How Does Industrial Digitalization Affect Enterprise Environmental Performance?

Huwei Wen
Nanchang University

Chien-Chiang Lee (cclee6101@gmail.com)
Nanchang University https://orcid.org/0000-0003-0037-4347

Ziyu Song
Dalian University of Technology

Research Article

Keywords: Industrial digitalization, Environmental performance, Structural effect, Technology effect, Cleaner production technology

Posted Date: March 30th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-310270/v1

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 influencing mechanisms. 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.

JEL Classification: Q56, O13, L86

1. 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). 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 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 (Oleaner 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, 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 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). Both effects form a nonlinear relationship between ICT penetration and pollutant emissions, leading to inconsistent conclusions drawn from different samples (Higón, 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. The contribution of this research to literature mainly 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: Section 2 provides a review of the literature and hypotheses. Section 3 introduces the data, variables, and econometric models. Section 4 presents the empirical results. Section 5 investigates the role of technology factors in the environmental effects of industrial digital transformation. The final section concludes.

2. Literature Review And Hypotheses

2.1 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 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, 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, 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, structure 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.

2.2 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, we find that industrial digitalization has a positive impact on enterprise environmental performance through technology and structural effects. 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.*

3. Data And Methodology

3.1. 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. 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.

The Enterprise Pollution Database, also named the Enterprise Green Development Database (1998–2012), is the most authoritative database for investigating the enterprise environmental performance 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.

3.2. 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 Figure A 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 A in the appendix shows the descriptive statistics of the variables.

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
	LnCOD	Logarithm of COD emissions plus one
	COD Production	100×COD productions / total output
	COD Disposal	100×(COD productions-COD emissions) / total output
	lnOutput	Logarithm of total output
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

3.3. 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:

$$Pollution_{ijpt} = \alpha + Digitalization_{jpt}\delta + \mathbf{X}_{ijpt}\boldsymbol{\beta} + \mathbf{Z}_{1pt}\boldsymbol{\gamma}_1 + \mathbf{Z}_{2jt}\boldsymbol{\gamma}_2 + \mu_p + \lambda_t + \varepsilon_{ijpt} \qquad (1)$$

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 is significant and negative, then it indicates that industrial digital transformation has a positive effect on firm environmental performance. **X** represents the control variables for enterprise characteristics, $\mathbf{Z_1}$ refers to the control variables for regional characteristics, and $\mathbf{Z_2}$ refers 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.

4. Empirical Result And Analysis

4.1. Impact of industrial digitalization on enterprise pollution intensity

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. Columns (1)–(3) in Table 2 measure the degree of industrial digitalization by the ratio of ICT capital to industrial added value, and Columns (4)–(6) use the intermediate input of ICT service as the measure index. 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 of enterprises. 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. The empirical evidence suggests that industrial digitalization or the intermediate input of ICT capital and ICT services has a significant positive impact on enterprise environmental performance.

Table 2
Impact of industrial digitalization on COD intensity

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***
	(0.1220)	(0.1150)	(0.1090)	(0.1200)	(0.1150)	(0.1080)	(0.1090)
lnAge	0.0013	-0.0170	0.0338	0.0114	-0.0193	0.0461	0.0488
	(0.1170)	(0.0644)	(0.1140)	(0.1160)	(0.0645)	(0.1130)	(0.1140)
Leverage	0.0266	0.0303	-0.0737	-0.0236	0.0231	-0.0836	-0.0801
	(0.2210)	(0.1760)	(0.1870)	(0.2210)	(0.1760)	(0.1850)	(0.1860)
lnKL	-0.690***	-0.999***	-0.495***	-0.591**	-1.017***	-0.458***	-0.449**
	(0.2620)	(0.1660)	(0.1690)	(0.2670)	(0.1680)	(0.1750)	(0.1750)
FDI	-0.527***	-0.0280	-0.348***	-0.483***	-0.0435	-0.320**	-0.297**
	(0.1770)	(0.1180)	(0.1320)	(0.1680)	(0.1190)	(0.1300)	(0.1280)
SOE	-0.7790	-0.579**	-0.8550	-0.6840	-0.584**	-0.7890	-0.7880
	(0.5700)	(0.2760)	(0.5970)	(0.5660)	(0.2760)	(0.5900)	(0.5890)
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
	(0.1760)	(0.1210)	(0.1530)	(0.1870)	(0.1260)	(0.1600)	(0.1600)
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***
	(1.9530)	(1.2540)	(1.2990)	(1.9120)	(1.3100)	(1.4410)	(1.3480)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	No	Yes	Yes	No	Yes	Yes	Yes

