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Can the Digitalization Reduce Carbon Emission Intensity?—The Moderating Effects of the Fiscal Decentralization

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Abstract: Carbon emission reduction is the top priority in improving green production efficiency and achieving sustainable development, while digitalization (Digi) is an important engine that drives efficient carbon emission reduction. However, in China, the government and the market jointly influence economic and social development, and the effectiveness of Digi in promoting carbon emission reduction is also influenced by the external fiscal system. In this study, we first establish a theoretical framework for digitalization that can reduce carbon emission intensity (CEI) and reveal the important role of fiscal decentralization (FD) on the impact of Digi on CEI and is based on the typical features of the Chinese FD system. Second, we investigate the relationship between Digi and CEI and the moderating effect of FD based on panel data from 30 Chinese provinces from 2011 to 2019, and we utilize a fixed-effects panel model that introduces moderating variables and a panel threshold model. By testing the econometric model, we observe that increasing the level of Digi significantly reduces CEI. FD reinforces this reduction effect, and Digi has a significant dampening effect on CEI only when the level of FD is higher than 0.84. Additionally, the inhibitory effect of Digi and positive moderating effect of FD are higher in the central and western regions of China. Finally, we suggest countermeasures to promote low-carbon development for accelerating digital transformation, thereby deepening the reform of "delegating power, improving regulation, and optimizing service" systems.

Keywords: fiscal decentralization; digitalization; carbon emissions intensity; threshold effect

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1. Introduction

Carbon dioxide generated by human economic activities is an important factor in global warming, therefore, promoting decarbonization is an important initiative to mitigate climate change and achieve sustainable development, and it is the common responsibility of all countries. In November 2021, the representatives of nearly 200 parliaments signed the Glasgow Climate Pact at the United Nations Climate Change Conference (COP26) held in Glasgow and pledged that all nations would achieve net-zero emissions by 2050. As the world's top carbon-emitting country in 2021, China, which has a total primary energy consumption of 5.24 billion tons of standard coal and CO_2 emissions as high as 1.147 Gt (https://www.statista.com/statistics/276629/global-co2-emissions/ (accessed on 25 April 2023)), is under tremendous pressure. To effectively address carbon emissions, the Chinese government proposed the goal to "Reach a peak in its carbon dioxide emissions before 2030 and achieve carbon neutrality by 2060", which is abbreviated as "double carbon" goal, in September 2020.

If the "double carbon" goal takes China in the direction of green economic transformation, digitalization provides inexhaustible power to the economy to achieve it. Along with other innovations, such as artificial intelligence, big data, cloud computing, and other high-end technologies, Digi can accelerate economic development from factor-driven to innovation-driven, and it is an important tool to achieve the "double carbon" goal. The China Academy of Information and Communication Technology has also released a white paper on "Digital Carbon Neutrality" in 2022 to provide a reference for promoting digital technology to achieve carbon peak and carbon neutrality in multiple dimensions. The literature indicates a significant impact of Digi on carbon emissions. Zhang, Jin, and Zeng (2022) use industry-level data and infer that Digi significantly increases carbon emissions both locally and in surrounding areas [1]. Yang and Hu (2022) focus on the impact of different types of digital inputs on industrial carbon emissions and infer that digital service inputs play a more prominent role in reducing industrial carbon emission intensity (CEI) than digital product inputs [2]. Xiao, Wang, and Qian (2023) demonstrate a U-shaped effect of Digi based on similar data from a firm's carbon performance perspective [3]. Jiao and Zhang (2023) report that Digi significantly reduces CEI based on transportation sector-level data and shows a nonlinear characteristic of increasing marginal utility [4]. Jin, Wang, and He (2023) utilize Driscoll–Kray standard error regression and spatial econometric regression to verify the carbon-reduction effect of Digi [5]. Li and Huang (2023) suggest that regional heterogeneity is observed in the carbon abatement effect [6]. Moreover, the "double carbon" goal, technological innovation, and residents' awareness of low-carbon living as a strategic practice to drive green and low carbon development can effectively transform internet traffic into green ecological value [7]. However, few studies have addressed the role of technological innovation and residents' awareness of low-carbon living in "bridging" the gap between Digi and carbon emissions. In fact, Digi not only strengthens the level of digital technology application of enterprises but also fully integrates green-related factor resources [8], thereby improving the level of regional innovation and helping enterprises to obtain green core competitiveness and realize low-carbon production. It also augments the benchmark effect and demonstration effect by promoting the convenience of public services in the field of ecology and environment, enhancing digital virtual experience, and forming the social identity of harmonious coexistence between humans and nature, thereby stimulating people's initiative and enthusiasm to participate in the low-carbon life [9]. Therefore, technological innovation and lifestyle of residents play an important role in Digi aiding carbon reduction.

