Environmental Science and Pollution Research (2021) 28:54826–54841
https://doi.org/10.1007/s11356-021-14474-5

RESEARCH ARTICLE

Digitalization and environment: how does ICT affect enterprise environmental performance?

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Received: 8 March 2021 / Accepted: 14 May 2021 / Published online: / Published online: 20 May 2021

Abstract

Despite the increasing use of digital technology in industrial production, how industrial digitalization affects the environmental performance of production activities remains unclear. This research contributes to the literature on the relationship between industrial digitalization and enterprise environmental performance by employing a large sample of Chinese manufacturing enterprises. Results indicate that the environmental performance of manufacturing enterprises has been significantly improved in the process of industrial digital transformation. Structural and technology effects are the transmission channels; additionally, structural effect is the main contributor to the positive environmental effects of information and communications technology (ICT) penetration. Industrial digitalization reduces the production scale of heavy-polluting enterprises and improves product innovation and green total factor productivity, but it has an insignificant effect on total factor productivity. Moreover, industrial digitalization improves enterprise environmental performance by introducing front-end cleaner production technologies, rather than by increasing pipe-end pollutant treatment facilities.

Keywords Industrial digitalization · Environmental performance · Structural effect · Technology effect · Information and communications technology (ICT)

JEL Classification Q56 · O13 · L86

Introduction

With the development of the big data analytic, cloud computing, artificial intelligence, Internet of Things, and other next-generation information and communications technology (ICT), the industrial sectors around the world are at a critical stage of integration with the digital economy. Digital transformation has gradually become a new pathway for the sustainable development of industrial economy, and digital technology has become the driving force of economic growth (Kunkel and Matthess 2020). In addition, environmental quality has been declining in industrializing countries, and the environmental performance of manufacturing enterprises in these countries tends to be poor (Wen and Lee 2020; Yuan et al. 2020). Can industrial digital transformation break the mantra that industry is inseparable from pollution? Judging from China's experience that environmental performance has been significantly improved during the past two decades of the rapid development of the ICT industry, digital technologies should have contributed to improving environmental performance and industrial green development.

Digital technology includes the adoption of the Internet or smart devices to collect, store, analyze, and share information, including the application of ICT to improve the efficiency of production and economic activities. However, two confusing words exist in terms of digital transformation: digitization and digitalization. Digitization refers to the transition from analog to digital, whereas digitalization refers to the integration of digital technologies and various industrial processes of

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manufacturing enterprises. As defined by Lange et al. (2020), digitalization means the increase of ICT in the whole economy and society. Therefore, the digital transformation of economy and society in the digital economy can be expressed by the word "digitalization," and industrial digitalization refers to the adoption of ICT or digital technologies in industrial development. This study holds that the concepts of industrial digital transformation and industrial digitalization are consistent, and both are based on the application of ICT.

Although the trend of industrial digital transformation is inevitable and brings opportunities to the development of the industry, the relationship between industrial digitalization and enterprise performance in economic and environmental terms remains understudied (Li et al. 2020). The Solow Productivity Paradox, which describes the paradoxical relationship between high-speed information technology investment and slow-growing productivity, has been a widely discussed topic in the economics literature (Oliner and Sichel 2000; Acemoglu et al. 2014). Certain contributions sustain the assertion for the existence and non-existence of ICT Productivity Paradox. However, most studies argue that enterprises not only use ICT to improve process efficiency but also improve the capabilities of product design and service innovation (Neuhofer et al. 2015; Martínez-Caro et al. 2020). An explanation of ICT Productivity Paradox is that ICT is used to achieve some social goals, such as reducing labor fatigue and reducing pollution, which cannot be observed in traditional statistical indicators. As China has experienced over the past few decades, ICT may help decouple industrial sector growth from various environmental indicators.

The net impact of ICT on the environment is not only mixed in empirical evidence but also theoretically ambiguous (Dedrick 2010; Lange et al. 2020). Empirically, some studies show the environmental benefits from ICT adoption (Lu 2018; Khan 2019), whereas others find that ICT adoption increases energy consumption and pollution (Park et al. 2018; Avom et al. 2020). Berkhout and Hertin (2001), Beier et al. (2018), and Kunkel and Matthess (2020) propose a theoretical framework, which classifies the environmental effects of ICT adoption into two aspects, to reconcile the two pieces of conflicting evidences. The first is the direct effect, which means that ICT increases the energy consumption and resource use in the life cycle, thus reducing environmental performance (Berkhout and Hertin 2001). The second is the indirect effect, which indicates that ICT adoption affects the production scale, product structure, and process efficiency, thus affecting environmental performance (Beier et al. 2018; Kunkel and Matthess 2020). The above two effects form a nonlinear relationship between ICT penetration and pollutant emissions, leading to inconsistent conclusions drawn from different samples (Higón et al. 2017; Avom et al. 2020). Therefore, clarifying how industrial digitalization affects the environment is more important than identifying their correlation.

Enterprise investment in improving environmental performance is the driving force for sustainable economic development, although the government also plays an important role. Exploring the driving factors of enterprise environmental performance is also an important topic in the field of environmental economics, as the number of studies on the environmental behavior of microenterprises is increasing (Zhang et al. 2020; Wen and Lee 2020). However, literature on the influence and mechanism of how industrial digitalization affects the enterprise environmental performance is limited. Environmental technologies have two types: front-end cleaner production technologies and pipe-end treatment technologies. The type of environmental technology adopted by manufacturing enterprises to achieve their environmental goals has different policy implications to the sustainable economic development. However, identifying which environmental technology is being used on the basis of macro data is difficult. To decouple industrial economic development from environmental indicators in the era of digital economy, further exploring the relationship between industrial digital transformation and the choice of environmental technology is necessary.

This study aims to explore the impact and mechanism of industrial digitalization on the environmental performance of manufacturing enterprises in China. Data about environmental information at the enterprise level are scarce, and most related studies use the data of listed enterprises or survey data from small samples (Hu et al. 2019). Different from most studies, this research uses a unique dataset at the enterprise level from 2002 to 2012, including pollutant information and financial information. The large sample of microenterprise data leads to some additional interesting findings in this study, which enriches the literature in this field of enterprise environmental behavior and the theory of digital economy. Some scholars have studied the relationship between digitalization and environmental quality (Avom et al. 2020; Lange et al. 2020; Ren et al. 2021). The marginal contribution of this research is to focus on water pollution emissions rather than energy-related emissions. Therefore, this research enriches the existing related literature. Because the proxy variables of environmental quality are different, this research also finds some conclusions different from the existing literature.