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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.

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. 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. However, a significant positive correlation exists between the capital–labor ratio and firm environmental performance. 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.

Table 3
Empirical results of the robust analysis

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)	(0.2080)	(0.2040)	(0.5620)	(0.4960)
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 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 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, but 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 empirical results of the robust analysis in Table 3 indicate that

the results of this study are robust, and the environmental performance of manufacturing enterprises has been significantly improved in the process of industrial digital transformation.

4.2. Total emissions effect, structure effect, and network effect

To further understand the impact of industrial digitalization on enterprise environmental performance, this part examines the effects of industrial digitalization in three aspects. First, we use the logarithm of COD emission as the explained variable to investigate the impact of industrial digitalization on the total pollution emissions of enterprises, namely, total emission effect. Second, we examine the structural effect of industrial digitalization, that is, whether industrial digitization limits the production scale of heavy polluters. Third, we examine the network effect of ICT capital and ICT services. That is, as the total amount of ICT capital and ICT services increases, does the environmental effect increase? The empirical test results of total emissions effect and structure effect are shown in Table 4, and those of network effect are presented in Table 5.

Table 4
Empirical test results of total emissions effect and structure effect

Variable	**Dep. Variable: *lnCOD***			**Dep. Variable: *lnOutput***		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ICT_Capital	-0.0752**		-0.0593	0.0217***		0.0145**
	(0.0379)		(0.0369)	(0.0072)		(0.0067)
ICT_Service		-0.0211***	-0.0208***		0.0023**	0.0019**
		(0.0039)	(0.0039)		(0.0009)	(0.0009)
ICT_Capital×COD Intensity				-0.0109***		-0.0084***
				(0.0028)		(0.0024)
ICT_Service×COD Intensity					-0.0017***	-0.0015***
					(0.0004)	(0.0004)
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	0.335	0.340	0.340	0.557	0.559	0.561
Observations	446751	447556	446464	446748	447553	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.

The empirical results suggest that industrial digitalization not only reduces the COD intensity of enterprises but also reduces the total COD emission, as shown in Columns (1)–(3) in Table 4. Although the coefficient of *ICT_Capital* in Column (3) is insignificant, the T value is 1.607. In addition, the coefficients of *ICT_Service* are significantly negative at the 1% level. The COD intensity mentioned above measures the COD emission per unit of output. The variables of *ICT_Capital* and *ICT_Service* also have significant positive effects on the total output of enterprises; the coefficients of both variables are significantly positive, as presented in Columns (5)–(6). Given that ICT technology can promote the total production of enterprises to increase, the negative effects of *ICT_Capital* and *ICT_Service* on COD emission indicates that industrial digitalization has a strong impact on the improvement of enterprise environmental performance.

This study introduces the interaction term between COD intensity and these two proxy variables of industrial digitalization in Columns (4)–(6) in Table 4. 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 of enterprises. With the increase of ICT application in the industry, manufacturing enterprises with high pollution intensity can reduce their total production scale, and the structure effect of industrial digitalization 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.