In addition, in China's "dual-track" model that allows economic and social governance by both local governments and the market, the fiscal decentralization (FD) vests the power of revenue to the central government, while the responsibility of fiscal expenditure and public service provision is with local governments, and FD may affect the effect Digi has on CEI. Digi, a resource that benefits society as a whole, has strong externalities, and also determines that digital development needs that require the necessary support and resources from local governments. Therefore, its development direction is determined by the acceptance and approval of local governments in the region. In other words, Chinese-style FD is an external driver that stimulates green and low-carbon digital practices in this region. Therefore, it is important to explore the moderating role of FD between Digi and carbon emission reduction to promote sustainable economic development with Digi. The moderating effect of FD has been discussed in the literature. Ji and Lian (2021) demonstrate that FD significantly enhances the carbon reduction for manufacturing conglomerates in large- and medium-sized cities compared to small cities [10]. Liang, Cao, and Ge (2022) believe that FD weakly suppresses the effect of green credit on per capita carbon emissions [11], while Yang and Qiao (2023) suggest that FD negatively moderates the effect of agro-industrial clusters on the efficiency of agricultural carbon emissions [12].

However, these studies have the following limitations. First, in terms of carbon emission measurement, most existing research results measure the carbon emission level from the perspective of carbon emissions, which fails to reflect the significance of the economic efficiency of carbon emissions. Second, in terms of the impact of Digi on carbon emissions, the research is mainly focused on the direct impact of Digi on carbon emissions, and the literature on the boundary conditions of Digi's impact on carbon emissions is relatively insufficient. Therefore, to improve the credibility of the data, we used the Digi index (at the provincial level) published by the Digital Finance Research Center of Peking University and the data from various statistical yearbooks published by China's National Statistics to explore the relationship between the Chinese-style FD, Digi, and CEI. The research questions were as follows: what is the impact of Digi on CEI? and what is the moderating role of Chinese-style FD in the relationship between Digi and CEI?

The remainder of this paper is organized as follows: Section 2 is a literature review, Section 3 delineates the theoretical analysis and research hypothesis, Section 4 outlines the research design, Section 5 presents the empirical analysis, and Section 6 summarizes the research conclusions and insights.

2. Literature Review

In recent years, owing to the severity of global climate deterioration, the issue of carbon emissions has received significant attention from scholars. The research on this topic has focused on three main areas.

2.1. Studies on the Influencing Factors of Carbon Emission Intensity (CEI)

The literature provides a more systematic and comprehensive account of the specific factors affecting carbon emissions from different perspectives, which can be broadly summarized into two research paths: micro and macro. At the micro level, studies on household micro-research data have pointed out that political trust, carbon literacy, and social awareness impact people's carbon emissions behavior [13–16]. At the macro level, studies using regional macroeconomic statistics have empirically found that socio-environmental factors, such as population aging, economic growth, regional development patterns, resource abundance, urbanization, carbon trading mechanisms, and financial structure significantly reduce carbon emissions [17–24]. Furthermore, financial development, agricultural activities, household consumption, trade openness in low-income countries, and poverty reduction show a significant positive relationship with carbon emissions [25–29].

