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The Convergence between Digital Industrialization and Industrial Digitalization and Export Technology Complexity: Evidence from China

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Abstract: The wave of digitalization is driving the restructuring of the global value chain, providing an excellent opportunity for China to leapfrog into the digital era. The convergence between digital industrialization and industrial digitalization (hereinafter referred to as CDIID) is an indicator to measure the sustainability of the digital economy. The main objective of this paper is to measure the level of CDIID in China and verify the impact of CDIID on export technology complexity and its mechanism. The nonparametric stochastic frontier method is used to measure the level of CDIID of each province in China from 2013 to 2019, and the fixed-effect model is used to investigate the impact effect and mechanism of CDIID on export technology complexity. Empirical research finds that the level of CDIID plays a positive role in promoting the export technology complexity, and in the short term, more attention should be paid to the development of industrial digitalization to enhance export technology complexity. The mechanism test results show that CDIID enhances export technology complexity through the channels of industrial structure upgrading and innovation ability improvement. In terms of industrial digitalization driven by digital industrialization, the channel of innovation ability improvement has a significant impact. In terms of the path of industrial digitalization to promote digital industrialization, it has an inhibitory effect on both channels in the short run. This paper provides empirical evidence and a decision-making basis for China to promote the sustainable development of the digital economy and build new advantages in international competition.

Keywords: digital industrialization; industrial digitalization; export technical complexity; nonparametric frontier



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Citation: Xu, Y.; Xu, L. The Convergence between Digital Industrialization and Industrial Digitalization and Export Technology Complexity: Evidence from China. *Sustainability* **2023**, *15*, 9081. <https://doi.org/10.3390/su15119081>

Academic Editor: Giada La Scalia

Received: 4 May 2023

Revised: 29 May 2023

Accepted: 30 May 2023

Published: 5 June 2023



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1. Introduction

The digital economy facilitates high-quality development by updating production factors, accelerating the upgrading of traditional industries, and promoting quality upgrades. With these accumulated advantages, developed countries have firmly occupied a dominant position in the global value chain (GVC), while developing countries can only obtain less domestic added value for trade. However, the digital economy creates favorable conditions for knowledge generation and technology diffusion and has a strong “penetration effect”. The “multiplier effect” and “cumulative effect” of the widespread application of digital technology have spawned new business models, providing momentum for high-quality development of regional economies [1,2]. It should be noted that digital technology has increasingly become a key driving force for reshaping a country’s competitiveness and will profoundly affect GVC specialization and governance, which is to say that developing a digital economy may provide an opportunity to build new technological advantages and improve trade profitability for developing countries, such as China. “The 14th Five-Year Plan”, which was proposed to “promote digital industrialization and industrial digitalization”, gives impetus to the deep convergence of the digital economy and real economy, the upgrade of industrial structure, and the improvement of innovation ability.

The digital economy is mainly characterized by convergence, and its development revolves around the dynamic integration of digital industrialization and industrial digitalization. The sustainable development of the digital economy means that it can meet the needs of the existing real economy without compromising the potential of future digital technology development. The Chinese government has been trying to develop an edge in technology, especially in some emerging fields. In other words, China not only wants to participate in the low-end division of labor in the GVC, but also has a strong motivation and potential to migrate to the core links of the GVC, which is embodied in the transfer from low-tech fields to high-tech fields. As digitalized technologies become extremely important and the international trade situation becomes increasingly complex, it will be of great significance to explore the correlation between the digital economy and the upgrade of the export technology structure.

In the current changing macroeconomic context, the path of high-quality exports would require technological self-reliance, which would be determined not by the quantity a country exports but by the quality. In 1961, Posner first put forward the role of technology-based competitive strengths in determining trade [3]. Hausmann expanded the concept by stating that countries with comparative advantages in exporting technology-intensive products face better growth and development than those with poorer performance in these categories [4]. In a series of papers, Hausmann proposed an empirical measure of product technical complexity, which is calculated as a weighted average of the per capita GDP of the countries that are exporting the products. Existing studies believe that the export technology complexity can well-represent the export quality of a country or region, or its technical status in the GVC [4,5]. Increasing export technology complexity has a positive impact on promoting trade upgrades and economic growth [6].

Over time, a large body of empirical and theoretical literature emerged, which focused on the digital economy and trade. The views from this body of work can be divided into three categories: digital economy, digital industrialization, and industrial digitalization. Based on the digital economy, Gonzalez and Jouanjean [7] stated that the digital economy has a positive impact on the embeddedness and upgrading of GVC. Furthermore, Li Yabo and Cui Jie [8] constructed a digital economy index using four dimensions including internet infrastructure, internet usage, internet companies, and digital finance, from which they proposed that trading companies benefit from the digital economy, causing a shift from the “quantity” to the “quality” of export products. He Wenbin [9] measured the digital economy of China’s manufacturing industry by looking at the investment in communication and information services, compared the heterogeneous role of the digital economy in promoting enterprises to improve their position in the GVC in low-knowledge-intensive and high-knowledge-intensive manufacturing sectors, and pointed out that the effect is more significant in sectors with higher R&D investment. Regarding the digital industry level, He Yu et al. [10], based on a deduction of the multi-country and multi-stage GVC competition model, suggested that developed countries empowered by artificial intelligence could reduce labor costs, promote industrial return, and expand their competitive advantages in the trade pattern. Moreover, Jorgenson et al. [11] found that the use of information and communication technology and computers plays an important role in promoting the improvement of domestic productivity and is conducive to the improvement of trade efficiency. Regarding industrial digitalization, the trend of internetization not only helps multinational companies to improve their cultural output capabilities [12] but also guides developing countries to participate in high value-added trade activities [13], thereby promoting the reshaping of the global competition pattern. As an important form of intelligent manufacturing, intelligent industrial robots can improve the quality and efficiency of export products by improving resource efficiency and reducing labor intensity [14].

