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THE IMPACT OF THE DIGITAL ECONOMY ON CARBON EMISSIONS: EVIDENCE FROM CHINA

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ABSTRACT

To achieve net-zero carbon dioxide emissions, countries including China have taken actions to transform their energy-intensive industries and optimize their energy consumption structure. One possible way is to integrate the development of the digital economy into the green-economy efficiency promotion. This study examines the effects of the development in the digital economy on carbon emissions based on the panel data of 31 provinces in mainland China spanning from 2009 to 2019. The regression results show that there was a negative relationship between the digital economy and carbon emissions, which seems to run counter to the prior hypothesis. This is probably because since the beginning of this period China has already been taking advantages of developments in the digital economy to reduce carbon dioxide pollution. Based on the empirical results, I suggest that the digital economy be used to increase the overall productivity and efficiency of the economy, especially in under-developed areas like the northeastern region.

Contribution/Originality: As digital economy gradually becomes one of the driving forces of economic growth, this paper investigates its effects on reducing carbon emissions. Using the example of China, this study presents ways in which all developing countries can achieve the goal of environmental protection.

1. INTRODUCTION

In 2015, China made a commitment at the World Climate Change Conference in Paris to peak carbon emissions around 2030 and strive to reach the peak as early as possible, and to reduce carbon emissions per unit of GDP by 60% to 65% compared to 2005. With only eight years left, China will take stronger measures and policies. It is foreseeable that carbon emissions will become one of the most important indicators of economic development. Meanwhile, with the rapid development of the digital economy, digital technology is deeply integrated with agriculture, manufacturing, and the service industry, bringing about economies of scale and the long-tail effect. Improved total factor productivity is becoming a new force driving China's economic growth. Therefore, it is of practical importance to analyze the impact of the development of digital economy on carbon emissions in order to further expand the scale of the digital economy and achieve the goal of carbon neutrality and carbon peaking by 2030. Recent theoretical and empirical studies have mostly focused on analyzing the impact of variables related to the digital economy on carbon emissions. One variable selected is information and communication technology (ICT), the core factor of the digital economy, as an explanatory variable. Zhang and Liu (2015) and Bekaroo, Bokhoree, and Pattinson (2016) argue that on the one hand ICT increases the use of related electrical equipment, leading to more carbon emissions, and on the other hand

ICT helps to improve energy efficiency and reduce net energy consumption and carbon emissions. Ozcan and Apergis (2018); Lu (2018) and Higón, Gholami, and Shirazi (2017) argue that ICT only has a one-sided negative effect on carbon emissions. The digital economy relies heavily on energy consumption. Mining of rare-earth metals, e-waste and carbon emissions have led to increasingly serious environmental problems. Malmodin, Lundén, Moberg, Andersson, and Nilsson (2014) analyzes the issue from a perspective of economic development, maintaining that ICT development may attract foreign companies and increase carbon emissions in the host country. Another frequently chosen variable is industrial structure. The positive effects of digital economy on industrial structure upgrading are unanimously affirmed by scholars. Therefore, the relationship between industrial structure and carbon emissions is highly correlated with that between the digital economy and carbon emissions. Guo, Liu, and Zhao (2021) finds that industrial structure is associated with the level of economic development. Developing countries can promote productivity by adjusting their industrial structure, and by doing so, they can cut carbon emissions. Zhang (2018) studies the influence of several factors on carbon emissions, among which industrial structure is shown to have a negative driving effect on energy consumption and carbon dioxide emissions.

By reviewing the literature we see that existing studies in related areas have not reached any serious consensus, and few studies have tackled directly the relationship between the digital economy and carbon dioxide emissions. In view of this, the current paper establishes an indicator evaluation system for the level of development of the digital economy in China. Provincial-level panel data are then used to empirically examine whether there exists a U-shaped relationship between carbon emissions and the development level of the digital economy, and determine whether the impact of the digital economy on carbon dioxide emissions is heterogeneous among different parts of China.

2. THE MECHANISM

The potential impact of the digital economy on carbon emissions is twofold: one is to increase carbon emission intensity and the other is to reduce it. On the one hand, the deepening integration of the digital economy with more and more industries can promote production efficiency and accelerate the transformation and upgrading of the industrial structure, leading to more capital investment in new information, technology, and smart services industries and the withdrawal of traditional high-polluting industrial enterprises. In the long run, it could help to reduce carbon dioxide through technology spillovers and other effects. On the other hand, the development of the digital economy may not be able to reduce the emission of pollutants in the production chain but will cause rapid growth of industrial production capacity, which will unavoidably bring more carbon emissions. On balance, it is of central importance to evaluate the speed of carbon emissions versus the speed of carbon dioxide reduced by digitization.