2.2. Studies on the Impact of Digitalization on Carbon Emissions

The current literature on the relationship between Digi and carbon emissions focuses on two aspects. The first is the study of the impact of traditional information and communication technology (ICT) or the Internet on carbon emissions. Gelenbe and Caseau (2015), Haini (2021), and Cui et al. (2022) have established that ICT significantly suppresses carbon emissions [30–32], while Moyer and Hughes (2012) conclude that ICT's carbon-reduction effect is limited [33]. Zhou et al. (2019) infer that ICT is a significant source of carbon emissions [34] and that ICT agglomeration also increases carbon emissions [35]. Raheem, Tiwari, and Balsalobre–Lorente (2020) demonstrate that ICT significantly increases carbon emissions by introducing financial development as a moderating variable [36], but the interaction term between ICT and financial development significantly reduces carbon emissions. Wang, Wang, and Jin (2023) report that the carbon-reduction effect of ICT is significant only when the degree of ICT embeddedness is high [37]. The second factor is the study of the impact of the digital economy on carbon emissions. An empirical study by Li et al. (2021) infer that the digital economy reduces the driving effect of a coal-based energy mix on carbon emissions [38]. Dong et al. (2022) believe that while the digital economy reduces carbon intensity, it increases carbon emissions per capita [39]. Zhu et al. (2022) and Yi et al. (2022) point out that the digital economy not only helps suppress local carbon emissions but also has a significant spatial spillover effect on the reduction of carbon emissions in the surrounding areas [40,41]. Zhang et al. (2022) argue that the digital economy exacerbates carbon emissions by reducing energy efficiency [42].

2.3. Studies on the Impact of Fiscal Decentralization on Carbon Emissions

Studies have explored the impact of FD on carbon emissions using two dimensions: nonlinear effects and spatial spillover effects. Shan et al. (2021) suggest that the nonlinear nature of the carbon-reduction effect of FD is reflected in the inverse "U" relationship between FD and carbon emissions [43]. Lv, Pang, and Doğan (2022) ascertain an inverse N-shaped relationship between the two [44]. Du and Sun (2021) explain that the nonlinear nature of the carbon emission-reduction effect of FD is due to the influence of the local level on the technological environment and the level of bias in technological progress [45]. In terms of spatial spillover effects, Yang, Tang, and Zhang (2020) conclude that FD leads to the "free-riding" behavior of neighboring local governments in managing carbon emissions [46]. Xia et al. (2021) confirm that FD boosts both local and regional carbon emissions [47].

The aforementioned literature provides an important theoretical reference and logical starting point for this study; however, it mainly focuses on the influence of FD and Digi on CEI. There is little evidence linking the three (Digi, FD, and CEI), analyzing the moderating role of FD in the relationship between Digi and CEI, and establishing how the influence of Digi on CEI will change with different degrees of FD. Compared with existing studies, our possible contributions are the following: first, we examine the mechanism of the impact of Digi on CEI at the macro level, and use the Chinese provincial panel data to empirically test the effect of Digi on CEI, which helps to enrich and expand the literature on the environmental protection effect of Digi. Second, we introduce FD as a moderating variable to further explore the synergistic effect of FD and Digi and can suggest new ideas for carbon emission reduction. Third, we utilize a threshold regression model to test the conditions of the effect of Digi on CEI and reveal the threshold effect of FD on this effect.