Scholars are increasingly paying more attention to the impact of the digital economy on trade. A review of the research on the digital economy shows that scholars use different methods to measure its scale but neglect the consideration of the sustainable development of the digital economy. In the meantime, existing research often focuses on the overall level

of the digital economy, digital industrialization, or industrial digitalization to discuss its impact on export trade. As such, very little literature, both empirical and theoretical, has paid attention to CDIID and its impact on export technology complexity. To this end, our paper regards the digital economy as a system and employs the nonparametric stochastic frontier method based on technical efficiency to measure the relative level of digital industrialization and industrial digitalization, thereby assessing the degree of sustainable development of the digital economy. The nonparametric stochastic frontier model applies technical efficiency to the measurement of the ideal level of digital industrialization and industrial digitalization. Due to the nonparametric characteristics of the method, it can better fit the abstract process of the mutual influence of the two sub-paths of industrial digitalization driven by digital industrialization and industrial digitalization to promote digital industrialization. The export technology complexity was calculated using three methods and applied to test the robustness of the conclusion. Panel data from 30 Chinese provinces from 2013 to 2019 were used in this paper to conduct empirical tests. Our paper finds that CDIID can facilitate the improvement of export technology complexity. The contributions of this paper are summarized as follows:

1. This paper uses nonparametric stochastic frontiers to measure the convergence between digital industrialization and industrial digitalization (CDIID) to reflect the sustainability of digital economic development, providing a new perspective for the study of digital economy.
2. From the perspective of the relative development of digital industrialization and industrial digitalization, this paper reveals the impact of CDIID on export technology complexity.
3. This paper further incorporates the upgrading of industrial structure and the enhancement of innovation capabilities into the model and explores the mechanism by which CDIID and its subsystems affect the export technology complexity.

The rest of this paper proceeds as follows. Section 2 analyzes how CDIID affects export technology complexity and provides the research hypotheses. Section 3 describes the data sources, methodology, and variable definition. Section 4 provides empirical analysis and results. Section 5 summarizes the conclusion and implications of the study.

2. Theory and Hypothesis

2.1. *The Convergence between Digital Industrialization and Industrial Digitalization*

Based on a dynamic viewpoint, digital industrialization is the process of digital technology as the core element, and the scale development of products, services, and infrastructure after digital technology empowerment, resulting in the formation of a digital industry represented by the information and communication technology (ICT) industry. Backed by digital technology, industrial digitalization is the process of the digital upgrading, transformation, and reconstruction of the entire industrial chain with data as the central component, value extraction as the core, and data empowerment as the main line. Digital industrialization is the foundation of industrial digitalization and takes industrial digitalization as the ultimate goal. The development backdrop of the integration of digital technology and real industry is shaped by the process of digital industrialization and industrial digitalization, which mutually encourage, overlap, and progress [15]. In the process of digital industrialization driving industrial digitalization, the former provides the latter with technologies and supporting products, services, and solutions and promotes the optimization, upgrading, and digital transformation of traditional industries. In the process of industrial digitalization to promote digital industrialization, the former provides application scenarios for the latter and spawns new digital industries such as the digital product manufacturing industry, digital service industry, etc. The healthy development of the digital economy system should emphasize the integration of digital industrialization and industrial digitalization at a deep level and require that the two subsystems of “digital industrialization to drive industrial digitalization” and “industrial digitalization to promote digital industrialization” can coordinate with one another and that benign interactions increase efficiency [16,17].

2.2. Impact of CDIID on Export Technology Complexity

Existing studies proposed that export technical complexity can well-represent the export quality of a country or region [5], and it is a comprehensive reflection of the technical content and production efficiency of export products [4], which will be affected by driven factors such as lower trade costs [18,19], technological innovation, and technological progress [20]. As far as trade costs are concerned, CDIID regards the “no time lag” matching between innovation and application as its core feature [21], which will facilitate the simplification and digitization of production processes, reduce search and information costs, decision costs, and policing and enforcement costs. The precise matching of the R&D end and the application end can provide enterprises with accurate market information, which is conducive to the effective implementation of factor investment by enterprises, thereby reducing the costs of adjustment. The reduction in trade costs can effectively improve trade efficiency and expand market share [22]. To obtain a larger transaction scale in the export market, the competitive pressure will force enterprises to continuously improve their product innovation capabilities, promote product diversity, and realize “learning from export” [23], thereby continuously improving the technological content of export products. In terms of technology, the application of digital technology and its penetration into other economic sectors have made CDIID more prominent in economic and social activities [24]. CDIID has broken the barriers between traditional industries, enabling the resources of different industries to be well-integrated and shared. By means of knowledge spillover, technology diffusion, and human capital agglomeration, the production efficiency and technological level can be improved, ultimately promoting export technology complexity. Therefore, this paper puts forward the following assumption.

H1. *CDIID plays a positive role in promoting export technology complexity.*

2.3. Impact Mechanism Analysis

2.3.1. Industrial Structure Upgrading Mechanism

CDIID improves the original information mechanism of the enterprise, making the flow and processing of information in the production process more rapid and efficient. It can promote the optimization and improvement of the enterprise’s production factor allocation ability and the level of collaboration between elements, shorten production time, and save production costs [25,26]. Through this efficiency enhancement mode, the digital economy integrates with traditional agriculture, industry, and service industries for innovative development, integrates digital technology into all stages of production and circulation, and promotes the upgrading of industrial structure [27].

The market scale effect proposed by Krugman [28] pointed out that under the condition of incomplete market competition, the advanced level of a country’s industrial structure plays an important role in exports. The essence of industrial structure upgrading is that industries with comparatively high added value gradually replace those with a poor performance until they become the dominant industry [29]. First, the steady migration of input factors from low-productivity sectors to high-productivity sectors improves the production efficiency and technological level of the the entire region, thereby promoting the upgrading of regional export technology complexity. Second, the upgrading of industrial structure helps to form economies of scale within or between industries, which contributes to the sharing and dissemination of industrial funds and production technologies, thereby improving regional export technology complexity. Therefore, we propose the following.