3. BUILDING AN INDICATOR EVALUATION SYSTEM

Basically, there are two main methods to measure the digital economy. One is to directly estimate the degree of the development of digital economy in a certain region under the defined scope. But this method is not used widely because of its lack of accuracy. Most scholars have adopted the comparative method, which seeks to select multidimensional indicators to measure the development level of the digital economy. In this respect, Measuring the Information Society Report published by the International Telecommunication Union covers infrastructure construction, industrial applications, and the human capital situation in its evaluation system. Jiao and Sun (2021) adds innovation input and output indicators on this basis, taking into account the impact of the innovation capacity of the digital economy. Referring to the indicator evaluation system presented in Table 1, this paper includes the three factors of ICT infrastructure, ICT application, and innovation capability with each factor covering a couple of dimensions.

Table 1. Indicators of the digital economy development.

Indicator	Secondary Indicator	Unit	Index Attribute
ICT infrastructure	The number of domain names	Ten thousand units	Positive
	The number of websites	Ten thousand units	Positive
	Length of long-distance fiber optic cables	Ten thousand km	Positive
	Penetration rate of cell phones	Units/ hundred people	Positive
	the number of Internet broadband access ports	Ten thousand units	Positive
ICT application	Internet penetration rate	%	Positive
	Software business income	Ten thousand yuan	Positive
	Software product income	Ten thousand yuan	Positive
Innovation capability	Technology expenditure	Ten thousand yuan	Positive
	The number of college graduates	Ten thousand units	Positive
	The number of R&D projects in high-tech industries	Unit	Positive
	R&D expenditure in high-tech industries	Ten thousand yuan	Positive

4. THE DATA AND VARIABLES

A. The Main Explanatory Variables

The data of twelve secondary indicators is collected from the National Bureau of Statistics Database, China Stock Market & Accounting Research Database and the Statistics report for China Internet Developing Situation published by China Internet Network Information Center. Since the entropy method can reflect the utility value of information entropy, eliminate human interference factors, and can reflect the development of the digital economy in a more objective way, I apply the entropy method to give the entropy weight to each indicator. I state the details as follows.

(i) Standardizing the data: Because the data have different magnitudes and units, it cannot be calculated directly and need to be standardized first. In this paper, the polarization method is used to process the data, and since the data are all positive indicators, the following formula is used:

$$r_{ij} = \frac{x_{ij} - x_{jmin}}{x_{jmax} - x_{jmin}}, i = 1,2, \dots, m; j = 1,2, \dots, n$$

r_{ij} is the standardized value of the *j*-th indicator in the *i*-th year; x_{ij} is the level from the original data; x_{jmin} and x_{jmax} are the minimum and maximum values of each indicator in the corresponding calendar year. For the data used in this paper, *m* is taken to be 10 while *n* is taken to be 12. In order to eliminate the impact of 0 on the result, it is necessary to do a linear transformation by adding 0.00000001.

(ii) Calculating the proportion of the *j*-th indicator: I calculate the proportion of the *j*-th indicator P_{ij} as;

$$P_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$$

(iii) Calculating the entropy value of the *j*-th indicator: Calculate the entropy value of the *j*-th indicator e_j as;

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij}, \quad \text{where } k = \frac{1}{\ln m}$$

(iv) Calculating the redundancy and weight of the *j*-th indicator: I then calculate the redundancy and weight of the *j*-th indicator respectively as;

$$g_j = 1 - e_j$$

$$W_j = \frac{g_j}{\sum_{j=1}^{m} g_j}$$

(v) Calculating the level of the digital economy development: I can now calculate the level of the digital economy development as;

$$S_i = \sum_{j=1}^{N} (W_j \times P_{ij})$$

The smoothing variable *lndi* was obtained after taking the natural logarithm of the digital economy. *lndi* is squared to obtain the quadratic term, denoted *lndi2*, to take care of a nonlinear relationship (the potential U-shaped relationship between carbon emissions and the level of digital economy development).