The contribution of this research to literature also includes the following aspects. First, it provides a novel explanation for the decoupling of industrial sector growth from various environmental indicators from the perspective of industrial digital transformation. The research not only provides a new perspective for understanding the improvement of environmental performance in China during the process of industrialization but also gives ideas for developing or industrializing countries to explore the pathway of sustainable industrial development. Second, this study enriches the literature on ICT Productivity Paradox. Although industrial digitalization does not improve productivity, it enhances the green total factor productivity (GTFP) and environmental performance. ICT investment or industrial digitalization has brought about many welfare improvements that cannot be observed in traditional statistical indicators. Third, this work identifies the structural and technology effects of industrial digital transformation on the enterprise environmental performance. Specifically, it provides a detailed discussion of the influence of industrial digitalization on the environmental technology choice of enterprises. This study shows that industrial digitalization promotes manufacturing enterprises to adopt front-end cleaner production technologies, rather than pipe-end pollutant treatment technologies. It also suggests that digital transformation is an important driving force for the decoupling of industrial development and environmental indicators in the era of digital economy.

The remainder of this paper is structured as follows: the "Literature review and hypotheses" section provides a review of the literature and hypotheses. The "Data and methodology" section introduces the data, variables, and econometric models. The "Empirical result and analysis" section presents the empirical results of the digitalization-environment nexus. The "Further analysis of the transmission channels" section provides the further analysis of the transmission channels. The final section concludes.

Literature review and hypotheses

Literature review

Industrialization is one of the most important determinants of changes in pollution emissions, and the mantra of scholars and media is that industrial economic development is inseparable from environmental pollution (Cherniwchan 2012). Therefore, exploring the driving forces of decoupling industrial economic development from environmental indicators is always an important topic in the field of environmental economics (Hu et al. 2020). Considerable literature on the nexus between industrial digital transformation and environmental performance is available, but empirical studies show conflicting results (Berkhout and Hertin 2001; Haseeb et al. 2019; Kunkel and Matthess 2020).

Research on the economic effects of ICT can be traced back to the production theory. Ever since Robert Solow proposed the Productivity Paradox, many studies have been conducted on how ICT affects productivity. Although uncertainty remains, the increasing application of ICT in the industrial sector has triggered great hopes of improving productivity and reducing pollution emissions (Higón et al. 2017). ICT penetration helps manufacturing enterprises improve process efficiency, provide better service to customers than before, optimize work practices, and enhance product design (Neuhofer et al. 2015; Martínez-Caro et al. 2020). Another study suggests that ICT can be used to achieve other goals, resulting in an irrelevance between ICT and productivity. As revealed by DeStefano et al. (2018), manufacturing enterprises adopt ICT to achieve the goal of sales growth, rather than productivity.

The literature on the environmental effects of ICT is mainly based on the direct effects that ICT increases energy consumption and carbon emissions. It indicates that industrial digitalization leads to more energy consumption and poorer environmental performance than usual. Salahuddin and Alam (2016) find that electricity consumption per capita increases by 0.026% if Internet users increase by 1% by using a panel data of OECD countries. Haseeb et al. (2019) observe a unidirectional causality from ICT toward energy consumption in BRICS countries. Zhou et al. (2019) show that the ICT sector contributes a large amount of carbon emissions due to its energy consumption and intermediate inputs of energy-intensive products. However, some studies suggest that industrial digitalization also affects energy consumption and environmental quality through indirect effects. The indirect effects of digital transformation result from its influence on factors such as production efficiency, technology progress, and production scale (Kunkel and Matthess 2020). Industrial digitalization may boost sustainability if the indirect effect is greater than the direct effect (Lange et al. 2020).

The indirect impacts of ICT on environment can be divided into scale effect, structural effect, and technology effect; therefore, the comprehensive effect is uncertain (Hao et al. 2020; Avom et al. 2020). The scale effect refers to the fact that digital transformation promotes industrial expansion and leads to increased pollution. Structural effect indicates that industrial transformation leads to the advancement and rationalization of structure or the reduction of pollution-intensive production activities. Technology effect means that ICT increases productivity and thus leads to improved environmental performance. Lange et al. (2020) discuss the direct effect and three indirect effects in detail and explain that the environmental effects of industrial digitalization depend on the net effect of these four effects.

Research hypothesis

The studies discussed in the "Literature review" section are all macroscopic research, mainly focusing on energy consumption, total environmental pollution, and carbon emissions. These four effects of industrial digitalization also exist in microenterprises, and environmental performance is affected by positive and negative impacts. However, the research design of the present study mainly focuses on structural and technology effects, suggesting that industrial digitalization has a positive effect on enterprise environmental performance.

The pollutant used in this study is chemical oxygen demand (COD) pollution or water pollution to investigate the choice of environmental technology in manufacturing enterprises. Although many types of pollutants exist, COD is a commonly used pollutant in literature and is mainly determined by the endogenous technology choice of enterprises. Therefore, COD is an ideal indicator of enterprise environmental performance. The direct effects are mainly energy-related pollutants, which are not discussed in this study. That is, the research mainly focuses on the indirect effects of industrial digitalization. Considering that the objective of this study is enterprise environmental performance, scale effects are also controlled in this work. After controlling the output scale factor of enterprises, it can be concluded that industrial digitalization has a positive impact on the environmental performance of enterprises through technological and structural effects (Lange et al. 2020). Hence, this study proposes the following hypothesis:

Hypothesis 1. *Industrial digitalization or ICT penetration has a significant positive impact on the environmental performance of manufacturing enterprises.*

Production activities related to pollutants in the industrial sector can be divided into two sub-stages: the production stage and the treatment stage. At the production stage, enterprises produce undesired pollutants during production. Enterprises need the treatment stage to remove undesired pollutants. Two pathways are available to reduce pollutant emissions and improve environmental performance in industrial production activities: either by reducing the volume of produced pollutants or by increasing the volume of removal pollutants (Wang et al. 2021). Correspondingly, environmental technologies in these two stages are classified as cleaner production technologies and pipe-end treatment technologies. Both affect enterprise environmental performance in different ways and have completely different policy implications for industrial sustainable development. Wang et al. (2021) argue that cleaner production technologies have become the dominant approach for pollutant reduction in China. Industrial digital transformation can help enterprises realize the leapfrog transformation of production activities and achieve the goal of improving environmental performance. With the influence of industrial digital transformation, industrial enterprises can break through the emission reduction pathway of pollution first and treatment later. Therefore, they tend to adopt cleaner production technologies, rather than increase pipe-end treatment facilities. Hence, this study proposes the following hypothesis:

Hypothesis 2. *Industrial digitalization significantly affects the choice of environmental technologies, and enterprises tend to adopt front-end cleaner production technologies.*

Data and methodology

Data collection

To verify the proposed hypotheses, this study utilizes the data of a large sample of Chinese manufacturing enterprises from two microenterprise databases. The first is China Industrial Enterprise Database, which covers all state-owned and non-state-owned industrial enterprises whose main business income is above the designated amount. The second is the Enterprise Pollution Database from the Ministry of Ecology and Environment (or formerly the State Environmental Protection Administration) of the People's Republic of China, which is the most authoritative enterprise environmental performance survey database in China. It mainly reports the information on the production and discharge of water pollutants, gas pollutants, and solid pollutants, including COD and sulfur dioxide (SO_2).

