agricultural trade. *Procedia Economics and Finance*, *14*, 164–172. https://doi.org/10.1016/S2212-5671(14)00699-6

Deng, X., Zhou, M., & Cheng, Y. (2022). Synergistic development of digital economy and urban agglomeration: A study based on night lighting data. *Journal of Zhejiang University* (*Humanities and Social Sciences Edition*), *52*(4), 32–49 (in Chinese).

Dong, K., Liu, Y., Wang, J., & Dong, X. (2024). Is the digital economy an effective tool for decreasing energy vulnerability? A global case. *Ecological Economics*, *216*, Article 108028. https://doi.org/10.1016/j.ecolecon.2023.108028

Fan, H. L., Trinh Thi, V. H., Zhang, W., & Li, S. (2022). The influence of trade facilitation on agricultural product exports of China: Empirical evidence from ASEAN countries. *Economic Research – Ekonomska Istrazivanja*, *36*(2), Article 2143845. https://doi.org/10.1080/1331677X.2022.2143845

Freund, C., & Weinhold, D. (2002). The Internet and international trade in services. *American Economic Review*, *92*(2), 236–240. https://doi.org/10.1257/000282802320189320

Gereffi, G., Humphrey, J., & Sturgeon, T. (2005). The governance of global value chains. *Review of International Political Economy*, *12*(1), 78–104. https://doi.org/10.1080/09692290500049805

Görg, H., & Mao, H. O. (2022). Does the belt and road initiative stimulate Chinese exports? Evidence from micro data. *The World Economy*, *45*(7), 2084–2100. https://doi.org/10.1111/twec.13258

Guo, P., Hamzah, H. Z., & Chin, L. (2025). Has trade facilitation of the 'Belt and Road' countries promoted China's cross-border E-commerce exports? *The World Economy*, *48*(2), 238–266. https://doi.org/10.1111/twec.13646

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, *93*(2), 345–368. https://doi.org/10.1016/S0304-4076(99)00025-1

He, L.-Y., Lin, X., & Zhang, Z. X. (2020). The impact of de-globalization on China's economic transformation: Evidence from manufacturing export. *Journal of Policy Modeling*, *42*(3), 628–660. https://doi.org/10.1016/j.jpolmod.2020.02.001

Heavilin, J., & Songur, H. (2020). Institutional distance and Turkey's outward foreign direct investment. *Research in International Business and Finance*, *54*, Article 101299. https://doi.org/10.1016/j.ribaf.2020.101299

Herman, P. R., & Oliver, S. (2023). Trade, policy, and economic development in the digital economy. *Journal of Development Economics*, *164*, Article 103135. https://doi.org/10.1016/j.jdeveco.2023.103135

Hottman, C. J., Redding, S. J., & Weinstein, D. E. (2016). Quantifying the sources of firm heterogeneity. *Quarterly Journal of Economics*, *131*(3), 1291–1364. https://doi.org/10.1093/qje/qjw012

Kim, J. (2006). Infrastructure of the digital economy: Some empirical findings with the case of Korea. *Technological Forecasting and Social Change*, *73*(4), 377–389. https://doi.org/10.1016/j.techfore.2004.09.003

Lan, X., Hu, Z., & Wen, C. (2025). Can digital transformation reduce the zombification of enterprises? *China* & *World Economy*, *33*(2), 171–208. https://doi.org/10.1111/cwe.12577

Li, H., & Xiao, B. (2025). Strengthening provincial export resilience through the digital economy: Analysis of impacts, global value chain integration, and regional disparities in China. *Finance Research Letters*, *76*, Article 106990. https://doi.org/10.1016/j.frl.2025.106990

Li, H., Han, J., & Xu, Y. (2023). The effect of the digital economy on services exports competitiveness and ternary margins. *Telecommunications Policy*, *47*(7), Article 102596. https://doi.org/10.1016/j.telpol.2023.102596

Liang, S., & Tan, Q. (2024). Can the digital economy accelerates China's export technology upgrading? Based on the perspective of export technology complexity. *Technological Forecasting and Social Change*, *199*, Article 123052. https://doi.org/10.1016/j.techfore.2023.123052