B. The Dependent Variable

For the calculation of carbon emissions, this paper refers to Li, Guo, Gao, and Gu (2020) method:

$$E_{CO2} = \sum_i \sum_e EN_{e,i} \times V_{e,i} \times C_{e,i} \times O_{e,i}$$

E_{CO2} is the total carbon emission from energy use in economic activities in tons; $EN_{e,i}$ is the consumption of the *e*-th energy source used by the *i*-th economic activity; $V_{e,i}$ is the lower calorific value of the *e*-th energy source used by the *i*-th economic activity; $C_{e,i}$ is the carbon content per unit calorific value of the *e*-th energy source used by the *i*-th economic activity; $O_{e,i}$ is the average combustion rate of the *e*-th energy source used by the *i*-th economic activity. $V_{e,i} \times C_{e,i} \times O_{e,i}$ is the carbon emissions coefficient of the *e*-th energy source. In this paper, eight major fossil energy sources presented in Table 2 are selected and used to calculate carbon emissions.

Table 2. Carbon emissions coefficients of eight fossil energy sources.

Fossil Energy Source	Carbon Emissions Coefficient	Unit
Raw Coal	1.9003	kg-co2/kg
Coke	2.8604	kg-co2/kg
Crude Oil	3.0202	kg-co2/kg
Gasoline	2.9251	kg-co2/kg
Kerosene	3.0179	kg-co2/kg
Diesel Oil	3.0959	kg-co2/kg
Fuel Oil	3.1705	kg-co2/kg
Oilfield Natural Gas	2.1622	kg-co2/m3

Carbon emissions are the product of each province's annual consumption of each fossil energy source and the corresponding carbon emission coefficient. Consumption of eight fossil energy sources is obtained from the China Energy Database under the EPS data platform. Some of the missing data are filled in by interpolation. Other missing data, such as missing crude oil data for Shanxi province, are due to the lack of crude oil refining equipment in these provinces, thus are calculated with a zero value.

Table 3. Descriptive statistics of all variables.

Variables	Observations	Mean	SD	Minimum	Maximum
lndi	330	-2.593	0.883	-4.62	-0.33
lndi2	330	7.504	4.444	0.109	21.306
lncar	330	10.376	0.736	8.33	11.92
lncitypeople	330	4.009	0.217	3.4	4.5
lngdpperson	330	10.651	0.499	9.29	12.01
lnelectricity	330	7.284	0.700	4.9	8.81
lnsecindustry	330	3.776	0.231	2.79	4.08
lntechmarketturnover	330	13.613	1.802	8.62	17.86
lnforeigninves	330	3.521	1.678	-3.22	5.88

C. The Control Variables

Based on previous studies, the factors influencing carbon emissions are usually considered to be demographic factors, technological factors, economic development, energy consumption, international investment, etc. Therefore, this paper selects the proportion of the urban population (*citypeople*), GDP per capita (*gdpperson*), electricity consumption (*electricity*), share of secondary industry (*secindustry*), foreign direct investment (*foreigninves*) and technology market turnover (*techmarketturnover*) as the control variables. The data are selected from the National Bureau of Statistics Database and China Stock Market & Accounting Research Database.

D. Descriptive Statistics

I take the natural logarithm of all the variables. The purpose of that, among others, is to reduce potential heteroskedasticity as much as possible. The descriptive statistics of the variables are shown in Table 3.

5. EMPIRICAL ANALYSIS

A. The Hypothesis and Econometric Model

Based on the theoretical analysis earlier, I put forward the following hypothesis. There is an inverted U-shaped relationship between carbon emissions and digital economy. That is, in the early stage of the development of digital economy, carbon emissions increase gradually to the peak, and with further development of the digital economy, carbon emissions then decrease after reaching the peak.

$$lncar_{it} = \beta_0 + \beta_1 lndi2_{it} + \beta_2 lndi_{it} + \beta_3 \mathbf{X}_{it} + \varepsilon_{it}$$

The model above is established to test the hypothesis. If β_1 is (significantly) negative and β_2 is (significantly) positive, then I can reasonably conclude that there exists an inverted U-shaped relationship between carbon emissions and the development of digital economy. In this (panel data) model, the subscript i represents the i-th region and the subscript t represents the t-th time period. *lncar* is the dependent variable to be explained. *lndi* and *lndi2* (which stands for the quadratic term of *lndi*) are jointly the core explanatory variables. **X** represents a vector of the control variables including *lncitypeople*, *lngdpperson*, *lnelectricity*, *lnsecindustry*, *lntechmarketturnover* and *lnforeigninves*, which are the log forms of the group of control variables I mentioned earlier.

B. Empirical Results

The empirical results are summarized in Table 4. I apply three versions of the regression, namely, the fixed effects (FE), the pooled OLS, and the two-way FE, in all of which the development of the digital economy is shown to have a significantly negative effect on carbon emissions. However, as the coefficients on *lndi* and *lndi2* are both negative, no inverted U-shaped relationship is manifested between the development of digital economy and carbon emissions, which runs counter to the prior hypothesis.

