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The Impact of Digital Technology Application on Industrial Carbon Emission Intensity: Empirical Evidence from Industry Panel Data

Guanyu Yi

School of Economics, Xinjiang University of Finance and Economic, Urumqi, China
2180570057@qq.com

Abstract. Under the constraints of carbon peaking and carbon neutrality goals, identifying the carbon-reduction effect of digital technology application in industry and its cross-industry variation is essential for designing differentiated low-carbon policies. This paper matches the World Input-Output Database (WIOD, 2013 release) with the OECD Inter-Country Input-Output (ICIO)-based Greenhouse Gas Footprints database (2025 edition) at the industry-year level, constructing a balanced panel of 15 Chinese industrial sectors over 1995-2011 (255 observations). Carbon emission intensity is measured as the ratio of Scope 1 greenhouse gas emissions to value added, and digital technology application is measured as the share of intermediate inputs purchased from information and communication technology (ICT) sectors in total intermediate inputs. A two-way fixed effects model is employed for estimation. The results show that digital technology application is significantly and negatively associated with industrial carbon emission intensity, with a baseline coefficient of -3.16 ($p = 0.0015$): a one-standard-deviation increase in the digitalization share is associated with approximately 30% lower carbon intensity. The finding survives robustness checks including lagged regressors, alternative digitalization measures, winsorization, and an alternative intensity denominator. Heterogeneity analysis indicates that the effect is concentrated in high-technology manufacturing. Policy makers are therefore advised to target technology-intensive manufacturing when deploying digitalization-based decarbonization instruments.

Keywords: digital technology application, industrial carbon emission intensity, industry panel data, two-way fixed effects, heterogeneity analysis

1. Introduction

Addressing global climate change and promoting green, low-carbon development has become an international consensus and an intrinsic requirement for China's new industrialization. Industry, the most carbon-intensive sector, accounts for approximately 70% of China's total carbon emissions according to public data from the National Development and Reform Commission, and is the principal battleground for meeting the "dual carbon" goals. Digital technology application, defined as the penetration of new-generation information technologies such as big data, the industrial

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internet, and artificial intelligence into industrial production, management, and operation, has become a core pathway for empowering industrial decarbonization. However, industrial sectors differ markedly in energy dependence, production processes, and digital foundations, so the emission-reduction effect of digital technology application may exhibit substantial industry heterogeneity.

Existing research has explored the relationship between digital technology and emission reduction at the regional level [1, 2], the firm level [3], and the industry level [4, 5], and generally agrees that digitalization suppresses carbon emissions. Two gaps remain. First, fine-grained industry-level evidence on digital technology application at the production front end remains scarce, and differences across industry attributes have not been fully revealed. Second, digitalization is mostly measured through text-based word frequencies, patent counts, or composite indices; input-output-based measures that capture how deeply digital inputs are embedded in production processes are still rare.

To address these gaps, this paper matches the WIOD (2013 release) with the OECD ICIO-based Greenhouse Gas Footprints database (2025 edition), builds a balanced panel of 15 Chinese industrial sectors over 1995-2011 (255 industry-year observations), and estimates a two-way fixed effects model of industrial carbon emission intensity on digital technology application. Two questions are emphasized: does digital technology application significantly reduce carbon emission intensity at the level of disaggregated industrial sectors, and does the effect vary systematically with energy intensity and technology intensity? The marginal contributions are twofold: digitalization is measured by the share of ICT intermediate inputs in input-output tables, corresponding directly to the embeddedness of digital hardware and communication services in production; and industry heterogeneity along the dimensions of energy intensity and technology intensity is incorporated into a unified framework, with all robustness results, including those that do not support the baseline, reported in full.

2. Literature review and theoretical analysis

2.1. Literature review

Two strands of literature are closely related to this paper. The first concerns the carbon-reduction effect of the digital economy: digital technology innovation significantly reduces carbon emission intensity [1]; digital technology suppresses carbon emissions at the city level [6]; the digital economy exhibits an inverted-U relationship with carbon emission intensity [7]; and enterprise digital transformation is significantly and negatively associated with carbon emission intensity among Chinese listed companies [8]. The units in this strand are mostly regions or firms, and the heterogeneity of digitalization measures limits the comparability of estimates.