Liao, S. C., Chou, T. C., & Huang, C. H. (2022). Revisiting the development trajectory of the digital divide: A main path analysis approach. *Technological Forecasting and Social Change*, *179*, Article 121607. https://doi.org/10.1016/j.techfore.2022.121607

Limão, N., & Venables, A. J. (2001). Infrastructure, geographical disadvantage, transport costs, and trade. *The World Bank Economic Review*, *15*(3), 451–479. https://doi.org/10.1093/wber/15.3.451

Lin, B. Q., & Liu, Y. D. (2025). Renewable energy trade destruction and deflection: Effects of antidumping and countervailing measures on Chinese solar photovoltaic exports. *Energy Policy*, *204*, Article 114687. https://doi.org/10.1016/j.enpol.2025.114687

Liu, A. L., Lu, C. C., & Wang, Z. X. (2020). The roles of cultural and institutional distance in international trade: Evidence from China's trade with the Belt and Road countries. *China Economic Review*, *61*, Article 101234. https://doi.org/10.1016/j.chieco.2018.10.001

Liu, D., Wang, Q. H., Wang, A. D., & Yao, S. J. (2023). Export profitability and firm R&D: On China's export diversification under trade war. *Structural Change and Economic Dynamics*, *67*, 151–166. https://doi.org/10.1016/j.strueco.2023.07.012

Liu, J., Wang, P., & Wu, H. (2021). Trade facilitation and China's agricultural products exports: Empirical evidence from Japan and Korea. *Journal of Korea Trade*, *25*(7), 92–107. https://doi.org/10.35611/jkt.2021.25.7.92

Liu, K., Fu, Q., Ma, Q., & Ren, X. (2024a). Does geopolitical risk affect exports? Evidence from China. *Economic Analysis and Policy*, *81*, 1558–1569. https://doi.org/10.1016/j.eap.2024.02.035

Liu, Y., Dong, Y., & Qian, W. (2024b). Digital economy and China's agricultural exports: Based on trade cost and market competition effect. *China Agricultural Economic Review*, *16*(3), 489–506. https://doi.org/10.1108/CAER-08-2023-0213

Liu, Y., Dong, Y., & Zhou, H. (2024c). The impact of the agricultural digital economy on China's agricultural export growth: Examining mechanisms from supply- and demand-side path perspectives. *Agribusiness*, *42*(1), 51–77. https://doi.org/10.1002/agr.21930

Liu, Y., Chen, J., & Sun, C. (2022). Partnership diplomacy and China's exports. *Sustainability*, *14*(19), Article 12147. https://doi.org/10.3390/su141912147

Lohmann, J. (2011). Do language barriers affect trade? *Economics Letters*, *110*(2), 159–162. https://doi.org/10.1016/j.econlet.2010.10.023

Lythreatis, S., Singh, S. K., & El-Kassar, A.-N. (2022). The digital digital divide: A review and future research agenda. *Technological Forecasting and Social Change*, *175*, Article 121359. https://doi.org/10.1016/j.techfore.2021.121359

Ma, Shu., Wu, P., & Fang, C. (2024). International submarine optical cables, bilateral information flow and Chinese cross-border M&A. *World Economy*, (4), 3–30 (in Chinese).

Mao, F. L., & Zhang, F. (2021). The evolution of the regional digital economy in China: 1994 to 2018. *Quantitative and Technical Economic Studies*, *38*(7), 3–25 (in Chinese).