H2. *CDIID promotes export technology complexity by promoting the upgrading of industrial structure.*

2.3.2. Innovation Ability Improvement Mechanism

In the face of potential competitors in the market, companies that are closer to cutting-edge technologies are more motivated to carry out R&D and innovation to maintain market competitive advantages [30,31]. The CDIID process can promote traditional enterprises

to acquire digital technology through imitation and gradually realize the digital transformation and innovation of the entire industry with the learning effect and scale effect of technological innovation [32]. By eliminating information asymmetry, the CDIID process, on the one hand, reduces the risk of R&D innovation and, on the other, motivates businesses to aggressively pursue innovation in the marketplace [33]. At the same time, the self-innovation capability of digital technology can realize instant integrated innovation in the context of the extension of the industrial chain to the industrial network, prompting the traditional industry to undergo digital transformation [34]. The rapid expansion of digital industrialization and industrial digitalization, as well as the fusion impact between the two, creates a new connectivity and sharing mode in the area, indicating a regional innovation trend.

Export technological complexity is a function of innovation, and both innovation resources and innovation output can directly or indirectly affect export technology complexity [35]. On the one hand, technological innovation, organizational innovation, and management innovation behaviors will enhance enterprise efficiency and product competitiveness. According to the heterogeneity of “new” new trade theory, enterprise efficiency is an important foundation for enterprise product export. Therefore, innovative behaviors that improve enterprise efficiency can create conditions for expanding export markets of enterprise products. On the other hand, innovation will directly increase the technical content of enterprise products. Enterprise R&D and innovation investment increase the technical content of export-oriented industries, which can strengthen the impact on the complexity of export technology [36]. Based on these considerations, the following hypothesis is proposed.

H3. *CDIID promotes export technology complexity by improving innovation ability.*

3. Data and Econometric Model

3.1. Data Sources

To test our hypotheses, we use data on a sample of provinces in China from 2013–2019. The original sample is processed as follows: (1) we select 30 provincial regions (except Tibet, Hong Kong, Macao, and Taiwan) as the sample to ensure the integrity of the data; (2) we approximate certain missing variables using the average growth rate; (3) we winsorize all continuous variables at the 1% and 99% levels to avoid the influence of extreme values. Finally, a set of balance panel data consisting of 30 provinces is obtained. The data for calculating the export technology complexity mainly come from “China Customs Data”. The level of CDIID is obtained from the “China Statistical Yearbook”, “Provincial Statistical Yearbook”, “Chinese Research Data Services Platform”, and “Wind Database”.

3.2. Measurement of Variables

3.2.1. Dependent Variables

The dependent variable of this paper is the export technology complexity. As indicated in the following equation, we use the two-step method of Hausmann et al. [4] to determine the technical complexity of each product using HS6 code export data.

$$Prody_p = \frac{\bar{a}_i}{\bar{a}_i} \frac{\frac{x_{ip}}{X_i}}{\frac{x_{ip}}{X_i}} \times agdp_i \quad (1)$$

where p represents the product; t denotes the province; $Prody_p$ stands for the technical complexity of the product (p); x_{ip} denotes the export value of the product (p) in the province (i); and X_i stands for the total export value of province i . $agdp_i$ represents the real GDP per capita of the province (i).

According to the export of each province, the product complexity is aggregated to the provincial level, as shown in the following formula.

$$ETC_1 = \hat{\alpha}_p \frac{x_{ip}}{X_i} \times Prody_p \quad (2)$$

where ETC_1 is export technology complexity. Since the formula is predicated on the idea that all products with the same HS6-bit code are of equal quality, it does not reflect reality. To address this issue, this paper employs the method of Sheng Bin and Mao Qilin [37] to determine the product quality adjustment factor:

$$q_{ip} = \frac{price_{ip}}{\hat{\alpha}_i \mu_{ip} \times price_{ip}} \quad (3)$$

$$Prody_p^a = q_{ip}^\lambda \times Prody_p \quad (4)$$

where $price_{ip}$ represents the export unit price of the product (p) in the province (i); μ_{ip} represents the proportion of the export value of the product (p) in the province (i) in the total export volume of the country; $Prody_p^a$ indicates the technical complexity of the product (p) after considering the quality, and λ is set to 0.2. The product complexity is aggregated to the provincial level ESI_2 , following the previous Equation (2).

In addition, due to the overestimation of technical complexity caused by the import of high-tech intermediate products in trade, we only use the samples of general trade to measure the export technical complexity ESI_3 based on previous research [38].

3.2.2. Independent Variables

The independent variable of this paper is the convergence between digital industrialization and industrial digitalization (CDIID). In terms of the path of digital industrialization to drive industrial digitalization, the former is “factors of production”, and the latter is “output”, whereas the situation is reversed on the path of industrial digitalization promoting digital industrialization. First, the actual level of digital industrialization and industrial digitalization must be determined. The second phase is to estimate the optimal level of digital industrialization and industrial digitalization. The third step is to calculate the total fusion coefficient using the two subsystem fusion coefficients of “digital industrialization to drive industrial digitalization” and “industry digitalization to promote digital industrialization”.

Specifically, the first step is to measure the level of digital industrialization and industrial digitalization using principal component analysis (PCA). In terms of digital industrialization, this article examines the three dimensions of digital infrastructure, digital environment, and digital talents and develops indicators for measuring the extent of digital industrialization in each province. Meanwhile, this paper measures the amount of industrial digitalization in each province based on three dimensions including digital finance [39], digital transactions [40], and digital assistance [41]. Table 1 details a selection of specific indicators.