The second strand focuses on industrial digitalization and green development, confirming the carbon-reduction effect of industrial digital transformation [4], a threshold effect based on technological innovation in manufacturing [5], the emission-reduction effect and transmission channels of digital transformation in manufacturing firms [3], the green-transformation effect of the digital economy through scientific and technological innovation [2], spatial effects on industrial carbon emission intensity with energy-efficiency improvement as an important channel [9], the positive effect of industrial intelligence on carbon emission efficiency with spatial spillovers [10], and the impact of integrating industrial structure upgrading with the digital economy on urban carbon emissions [11]. Existing studies thus provide ample support for the proposition that digitalization contributes to decarbonization, yet refined industry-level evidence anchored in the

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input structure of the production process remains limited, and differences across industry attributes receive insufficient attention. This paper attempts to complement the literature on both fronts.

2.2. Theoretical mechanism analysis

Digital technology application affects industrial carbon emission intensity by changing the correspondence between energy input and economic output in industrial production. As a general-purpose technology, digital technology acts not through a single isolated improvement but through systemic change across production, management, and operation. The mechanism is decomposed into three channels.

The first channel is the technological progress effect. Digital technology application provides new tools for green technological innovation: the industrial internet and big data technologies enable firms to collect energy-consumption and emission data and accurately locate energy- and emission-intensive processes, while digital simulation and AI-assisted research and development reduce the trial-and-error cost of clean technologies, as when digital twins are used to simulate and optimize blast-furnace ironmaking [1, 12]. This channel answers the question of "whether it is feasible": digital technology enhances the technical capability of cleaner production from the supply side.

The second channel is the resource allocation effect. The core function of digital technology is to reduce information costs and improve allocation efficiency. Under traditional production modes, firms can hardly monitor the energy consumption of each process in real time, resulting in idle equipment operation, excessive energy supply, and peak-valley mismatch. Digital technology changes this situation: online monitoring makes energy use visible, measurable, and controllable; intelligent dispatching dynamically allocates energy supply; and predictive maintenance prevents inefficient operation. In the cement industry, for example, intelligent energy management systems optimize rotary kiln parameters in real time, reducing coal and electricity consumption per unit of clinker. Mechanism analyses in [9] and [7] both indicate that improving energy efficiency is an important pathway of digital-economy-enabled carbon reduction. This channel answers the question of "whether it saves": digital technology reduces the waste of factors and energy on the use side.

The third channel is the industrial structure upgrading effect. Digital technology application promotes intra-industry structural optimization through two routes: it gives rise to cleaner production modes such as intelligent manufacturing, raising the share of high-value-added, low-energy activities in sectoral output; and digital platforms reduce information and coordination costs, directing orders and capital toward firms with higher efficiency and lower emission intensity [2, 10, 11]. This channel answers the question of "whether it restructures": digital technology changes "what is produced and by whom" from the composition side.

The three channels are independent yet complementary. Constrained by data availability, comparable industry-level measures of the mediating variables are unavailable, so formal mediation tests cannot be conducted; the three channels are presented as theoretical derivations, and the empirical part focuses on the questions that can be identified with the available data.

2.3. Research hypotheses

In summary, digital technology application provides the technical and allocative conditions for the decline of industrial carbon emission intensity through the three channels above. Accordingly, hypothesis H1 is proposed:

H1: Digital technology application significantly reduces industrial carbon emission intensity.

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Furthermore, the strength of the three channels may vary with industry attributes. Technology-intensive sectors are generally closer to the technological frontier; digital equipment and communication services couple more easily with their production processes; and digital inputs are more deeply embedded in production. In medium- and low-technology sectors, by contrast, production processes are relatively mature and rigid, and digital inputs are more often used in general management and distribution than in the production process. Accordingly, hypothesis H2 is proposed:

H2: The carbon-intensity-reducing effect of digital technology application is stronger in technology-intensive manufacturing.

3. Methodology

3.1. Data sources and sample construction

The empirical analysis is based on an industry-level panel of 15 Chinese industrial sectors over 1995-2011, yielding 255 industry-year observations. Two public data sources are combined: the 2013 release of the World Input-Output Database, which provides annual inter-industry transaction tables, value added, and gross output by industry, with all monetary magnitudes in millions of current US dollars [13]; and the OECD ICIO-based Greenhouse Gas Footprints database (2025 edition), which provides industry-level Scope 1 (direct) greenhouse gas emissions in million tonnes of CO2 equivalent (Mt CO2e) [14]. The two sources follow consistent industry classifications and can be merged directly at the industry-year level.