Martínez-Zarzoso, I. (2013). The log of gravity revisited. *Applied Economics*, *45*(3), 311–327. https://doi.org/10.1080/00036846.2011.599786

Martínez-Zarzoso, I., & Nowak-Lehmann, F. (2007). Is distance a good proxy for transport costs? The case of competing transport modes. *The Journal of International Trade & Economic Development*, *16*(3), 411–434. https://doi.org/10.1080/09638190701527186

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1725. https://doi.org/10.1111/1468-0262.00467

Mignamissi, D., & Bio, I. (2025). Digital divide and bilateral trade in Africa. *Economics of Innovation and New Technology*, 1–28. https://doi.org/10.1080/10438599.2025.2474432

Nath, H. K., & Liu, L. (2017). Information and communications technology (ICT) and services trade. *Information Economics and Policy*, *41*, 81–87. https://doi.org/10.1016/j.infoecopol.2017.06.003

Nham, N. T. H., Bao, N. K. Q., & Ha, L. T. (2023). Nonlinear effects of digitalization on export activities: An empirical investigation in European countries. *Technological and Economic Development of Economy*, *29*(3), 1041–1079. https://doi.org/10.3846/tede.2023.17061

Novy, D. (2013). Gravity redux: Measuring international trade costs with panel data. *Economic Inquiry*, *51*(1), 101–121. https://doi.org/10.1111/j.1465-7295.2011.00439.x

Oum, T. H., Wu, X., & Wang, K. (2024). Impact of air connectivity on bilateral service export and import trade: The case of China. *Transport Policy*, *148*, 219–233. https://doi.org/10.1016/j.tranpol.2024.01.015

Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *Journal of Business Research*, *139*, 303–311. https://doi.org/10.1016/j.jbusres.2021.09.061

Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review*, *92*(11), 64–88.

Rodriguez-Crespo, E., Marco, R., & Billon, M. (2021). ICTs impacts on trade: A comparative dynamic analysis for internet, mobile phones and broadband. *Asia-Pacific Journal of Accounting & Economics*, *28*(5), 577–591. https://doi.org/10.1080/16081625.2018.1519636

Santos Silva, J. M. C., & Tenreyro, S. (2006). The log of gravity. *Review of Economics and Statistics*, *88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

Shahbaz, M., Wang, J. D., Dong, K. Y., & Zhao, J. (2022). The impact of digital economy on energy transition across the globe: The mediating role of government governance. *Renewable and Sustainable Energy Reviews*, *166*, Article 112620. https://doi.org/10.1016/j.rser.2022.112620

Shen, N., Zhang, G. P., Zhou, J. W., Zhang, L., Wu, L. J., Zhang, J., & Shang, X. F. (2024). Can big data policy drive urban carbon unlocking efficiency? A new approach based on double machine learning. *Journal of Environmental Management*, *372*, Article 123296. https://doi.org/10.1016/j.jenvman.2024.123296

Tang, W., Lan, Q. X., & Yang, Y. L. (2025). Digital economy's role in shaping China's outward investment in Belt and Road countries. *Technological and Economic Development of Economy*, *31*(2), 412–446. https://doi.org/10.3846/tede.2024.21905

Thorbecke, W. (2015). China–US trade: A global outlier. *Journal of Asian Economics*, *40*, 47–58. https://doi.org/10.1016/j.asieco.2015.09.001

Wang, C., Liu, T., Wen, D., Li, D., Vladislav, G., & Zhu, Y. (2021). The impact of international electronic commerce on export trade: Evidence from China. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(7), 2579–2593. https://doi.org/10.3390/jtaer16070142

Wang, D., Xu, P. Y., An, B. W., & Song, Y. Y. (2024a). How does the development of the digital economy in RCEP member countries affect China's cross-border e-commerce exports? *PLoS ONE*, *19*(12), Article e0310975. https://doi.org/10.1371/journal.pone.0310975

Wang, J., Wang, K., Dong, K., & Shahbaz, M. (2022). How does the digital economy accelerate global energy justice? Mechanism discussion and empirical test. *Energy Economics*, *114*, Article 106315. https://doi.org/10.1016/j.eneco.2022.106315

Wang, S., & Zhu, Y. (2024). An inquiry into the effect of trade facilitation on China's digital product exports to countries along the "Belt and Road". *International Review of Economics & Finance*, *93*, 1246–1259. https://doi.org/10.1016/j.iref.2024.04.041