In the second phase, the nonparametric local linear regression in the stochastic frontier model developed by Henderson et al. [42,43] and Zhou et al. [44] was applied to estimate the optimal level of digital industrialization and industrial digitalization. The model for digital industrialization to drive industrial digitalization is set as:

$$IND_{it} = y(DIG_{it}, i, t) + \varepsilon_{it} \quad (5)$$

Similarly, the model for industrial digitalization to promote digital industrialization is:

$$DIG_{it} = y(IND_{it}, i, t) + \varepsilon_{it} \quad (6)$$

where i and t refer to provinces and years, respectively; IND_{it} and DIG_{it} represent the actual levels of industrial digitalization and digital industrialization, respectively; $f(DIG_{it}, i, t)$ and $f(IND_{it}, i, t)$ respectively represent the optimal level of industrial digitalization required by the development of digital industrialization and the optimal level of digital industrialization required by the development of industrial digitalization; and ε_{it} represents the random disturbance term.

Table 1. Indicator measurement system.

Primary Indicators	Secondary Indicators	Tertiary Indicators
Digital Industrialization	Digital Infrastructure	Length of optical cable lines
		Number of mobile phone base stations
	Digital Environment	Number of internet broadband access ports
		Number of internet domain names
		Software industry revenue
		Information services output
	Digital Talent	Total telecommunications business
		Number of people employed in information services
		Number of people working in the software industry
		R&D staff full time equivalent
Industrial Digitalization	Digital Finance	Breadth of digital financial coverage
		Depth of use of digital finance
		Digitalization of digital finance
	Digital Transactions	Online mobile payment levels
		E-commerce transactions
		Number of e-commerce businesses conducted
	Digital Assisatance	Number of companies with websites
		Number of computers in use at the end of the period
		Mobile phone penetration rate

In the third step, the subsystem coefficient of “industrial digitalization driven by digital industrialization” $CDIID_{it}^1$ reflects the gap between the industrial digitalization level required by the digital industrialization of the province (i) in the year (t) and this indicator in all provinces in the same year.

$$CDIID_{it}^1 = \exp(\hat{y}(DIG_{it}, i, t) - \max_{i=1, \dots, n} \hat{y}(DIG_{it}, i, t)) \quad (7)$$

Similarly, the subsystem coefficient of “industrial digitalization promotes digital industrialization” is $CDIID_{it}^2$.

$$CDIID_{it}^2 = \exp(\hat{y}(IND_{it}, i, t) - \max_{i=1, \dots, n} \hat{y}(IND_{it}, i, t)) \quad (8)$$

The $CDIID$ coefficient $CDIID_{it}$ was finally computed utilizing the coordinated development coefficient method [45].

$$CDIID_{it} = \frac{\min(CDIID_{it}^1, CDIID_{it}^2)}{\max(CDIID_{it}^1, CDIID_{it}^2)} \quad (9)$$

where $CDIID_{it} \in [0, 1]$; the closer the value is to 1, the better the convergence between digital industrialization and industrial digitalization and the higher the efficiency of the development of the digital economy system.

3.2.3. Mediating Variables

The upgrading of the industrial structure refers to the transfer from the primary industry to the secondary and tertiary industries, ultimately achieving high-level service in the overall industry. Y_i is the total output of the i -th industry, where i is the industrial type (1, 2, and 3 for the primary, secondary, and tertiary industries, respectively).

$$UG = \sum_{i=1}^3 Y_i \times i \quad (10)$$

In addition, this research employs the methodology of Xu Ziyao et al. [46], assesses regional innovation capability from the standpoint of innovation output, and uses the total number of patent authorizations as a proxy variable for measuring regional innovation capability.

3.2.4. Control Variables

Based on the existing literature [47–49], we control for the following variables: the degree of regional openness (Open), as measured by foreign trade dependence; government support (Gov), as measured by the ratio of scientific research expenditure to GDP; human capital (Lnhr), as measured by the logarithm of the number of high school graduates in the region; foreign capital (Fdi), as measured by the ratio of total foreign direct investment to GDP; and economic development level (Lngdp), as measured by the ratio of regional GDP.

The definitions of the key variables are provided in Table 2 below.

Table 2. Definition of key variables.

Variable	Symbol	Meaning of Variables
Export Technical Complexity 1	LnETC	Export technology complexity based on Hausmann's two-step method
Export Technical Complexity 2	LnETC2	Export technical complexity corrected for product quality
Export Technical Complexity 3	LnETC3	Technical complexity of exports considering only general trade scenarios
The Convergence between Digital Industrialization and Industrial Digitalization	CDIID	Measurement based on nonparametric stochastic frontier and coordination coefficient
Digital Industrialization Factor (abbreviated)	CDIID1	"Digital industrialization promotes industrial digitalization" subsystem integration coefficient
Industrial Digitalization Factor (abbreviated)	CDIID2	"Industrial digitalization promotes digital industrialization" subsystem integration coefficient
The Upgrading of Industrial Structure	UG	The main composition of industry is gradually transferred from the primary industry to the secondary and tertiary industries
Regional Innovation Capacity	Lnpatent	Logarithm of the number of patents granted in the province
Human Capital	Lnhr	Logarithm of the number of students graduating from high school in the province
Level of Government Support	Gov	Fiscal expenditure on scientific research as a proportion of GDP
Business Environment for Foreign Investors	Fdi	Direct foreign investment in the province
Degree of Regional Openness	Open	Foreign trade dependence
Level of Economic Development	Lngdp	Logarithm of regional GDP

3.3. Model Specification

The benchmark regression model to investigate the nexus between CDIID and export technology complexity is reported in Equation (11).

$$LnETC_{it} = \alpha_0 + \alpha_1 CDIID_{it} + \sum_{m=1}^M \beta_m Controls_{it} + \varepsilon_{it} \quad (11)$$

where the term $LnETC_{it}$ is the export technological complexity; $CDIID_{it}$ is the convergence of digital industrialization and industrial digitalization; $Controls_{it}$ is the regression analysis control variable.