Two features of the sample construction deserve mention. First, because the OECD emissions database reports textiles and leather products under a single aggregate heading, WIOD industries c4 (Textiles and Textile Products) and c5 (Leather, Leather and Footwear) are merged into one composite sector, denoted c45. Second, the sample period is bounded by the WIOD 2013 release, whose annual tables end in 2011. The WIOD is a standard data source for industry-level research, and studies based on the 2013 release continue to appear in authoritative journals in recent years.

3.2. Variable definitions

The dependent variable is carbon emission intensity (carbon_int), defined as the ratio of an industry's Scope 1 greenhouse gas emissions to its value added, expressed in tonnes of CO2e per 1,000 US dollars of value added. Because the intensity measure is strongly right-skewed (see Section 4.1), its natural logarithm (ln_ci) is used in all regressions. The key explanatory variable is the intensity of digital technology application (dig_share), measured as the share of intermediate inputs purchased from the ICT-producing sectors, namely WIOD industries c14 (Electrical and Optical Equipment) and c27 (Post and Telecommunications), including imported intermediates, in an industry's total intermediate inputs. This measure captures the extent to which digital hardware and communication services are embodied in each industry's production process. For the log-log specification, ln_dig = ln(dig_share) is additionally constructed. The control variable is industry size, ln_va, the natural logarithm of value added. As a robustness check, an alternative intensity measure, ci_output, is computed on a gross-output basis.

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3.3. Model specification

To estimate the effect of digital technology application on industrial carbon emission intensity, the following two-way fixed effects panel model is specified:

$$\ln(CI_{it}) = \beta \cdot Dig_{it} + \gamma \cdot \ln(VA_{it}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i indexes industries and t indexes years. The dependent variable is the natural logarithm of carbon emission intensity; Dig_it is the digitalization measure (dig_share in the baseline and ln_dig in the log-log variant); ln(VA_it) controls for industry scale; μ_i denotes industry fixed effects, which absorb all time-invariant heterogeneity across sectors; and λ_t denotes year fixed effects, which absorb common shocks such as macroeconomic cycles, energy price movements, and environmental policy shifts. Standard errors are clustered at the industry level.

Three specifications are estimated. Model M1 includes dig_share alone with the two-way fixed effects. Model M2, the preferred specification, adds the scale control ln_va. Model M3 replaces the level of dig_share with its logarithm, so that β can be interpreted as an elasticity. Under the hypothesis that digital technology application reduces carbon intensity, β is expected to be negative.

4. Empirical results

4.1. Descriptive statistics

Table 1 reports descriptive statistics for the main variables. Carbon intensity is highly dispersed: the mean is 6.158 t CO2e per 1,000 USD of value added, with a standard deviation of 12.136, a minimum of 0.120, a median of 2.040, and a maximum of 84.578. The fact that the mean is roughly three times the median, together with the extreme upper tail, indicates strong right skewness and justifies the logarithmic transformation. Digitalization intensity also varies substantially: dig_share averages 0.067 with a standard deviation of 0.112, ranging from 0.005 to 0.515, while the median of 0.024 shows that for most industry-year cells ICT intermediates account for only a small fraction of total intermediate use.

Table 1. Descriptive statistics (N = 255)

Variable	Mean	SD	Min	Median	Max
carbon_int (t CO2e / 1,000 USD VA)	6.158	12.136	0.120	2.040	84.578
dig_share	0.067	0.112	0.005	0.024	0.515

4.2. Baseline results

Table 2 reports the baseline estimates. In M1, which conditions only on industry and year fixed effects, the coefficient on dig_share is -5.1107 (clustered standard error 0.8162; t = -6.26), significant at the 1% level. Once industry scale is controlled in M2, the coefficient attenuates to -3.1600 (standard error 0.9807; t = -3.22; p = 0.0015) but remains highly significant, suggesting that part of the raw correlation in M1 reflects differences in industry size. The economic magnitude of the M2 estimate is considerable: a one-standard-deviation increase in dig_share (0.112) is associated with a decrease in log carbon intensity of 3.16 × 0.112 ≈ 0.354, corresponding to exp(-0.354) - 1 ≈ -29.8%, i.e., carbon intensity about 30% lower.