COD and SO_2 are representative water pollutants and air pollutants, and their discharge is also the proxy indicator of environmental performance commonly used in literature (Clarkson et al. 2011; Wen and Lee 2020). SO_2 is closely related to energy consumption and is mainly affected by the exogenous intervention of energy policies, whereas COD is determined by the endogenous decision of the production technology. Hence, selecting the production and discharge of COD as the proxy indicators of enterprise environmental performance in this study is reasonable. The matching of the two micro databases is performed by a team with Beijing Forecast Information Technology Co., Ltd., the company that operates the EPS Database. This study also uses some macro variables from the EPS Database. On the one hand, it is limited by the development of ICT industry and the time when the input-output table data can be used for this study; on the other hand, it is limited by the time of the latest update of the Enterprise Pollution Database. The sample period of this study is from 2002 to 2012.

Variables definitions

The dependent variable is enterprise environmental performance, and the pollution emission intensity is selected as the proxy variable in this study. The lower the pollution intensity, the better the enterprise environmental performance. The primary proxy variable, *COD Intensity*, is defined as the ratio of COD emissions to the total output of a firm, multiplied by 100 to facilitate the presentation of coefficient. *SO_2 Intensity*, *Sewage Intensity*, and some other variables related to COD are also used in this research as dependent variables.

The core explanatory variable is the degree of industrial digital transformation, which is measured by the extent to which ICT is used in industrial production and operations. This study considers two proxy variables. The first proxy variable, *ICT_Capital*, is measured by the ratio of ICT capital to industrial added value. The second proxy variable, *ICT_Service*, is measured by the ratio of ICT service to intermediate inputs in the industry. ICT capital and ICT services are calculated using the input-output table. The ICT data used in the calculation are the ICT investment and ICT services at the provincial-city level, and the kernel density distribution is illustrated in Fig. 1 in the appendix.

The control variables include enterprise characteristics, regional characteristics, and industry characteristics. To analyze the influence mechanism of industrial digitalization on environmental performance from the perspective of technology factors, this study also introduces some variables, including *Product_Inno*, total factor productivity (*TFP*), *GTFP*, and *Technology_Up*. The variables of *TFP* and *GTFP* are estimated using the Solow residual method. This study also winsorizes the continuous variable at the 0.5 and 99.5 percentiles to leave out extreme outliers. Table 1 provides a detailed description for the definitions of the variables covered in this study. Table 11 in the appendix shows the descriptive statistics of the variables.

Model specification

Many factors affect enterprise environmental performance, including enterprise characteristics, regional characteristics, and industry characteristics. Referring to the modeling methods of Wen and Lee (2020), this study uses the panel regression model of mixed cross-section. The model framework used here is expressed as follows:

$$Pollution_{ijpt} = \alpha + Digitalization_{jpt}\,\delta + X_{ijpt}\beta + Z_{1pt}\,\gamma_1 + Z_{2jt}\gamma_2 + \mu_p + \lambda_t + \varepsilon_{ijpt} \quad (1)$$

where i, j, p, and t are subscripts referring to the firm, two-digit industry, province, and year, respectively. *Pollution* is the proxy variable of enterprise environment performance. *Digitalization* refers to the indicator of digital transformation at the provincial-industry level and is the core explanatory variable of this study. If δ is significant and negative, then it indicates that industrial digital transformation has a positive effect on firm environmental performance. $\boldsymbol{X}$ represents the control variables for enterprise characteristics, $\boldsymbol{Z_1}$ refers to the control variables for regional characteristics, and $\boldsymbol{Z_2}$ refers

Table 1 Variable definition

	Variable	Definition
Dependent variables	*COD Intensity*	100×COD emissions/total output
	SO_2 Intensity	100×SO_2 emissions/total output
	Sewage Intensity	100×Sewage emissions/total output
	COD Production	100×COD productions/total output
	COD Disposal	100×(COD productions-COD emissions)/total output
	lnOutput	logarithm of the total industrial output of enterprise
Independent variables	*ICT_Capital*	100×ICT capital/industrial added value
	ICT_Service	100×ICT service/industrial intermediate input
Enterprise characteristic	*lnSize*	Logarithm of the full-time employees
	lnAge	Logarithm of the survival year of the firm
	Leverage	Total debt/total assets
	FDI	Dummy variable of foreign enterprise
	SOE	Dummy variable of state-owned enterprise
	Export	Dummy variable of export enterprise
	lnKL	Logarithm of the capital-labor ratio
Regional characteristic	*GDP_Target*	Economic growth targets of local governments
	lnER	Logarithm of investment in environmental facilities
	Innovation	Index of regional innovation capability
Industry characteristics	*Industry_Open*	Gross export output/gross industrial output
	Industry_Size	Average size of enterprises in the industry
	Industry_Profit	Total industrial profit/ prime operating revenue
Technology factors	*Product_Inno*	New product sales/Industrial sales output
	TFP	Total factor productivity
	GTFP	Green total factor productivity
	Technology_Up	Dummy variable for environmental technology adoption

to the control variables for industry characteristics. This study also includes province fixed effects μ_p and year fixed effects λ_t to account for the time-invariant regional characteristics and the temporal characteristics of macro-environmental policies, which may affect firm environmental performance, respectively. In the empirical analysis, some regressions also introduce the fixed effects of two-digit industries.

Empirical result and analysis

Empirical results of the baseline regression analysis

Manufacturers in the same industry always have the same cleaner production technologies and alternative pollutant treatment technologies at their disposal, and their exposure to industrial technology shocks or other random shocks may be related. Hence, this study employs the robust standard errors adjusted for clustering at the four-digit industry to overcome the cross-sectional correlation among random disturbance terms. Table 2 presents the findings for the impact of industrial digitalization on enterprise environmental performance. All columns in the table use COD intensity as the dependent variable. This study considers not only the control variables of the firm characteristics but also those of regional and industry characteristics.

The benchmark results in Table 2 show that industrial digitalization significantly improves the environmental performance of manufacturing enterprises. In the table, the coefficients of *ICT_Capital* are all significantly negative at the 5% level, indicating that industrial ICT capital significantly reduces the pollution intensity. The coefficient of *ICT_Service* in column (5) is negative, and the *T* value is −1.09. Except for column (5), the coefficients of core explanatory variable are significantly negative at the 1% level; the intermediate input of ICT service also significantly reduces COD intensity. In column (7), the coefficient of *ICT_Capital* is −0.267, indicating that if the ratio of ICT capital to industry added value is increased by a standard error value, then the COD intensity of enterprises in the industry can decrease by approximately 6.83%. Meanwhile, the coefficient of *ICT_Service* is −0.0437, suggesting that COD intensity can decrease by approximately 19.37% when *ICT_Service* is increased by a standard error value. Different from the proposition of Avom et al. (2020), the empirical research results of this study found that ICT has a significant positive effect on corporate environmental performance. The difference in research results is due to different measures of environmental quality. Avom et al. (2020) have focused on the energy-related emissions, and energy consumption caused by ICT is one of its main contributors. This article focuses on water pollutants and has nothing to do with energy consumption. In addition, Lange et al. (2020) have found through theoretical research that digitalization can promote sustainability under certain conditions.