3. Theoretical Analysis and Research Hypothesis

3.1. Digitalization and Carbon Emission Intensity

In recent years, several scholars have conducted extensive research on Digi and defined it as an organizational shift from corporate production to big data and cloud computing [48] and have explored the improved use of traditional technologies [49]. The inhibitory effect of Digi on CEI is reflected in two aspects. First, Digi can significantly increase technological innovation. Under the wave of Digi, advanced technologies, such as blockchain, artificial intelligence, big data, and cloud computing, with their paperless features, break the space-time limitation of factors. This advantage, in turn, reduces transaction costs and improves the rational allocation of innovation factors, such as information, capital, and talent related to innovation subjects, thereby promoting innovative thinking and intellectual debate [50]. Technological innovation can improve the recycling rate of resources, promote the replacement of fossil energy with clean energy, and upgrade industries to improve energy efficiency [51,52], which, in turn, will encourage carbon emissions reduction to a certain extent. Second, Digi can persuade residents to adopt a green lifestyle. With the construction of digital platforms and the expansion of digital consumer groups, online activities, such as telecommuting, online transactions, and online meetings, directly reduce the frequency and magnitude of offline economic activities. It helps to cultivate a preference for the use of clean energy, such as electricity [53], and promotes the formation of a green low-carbon consumption philosophy of life.

Based on the analysis, the following hypothesis is proposed.

Hypothesis 1 (H1). *Digitalization is beneficial to reduce carbon emission intensity.*

3.2. Fiscal Decentralization as a Moderator

This Chinese-style FD has long contributed to China's rapid economic growth by providing local governments with an information advantage in local economic development [54]. As China's green economic transformation advances, the central government has begun to incorporate regional resource utilization, ecological protection, green living, and other environmental factors into the performance appraisal systems of local governments. When the degree of FD is low, which means that local governments face greater fiscal pressure, they are unable to improve infrastructure conditions and offer strong fiscal support for local Digi due to the constraint of high fiscal expenditure, and the carbon-reduction potential of Digi cannot be effectively harnessed. At higher levels of FD, the local governments proactively seek carbon-reduction tools in response to the central government's carbon-reduction targets. They will gradually increase the importance of Digi, in terms of optimizing the necessary conditions for Digi and supporting Digi for local enterprises according to the local development preferences, and also aid time tracking and monitoring of the implementation effect of Digi and the associated improvements. These measures, in turn, strengthen the driving effect of the government and provide a strong driving force for the realization of digital emission reduction in the region. Thus, the FD status of a region influences the role of local Digi in CEI. In other words, the magnitude of the effect of Digi on CEI exhibits significant differences depending on the degree of FD, and the inhibitory effect of Digi on CEI is higher in regions with a higher degree of FD.

Based on the above analysis, the following hypotheses are proposed.

Hypothesis 2 (H2). *Fiscal decentralization has a positive moderating effect on digitally reducing carbon emissions intensity.*

Hypothesis 3 (H3). *The inhibitory effect of digitalization on carbon emissions intensity is more significant at higher levels of fiscal decentralization.*

4. Research Design

4.1. Variable Description and Data Sources

4.1.1. Variable Selection and Description

(1) Explained variable

Based on previous studies [55,56], we decided that the explained variable was CEI. According to the Fourth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (IPCC) in 2007, fossil fuel combustion is the main source of greenhouse gases Therefore, we measured carbon dioxide emissions based on the IPCC Guidelines for National Greenhouse Gas Emissions Inventories and the end-use energy consumption of each province in calendar years. The calculation formula is as follows:

$$CE_{it} = \sum EC_{ijt} * CC_i \ (i = 30; j = 1, 2, \cdots, 9) \tag{1}$$

CE_{it} represents the total carbon emissions in province i in year t; EC_{ijt} represents the consumption of energy type j in province i in year t, including raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, and electricity; CC_i represents the carbon emissions factor provided by the IPCC. By referring to other studies, we found that CEI can accurately and directly represent the increase in carbon emissions resulting from the acquisition of a unit of GDP; and the specific calculation formula is as follows:

$$CEI_{it} = \frac{CE}{GDP} \tag{2}$$

(2) Core Explanatory Variable

The core explanatory variable was Digi. We chose the "digitalization" index of each province, which was published by the Digital Finance Research Center of Peking University in 2021, to measure the level of Digi. To facilitate analysis, we adjusted the Digi index by dividing it by 100 in the empirical process.

(3) Moderating Variable

The moderating variable was FD. Based on the research of Chen and Liu (2020) [57], we constructed FD indicators from the perspective of fiscal expenditure. Table 1 presents the specific measurement formulas.

$$FD = \frac{FE_i / POP_i}{FE_i / POP_i + FE_c / POP_n} \tag{3}$$

Table 1. Measurement Formulas for Fiscal Decentralization.