One possible explanation is that by the year of 2009 (the beginning year of the sample period) the positive effect of the development of digital economy on carbon emissions had already reached its peak and turned negative. In other words, the sample period records only a time span where the development of digital economy reduces carbon emissions. This point is also confirmed by Li, Liu, and Ni (2021) which covers 190 countries during the period from 2005 to 2016. Therefore, it is highly likely that at some point in time before 2009 the highest point of the inverted U-shaped curve had been passed.

For control variables, a positive effect running from the proportion of urban population towards carbon emissions is detected under the two-way fixed effects and pooled OLS, which is consistent with common sense. The growth of the urban population would increase carbon emissions through affecting energy demand, forest coverage and land use. All of the three regression methods applied above show that GDP per capita tends to decrease the quantity of carbon emissions. Increasing GDP per capita implies increasing ecological efficiency, which in turn suggests that China's economic development at that stage had gradually got rid of high pollution and high energy consumption.

In line with former researches, electricity consumption is shown to have a positive effect on carbon emissions. Thermal power consumption still accounts for a large share of total electricity consumption in China and has caused heavy coal consumption, which in turn has resulted in more carbon emissions. Therefore, it is necessary to optimize the electric power structure and make better use of eco-friendly resources such as hydro, nuclear, and wind.

Table 4. Results from three panel data regressions.

Variables	FE	Pooled OLS	Two-way FE
lndi	-0.216*** (-3.98)	-0.856*** (-8.45)	-0.233*** (-4.11)
lndi2	-0.0326*** (-3.48)	-0.0996*** (-4.69)	-0.0272** (-2.91)
lncitypeople	-0.0460 (-0.31)	1.367*** (7.15)	0.146 (0.96)
lngdpperson	-0.112 (-1.89)	-0.729*** (-8.04)	-0.459*** (-5.59)
lnelectricity	0.690*** (15.48)	1.221*** (26.28)	0.643*** (14.72)
lnsecindustry	0.233*** (4.34)	-0.247* (-2.57)	0.46*** (5.43)
lntechmarketturnover	0.0135 (1.42)	0.00255 (0.15)	0.004528 (0.55)
lnforeignives	-0.00990 (-1.04)	0.105*** (5.44)	-0.0152 (-1.61)
_cons	5.375*** (10.68)	2.814*** (3.30)	7.585*** (12.09)
N	330	330	330
R-sq	0.7100	0.8345	0.7490

Note: t statistics in parentheses.
***; **; * represents 1% ; 5% and 10% level of significance respectively.

The impact of the share of secondary industry on carbon emissions is found to be significantly positive under the fixed effects and the two-way fixed effects. A larger proportion of the secondary industry means greater use of natural resources and severer ecological environment damage. The result of pooled OLS model might seem confusing at first sight, but we have to note that with stricter policies pollution of the secondary industry has been gradually reduced.

Foreign direct investment is shown to be positively related to carbon emissions under the pooled OLS and negatively related with the dependent variable under the fixed effects and two-way fixed effects. On the one hand, foreign companies often invested in low-cost manufacturing industries, which are well known for their severe air and water pollution. On the other hand, manufacturing companies have been getting more and more modernized with less and less pollution being emitted. This observation is consistent with conflicting research results obtained by other scholars.

C. Robustness Test and Group Test

To ensure the reliability of the basic regression results above, I carry out a robustness test and the results are summarized in Table 5. Data on Sulfur dioxide emissions, obtained from *China Statistical Yearbook of Environment*, are applied to replace carbon emissions.

The results show a significantly negative relationship between sulfur dioxide emissions and the development of digital economy, which is consistent with the prior results with carbon emission data. Moreover, the regression coefficients on *lndi2* in Table 5 are -0.0910 and -0.214 respectively, whose absolute magnitudes are larger than those in column 1 and 3 of Table 4. This implies that sulfur dioxide emissions tend to drop faster than carbon dioxide emissions with the development of the digital economy.

For further analysis, parallel regressions by group are also conducted. According to the National Bureau of Statistics, China can be geographically divided into four major regions: the eastern region, central region, western region and northeast region. This geographical division is highly linked to the regions' socio-economic development status. Table 6 illustrates the differences in the effect of the development of digital economy on carbon emissions across the four regions.

Table 5. Robustness test of carbon emissions and the digital economy.