To describe the mechanism by which $CDIID_{it}$ affects the export technical complexity, this paper uses industrial structure upgrading (UG) and innovation capability improvement (Lnpatent) as mediating variables and establishes recursive Equations (12) and (13), where M_{it} is the mediating variable.

$$M_{it} = \beta_0 + \beta_1 CDIID_{it} + \sum_{m=1}^M \beta_m Control_{it} + \varepsilon_{it} \quad (12)$$

$$LnETC_{it} = \alpha_0 + \alpha_1 CDIID_{it} + \alpha_2 M_{it} + \sum_{m=1}^M \beta_m Control_{it} + \varepsilon_{it} \quad (13)$$

4. Results and Discussion

4.1. Descriptive Statistics

Table 3 presents the descriptive statistics for variables in our models. The independent variable $CDIID$ ranges from 0.573 to 0.993, with a mean value of 0.810, demonstrating a large variance in $CDIID$ amongst provinces in China. The disparity between the average value of export technical complexity before and after quality correction of export products is rather pronounced, showing that the technical complexity of identical items of varying quality differs significantly. The average value of the subsystem fusion coefficient indicates that the convergence effect of industrial digitalization promoting digital industrialization is marginally superior to the path of digital industrialization driving industrial digitalization. Overall, the development of the digital economy system across provinces is exceedingly disparate, and the driving capacities of digital industrialization and industrial digitalization have not been fully realized.

Table 3. Summary Statistics.

Variables	Mean	Standard Deviation	Minimum	Maximum
LnETC	9.128	0.132	8.888	9.359
LnETC2	7.101	0.345	6.481	7.744
LnETC3	7.027	0.345	6.515	7.681
CDIID	0.810	0.116	0.573	0.993
CDIID1	0.526	0.143	0.380	0.961
CDIID2	0.579	0.160	0.317	0.963
UG	2.381	0.113	2.225	2.696
Lnpatent	10.162	1.312	7.359	12.444
Lnhr	12.230	0.768	10.813	13.358
GOV	0.016	0.009	0.005	0.040
Open	0.249	0.088	0.128	0.453
Lngdp	9.881	0.814	7.977	11.245

4.2. The Convergence between Digital Industrialization and Industrial Digitalization

Based on the nonparametric stochastic frontier model, this paper measured the level of $CDIID$ of different provinces from 2013 to 2019. Table 4 represents the results. Horizontal comparisons revealed that there was no association between $CDIID$ and economic development level. In 2018, the convergence coefficients of Gansu and Yunnan were as high as 0.9439 and 0.9926, respectively, whereas Beijing's was just 0.5733. A longitudinal study revealed that the $CDIID$ levels of all provinces varied substantially. Between 2014 and 2016, the level of $CDIID$ of Beijing and Shanghai was high but not in following years. This demonstrates that in the early years, the benefits of digital technology began to appear, and areas with faster economic development led in implementing industrial digitalization, which facilitated the real economy more effectively. With the further expansion of industrial digitalization and the failure of breakthroughs in core technologies in key fields, the level

of digital industrialization began to restrict the development of CDIID, and CDIID levels declined in the following years. In economically underdeveloped areas, however, the overall level of digitalization is generally low, and the industrial digitalization expansion is moderate, which can keep pace with the development of digital industrialization. Thus, CDIID performs better than economically developed provinces. In general, CDIID in provinces in different years exhibit unstable features.

Table 4. The Convergence between Digital Industrialization and Industrial Digitalization.

	2013	2014	2015	2016	2017	2018	2019
Beijing	0.8840	0.9088	0.9133	0.9152	0.7769	0.5733	0.5733
Tianjin	0.6951	0.8917	0.9436	0.8473	0.9109	0.7758	0.5979
Hebei	0.7111	0.7192	0.9693	0.7940	0.7265	0.9239	0.9144
Shanxi	0.5876	0.8113	0.7874	0.8970	0.8741	0.9926	0.7655
Inner Mongolia	0.6279	0.7292	0.9581	0.7934	0.9926	0.8469	0.6966
Liaoning	0.6962	0.7345	0.7947	0.8009	0.8050	0.8485	0.7519
Jilin	0.6225	0.7949	0.8106	0.7889	0.9277	0.9037	0.6292
Heilongjiang	0.6796	0.7045	0.8550	0.7153	0.7866	0.8703	0.7889
Shanghai	0.6946	0.9895	0.9300	0.8978	0.8595	0.6224	0.5733
Jiangsu	0.9356	0.9422	0.8516	0.7328	0.7490	0.8933	0.9693
Zhejiang	0.9926	0.9721	0.9630	0.8271	0.8192	0.9739	0.8872
Anhui	0.6399	0.9811	0.9421	0.9668	0.8419	0.9379	0.7793
Fujian	0.6703	0.7739	0.9893	0.8932	0.9914	0.8879	0.7329
Jiangxi	0.5733	0.7231	0.8039	0.8350	0.8675	0.7985	0.7766
Shandong	0.8206	0.7874	0.8712	0.8441	0.8954	0.8882	0.8314
Henan	0.7002	0.8471	0.7842	0.7215	0.7820	0.9706	0.8644
Hubei	0.6474	0.8550	0.9528	0.8116	0.8693	0.8777	0.6942
Hunan	0.6363	0.7279	0.8656	0.8691	0.8150	0.9461	0.8125
Guangdong	0.9612	0.9900	0.9926	0.9926	0.9926	0.9926	0.9926
Guangxi	0.5733	0.9716	0.7736	0.7369	0.8664	0.8829	0.8476
Hainan	0.6239	0.7794	0.8961	0.8350	0.9313	0.7635	0.5733
Chongqing	0.6030	0.6720	0.8461	0.8886	0.8826	0.8560	0.6684
Sichuan	0.6715	0.6703	0.7170	0.7419	0.7867	0.8834	0.9895
Guizhou	0.5733	0.8042	0.7956	0.7356	0.8422	0.8542	0.8008
Yunnan	0.6134	0.6466	0.8451	0.7401	0.7579	0.9926	0.7839
Shaanxi	0.5733	0.7486	0.7753	0.6591	0.8251	0.9275	0.7573
Gansu	0.6619	0.6876	0.8783	0.7354	0.8453	0.9439	0.7721
Qinghai	0.6470	0.8016	0.8527	0.8938	0.9080	0.7741	0.6615
Ningxia	0.6257	0.7777	0.9926	0.8495	0.9802	0.8133	0.6210
Xinjiang	0.5733	0.6538	0.7872	0.7781	0.7808	0.9889	0.8174

Data source: calculated based on the “China Statistical Yearbook”, “Provincial Statistical Yearbook”, “Chinese Research Data Services Platform”, and “Wind Database”.