Formula	Variable Meaning
Equation (3)	FE_i: Local government public budget expenditure FE_c: Central government public budget expenditure POP_i: Total local population POP_n: Number of people in the country

(4) Control Variables

As many factors affect CEI, based on the criteria for selecting control variables in the existing research literature [29,58–60], we selected the following control variables: industrial structure (IND), measured by the ratio of value added of secondary industry to regional GDP; human capital (EDU), measured by the number of years of education per capita of the population over six years of age; government intervention (GOV), measured by the ratio of the local government general budget expenditure to regional GDP; foreign direct investment (FDI), measured by the ratio of actual foreign capital utilization to regional GDP; and urbanization rate (URB), measured by the ratio of urban population to the regional population.

4.1.2. Data Sources

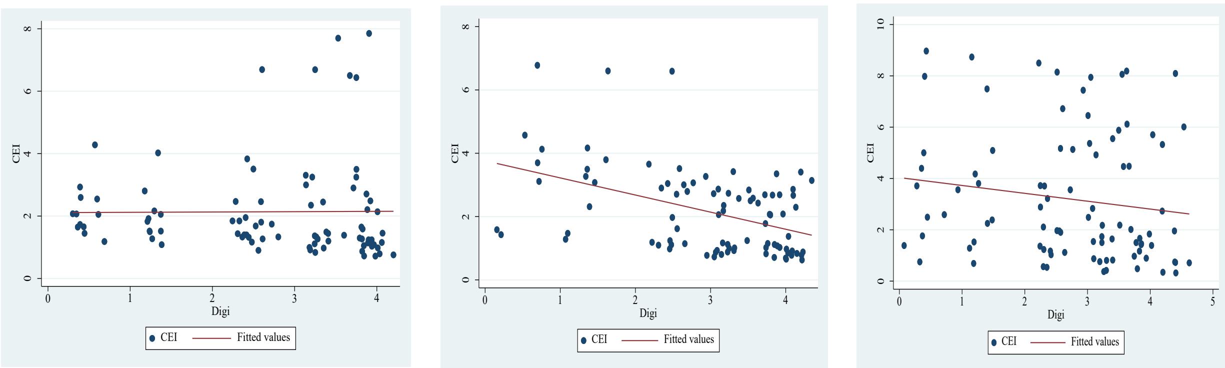
As the data related to Digi was made available by Peking University to the community from 2011; however, the Chinese officials have not yet published the data related to energy consumption beyond 2019, our study sample comprised 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan that showed large data volatility) from 2011–2019. The relevant data were obtained from the China Energy Statistical Yearbook, China Finance Yearbook, China Population and Employment Statistical Yearbook, and the statistical yearbooks of each province in each year. To ensure the comparability of the research data, all variables involving measurement in monetary terms were deflated with 2011 as the base period.

Table 2 presents the results of the descriptive statistics of the main variables and multiple cointegration tests. The OLS model variance inflation factors (VIFs) are all less than 10, thereby indicating that there is no serious cointegration problem among the variables. In addition, the maximum and minimum CEI values are 8.967 and 0.32, respectively, with a standard deviation of 1.92, thereby suggesting that CEI in China is uneven among different provinces. By checking the data, we find that Ningxia, with an industrial structure dominated by heavy industries, is the only province with a CEI greater than 8 and stays above 8 (t/10 thousand yuan) in all years except in 2016 and 2017 when it dropped to 7.44 (t/10 thousand yuan) and 7.94 (t/10 thousand yuan), respectively. On the contrary, Beijing, with an industrial structure dominated by emerging technology industries, such as cloud computing, blockchain, and artificial intelligence) is the only province with a CEI below 0.5 (t/10 thousand yuan) and has remained below 0.5 from 2013 to 2019. This result is in line with reality. The maximum and minimum values of Digi are 4.622 and 0.076, respectively, with a standard deviation of 1.18, thereby implying that there is still a large difference in the level of Digi within China and that there is room for improvement.