The regression coefficients of the control variables are basically consistent with the theoretical expectation, indicating that the empirical results are relatively robust and reliable. In terms of firm characteristics, operating scale, foreign direct investment, and state-owned ownership are significantly and negatively correlated with COD intensity. Large-scale enterprises can benefit from the advantages of economies of scale and improve their environmental performance (Wen and Lee 2020). Meanwhile, state-owned enterprises have a strong incentive to pursue socially responsible goals, including environmental quality improvement. Foreign direct investment is also conducive to the improvement of the production technology and productivity level of enterprises. In addition, a significant positive correlation exists between the capital–labor ratio and firm environmental performance. On the one hand, some technologies are embedded in capital input, and the technological progress embodied in capital improves the environmental performance of enterprises. On the other hand, more capital may mean less investment of resources, thus improving the environmental performance. The coefficients of *Leverage*, *lnAge*, and *Export* are insignificant. In fact, these three characteristic variables all have a relatively complex relationship with the financial performance and social performance of enterprises. In terms of regional characteristics, the economic growth target constraint of local governments can increase the COD intensity of enterprises; a surrogate relationship is also observed between economic growth and environmental quality to a certain extent. After controlling for the provincial fixed effects and the industry characteristics, environmental regulation and technology innovation can reduce the pollution emission intensity and improve the environmental performance of enterprises. Industry characteristics also have significant impacts on pollution emission intensity, which is neither discussed in detail here and nor is reported in the table.

Empirical results of the robust analysis

To ensure the robustness of the estimated results, this study conducts a series of robust regression analyses, and the results are shown in Table 3. First, it considers potential threats from the differences in data quality over the years and changes the sample period. Column (1) deletes the sample observations in 2010, a year in which many variables are missing. Column (2) uses the sample period from 2002 to 2007 because the data quality of China's industrial enterprise database before 2007 is high. To avoid the potential problem that some enterprises do not report the pollutant emissions and mistakenly count as zero emissions, column (3) only uses the enterprises with COD emission as the research samples. Second, SO_2 intensity is used as the proxy variable of enterprise environmental

Table 2 Empirical results of the baseline regression analysis

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ICT_Capital	−0.231**	−0.106**	−0.300***				−0.267***
	(0.1150)	(0.0525)	(0.0934)				(0.0890)
ICT_Service				−0.0412***	−0.0131	−0.0446***	−0.0437***
				(0.0082)	(0.0120)	(0.0097)	(0.0097)
lnSize	−0.370***	−0.218*	−0.340***	−0.327***	−0.217*	−0.286***	−0.284***
	(0.122)	(0.115)	(0.109)	(0.120)	(0.115)	(0.108)	(0.109)
lnAge	0.0013	−0.0170	0.0338	0.0114	−0.0193	0.0461	0.0488
	(0.117)	(0.064)	(0.114)	(0.116)	(0.065)	(0.113)	(0.114)
Leverage	0.0266	0.0303	−0.0737	−0.0236	0.0231	−0.0836	−0.0801
	(0.221)	(0.176)	(0.187)	(0.221)	(0.176)	(0.185)	(0.186)
lnKL	−0.690***	−0.999***	−0.495***	−0.591**	−1.017***	−0.458***	−0.449**
	(0.262)	(0.166)	(0.169)	(0.267)	(0.168)	(0.175)	(0.175)
FDI	−0.527***	−0.0280	−0.348***	−0.483***	−0.0435	−0.320**	−0.297**
	(0.177)	(0.118)	(0.132)	(0.168)	(0.119)	(0.130)	(0.128)
SOE	−0.7790	−0.579**	−0.8550	−0.6840	−0.584**	−0.7890	−0.7880
	(0.570)	(0.276)	(0.597)	(0.566)	(0.276)	(0.590)	(0.589)
Export	−0.0633	0.0110	−0.0282	−0.0842	0.0102	−0.0379	−0.0350
	(0.0580)	(0.0555)	(0.0610)	(0.0563)	(0.0552)	(0.0595)	(0.0592)
GDP_Target	0.0129	0.1290	0.202**	0.0371	0.148*	0.248**	0.222**
	(0.0666)	(0.0833)	(0.0941)	(0.0694)	(0.0876)	(0.0970)	(0.0942)
lnER	0.339*	−0.220*	−0.2310	0.452**	−0.1950	−0.1580	−0.1750
	(0.176)	(0.121)	(0.153)	(0.187)	(0.126)	(0.160)	(0.160)
Innovation	−0.0188**	−0.0239***	−0.0226***	−0.0160**	−0.0237***	−0.0209***	−0.0210***
	(0.0074)	(0.0041)	(0.0063)	(0.0076)	(0.0041)	(0.0064)	(0.0064)
Constant	8.262***	8.471***	5.797***	7.271***	7.991***	4.351***	5.313***
	(1.953)	(1.254)	(1.299)	(1.912)	(1.310)	(1.441)	(1.348)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	No	Yes	Yes	No	Yes	Yes	Yes
Industry characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Adjusted R^2	0.069	0.215	0.092	0.074	0.215	0.097	0.098
observations	446748	446748	446748	447553	447553	447553	446461

Notes: The cluster-robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. Columns (2) and (5) use industry fixed effects to control industry characteristics; columns (3), (6), and (7) control industry characteristic variables, such as trade openness, market competition, and profit margins

performance, and the results are shown in columns (4) and (5). Third, sewage intensity is used as the proxy variable of enterprise environmental performance, as presented in columns (6) and (7).

In Table 3, all the coefficients of *ICT_Service* are significantly negative at the 1% level, indicating that the intermediate input of ICT services significantly improves the environmental performance of enterprises. *ICT_Capital* has a significant negative impact on COD discharge intensity and sewage discharge intensity, in contrast to its effect on SO_2 discharge intensity is insignificant. The results in columns (4) and (5) are not contradictory with other empirical results because SO_2 emissions are mainly affected by exogenous factors, such as national energy policies, rather than an endogenous choice of production technology. The effect of SO_2 intensity is also consistent with the findings of Ren et al. (2021), that is, digitalization has not significantly increased China's energy consumption intensity, and thus does not increase energy-related pollution.