4.3. Benchmark Empirical

The results of the Hausman test indicate that the fixed-effects model outperforms the random-effects model. Table 5 represents the results of benchmark regression of

CDIID on the export technology complexity. Column (1) examines how CDIID affects export technology complexity without adding any control variables. The coefficient of the independent variable is significantly positive, which means that CDIID has a positive effect on export technical complexity. Based on column (1), columns (2)–(6) add the control variables step by step. In the process of gradually introducing the control variables, the regression coefficient of CDIID is significant at a 1% level. This indicates that CDIID can indeed increase export technology complexity.

Table 5. Benchmark regression results.

Variables	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
CDIID	0.292 *** (0.0673)	0.236 *** (0.0636)	0.220 *** (0.0533)	0.245 *** (0.0535)	0.246 *** (0.0496)	0.109 *** (0.0327)
Open		1.801 *** (0.340)	1.071 *** (0.297)	0.950 *** (0.297)	0.546 * (0.285)	1.475 *** (0.190)
Gov			35.17 *** (4.024)	35.72 *** (3.975)	30.14 *** (3.820)	7.190 ** (2.824)
Lnhr				−0.192 ** (0.0788)	−0.138 * (0.0737)	−0.109 ** (0.0470)
Fdi					1.515 *** (0.276)	0.733 *** (0.183)
Lngdp						0.433 *** (0.0270)
Constant term	8.892 *** (0.0549)	8.490 *** (0.0916)	8.113 *** (0.0880)	10.46 *** (0.968)	9.900 *** (0.903)	5.563 *** (0.636)
Number of periods	7	7	7	7	7	7
Number of provinces	30	30	30	30	30	30
R ²	0.095	0.218	0.454	0.472	0.549	0.818

Note: (1) standard errors in parentheses; (2) asterisks indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Robustness Test

In this research, the robustness is evaluated using the following methods, and the findings are presented in Table 6.

Table 6. Robustness test results.

Variables	(1) LnETC2	(2) LnETC3	(3) LnETC	(4) LnETC
CDIID	0.217 ** (0.114)	0.297 *** (0.108)		
DIG			0.143 *** (0.0307)	
IND				0.0409 ** (0.0229)
Constant term	4.753 ** (2.214)	4.158 ** (2.093)	5.691 *** (0.616)	5.134 *** (0.632)
Control variables	YES	YES	YES	YES
Number of periods	7	7	7	7
Number of provinces	30	30	30	30
R ²	0.273	0.378	0.828	0.810

Note: (1) standard errors in parentheses; (2) asterisks indicate significance levels: ** $p < 0.05$, *** $p < 0.01$.

The dependent variables are remeasured. This paper remeasures the technical complexity of the province using multiple approaches. In column (1), technical sophistication is adjusted for product quality, while in column (2), only general trade is taken into consideration. The fact that the coefficients of CDIID are all significantly positive demonstrates the reliability of the benchmark regression results.

The independent variables are remeasured. Different from the discussion on the scale of the digital economy, this paper constructs the CDIID to measure the sustainable development of a digital economy, mainly considering the interactive relationship between the two paths of industrial digitalization driven by digital industrialization and digital industrialization promoted by industrial digitalization. That is to say, we pay more attention to the relative level of digital industrialization and industrial digitalization, while ignoring the consideration of its absolute level. Therefore, in addition to using CDIID as the core explanatory variable in the benchmark model, this paper replaces the core explanatory variable with the levels of digital industrialization and industrial digitalization that constitute the digital economy for a robustness test. In particular, this paper replaces the independent variable, which is “digital industrialization” in column (3), whereas “industrial digitalization” is in column (4). Regardless of the relative or absolute level of any structure inside the digital economy, the regression coefficients are all significantly positive, as shown by the results.

4.5. Endogeneity Test

The least square estimation of the panel fixed effects model in the benchmark regression model may have endogeneity problems. On the one hand, the CDIID may have reverse causality on export technology complexity. On the other hand, omitted variables may also lead to the existence of unavoidable endogeneity problems in OLS.

To solve the problem of reverse causality, the lag term $CDIID_{t-1}$ is employed as an instrumental variable, and the model for the lag variable takes into account the influence of time. The findings of the 2SLS regression are displayed in columns (1) through (3) of Table 7. These results indicate that CDIID can indeed significantly affect the technological upgrading of export products, which is generally consistent with previous findings.

Table 7. Endogeneity test results.

Variables	L.CDIID			Bartik_IV		
	(1) LnETC	(2) LnETC2	(3) LnETC3	(4) LnETC	(5) LnETC2	(6) LnETC3
CDIID _{t-1}	0.807 *** (0.254)	0.666 ** (0.647)	0.666 ** (0.647)			
Bartik_IV				0.242 *** (4.09)	0.307 * (1.46)	0.282 ** (1.40)
Constant term	8.428 *** (0.302)	9.270 *** (0.770)	7.712 *** (0.808)	5.061 *** (8.33)	3.746 * (1.74)	2.766 (1.34)
Control variables	YES	YES	YES	YES	YES	YES
Number of periods	7	7	7	7	7	7
Number of provinces	30	30	30	30	30	30
R ²	0.134	0.312	0.234	0.823	0.267	0.358

Note: (1) standard errors in parentheses; (2) asterisks indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Second, we use shift-share design to construct suitable instrumental variables, also known as Bartik instrumental variables, to solve possible endogeneity problems. The basic idea is to use the initial share composition of the analysis unit and the overall growth rate to simulate the estimated value over the years. The estimated value is highly correlated with the actual value but not correlated with other residual items. The independent variable in this paper is CDIID. Then, the Bartik instrumental variable ($CDIID_IV_{it}$) in the paper can be expressed as:

$$CDIID_IV_{it} = CDIID_{it_0} \times (1 + G_{it}) \quad (14)$$

where $CDIID_{it_0}$ is the initial value of a province's CDIID, and G_{it} is the growth rate of CDIID in year t relative to the initial year t_0 . The results in columns (4)–(6) show that the instrumental variable results are consistent with previous findings, which again supports the robustness of the empirical results obtained in this study.