Table 2. Results Of Descriptive Statistics of Main Variables.

Variables	Obs	Mean	Std. Dev.	Min	Max	VIFs
CEI	270	2.5	1.92	0.32	8.967	
Digi	270	2.784	1.18	0.076	4.622	1.5
FD	270	0.86	0.037	0.787	0.937	5.3
IND	270	0.439	0.086	0.162	0.59	1.75
EDU	270	9.172	0.893	7.474	12.782	4.62
GOV	270	0.264	0.115	0.12	0.758	4.3
FDI	270	0.022	0.02	0	0.121	1.56
URB	270	0.576	0.122	0.35	0.896	7.53

Based on previous measurements, Figure 1 illustrates a plot of the changes in Digi and CEI from 2011 to 2019 based on a sample of FD degree heterogeneity. It shows no significant correlation between Digi and CEI in the Low FD sample, while there is a significant negative correlation between Digi and CEI in the Medium FD sample and High FD samples. Therefore, we can conclude that increasing FD is beneficial in improving the inhibitory effect of Digi on CEI. This finding is consistent with our expectations. However, further empirical studies are required to assess the statistical significance of the above conclusion.



Low FD sample Medium FD sample High FD sample

Figure 1. Plot of the changes in digitization and carbon intensity for different degrees of fiscal decentralization between 2011 and 2019. Note: The FD degree heterogeneity sample was divided equally into low, medium, and high FD samples based on the FD from 2011 to 2019, with a division node of 0.84 and 0.867.

4.2. Model Design and Description

4.2.1. Baseline Regression Model

To investigate the effect of Digi on CEI, we constructed an econometric model (4), with CEI as the explained variable and Digi as the explanatory variable, and is as follows:

$$CEI_{it} = \alpha_0 + \alpha_1 Digi_{it} + \alpha_2 FD_{it} + \alpha_3 IND_{it} + \alpha_4 EDU_{it} + \alpha_5 GOV_{it} + \alpha_6 FDI_{it} + \alpha_7 URB_{it} + \mu_i + \varepsilon_{it} \quad (4)$$

The subscript i represents the province and the subscript t represents the year; μ_i represents the individual fixed effect; ε_{it} is the random error term; CEI_{it} is the explained variable, which represents the CEI and the data are measured above; $Digi_{it}$ is the core explanatory variable, which represents the Digi indicator. FD_{it}, IND_{it}, EDU_{it}, GOV_{it}, FDI_{it}, and URB_{it} are fiscal decentralization, industrial structure, human capital, government intervention, foreign direct investment, and urbanization rate, respectively.

4.2.2. Moderating Effect Model

To further test the moderating effect of FD on the relationship between Digi and CEI, we introduced the moderating variable FD based on the baseline regression model and centered the explanatory and moderating variables to construct the moderating effect model as follows:

$$CEI_{it} = \beta_0 + \beta_1 Digi_{it} + \beta_2 FD_{it} + \beta_3 Digi_{it} \times FD_{it} + \beta_4 IND_{it} + \beta_5 EDU_{it} + \beta_6 GOV_{it} + \beta_7 FDI_{it} + \beta_8 URB_{it} + \mu_i + \varepsilon_{it} \quad (5)$$

where $Digi_{it} \times FD_{it}$ denotes the interaction term between FD and Digi, and the remaining variables are defined in the same way as in Model (4).

5. Results

5.1. Analysis of Baseline Regression Model and Moderating Effects Model

We conducted multiple tests before examining the relationship between FD, Digi, and CEI. Table 3 presents the results. The Breusch–Pagan LM test indicates that the random effects (RE) model is more suitable than the pooled ordinary least squares (POLS) regression, while the panel set F test reveals that the fixed effects (FE) model is more suitable than the POLS regression, and therefore, the POLS regression cannot be used. Second, the Hausman test was conducted to compare the applicability of FE and RE models. Subsequent analysis was performed using a fixed effects model. In addition, the *p*-values of both the Wald test and Pesaran CD-test strongly reject the original hypothesis, thereby indicating significant heteroskedasticity and cross-sectional dependence in the panel model. To solve the problems of heteroskedasticity and autocorrelation, we chose a fixed effects model (XTSCC) based on Driscoll–Kray standard errors for testing.