Table 5
Empirical test results of network effect

Variable	**Dep. Variable: *COD Intensity***				**Dep. Variable:*lnCOD***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ICT_Capital	-0.260***		-0.257***	-0.0545	-0.0581	-0.0882
	(0.0841)		(0.0852)	(0.1990)	(0.0358)	(0.0744)
ICT_Service		-0.0443***	-0.0098	-0.0438***	-0.0112**	-0.0205***
		(0.0149)	(0.0096)	(0.0097)	(0.0046)	(0.0039)
ICT_Capital_Network	-0.512***		-0.458***		-0.127**	
	(0.1240)		(0.1470)		(0.0592)	
ICT_Service_Network		-0.4200		-0.4200		0.0543
		(0.6240)		(0.4880)		(0.1740)
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	0.103	0.099	0.103	0.099	0.341	0.339
Observations	446740	447553	446461	446461	446464	446464

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.

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. In Table 5, 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 Table 5, ICT capital has a significant negative influence on the COD emission intensity and the total COD emission at the 5% level, whereas the coefficient of *ICT_Service_Network* is insignificant, and the coefficient in Column (6) is positive. 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.

4.3. Industry heterogeneity of environmental effects

Existing studies find significant differences in the degrees of digitalization and pollution intensity among enterprises in different industries. Therefore, this research conducts the following industry heterogeneity analysis of the environmental effects of industrial digitalization. As shown in Table 6, 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 expectations.

Table 6
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.

5. Further Analysis: Perspective Of Technology Factors

5.1. Influence of industrial digitalization on the technology progress of enterprises

In the information age, the digitization of economy promotes the progress and diffusion of technology (Vu and Asongu, 2020). Therefore, technology factors have an important impact on the relationship between industrial digitalization and enterprise environmental performance. In this part, we investigate how industrial digitalization affects enterprise environmental performance from the perspective of technology factors. Table 7 shows the empirical results of how industrial digitalization affects the technology progress of enterprises. 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, 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 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.

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

Variable	Dep. Variable:*Product_Inno*		Dep. Variable: *TFP*		Dep. Variable: *GTFP*	
	(1)	(2)	(3)	(4)	(5)	(6)
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.

5.2. Influence of industrial digitalization on the technology choice of enterprises

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 first 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, ICT input or industrial digitalization encourages manufacturing enterprises to choose front-end cleaner production technologies, rather than pipe-end treatment technologies.

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.

6. 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 and mechanism 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 and even significantly reduced the total COD emission. 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.

In terms of the influence mechanism, industrial digitalization has two mechanisms on the improvement of enterprise environmental performance: structure 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. This study employs a series of econometric models to identify the role of technology factors in the relationship between industrial digitalization and enterprise environmental performance. 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.

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.

-Authors' Contributions:

Huwei Wen: Resources, Methodology, Formal analysis, Writing - Review & Editing.

Chien-Chiang Lee: Conceptualization, Supervision, Writing - Review & 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: Project supported by the Youth Program of National Natural Science Foundation of China (Grant No. 20CJY031).

-Competing Interests: The authors declare that they have no competing interests.

-Availability of data and materials: Data are available from the authors upon request.