4.6. Impact of the Subsystem of CDIID on Export Technology Complexity

CDIID is the outcome of two subsystems working together: “digital industrialization drives industrial digitalization” and “industrial digitalization promotes digital industrialization”. This paper further explores the impact of the subsystem of CDIID on export technology complexity. The coordinated development of digital industrialization and industrial digitalization will contribute to the improvement of export technological complexity.

On the path of industrial digitalization driven by digital industrialization, digital industrialization can be seen as “input” and industrial digitalization can be seen as “output”. The results are displayed in columns (1)–(2) of Table 8; the better the convergence driven by digital industrialization, the higher the export technology complexity. Under the established level of digital industrialization, businesses apply digital technology and capitalize on the digitalization trend to increase the technological content of export products.

Table 8. Results based on subsystems of CDIID on Export Technology Complexity.

Variables	(1) LnETC	(2) LnETC	(3) LnETC	(4) LnETC
CDIID1	0.209 ** (0.0835)	0.190 *** (0.0623)		
CDIID2			−0.850 *** (0.0333)	−0.400 *** (0.0640)
Constant term	9.019 *** (0.0460)	5.161 *** (0.621)	9.621 *** (0.0196)	7.160 *** (0.667)
Control variables	NO	YES	NO	YES
Number of periods	7	7	7	7
Number of provinces	30	30	30	30
R2	0.753	0.816	0.784	0.842

Note: (1) standard errors in parentheses; (2) asterisks indicate significance levels: ** $p < 0.05$, *** $p < 0.01$.

Moreover, due to the near-zero marginal cost of data elements, the explosive innovation spawned by the digital-industrialization-driven path should play a key role in improving export technology complexity.

Industrial digitalization is considered to be “input” along the path to promote digital industrialization, whereas digital industrialization is considered the “output”. The results are displayed in columns (3)–(4), and the integration coefficient of industrial digitalization to promote digital industrialization is negative. This paper argues that, first, digital industrialization lags behind the development of industrial digitalization in China, and the core technologies in key fields have not been successfully developed, which impedes the convergence of digital technology and the real economy [50]. Second, though the degree of industrial digitalization development is superior to that of digital industrialization, there is still significant differences in the level of industrial digitalization among different industries [51]. Third, the digital transformation of market participants has a crowding-out effect on nondigital innovation behaviors [52]. In general, the disorderly expansion of the digital economy will have “destructive” consequences for the real economy, and the resulting unbalanced development will exacerbate the development gap between local industries, which will not only be detrimental to the rationalization of the industrial structure but also have a negative impact on export technology complexity and hinder regional coordinated development [53].

4.7. Mechanism Analysis

4.7.1. The Upgrading of Industrial Structure

To further study the mechanism between CDIID and export technology complexity, this paper takes the upgrading of industrial structure as the mediating variable and uses the causal-step approach to examine the mediating effect [54]. Table 9 presents the estimation results of the mechanism analysis. The impact of CDIID and subsystems on the upgrading of industrial structure is examined in columns (1) through (3). The coefficients of CDIID

and the process of “industrial digitalization to promote digital industrialization” (CDIID2) are 0.0907 and -0.204 , respectively, which are significant at a 1% level, whereas the process of “digital industrialization to drive industrial digitalization” (CDIID1) on the upgrading of industrial structure did not pass the significance test. The results show that CDIID has promoted the upgrading of the industrial structure. However, at this stage, it is still constrained by core technologies in key fields and cannot effectively achieve the upgrading of industrial structure brought about by technological breakthroughs. Furthermore, the results of columns (4)–(5) show that the coefficient of the upgrading of industrial structure is significantly positive at a 1% level, indicating CDIID drives the upgrade of export technology complexity by upgrading industrial structure.

Table 9. Mechanism test I: industrial structure upgrading.

Variables	(1) UG	(2) UG	(3) UG	(4) LnETC	(5) LnETC
CDIID	0.0907 *** (0.0212)			0.0527 * (0.0315)	
CDIID1		0.0379 (0.0422)			
CDIID2			-0.204 *** (0.0442)		-0.293 *** (0.0634)
UG				0.626 *** (0.107)	0.524 *** (0.103)
Constant term	1.211 *** (0.413)	0.803 * (0.420)	1.858 *** (0.461)	4.805 *** (0.597)	6.186 *** (0.652)
Control variables	YES	YES	YES	YES	YES
Number of periods	7	7	7	7	7
Number of provinces	30	30	30	30	30
R2	0.710	0.681	0.714	0.848	0.863
Sobel Test				3.453 (0.0006)	-3.425 (0.0006)

Note: (1) standard errors in parentheses; (2) asterisks indicate significance levels: * $p < 0.1$, *** $p < 0.01$.

4.7.2. Innovation Capacity Enhancement

Table 10 presents the results of the innovation mechanism. The number of patents with one delayed period is used as a mediating variable because the patents require at least a few months from application to granting. The effects of CDIID and subsystems on regional innovation capabilities are examined in columns (1)–(3), where the coefficients of CDIID and CDIID1 are significantly positive, while the coefficient of CDIID2 is notably negative. From the standpoint of innovation and R&D risks, this article argues that there is a “gap” between digital technology and digital applications. The breakthroughs in core technologies in key fields demand a substantial investment, and it faces a risk that the technology will not be able to enhance the innovation capacity in the short term. The results in columns (4)–(6) indicate that the coefficient of regional innovation capability is significantly positive, indicating that CDIID can boost the upgrade of China’s export technology complexity by promoting innovation.