Wang, W., Wu, Q., Su, J., & Li, B. (2024b). The impact of international logistics performance on import and export trade: an empirical case of the "Belt and Road" initiative countries. *Humanities & Social Sciences Communications*, *11*, Article 1028. https://doi.org/10.1057/s41599-024-03541-0

Weidner, M., & Zylkin, T. (2021). Bias and consistency in three-way gravity models. *Journal of International Economics*, *132*, Article 103513. https://doi.org/10.1016/j.jinteco.2021.103513

Wilson, J. S., Mann, C. L., & Otsuki, T. (2003). Trade facilitation and economic development: A new approach to quantifying the impact. *World Bank Economic Review*, *17*(3), 367–389. https://doi.org/10.1093/wber/lhg027

Wu, H., Xue, Y., Hao, Y., & Ren, S. (2021). How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Economics*, *103*, Article 105577. https://doi.org/10.1016/j.eneco.2021.105577

Xiao, Y. T., & Abula, B. (2024). Examining the impact of digital economy on agricultural trade efficiency in RCEP region: A perspective based on spatial spillover effects. *Journal of the Knowledge Economy*, *15*, 9907–9934. https://doi.org/10.1007/s13132-023-01484-6 (Retraction published 2025, *Journal of the Knowledge Economy*, *15*, 9907–9934)

Xing, L., Yin, X., Cao, C., Elahi, E., & Wei, T. (2023). The impact of multidimensional distance on agricultural exports: Evidence from China based on the technological added value. *Sustainability*, *15*(1), Article 393. https://doi.org/10.3390/su15010393

Xing, Y. (2018). Rising wages, yuan's appreciation and China's processing exports. *China Economic Review*, *48*, 114–122. https://doi.org/10.1016/j.chieco.2017.04.002

Yang, Q., Geng, Y., Dong, H., Zhang, J., Yu, X., Sun, L., Lu, X., & Chen, Y. (2017). Effect of environmental regulations on China's graphite export. *Journal of Cleaner Production*, *161*, 327–334. https://doi.org/10.1016/j.jclepro.2017.05.131

Yaprak, A., Yosun, T., & Cetindamar, D. (2018). The influence of firm-specific and country-specific advantages in the internationalization of emerging market firms: Evidence from Turkey. *International Business Review*, *27*(1), 198–207. https://doi.org/10.1016/j.ibusrev.2017.07.001

Yin, Z. H., & Choi, C. H. (2024). How does digitalization affect trade in goods and services? Evidence from G20 countries. *Journal of the Knowledge Economy*, *16*, 3614–3638. https://doi.org/10.1007/s13132-024-02029-1

Yu, C., & Luo, Z. (2018). What are China's real gains within global value chains? Measuring domestic value added in China's exports of manufactures. *China Economic Review*, *47*, 263–273. https://doi.org/10.1016/j.chieco.2017.08.010

Zhan, J. Y., Wang, X., Li, Q., & Zhao, J. (2025). Digital industry agglomeration and export product diversification: Evidence from Chinese firms. *China* & *World Economy*, *33*(1), 64–100. https://doi.org/10.1111/cwe.12567

Zhang, H. S., Liu, Q. Q., & Wei, Y. L. (2023). Digital product imports and export product quality: Firm-level evidence from China. *China Economic Review*, *79*, Article 101981. https://doi.org/10.1016/j.chieco.2023.101981

Zhang, L., Cui, L., Li, S., & Lu, J. (2018). Who rides the tide of regionalization: Examining the effect of the China-ASEAN Free Trade Area on the exports of Chinese firms. *International Business Review*, *27*(3), 501–513. https://doi.org/10.1016/j.ibusrev.2017.10.002

Zhang, Z., Xu, H., & Qiao, Z. (2024). Has the digital economy enhanced the income distribution effect among industries? Evidence from China. *Sustainability*, *16*(20), Article 8969. https://doi.org/10.3390/su16208969

Zhou, F., Wen, H., & Lee, C.-C. (2022). Broadband infrastructure and export growth. *Telecommunications Policy*, *46*(5), Article 102347. https://doi.org/10.1016/j.telpol.2022.102347