Empirical results of the endogenous analysis

In this study, the core explanatory variable is measured at the industry level, while the explained variable is measured at the enterprise level. Therefore, the endogeneity problem caused by the reverse causality of enterprise environmental behavior

Table 3 Empirical results of the robust regression

Variable	Dep. variable: *COD Intensity*			Dep. variable: SO_2 *Intensity*		Dep. variable: *Sewage Intensity*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ICT_Capital	−0.259***	−0.502***	−0.399***	0.010	0.006	−1.031*	−1.139**
	(0.0825)	(0.0975)	(0.1150)	(0.208)	(0.204)	(0.562)	(0.496)
ICT_Service	−0.044***	−0.078***	−0.044***	−0.053***	−0.050***	−0.321***	−0.329***
	(0.0097)	(0.0159)	(0.0100)	(0.0156)	(0.0160)	(0.0803)	(0.0784)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	No	Yes	No	Yes
Adjusted R^2	0.105	0.075	0.147	0.185	0.187	0.058	0.065
Observations	395578	207481	340867	446486	446486	446461	446461

Notes: The cluster-robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. This table uses a series of industry-level explanatory variables to control industry characteristics, rather than industry fixed effects

to industrial ICT penetration is relatively weak. In the above research, we have tried to overcome the potential endogeneity by controlling inter-provincial fixed effects, industrial characteristics, and regional characteristics. Furthermore, we use instrumental variable regression and cross-sectional explanatory variable regression to reduce the interference of endogeneity on the estimation results in this section. Empirical results of the endogenous correction regression are shown in Table 4.

In the instrumental variable regression, the coefficients of ICT penetration are significantly negative at the 5% level, indicating that there is a positive correlation between industrial digitalization and environmental performance. At the same time, in the cross-sectional explanatory variable regression, except for *ICT_Capital* in column (6), the coefficients of ICT penetration are also significantly negative, which shows that industrial digitalization has significantly reduced enterprises pollution emissions. The empirical results in Table 3 and Table 4 confirm that Hypothesis 1 is true and robust. That is, the environmental performance of Chinese manufacturing enterprises has been significantly improved in the process of industrial digital transformation.

Industry heterogeneity of environmental effects

Existing studies have found the differences in the degrees of digitalization and pollution intensity among enterprises in different industries. This research conducts the following heterogeneity analysis of the environmental effects of industrial digitalization. As shown in Table 5, the industries are divided into several categories according to the capital intensity, energy intensity, and COD pollution intensity of the industry.

Although industrial digitalization entirely improves the environmental performance of manufacturing enterprises, its environmental effects have significant industry heterogeneity. For these enterprises in non-capital intensity industries, the coefficients of *ICT_Capital* and *ICT_Service* are significantly negative at the 5% level and larger in absolute value than those for enterprises in capital-intensive industries. ICT technology is conducive to the improvement of the environmental performance of traditional industries with low capital intensity because it solves the problem of low labor quality and enables enterprises to use cleaner production technologies. Similarly, the environmental effects of industrial digitalization on enterprises in heavy-polluting industries are greater than those in other industries. The heterogeneity of environmental effects between heavy-polluting industries and other industries is in line with the expectations of mitigation potential. The idea that the impact of industrial digitalization on enterprise environmental performance is only significant in non-energy-intensive industries may seem counterintuitive. However, this result does not contradict our conclusion. Although energy-intensive industries also have serious pollution emission problems (Wen et al. 2021), their pollutants are mainly air pollutants, such as SO_2. The empirical results of industry heterogeneity analysis further indicate that the positive effect of industrial digitalization on enterprise environmental performance is robust and in line with the theoretical expectations.

Further analysis of the transmission channels

Empirical results of structural effect and network effect

To further understand the impact of industrial digitalization on enterprise environmental performance, we firstly examine the

Table 4 Empirical results of the endogenous correction regression

Variable	Instrumental variable regression			Cross-sectional explanatory variable regression		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT_Capital	−0.332**		−0.285**	−0.208**	−0.932***	−0.139
	(0.132)		(0.128)	(0.087)	(0.192)	(0.092)
ICT_Service		−0.050***	−0.049***	−0.067***	−0.100***	−0.051***
		(0.012)	(0.012)	(0.014)	(0.023)	(0.012)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.091	0.096	0.096	0.079	0.081	0.088
Observations	413775	414776	413488	147478	126357	312021

Notes: The cluster-robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. Columns (1)–(3) use variables with a lag of 1 year as the instrumental variables. Column (4) investigates the impact of industry digitalization in 2002 and 2007 on enterprises in the following 2 years. Column (5) investigates the impact of industry digitalization in 2002 on enterprises in the following 4 years. Column (6) investigates the impact of industry digitalization in 2002 and 2007 on enterprises in the following 4 years

Table 5 Empirical results of industry heterogeneity analysis

Variable	Industry capital intensity		Industry energy intensity		Industry pollution intensity	
	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
ICT_Capital	−0.0809	−0.667***	0.0172	−0.405***	−0.227**	−0.0805
	(0.0750)	(0.2340)	(0.0616)	(0.1110)	(0.1040)	(0.1080)
ICT_Service	−0.0211***	−0.0626***	−0.0066	−0.0580***	−0.0429*	−0.0313***
	(0.0059)	(0.0158)	(0.0081)	(0.0110)	(0.0259)	(0.0057)
lnSize	−0.1660	−0.469***	0.1110	−0.595***	−0.1640	−0.398***
	(0.1570)	(0.1290)	(0.2000)	(0.1220)	(0.1500)	(0.1310)
lnAge	0.269**	−0.1200	0.2260	−0.1100	0.1460	−0.150*
	(0.1240)	(0.1340)	(0.1440)	(0.0886)	(0.1950)	(0.0850)
Leverage	0.1750	−0.2910	0.2300	−0.2210	−0.1140	0.0629
	(0.2630)	(0.2290)	(0.1850)	(0.2190)	(0.2460)	(0.2480)
lnKL	−0.0933*	0.0346	−0.0332	−0.0190	−0.165**	0.0897
	(0.0511)	(0.1540)	(0.0491)	(0.0725)	(0.0812)	(0.0635)
FDI	−0.519***	−0.2720	−0.312***	−0.849***	−0.438*	−0.358***
	(0.1180)	(0.2690)	(0.1040)	(0.2320)	(0.2370)	(0.1120)
SOE	−0.1780	−0.342*	0.0834	−0.343*	−0.2420	−0.1820
	(0.1790)	(0.1970)	(0.1100)	(0.1900)	(0.1600)	(0.2010)
Export	−0.0350	−1.3450	0.2760	−1.464**	−0.8660	−0.465*
	(0.3040)	(0.9040)	(0.3920)	(0.7220)	(0.8570)	(0.2530)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year/province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.102	0.128	0.059	0.150	0.110	0.137
Observations	222561	223900	170274	276187	269193	177268

Notes: The cluster-robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. This table uses a series of industry-level explanatory variables to control industry characteristics

structural effect, that is, whether industrial digitalization limits the production scale of heavy polluters. Beside, we examine the network effect of ICT capital and ICT services, that is, as the ICT capital and ICT services increases, does the environmental effect increase? The empirical results of structural effect are shown in columns (1) to (3) of Table 6, and those of network effect are presented in columns (4) to (7) of Table 6.

