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Does the Development of the Digital Economy Benefit Urban Carbon Reduction? Evidence from the Yangtze River Delta Region

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Abstract. The Yangtze River Delta (YRD) is an experimental location of high-quality holistic growth in China and an important area for realizing the "dual carbon" goal. Utilizing panel data from 27 important municipalities in the YRD urban agglomeration from 2010 to 2020, the fixed-effect model is used to evaluate the stage of advancement in the digital economy on urban emission levels. As an intermediary variable, industrial structure modification was tested to see how the digital economy affected local dioxide emissions. The results show that: (1) After an array of robustness tests, the overall impact on both core variables is inverted U-shaped, facilitating and then constraining emissions; (2) As part of its function in cutting emissions, the digital economy also impacts the industrial framework, which has an indirect, nonlinear, U-shaped effect on the intensity of regional dioxide emissions; (3) Looking further, regions with high levels of government spending and investment in innovation are those where carbon emissions are most clearly affected by digitalization. There is still opportunity for evolution and optimization of the YRD region's energy consumption process. The study's findings expand our comprehension of the factors that influence high-quality community growth as well as how the digital economy works to support it.

Keywords. Digital economy; carbon emissions; Yangtze River Delta (YRD); industrial structure

1. Introduction

Carbon emissions and numerous connected environmental issues have received global attention. The YRD region stands out as a hub of intense economic development, high levels of openness, and strong innovation capacities in China. The concept of digital economy states that the full evaluation index of the sector is built from the two dimensions of “digital industrialization” and “industrial digitization” by CAICT (2019). Most studies about digitalization are focused at the scale of the province, and a few are measured at prefecture-level cities and below in a comprehensive index evaluation method [1]. The digitalization can be measured from several levels, for example, digital innovation capability, digital business emergence, digital infrastructure, and digital trade

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level [2]. Meanwhile, the methods used to calculate dioxide emissions mainly include IPCC method, life cycle method, mass balance method and actual measurement method. Digital economy has a multi-path and multi-dimensional comprehensive impact on carbon emissions. Also, it can change urban environments in three areas: production, life, and ecological space and examined the effect of digitalization on the transition to a greener urban environment [3]. From a different perspective, digitalization has greatly decreased the sum of emissions and has a nonlinear relationship with intensity of emissions, which shows as a U-shaped curve [4,5]. Furthermore, comparing with the labor efficiency improvement effect, reducing energy intensity can further promote reducing the emissions [1].

However, the possible margin of contribution of this research in comparison to the existing literature includes: First, most of the current academic study in this field is provincial or national, and relatively few studies are based on urban agglomerations, our study enriches relevant research experience. Second, to better understand how industrial structure may play a part in the nonlinear link of the benchmark result, this research also adds industrial structure as an intermediate variable. Third, we conduct heterogeneity analysis for investigating the variations in how the digitalization affects dioxide emissions under various policy contexts.

In summary, employing the data of 27 YRD's cities from 2010 to 2020, we attempt to construct a development of digitalization index system from the definition of digitalization, and use the fixed effect model to empirically analyses the effect mechanism, as well as the intermediary effect of industrial structure.

2. Research hypothesis

The following three factors may show how digitalization may affect carbon emissions: Digitalization has significantly boosted the prosperity of e-commerce market, given consumers access to a wider range of goods and services, greatly boosted demand, and allowed businesses to scale up production, which has increased usage of resources and carbon emissions [6]. Contrarily, it may also lead to the phenomenon of "Jevons Paradox" [7], that is, the efficiency of energy production will greatly improve the energy supply capacity, and in turn, the market competition of energy companies will intensify, leading to a decline in energy prices, promoting energy consumption.

According to the preceding analysis assumptions:

H1: The development of digitalization first increases and then reduces dioxide emissions, forming an inverted U-shaped curve.

Two factors may reflect how digitalization is affecting the manufacturing framework: (1) The digital economy can restructure the traditional energy sectors which makes it necessary to update or rebuild a cleaner and more complete manufacturing industry at the early stage of the development cycle. (2) The improvement of digitalization can hasten the transfer of information and production components between geographical areas, truly raising the bar for intelligent production while fostering the production of labor, land, technology, capital, etc. which can raise the proportion of the tertiary sector with relatively low emissions of carbon.