Variables	Fixed effect (use lnso2 as dependent variable)	Pooled-OLS (use lnso2 as dependent variable)
lndi	-0.618** (-3.06)	-1.626*** (-5.16)
lndi2	-0.0910** (-2.80)	-0.214*** (-4.13)
control variables	all controlled	all controlled
_cons	11.70*** (7.63)	-2.188 (-1.00)
N	330	330
R-sq	0.7703	0.5793

Note: t statistics in parentheses.
** Significant at the 5% level; *** Significant at the 1% level.

Table 6. Group test of carbon emissions and the digital economy.

Variables	Eastern Region	Central Region	Western Region	Northeastern Region
lndi	-0.430*** (-5.76)	-1.658*** (-8.10)	-0.774*** (-4.68)	-0.311 (-0.73)
lndi2	-0.115*** (-6.16)	-0.276*** (-6.42)	-0.129*** (-5.05)	-0.0193 (-0.25)
Control variables	all controlled	all controlled	all controlled	all controlled
_cons	6.778*** (6.50)	7.198*** (6.90)	6.919*** (5.36)	9.842*** (6.03)
N	99	66	121	33
R-sq	0.8011	0.8834	0.7798	0.6656

Note: t statistics in parentheses.
*** Significant at the 1% level.

The main observed variables, the digital economy development indicator and its square, are both significant for the eastern region, western region, and the northeastern region, and insignificant for the northeastern region. This is supposed to be largely due to the much lower speed of digital economy development in the northeastern region; digital economy has not been widely used by highly polluting industries to improve eco-efficiency there. Though the results of parameter estimates and significance levels are slightly different from their prior counterparts shown in Table 4 based on nationwide (provincial-level) data, the estimated coefficients on *lndi* and *lndi2* here (in Table 6) remain negative, indicating an unchanged negative relationship between digital economy and carbon emissions. Therefore, I conclude that the relation between the main variables is robust across different versions of the regression exercise.

D. Endogeneity Test

The endogeneity problem is usually caused by omitted variables, simultaneous causality and measurement error. As for omitted variables, this paper has selected 11 factors that may affect the digital economy to mitigate (if not eliminate) this problem. In addition, to avoid endogeneity caused by simultaneous causality between carbon emissions and the digital economy and potential risk of measurement error, I apply the instrumental variables (IV)-two-stage least-squares (2SLS) method.

Following Song, Hao, Hao, and Gozgor (2021) and He, Wen, and Zhang (2022) I use the first-order lag terms of *lndi* and *lndi2* as instrumental variables to examine the reliability of the regression results. Because the instrumental variables are shown to be significantly correlated with the explanatory variables, there is no weak instrumental variable. In addition, as the lag terms of the digital economy development indicators are chosen as instruments, the disturbance term in the current period is unable to affect the lag terms of the digital economy development indicators. So the exogeneity condition can be satisfied.

The results in Table 7 show a significantly negative relationship between the development of digital economy and carbon emission at the 1% significance level after correcting for the potential endogeneity in the model.

Table 7. Endogeneity test of carbon emissions and the digital economy.

Variables	2SLS
lndi	-0.812*** (-5.19)
lndi2	-0.243* (-2.34)
Control variables	all controlled
_cons	8.511 (1.52)
N	300
R-sq	0.6775

Notes: t statistics in parentheses.
* Significant at the 10% level ; *** Significant at the 1% level.

6. CONCLUDING REMARKS

In this paper I use the panel data of 31 provinces in mainland China from 2009 to 2019 to examine the relationship between carbon emissions and the development of digital economy by performing the fixed effects, pooled OLS and two-way fixed effects regressions. The results of the basic regressions show that the digital economy indicator and its square term are both significantly negative at the 1% level, which implies a negative relationship between the development of digital economy and carbon emissions. Robustness and endogeneity tests also support the conclusion, which is consistent with the theoretical hypothesis. In passing, by further dividing the 31 provinces into four geographical regions, I find that the results for the northeast-region group are not significant, probably owing to the under-developed level of digital economy there.

It is therefore urgent for the government to fund the construction and application of digital infrastructure in economically backward regions. For those provinces that have already put the digital economy into good use, certain policies can be implemented to encourage those provinces to adhere to upgrading the industrial structure by promoting the development of tertiary services and high-tech industries. In addition, the regression results about the positive relationship between GDP per capita and carbon emissions indicate that we can protect the environment without paying the cost of stifling economic growth. That means the government does not have to make environmental protection a single priority. Instead, the priority lies in developing the economy and simultaneously cutting down pollution by taking full advantages of the digital economy.

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