As shown in columns (1)–(3), the coefficients of *ICT_Capital* and *ICT_Service* are both significantly positive, indicating that industrial digitalization has a significant positive impact on the total output value of enterprises. This study introduces the interaction term between COD intensity and the proxy variables of industrial digitalization in columns (1) to (3). All the coefficients of *ICT_Capital× COD Intensity* and *ICT_Service× COD Intensity* are significantly negative at the 1% level, indicating that both proxy variables have significant negative impacts on the total output. With the increase of ICT application in the industry, manufacturing enterprises with high pollution intensity would reduce their total production scale, and the structural effect is established. On the one hand, ICT application increases production flexibility and operational agility (Škare and Soriano 2020); then, manufacturing enterprises can adjust the production plan according to the change of market demand for environmentally friendly products. On the other hand, ICT technology reduces the transaction cost and improves the investment efficiency, which leads to the reduction of the production scale of high-polluting enterprises.

In the literature of economic growth theory, general technology has a strong network effect and can exert its positive effect when applied to a large scale. ICT is a typical general technology and has the spillover of network scale. This study introduces the logarithm of total ICT capital and total ICT service input at the region-industry level as the explanatory variables, which are expressed as *ICT_Capital_Network* and *ICT_Service_Network*, respectively. As presented in columns (4) to (7) of Table 6, ICT capital has a significant negative influence on the COD emission intensity at the 1% level, whereas the coefficient of *ICT_Service_Network* is insignificant. These pieces of evidence suggest that the network externalities of ICT capital are in place, but ICT services are not. In this study, samples up to 2012 are used. Digital services were relatively immature during this period; therefore, the ICT services in the manufacturing sector did not exhibit network effect. The empirical results indicate that not only does the degree of industrial digitalization have a significant impact on the improvement of enterprise environmental performance but also the digital transformation can further release the dividend or network effect of the digital economy when it reaches a certain scale.

Table 6 Empirical results of structural effect and network effect

Variable	Dep. variable: *lnOutput*			Dep. variable: *COD Intensity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ICT_Capital	0.0217***		0.0145**	−0.260***		−0.257***	−0.0545
	(0.0072)		(0.0067)	(0.0841)		(0.0852)	(0.1990)
ICT_Service		0.0023**	0.0019**		−0.0443***	−0.0098	−0.0438***
		(0.0009)	(0.0009)		(0.0149)	(0.0096)	(0.0097)
ICT_Capital× COD Intensity	−0.0109***		−0.0084***				
	(0.0028)		(0.0024)				
ICT_Service× COD Intensity		−0.0017***	−0.0015***				
		(0.0004)	(0.0004)				
ICT_Capital_Network				−0.512***		−0.458***	
				(0.1240)		(0.1470)	
ICT_Service_Network					−0.4200		−0.4200
					(0.6240)		(0.4880)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.557	0.559	0.561	0.103	0.099	0.103	0.099
Observations	446748	447553	446461	446740	447553	446461	446461

Notes: The cluster-robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. This table uses a series of industry-level explanatory variables to control industry characteristics

Empirical results of technology progress effect and technology choice effect

In the information age, the digitalization of economy promotes the progress and diffusion of technology (Vu and Asongu 2020). In this part, we investigate how industrial digitalization affects enterprise environmental performance from the perspective of technology factors, and Table 7 shows the empirical results. Specifically, we employ product innovation (*Product_Inno*), total factor productivity (*TFP*), and green total factor productivity (*GTFP*) as the proxy variables for technology progress.

The empirical results in Table 7 generally support the view that industrial digitalization promotes enterprise technology progress, but different and interesting results are also obtained. From the empirical results, ICT capital and ICT services have significant positive impacts on firm product innovation. As for productivity, the impact of ICT inputs is complex. After controlling for industry characteristics and province fixed effects, the coefficients of *ICT_Capital* and *ICT_Service* are insignificant, and this result supports the Solow Productivity Paradox, and ICT penetration has not improved the traditional indicator of productivity. When GTFP is used as the explained variable, the coefficient of *ICT_Service* is significantly positive at the

Table 7 Empirical results of the effects on technology progress

Variable	Dep. variable: *Product_Inno*		Dep. variable: *TFP*		Dep. variable: *GTFP*	
	(1)	(2)	(3)	(4)	(5)	(6)
ICT_Capital	0.326***	0.196***	0.0215***	−0.0037	0.0225***	0.0011
	(0.0836)	(0.0745)	(0.0030)	(0.0025)	(0.0032)	(0.0027)
ICT_Service	0.0722***	0.0763***	0.0005	0.0002	0.0013***	0.0011***
	(0.0098)	(0.0106)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
lnSize	1.478***	1.595***	−0.0153***	−0.0092	−0.0116**	−0.0068
	(0.1640)	(0.1630)	(0.0057)	(0.0056)	(0.0055)	(0.0054)
lnAge	0.449***	0.417***	−0.0012	−0.0041	−0.0055	−0.0085
	(0.1070)	(0.1060)	(0.0059)	(0.0058)	(0.0055)	(0.0056)
Leverage	−0.3010	−0.646***	0.0920***	0.0779***	0.0870***	0.0735***
	(0.2070)	(0.1970)	(0.0129)	(0.0119)	(0.0124)	(0.0117)
lnKL	0.929***	0.887***	0.0395***	0.0362***	0.0380***	0.0340***
	(0.1260)	(0.1160)	(0.0076)	(0.0076)	(0.0068)	(0.0068)
FDI	−2.617***	−1.986***	0.0959***	0.0909***	0.0981***	0.0936***
	(0.2600)	(0.2020)	(0.0113)	(0.0092)	(0.0112)	(0.0093)
SOE	−0.1220	0.1980	−0.0418***	−0.0338***	−0.0388***	−0.0321***
	(0.2090)	(0.1980)	(0.0091)	(0.0094)	(0.0092)	(0.0095)
Export	4.969***	4.742***	0.0363***	0.0273**	0.0293***	0.0238**
	(0.3790)	(0.3430)	(0.0134)	(0.0123)	(0.0106)	(0.0105)
GDP_Target	0.304***	0.0643	0.0219***	0.0029	0.0191***	0.0019
	(0.0683)	(0.0735)	(0.0039)	(0.0033)	(0.0042)	(0.0036)
lnER	−0.470***	−1.953***	−0.0028	−0.0093	−0.0197***	−0.0109
	(0.1100)	(0.2460)	(0.0058)	(0.0104)	(0.0069)	(0.0106)
Innovation	0.0092***	−0.0054	0.0008***	0.0005***	0.0008***	0.0007***
	(0.0035)	(0.0034)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Year fixed effectS	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	No	Yes	No	Yes	No	Yes
Industry characteristics	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.077	0.099	0.041	0.060	0.040	0.058
Observations	262158	262158	207837	207837	207258	207258

Notes: The cluster-robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. This table uses a series of industry-level explanatory variables to control industry characteristics

1% level. Meanwhile, the coefficients of *ICT_Capital* are all positive, and the coefficient of *ICT_Capital* in column (5) is significant at the 1% level. Therefore, ICT has a positive impact on GTFP. Although ICT does not improve productivity, it has improved GTFP. That is, industrial digitalization has brought about many welfare improvements that cannot be observed in traditional statistical indicators.