According to the preceding analysis assumptions:

H2: The digital economy indirectly affects regional dioxide emission by affecting the industrial structure.

3. Research design

3.1. Model Design

In formula (1), the subscripts i and t represent the city and the year respectively, the explained variable CE_{it}represents the carbon emission intensity of the i-th city in the t-year, and the explanatory variables DE_{it} and SDE_{it} represent the digital economy development comprehensive index of the i -th city in the t-year respectively the first-order and second-order items of , controls are a series of control variables, which $\mu_i$are city fixed effects, $\delta_t$time fixed effects, $\varepsilon_{it}$and random disturbance items.

$$CE_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 SDE_{it} + \sum_{i=3}^{n} \alpha_i controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

The intermediate effect test and intermediary effect model are built by referring to Wen's (2006) [8] research techniques in order to investigate the potential intermediary effect of digitization on the adjustment of industrial structure:

$$IS_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 SDE_{it} + \sum_{i=3}^{n} \beta_i controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$
$$CE_{it} = \gamma_0 + \gamma_1 DE_{it} + \gamma_2 SDE_{it} + \gamma_3 IS_{it} + \sum_{i=4}^{n} \gamma_i controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

In formulas (2) and (3), IS_{it}it represents the i-th city's industrial structure in t-year as an intermediary variable.

3.2. Variable Description

Carbon emission intensity (CE) as the interpreted variable is measured by common fossils, this study employs data on the energy supply that is rather simple to get and is based on the methodology of Miao et al. (2022) [9] and uses relatively easily available energy supply data to calculate common fossil, which includes crude oil, kerosene, natural gas, etc. The following equation is adopted to calculate the intensity in prefecture-level cities and is based on large part on the carbon emission factor technique described in the IPCC Inventory Guidelines:

$$C_E^t = \sum_{i=1}^{n} C_{Direct,i}^t = \sum_{i=1}^{n} \sum_{j=1}^{m} [E_{ij}^t \times LCV_{ij}^t \times CC_{ij}^t \times COF_{ij}^t \times \frac{44}{12}] \quad (4)$$

Among them, C_E^t represents the total amount of carbon emissions; E_{ij}^t represents the j energy consumption of the i region in t-year; LCV_{ij}^t represents the average low calorific value of the energy; CC_{ij}^t represents the carbon content per unit calorific; COF_{ij}^t represents the oxidation rate of an energy source; $\frac{44}{12}$ represents the ratio of the molar mass of carbon dioxide to the molar mass of carbon element.

Comprehensive index of digital economy development (DE) and DE square (SDE) are explanatory variables. Considering the accessibility of data and the scientific nature of system design, this paper draws lessons from Xu et al. (2022)[10], Xie (2022) [11], Zhao et al. (2020) [12] for the construction of the digital economy index system , employing the percentage of urban regions' Internet-broadband users, the amount of tele-business conducted per capita, and the number of smartphone users per 100 people, and the digital inclusive financial index, the comprehensive index is obtained through the entropy weight method.

Industrial structure (IS) is the intermediary variable of this article, learning from the research of Gan et al. (2011) [13], it selects the ratio that the added value of the tertiary industry is divided to the secondary in prefecture-level cities.

The control variables are set for researching the function of digitalization in urban emission reduction more thoroughly, as follows: Government interference (GOV) is measured as the ratio that local general budget expenditure divides to regional GDP. Energy consumption structure (ECS) is calculated as the ratio of fossil fuel usage to total energy usage. Urbanization rate (UR) is the percentage of built-up area to urban area. Transportation capacity (ROAD) is the logarithm of actual road space per person. Technical level (SCIENCE) is the percentage of local science expenditure to GDP.

In this study, the data includes 27 prefecture-level cities of YRD are chosen from 2011 to 2020. The "China City Statistical Yearbook", "China Energy Statistical Yearbook" and other city-specific statistical yearbooks are the origination of data. When values are absent, linear interpolation is used to fill them. Table 1 displays the descriptive analysis of all variables considered.