References

1. Acemoglu D, Dorn D, Hanson GH, Price B (2014) Return of the Solow paradox? IT, productivity, and employment in US manufacturing. Am Econ Rev 104(5):394–399
2. Avom D, Nkengfack H, Fotio HK, Totouom A (2020) ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. Technol Forecast Soc Chang 155:120028
3. Beier G, Niehoff S, Xue B (2018) More sustainability in industry through industrial internet of things? Applied Sciences 8(2):219
4. Berkhout F, Hertin J (2001) Impacts of Information and Communication Technologies on Environmental Sustainability: Speculations and Evidence. Report to the OECD, Brighton, p 21
5. Cherniwchan J (2012) Economic growth, industrialization, and the environment. Resour Energy Econ 34(4):442–467
6. Clarkson PM, Overell MB, Chapple L (2011) Environmental reporting and its relation to corporate environmental performance. Abacus 47(1):27–60
7. Dedrick J (2010) Green IS: concepts and issues for information systems research. *Communications of the Association for Information Systems*, 27(1), Article 11
8. DeStefano T, Kneller R, Timmis J (2018) Broadband infrastructure, ICT use and firm performance: Evidence for UK firms. J Econ Behav Organ 155:110–139
9. Hao Y, Guo Y, Guo Y, Wu H, Ren S (2020) Does outward foreign direct investment (OFDI) affect the home country's environmental quality? The case of China. Struct Change Econ Dyn 52:109–119
10. Haseeb A, Xia E, Saud S, Ahmad A, Khurshid H (2019) Does information and communication technologies improve environmental quality in the era of globalization? An empirical analysis. Environ Sci Pollut Res 26(9):8594–8608
11. Higón DA, Gholami R, Shirazi F (2017) ICT and environmental sustainability: A global perspective. Telematics Inform 34(4):85–95
12. Hu D, Feng C, Liang L, Wu P, Du Y (2019) Environmental performance of Chinese listing manufacturing enterprise: from investment perspective. Environ Sci Pollut Res 26(7):6625–6635
13. Hu M, Li R, You W, Liu Y, Lee CC (2020) Spatiotemporal evolution of decoupling and driving forces of CO2 emissions on economic growth along the Belt and Road. J Clean Prod 277:123272
14. Khan D (2019) Effects of information and communication technology and real income on co2 emissions: the experience of countries along belt and road. Telematics Inform 45:101300
15. Kunkel S, Matthess M (2020) Digital transformation and environmental sustainability in industry: Putting expectations in Asian and African policies into perspective. Environ Sci Policy 112:318–329
16. Lange S, Pohl J, Santarius T (2020) Digitalization and energy consumption. Does ICT reduce energy demand? Ecol Econ 176:106760
17. Li Y, Dai J, Cui L (2020) The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. Int J Prod Econ 229:107777
18. Lu WC (2018) The impacts of information and communication technology, energy consumption, financial development, and economic growth on carbon dioxide emissions in 12 Asian countries. Mitig Adapt Strat Glob Change 23(8):1351–1365

19. Martínez-Caro E, Cegarra-Navarro JG, Alfonso-Ruiz FJ (2020) Digital technologies and firm performance: The role of digital organisational culture. Technol Forecast Soc Chang 154:119962
20. Neuhofer B, Buhalis D, Ladkin A (2015) Smart technologies for personalized experiences: a case study in the hospitality domain. Electronic Markets 25(3):243–254
21. Vu KM, Asongu S (2020) Backwardness advantage and economic growth in the information age: A cross-country empirical study. Technol Forecast Soc Chang 159:120197
22. Oliner SD, Sichel DE (2000) The resurgence of growth in the late 1990s: is information technology the story? Journal of Economic Perspectives 14(4):3–22
23. Park Y, Meng F, Baloch MA (2018) The effect of ICT, financial development, growth, and trade openness on CO 2 emissions: an empirical analysis. Environ Sci Pollut Res 25(30):30708–30719
24. Salahuddin M, Alam K (2016) Information and Communication Technology, electricity consumption and economic growth in OECD countries: A panel data analysis. Int J Electr Power Energy Syst 76:185–193
25. Škare M, Soriano DR (2020) A dynamic panel study on digitalization and firm's agility: what drives agility in advanced economies 2009–2018. Technol Forecast Soc Chang 163:120418
26. Wang Y, Hangm Y, Wang Q, Zhou D, Su B (2021) Cleaner production vs end-of-pipe treatment: Evidence from industrial SO2 emissions abatement in China. J Environ Manage 277:111429
27. Wen H, Lee CC (2020) Impact of fiscal decentralization on firm environmental performance: evidence from a county-level fiscal reform in China. Environ Sci Pollut Res 27(29):36147–36159
28. Wen H, Lee CC, Zhou F (2021) Green credit policy, credit allocation efficiency and upgrade of energy-intensive enterprises. Energy Econ 94:105099
29. Zhang D, Li J, Ji Q (2020) Does better access to credit help reduce energy intensity in China? Evidence from manufacturing firms. Energy Policy 145:111710
30. Zhou X, Zhou D, Wang Q, Su B (2019) How information and communication technology drives carbon emissions: a sector-level analysis for China. Energy Econ 81:380–392

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix.docx