As discussed above, technology progress is an important transmission mechanism for industrial digitalization to affect enterprise environmental performance. However, technologies that improve environmental performance have many types, such as front-end cleaner production technologies and pipe-end treatment technologies. Which type of environmental technology do manufacturers prefer to choose? This study employs some proxy variables of technology types and then examines the impact of industrial digitalization on the technology choice. The empirical results are presented in Table 8.

The dependent variable in columns (1) and (2) is the intensity of COD pollutant production, which is the reverse index of cleaner production technologies. In columns (3) and (4), the dependent variable is the intensity of COD disposal, which is the index of pipe-end treatment technologies. In columns (5) and (6), the dependent variables are the dummy variables of the application of pollution treatment facilities and the application of cleaner production technologies. The regression results indicate that industrial digitalization significantly promotes the application of front-end cleaner production technologies and reduces the adoption of pollutant treatment facilities. The reduction in pollutant treatment facilities by manufacturers may be due to the use of front-end cleaner production technologies. Therefore, industrial digitalization significantly affects the choice of environmental technologies and encourages manufacturing enterprises to choose front-end cleaner production technologies. That is, Hypothesis 2 is true.

Effect decomposition of different transmission channels

On the basis of confirming the two transmission channels of structural adjustment and technological progress, we are interested in the contribution of each channel. Refer to the mediation analysis of Papyrakis and Gerlagh (2004), we examines and decomposes the environmental effects of ICT penetration at the province-industry level. The variables *Structural_Up* and *Technology_Up3* respectively represent the proportion of the total output value of high-polluting enterprises in the total industrial output value of the province and the proportion of enterprises adopting green production technology. The empirical regression results of mediation analysis are shown in Table 9, and the effect decomposition results of different transmission channels are shown in Table 10.

In columns (1) and (2) of Table 9, the coefficients of *ICT_Capital* and *ICT_Service* are both negative and significant at the 5% level, which again proves the structural effect and technology effect of ICT penetration. In columns (4), both of the two mediating variables are significantly negative, and the absolute values of the coefficients of *ICT_Capital* and *ICT_Service* are smaller than these of column (3), indicating

Table 8 Empirical results of the effects on technology choice

Variable	Dep. variable: *COD Production*		Dep. variable: *COD Disposal*		Dep. variable: *Technology_Up*	
	(1)	(2)	(3)	(4)	(5)	(6)
ICT_Capital	−0.222**	−0.331***	−0.0152	−0.112***	−0.0247**	0.0096
	(0.0991)	(0.1050)	(0.0333)	(0.0382)	(0.0096)	(0.0092)
ICT_Service	−0.0842***	−0.0945***	−0.0387***	−0.0443***	−0.0072***	0.0111***
	(0.0171)	(0.0195)	(0.0068)	(0.0076)	(0.0013)	(0.0019)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	No	Yes	No	Yes	No	Yes
Industry characteristics	No	Yes	No	Yes	No	Yes
Adjusted R^2/pseudo-R^2	0.060	0.073	0.052	0.062	0.072	0.049
Observations	420724	420724	419052	419052	442742	446828

Notes: The cluster-robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. This table uses a series of industry-level explanatory variables to control industry characteristics. The dependent variables are the dummy variables of pollution treatment technology and water-saving production technology in columns (5) and (6), both of which are estimated using the probit model

Table 9 Empirical results of the mediation model

Variable	Dep. variable: *Structural_Up*	Dep. variable: *Technology_Up₃*	Dep. variable: *COD Intensity*	
	(1)	(2)	(3)	(4)
ICT_Capital	0.0060**	0.0086***	−0.1190***	−0.0503**
	(0.0030)	(0.0019)	(0.0263)	(0.0251)
ICT_Service	0.0023***	0.0031***	−0.0290***	−0.0023*
	(0.0002)	(0.0002)	(0.0016)	(0.0014)
Structural_Up				−9.144***
				(0.302)
Technology_Up3				−1.720***
				(0.175)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.236	0.198	0.148	0.545
Observations	5078	5078	5078	5078

Notes: The robust standard errors are shown in brackets. Asterisks *** (1%), ** (5%), and * (10%) indicate significance at the corresponding levels. The control variables include *GDP_Target*, *lnER*, and three variables of industry characteristics. Fixed effects include both year and provincial level

that the mediating effect is significantly established. The decomposition results indicate that both structural effect and technology effect contribute to the environmental effects of industrial digitalization. However, the two types of transmission channels are different. The digital equipment affects enterprise environmental performance mainly through direct effect and structural effect, while digital services mainly through the channel of structural effect. It can be seen that there are more complicated channels for the environmental effects of digital equipment investment. Although both structural effects and technological effects are channels for information technology dissemination, structural effects are the main contributor to the positive environmental effects of information technology dissemination. As Lange et al. (2020) concludes, structural adjustment allows for sustainable development in the process of digital transformation.

Conclusion and implication

Driven by the next-generation ICT, digital technology is being embedded in the production of products and services with unprecedented breadth and depth. Based on the actual observation of industrial digital transformation, this study uses intermediate inputs of ICT capital and ICT services to measure industrial digitalization and investigates the impact of industrial digitalization on enterprise environmental performance.

Using a massive sample of manufacturing enterprises in the period from 2002 to 2012, this study leads to the following main findings. In the process of industrial digital transformation, manufacturing enterprises have significantly reduced their COD emission intensity. Combined with the robustness analysis, we conclude that industrial digitalization has a significant positive impact on enterprise environmental performance. The environmental effects of industrial digitalization also show significant industry heterogeneity. Industrial digitalization has a great impact on the COD emission intensity of enterprises in heavy-polluting industries and non-capital-intensive industries. Empirical evidence suggests that the network effect of ICT capital is in place, whereas ICT services are not. The digital transformation can further release the dividend or network effect of the digital economy when it reaches a certain scale.

Table 10 Effect decomposition of ICT on enterprise environment performance

Transmission channels		Other effect	Structural effect	Technology effect	Total effect
ICT_Capital	Absolute contribution	−0.0503	−0.0549	−0.0148	−0.1200
	Relative contribution	41.93%	45.73%	12.33%	100%
ICT_Service	Absolute contribution	−0.0023	−0.0210	−0.0053	−0.0287
	Relative contribution	8.02%	73.37%	18.60%	100%

Notes: The calculation method of the contributions of these transmission channels can also be referred to Papyrakis and Gerlagh (2004) and Avom et al. (2020)

In terms of the transmission channels, industrial digitalization has two transmission channels on the improvement of enterprise environmental performance: structural effect and technology effect. With the increase of ICT capital and ICT services in the industry, manufacturing enterprises with high pollution intensity can reduce their total production scale; therefore, the hypothesis of structural effect holds. The structural effect is the main contributor to the positive environmental effects of ICT penetration. This study employs a series of econometric models to identify the role of technology factors in the digitalization-environment nexus. Industrial digitalization has significantly increased product innovation and GTFP, but it has an insignificant effect on TFP. In the process of industrial digital transformation, manufacturing enterprises have improved the environmental performance by introducing front-end cleaner production technologies, rather than increasing pipe-end pollutant treatment facilities. Our findings also provide an explanation for the Solow Productivity Paradox, and ICT technology has led to social welfare improvements in the environment, rather than traditional productivity indicators.