Table 1 Variable descriptive statistics

Variables	ce	de	sde	is	gov	ecs	ur	road	science
N	270	270	270	270	270	270	270	270	270
Mean	0.01	0.174	0.038	1.011	0.142	0.114	0.123	2.568	0.007
Std.Dev	0.004	0.089	0.041	0.379	0.049	0.081	0.091	0.365	0.016
Min	0.004	0.061	0.004	0.269	0.075	0.041	0.015	1.396	0.001
Max	0.034	0.454	0.206	2.751	0.283	0.476	0.789	3.343	0.163

4. Empirical analysis

The F-test and Hausman test are utilized in selecting a suitable model in research. In the individual fixed effect model (column 1), The overall digital economy development index's regression coefficient is -0.021, which is statistically significant ($p<0.01$) , but in the column 2, after controlling the individual effect and time effect, there is a positive correlation among main variables ($p<0.05$). It is likely that institutional factors will affect digitalization and emissions simultaneously, and those factors are affected by time larger, making some variables become endogenous variables, so this model considering the interaction items of temporal dummy variables can better exclude the influence of such unobservable factors. The coefficient of DE is positively associated with independent variable, while its quadratic coefficient demonstrates a significant negative relationship. This finding supports Hypothesis 1 outlined in this paper.

The coefficients of energy usage framework and government intervention level are significantly positive ($p<0.01$), demonstrating that as government spending grows, the coal's share of energy use rises. It may lead to the time lag of policy implementation, also government fiscal expenditure is not yet fully utilized. The negative coefficients obtained from the regression analysis of urbanization rate and transportation level are statistically significant ($p<0.01$), indicating that greater urbanization and easier access to roads have a positive effect on lowering emissions. The coefficient of technological development level shows that the increase in science expenditure may suppress carbon emission, but this effect is not significant in the current model.

Table 2. Model regression results

	(1) ce_gdp	(2) ce_gdp	(3) ce_gdp	(4) is	(5) ce_gdp
de	-0.021 ***	0.006 **	0.022 **	-1.407 *	0.024 ***
	(0.004)	(0.003)	(0.009)	(0.954)	(0.009)
sde			-0.026 *	4.231 ***	-0.032 **
			(0.014)	(1.497)	(0.014)
is					0.001 **
					(0.001)
ecs	0.024 ***	0.006 ***	0.007 ***	0.256	0.006 ***
	(0.002)	(0.002)	(0.002)	(0.174)	(0.002)
gov	0.033 ***	0.054 ***	0.056 ***	-0.441	0.056 ***
	(0.009)	(0.005)	(0.005)	(0.572)	(0.005)
ur	-0.008 ***	-0.004 ***	-0.004 ***	-0.116	-0.004 ***
	(0.003)	(0.002)	(0.002)	(0.171)	(0.002)
road	-0.006 ***	-0.001 ***	-0.002 ***	-0.128 **	-0.001 ***
	(0.001)	(0.000)	(0.000)	(0.050)	(0.000)
science	-0.048 ***	-0.003	- 0.001	2.773 ***	-0.003
	(0.015)	(0.009)	(0.009)	(0.994)	(0.009)
_cons	0.022 ***	0.010 ***	0.008 ***	1.240 ***	0.006 ***
	(0.002)	(0.001)	(0.002)	(0.185)	(0.002)
N	270.000	270.000	270.000	270.000	270.000
r2	0.594	0.881	0.883	0.666	0.885
r2_a	0.539	0.859	0.861	0.605	0.863
individual	control	control	control	control	control
time	not control	control	control	control	control

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In this paper, industrial structure is used as an intermediary variable to build models, in which column (4) in table 2 represents formula (2), and column (5) represents formula (3). Column (4) shows that there is a U-shaped nonlinear link between digitalization and manufacturing framework. The digitalization leads to the updating and iterating of industrial equipment, which increases the consumption and added value of the secondary industry. Industries in the area with high energy usage and pollution have been influenced in more recent times by policy implementation and public pressure. The results in column (5) make it clear that there is a positive correlation between the first-order coefficient of DE and the intensity of emissions, while the second-order term shows a negative correlation ($p<0.05$), showing that the nonlinear, U-shape curve between main variables, in which the coefficient of IS is 0.001 ($p<0.05$). After eliminating intermediary variables in column (3), the absolute value of item coefficients for first-order and second-order of DE increased, while significance level also showed an increase when compared to its counterpart in column (5). This provides evidence that the digitalization has an indirect impact on carbon emissions through the intermediary variable of manufacturing framework, thereby verifying hypothesis 2.