Table 10. Mechanism test II: innovation capacity enhancement.

Variables	(1) Lnpatent	(2) Lnpatent	(3) Lnpatent	(4) LnETC	(5) LnETC	(6) LnETC
CDIID	0.387 *** (0.141)			−0.00235 (0.0365)		
CDIID1		0.521 ** (0.220)			0.104 * (0.0556)	
CDIID2			−1.207 *** (0.296)			−0.233 *** (0.0789)
Lnpatent				0.0699 *** (0.0211)	0.0771 *** (0.0207)	0.0496 ** (0.0211)
Constant term	−3.460 (2.871)	−5.276 * (2.783)	0.392 (3.059)	5.352 *** (0.729)	5.337 *** (0.699)	6.411 *** (0.773)
Control variables	YES	YES	YES	YES	YES	YES
Number of periods	7	7	7	7	7	7
Number of provinces	30	30	30	30	30	30
R ²	0.762	0.759	0.775	0.795	0.800	0.807
Sobel Test				1.915 (0.0554)	1.998 (0.0457)	−2.037 (0.0417)

Note: (1) standard errors in parentheses; (2) asterisks indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions

This study builds an indicator system for evaluating digital industrialization and industrial digitalization from the internal structure of the digital economy and measures the convergence between digital industrialization and industrial digitalization. Based on this, we measured the provincial CDIID and explored the effect and mechanism of the overall system and subsystem of CDIID on export technical complexity using panel data from various provinces in China from 2013 to 2019. The results indicate the following: first, there is no association between CDIID and provincial economic development levels. Specifically, CDIID in provinces in different years exhibit unstable features, as well as there being a gap between the overall level and the frontier. Second, CDIID can facilitate an increase in export technical complexity, and the path of “digital industrialization to drive industrial digitalization” plays a key role in improving export technology complexity. However, in terms of the path of industrial digitalization to promote digital industrialization, it has a negative impact on export technical complexity because of factors such as the crowding-out effect of resources and the inability of core technology breakthroughs. Third, CDIID improves export technical complexity through two channels including industrial structure upgrading and innovation ability improvement. In terms of digital industrialization to drive the industrial digitalization path, the channel of the improvement of innovation ability has a significant impact; in terms of industrial digitalization to promote digital industrialization, it has an inhibitory effect on both channels in the short run.

Based on the above conclusions, we can glean some managerial insights to assist Chinese policymakers in rationally planning the sustainable development of the digital economy and promoting the improvement of the export technology structure through sustainable innovation. The facets include:

(1) The government should make greater efforts to accelerate the development of new digital industries. First, accelerate the development of new-generation digital technologies such as artificial intelligence, big data, and blockchain, break through the bottleneck of core key technologies, and build a solid technical foundation for digital transformation. Second, vigorously develop the technology-based digital economy, especially to promote the efficient allocation of data-generation elements, and fully release the huge potential of data as an important market element. Third, the high penetration, high mobility, and high

spillover characteristics of digital technology and data information should be utilized to construct an industrial network with established key industries as the core and emerging industries as the support. New industries, formats, and models can be introduced by maximizing the effectiveness of the digital economy in facilitating industrial innovation and structural upgrading. Fourth, in terms of human resources, China should strengthen the training and incentives of digital talents and enhance the ability of digital technology innovation. The key to the development of CDIID lies in the ability to innovate, and digital talents are an important guarantee for the improvement of digital technology. China should actively build a sound digital economy talent development system with adequate talent support, practical evaluation and incentives, and smooth flow of talent and accelerate the formation of an internationally competitive talent system advantage.

(2) The government should actively promote the integration of the digital economy and the real economy. Policymakers should help construct the core industries of the digital economy, exploit the agglomeration effect of the digital economy industry, promote the deep integration of upstream and downstream industries in the value chain, enable traditional industries to transform and upgrade, and establish a digital economy industrial belt. There should be cultivation of new markets and growth points of industries with the new model of the digital economy, which should be actively integrated into the global industrial chain, and a focus on the digitization, networking, and intelligent upgrading and transformation of the infrastructure of the host nation.

(3) The government should also improve the planning and layout of digital economy construction, focusing on the long-term impact of CDIID. The study of this paper finds that the development of digital industrialization is not conducive to the improvement of the complexity of export technology, and there may be a crisis of short-term resource preemption. To this end, the government should seize the opportunity of the digital economy and improve the construction of digital infrastructure. At the same time, when planning digital construction, it is necessary to comprehensively consider the software and hardware environment of various places and rationally plan the digital economy development network according to the urban spatial layout and industrial distribution, so as to realize the rapid flow and optimal allocation of resources between cities and within enterprises.

The basic limitation of the study is that there are problems with the data quality of the past three years because of the impact of COVID-19, which broke out in December 2019, and the research data are only intercepted to 2019. Second, existing studies have proved that the digital economy has spatial spillovers. As for the future expanded study, it can further develop research on the spatial spillovers of CDIID on export technology complexity. It will enrich the research in related fields, which is also one of the directions of future work of this research.

Author Contributions: Conceptualization, Y.X.; methodology, Y.X. and L.X.; validation, L.X.; data curation, Y.X. and L.X.; writing—original draft preparation, Y.X. and L.X.; writing—review and editing, Y.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the “Humanities and Social Sciences Research Planning Fund Project of the Ministry of Education”, grant number 20YJA630013; the “National Social Science Fund of China”, grant number 21BGL119; and the “General Scientific Research Project of Zhejiang Provincial Department of Education”, grant number Y202250494.

Acknowledgments: The authors are grateful to the anonymous reviewers and editors for their comments and suggestions on this article.

Conflicts of Interest: The authors declare no conflict of interest.

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