Our findings imply that industrial digital transformation plays an important role in sustainable development. ICT has brought about the upgrading of production technology in the manufacturing sector, reducing the amount of pollutants produced in the front-end production process. Promoting the deep integration of digital economy and real economy is an important breakthrough to resolve the contradiction between economic growth and environmental quality, and it is an important driving force to promote sustainable economic development. Our findings have important policy implications for industrializing countries and China. Industrializing countries should learn from China's experience, embrace digital technology in the process of economic industrialization, and break the mantra that industry is inseparable from pollution. The Chinese government should continue to optimize the institutional environment for the development of digital economy, strengthen the construction of digital infrastructure, promote the digital transformation of the manufacturing industry, and release the dividends of the digital economy in the green development of the manufacturing industry.

Appendix

Table 11 Descriptive statistics of variables

	Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent variables	*COD Intensity*	455,558	3.4575	8.1912	0.0000	32.7958
	SO_2 Intensity	455,584	9.9004	19.5631	0.0000	74.5600
	Sewage Intensity	455,558	27.6416	52.3837	0.0000	202.1410
	COD Production	429,614	5.5363	14.6244	0.0000	99.9991
	COD Disposal	427,911	2.0966	6.7903	0.0000	50.0000
	lnOutput	455,924	8.3816	1.7430	−2.3026	20.0301
Independent variables	*ICT_Capital*	5,100	0.6552	1.5617	0.0000	55.5512
	ICT_Service	5,128	10.2906	17.7854	0.0000	99.9915
Enterprise characteristic	*lnSize*	449,428	5.4502	1.1459	2.3026	12.2009
	lnAge	455,927	2.3299	0.8482	0.0000	7.6059
	Leverage	455,927	0.5798	0.2567	0.1121	1.0000
	FDI	455,927	0.2107	0.4078	0.0000	1.0000
	SOE	455,927	0.1049	0.3064	0.0000	1.0000
	Export	455,927	0.2726	0.4453	0.0000	1.0000
	lnKL	449,328	4.3217	1.3672	−6.7452	14.5032
Regional characteristic	*GDP_Target*	329	10.1444	1.4065	7.0000	15.0000
	lnER	329	4.3215	1.0713	0.0000	7.2564
	Innovation	4,629	58.2139	24.7032	1.0240	100.0000
Industry characteristics	*Industry_Open*	305	0.1557	0.1532	0.0045	0.6814
	Industry_Size	305	311.3494	198.0912	128.9000	1397.3500
	Industry_Profit	305	0.0597	0.0278	−0.0443	0.1674
Technical factors	*Product_Inno*	264,198	3.8916	14.8079	0.0000	100.0000
	TFP	210,113	0.7345	0.4866	0.1012	2.0142
	GTFP	209,532	0.7292	0.4866	0.1022	2.0123
	$Technology\_Up_1$	455,927	0.5047	0.5000	0.0000	1.0000
	$Technology\_Up_2$	451,790	0.5998	0.4899	0.0000	1.0000

Notes: The classification of variables and their meanings are consistent with those in Table 1.$Technology\_Up_1$ and $Technology\_Up_2$ refer to the dummy variables of pollution treatment technology and water-saving production technology, respectively

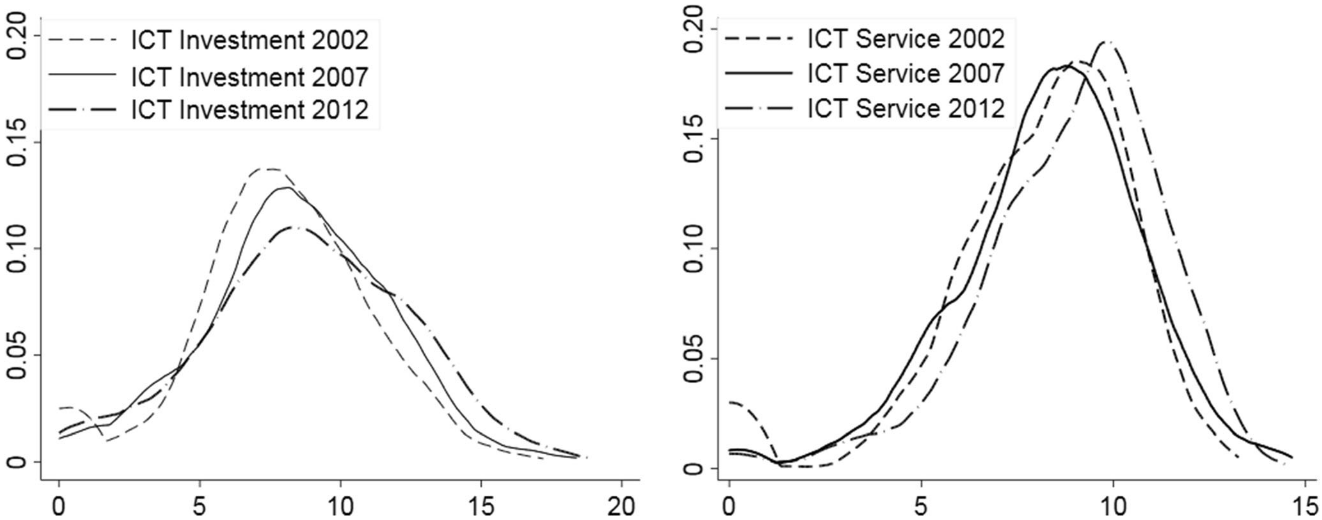

Fig. 1 Kernel density distribution of ICT investment and ICT services

Authors' contributions Huwei Wen: resources, methodology, formal analysis, writing (review and editing).

Chien-Chiang Lee: conceptualization, supervision, writing (review and editing), corresponding author.

Ziyu Song: data curation, visualization, writing (original draft).

All authors provided critical feedback and helped shape the research, analysis, and manuscript.

Funding This project is supported by the Youth Program of National Social Science Foundation of China (grant no. 20CJY031).

Data and materials availability Data are available from the authors upon request.

Declarations

Ethical approval This is an original article that did not use other information that requires ethical approval.

Consent to participate All authors participated in this article.

Consent to publish All authors have given consent to the publication of this article.

Conflict of interest The authors declare no competing interests.

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