4.1. Robust Test

The robust test includes three parts, firstly, considering the possible impact of extreme values of results, we replace the dependent variable as the original winsorized by 1%. Secondly, we change the method of calculating the the comprehensive index of DE from the entropy weight method to the PCA [14]. Thirdly, considering that policy-related control variables may have endogeneity, we use the level of government interference and the level of technological development as two tools with a one-period lag variable [15].

Table 3 Robustness analysis.

	(1)	(2)	(3)
de	0.021 ***	0.233 ***	0.034 *
	(0.007)	(0.075)	(0.022)
sde	-0.026 **	-0.155 ***	-0.039 ***
	(0.012)	(0.054)	(0.013)
_cons	0.008 ***	-0.073 ***	0.021 ***
	(0.001)	(0.025)	(0.003)
N	270.000	270.000	243.000
r2	0.906	0.889	0.567

The outcomes of the above three robust tests are shown in Table 3. In comparison to the benchmark regression findings presented in Table 2, it is evident that while there are differences observed in variable significance and coefficient magnitudes, the inverted U-shaped relationship still holds. Thus, this study's conclusion remains robust.

4.2. Heterogeneity analysis

Heterogeneity analysis is carried out from two perspectives. On the one hand, the sample is split into two equal portions by fiscal expenditure, that is measured by the percentage of area general fiscal expenditure in GDP, named high-level and low-level. Table 4 (1) and (2) display the findings. It may be concluded that the results are more significant in the cities with greater fiscal spending levels. On the other hand, this study separates urban innovation into two groups by the median level of technological advancement, citing Guo et al.'s approach from 2022 [16]. Column (3) and (4) of Table 4 display the regression findings. It is evident that the first-order and second-order terms of DE in cities with strong innovation input exceed the 5% significance level but fail to pass the significance test in cities with low innovation input.

Table 4 Heterogeneity analysis.

	Fiscal expenditure level		Urban Innovation Level	
	(1) Low	(2) high	(3) Low	(4) high
de	0.011	0.051 ***	-0.004	0.023 ***
	(0.008)	(0.016)	(0.018)	(0.007)
sde	-0.002	-0.081 ***	0.003	-0.024 **
	(0.010)	(0.027)	(0.033)	(0.009)
_cons	0.012 ***	0.003 ***	0.016 ***	0.008 ***
	(0.002)	(0.003)	(0.003)	(0.001)
N	135.000	135.000	135.000	135.000
r2	0.959	0.881	0.902	0.955
r2_a	0.945	0.842	0.869	0.939

5. CONCLUSION

From this study, we find the impact of digitalization on dioxide emissions shows an inverted U-shaped nonlinear pattern that first increase and then reduce. Meanwhile, within the time frame analyzed in this paper, manufacturing framework serves as a mediating factor. Also, this impact is more significant in regions with high fiscal expenditure and high innovation investment.

Considering the previous results, firstly, we propose to create a low-carbon industrial structure system in the YRD by a comprehensive plan, which will guide the upgrade of industrial structure and encourage to use greener energy, while simultaneously constraining the scale of high-pollution industries and high-carbon emission energy industries within the region. Secondly, to promote green development, it is imperative to enhance the low-carbon industrial system and the digital economy development standard system. To achieve this, we must foster digital innovation and promote economic growth that is both sustainable and environmentally friendly. Thirdly, the local policy on environment assessment is still in its early stages and has not yet completely tapped into the potential for energy saving and emission reduction, as well as the economic benefits of digitalization. To address these issues, it is important to increase urban science expenditures and enhance environmental monitoring capabilities and management flexibility.

The innovation of this paper is to study the relationship of digitalization and carbon emission intensity of urban agglomerations from a new research scale, to provide effective experience for digital emission reduction in different urban agglomerations and regions. Future researchers may benefit from these findings in their understanding of internal mechanisms among variables and in their evaluation and guidance of local governments' emission reduction initiatives. Also, the data used in this paper may not fully reflect the level of variables given the availability of data. Next, we can establish a more precise indicator system for digitalization and more comprehensive greenhouse gas data for calculating carbon emission indicators. The analysis of regional disparities study also focus mostly on economic factors. The next step is to investigate the driving mechanism from various angles considering the surroundings.

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