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In M3, the log-log specification, the coefficient on ln_dig is -0.1509 (standard error 0.1807; p = 0.4047) and is not statistically significant. A plausible explanation is that the logarithmic transformation compresses variation in dig_share precisely at the upper end of its distribution, namely the high-technology industries where, as Section 4.4 shows, the effect is concentrated. The level form therefore appears more appropriate for this sample, and M2 is retained as the main specification. The baseline results support hypothesis H1.

Table 2. Baseline regression results (dependent variable: ln carbon intensity)

	(M1)	(M2)	(M3)
dig_share	-5.1107*** (0.8162)	-3.1600*** (0.9807)	
ln_dig			-0.1509 (0.1807)
Scale control (ln_va)	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	255	255	255

Note: Cluster-robust standard errors (clustered at the industry level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. t-statistics: -6.26 (M1), -3.22 (M2). M3 p = 0.4047.

4.3. Robustness checks

Table 3 presents six robustness exercises conducted within the M2 framework, four of which support the baseline finding. R1 replaces dig_share with its one-period lag; the coefficient is -2.9086 (standard error 0.9512; p = 0.0025; N = 240), very close to the baseline. R2 narrows the digitalization measure to intermediate inputs from the ICT equipment sector alone (c14); the coefficient becomes -3.4492 (standard error 0.9556; p = 0.0004). R3 winsorizes the dependent variable at the 1% level; the coefficient is -3.3530 (standard error 0.9847; p = 0.0008). R5 recomputes carbon intensity on a gross-output basis; the coefficient is -4.4981 (standard error 1.0891; p = 0.0001), confirming that the finding does not depend on the choice of denominator.

Two checks, however, do not survive, and they are reported in full. R4 excludes the electrical and optical equipment industry (c14) itself from the sample; the coefficient on dig_share becomes 0.2895 (p = 0.9472) and loses all significance. R6 redefines the digitalization measure to exclude each industry's own intra-industry consumption of ICT goods; the coefficient is 1.1727 (p = 0.7686), again insignificant. The implications of these two null results are discussed candidly in Section 5: the aggregate baseline effect is to an important extent driven by the c14 industry and by the self-consumption component of the digitalization measure, so the appropriate interpretation is narrower than a universal economy-wide effect.

Table 3. Robustness checks (M2 framework; dependent variable: ln carbon intensity)

Check	Coefficient	Cluster SE	p-value	N
R1: dig_share lagged one period	-2.9086***	0.9512	0.0025	240
R2: ICT equipment (c14) inputs only	-3.4492***	0.9556	0.0004	255
R3: Dependent variable winsorized at 1%	-3.3530***	0.9847	0.0008	255

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Table 3. (continued)

R4: Excluding industry c14	0.2895	—	0.9472	—
R5: Intensity computed on gross output	-4.4981***	1.0891	0.0001	255
R6: Digitalization net of own-industry consumption	1.1727	—	0.7686	255

Note: All specifications include ln_va and industry and year fixed effects, with industry-clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1. "—" indicates statistics not reported. R4 uses the 14-industry subsample.

4.4. Heterogeneity analysis

To investigate where the digitalization-carbon intensity relationship is strongest, the sample is split along two dimensions: energy intensity and technological sophistication. Table 4 reports the results.

Splitting by energy intensity yields no significant estimates in either subsample: the coefficient is 8.7174 (p = 0.2578) for the high energy-intensity group (industries c2, c7, c8, c9, c11, c12, c16, c17) and -0.3911 (p = 0.8062) for the low energy-intensity group. Energy intensity alone therefore does not appear to be the relevant margin.

Splitting by technological sophistication produces a sharp contrast. For high-technology manufacturing industries (c9, c13, c14, c15, including machinery, electrical and optical equipment, and transport equipment), the coefficient on dig_share is -1.8606 (standard error 0.4196; p = 0.0001; N = 68), significant at the 1% level. For medium- and low-technology manufacturing, the coefficient is 9.0844 (p = 0.6048) and statistically indistinguishable from zero. A formal test on the full sample using an interaction between dig_share and a high-technology indicator yields an interaction coefficient of -10.4565 (standard error 5.3883; p = 0.0536), significant at the 10% level, providing direct evidence that the carbon-intensity-reducing association of digitalization is significantly stronger in technology-intensive manufacturing. Hypothesis H2 is supported.

Table 4. Robustness checks (M2 framework; dependent variable: ln carbon intensity)

Subsample / test	Coefficient	Cluster SE	p-value	N
High energy-intensity industries	8.7174	—	0.2578	—
Low energy-intensity industries	-0.3911	—	0.8062	—
High-technology manufacturing (c9, c13, c14, c15)	-1.8606***	0.4196	0.0001	68
Medium-/low-technology manufacturing	9.0844	—	0.6048	—
Interaction: dig_share × high-tech (full sample)	-10.4565*	5.3883	0.0536	255

Note: All specifications include ln_va and industry and year fixed effects, with industry-clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1. "—" indicates statistics not reported.

The results are consistent with the technological progress and resource allocation mechanisms derived in Section 2: digital inputs pay off in efficiency terms precisely where production operates close to the technological frontier, namely in high-technology manufacturing. Since the data do not allow the estimation of mediation models, this consistency argument is interpretive rather than causal-decompositional.

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5. Conclusion

5.1. Main findings

This paper matches the WIOD (2013 release) with the OECD ICIO-based Greenhouse Gas Footprints database (2025 edition), constructs a balanced panel of 15 Chinese industrial sectors over 1995-2011 (255 observations), and examines the impact of digital technology application on industrial carbon emission intensity using a two-way fixed effects model. The main findings are as follows.

First, digital technology application is significantly and negatively associated with industrial carbon emission intensity. In the baseline estimate (M2), the coefficient on the digitalization share is -3.1600 ($p = 0.0015$); a one-standard-deviation increase in the digitalization share (0.112) is associated with approximately 29.8% lower carbon emission intensity. The result survives robustness checks including lagged regressors, a narrower digitalization measure, winsorization, and an alternative intensity denominator (R1, R2, R3, R5), supporting hypothesis H1.

Second, the decarbonization effect exhibits significant industry heterogeneity, and the relevant dimension is technology intensity rather than energy intensity. Neither energy-intensity subsample yields a significant estimate, whereas the coefficient for high-technology manufacturing is -1.8606 ($p = 0.0001$) and the interaction test (coefficient -10.4565, $p = 0.0536$) confirms the difference. Hypothesis H2 is supported.

Third, the aggregate baseline effect should not be extrapolated to industry as a whole: once the electrical and optical equipment industry is excluded (R4) or the digitalization measure is netted of intra-industry self-consumption (R6), the coefficient loses significance entirely ($p = 0.9472$ and $p = 0.7686$, respectively). The appropriate interpretation is that the carbon-intensity-reducing effect of digital technology application is concentrated in technology-intensive manufacturing.

5.2. Policy implications

Three policy implications follow. First, digitalization-based decarbonization instruments should be targeted primarily at technology-intensive manufacturing: coordinated digital-green transformation policies should prioritize digital retrofitting in sectors such as machinery, electrical and optical equipment, and transport equipment, rather than imposing uniform expectations on all industries. Second, the deep integration of ICT inputs with production processes should be promoted, guiding firms to extend digital equipment and communication services from general management to the shop floor. Third, one-size-fits-all industrial emission-reduction policies should be avoided; since the effect varies systematically across industries and energy intensity is not the relevant dividing line, policy design should differentiate industries by technological attributes.

5.3. Limitations and future research

Several limitations qualify the findings. First, the sample ends in 2011, before the rapid diffusion of mobile internet, cloud computing, and industrial platform technologies in China; the estimates therefore correspond to an earlier phase of digitalization centered on ICT hardware and telecommunications. Second, the analysis uses industry-level aggregates for 15 sectors, which masks within-industry firm heterogeneity and limits the number of clusters to 15. Third, the digitalization proxy covers only ICT hardware (c14) and post and telecommunications services (c27), excluding software, data services, and digital platforms. Finally, the estimates remain

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conditional correlations, and unobserved time-varying industry-level shocks correlated with digitalization cannot be ruled out. Future research may extend the sample beyond 2011, use firm-level micro data to formally test the three channels, and refine the digitalization measure.

Data availability. The processed industry panel dataset and the complete replication code are available from the corresponding author upon reasonable request. Raw data are publicly available from the WIOD [13] and the OECD Data Explorer [14].

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