Table 3. Mechanism of Model Selection.

Test	Null Hypothesis	Baseline Regression Model	Moderating Effects Model
Breusch–Pagan LM-test	No individual random effect.	897.06 (0.000)	896.14 (0.000)
F-test	The regression coefficients of all explanatory variables in the model are 0.	344.52 (0.000)	360.94 (0.000)
Hausman-test	All explanatory variables are exogenous.	14.38 (0.045)	18.89 (0.015)
Wald-test	No heteroskedasticity exists within the panel data.	3580.32 (0.000)	2460.30 (0.000)
Pesaran CD-test	No cross-sectional dependence exists within the panel data	3.27 (0.001)	2.39 (0.017)

Notes: Null hypothesis is that no cross-sectional dependence exists within the panel data.

Table 4 presents the relationships among FD, Digi, and CEI. Models 1 and 2 show the results of the baseline regression analysis. The coefficients of both FD and Digi are significantly negative, thereby indicating that increasing the degree of FD and Digi is beneficial for reducing CEI. Thus, Hypothesis 1 is proven. According to the analysis of the moderating effects in Models 3–6, the coefficient of the cross-product term of FD and Digi is significantly negative, which suggests that the interaction between the two suppresses CEI. In other words, as the degree of FD increases, it plays a positive moderating role in the negative impact Digi has on CEI, thereby increasing digital carbon emission reduction. Thus, H1 and H2 are verified. In addition, the results of the regression coefficients of the variables based on FE effects are consistent with those of the regression coefficients based on the XTSCC model, which demonstrates the credibility of our findings using the model based on FE effects.

Table 4. Analysis of Baseline Regression Model and Moderating Effects Model.

	Baseline Regression Model		Moderating Effects Model			
	FE	XTSCC	FE	XTSCC	FE	XTSCC
	(1)	(2)	(3)	(4)	(5)	(6)
Digi	−0.115 ***	−0.115 ***			−0.091 ***	−0.091 ***
	(0.024)	(0.025)			(0.025)	(0.024)
FD	−6.141 *	−6.141 ***			−7.239 **	−7.239 ***
	(3.145)	(1.121)			(3.075)	(1.074)
Digi × FD			−1.724 ***	−1.724 ***	−1.422 ***	−1.422 ***
			(0.381)	(0.264)	(0.379)	(0.272)
IND	0.745	0.745	0.163	0.163	0.468	0.468
	(0.674)	(0.891)	(0.593)	(0.892)	(0.660)	(0.914)
EDU	−0.147	−0.147	−0.159	−0.159	−0.063	−0.063
	(0.099)	(0.109)	(0.102)	(0.088)	(0.099)	(0.099)
GOV	3.031 ***	3.031 ***	0.740	0.740	2.702 ***	2.702 ***
	(0.891)	(0.786)	(0.778)	(0.532)	(0.872)	(0.691)
FDI	3.265 **	3.265 ***	2.580 *	2.580 **	3.336 **	3.336 ***
	(1.488)	(0.631)	(1.394)	(1.016)	(1.448)	(0.738)
URB	−6.423 ***	−6.423 ***	−11.058 ***	−11.058 ***	−8.251 ***	−8.251 ***
	(0.948)	(1.116)	(0.897)	(1.133)	(1.043)	(1.042)
_cons	11.952 ***	11.952 ***	10.009 ***	10.009 ***	6.845 ***	6.845 ***
	(2.464)	(1.224)	(1.094)	(1.563)	(1.253)	(1.720)
N	270	270	270	270	270	270
Within_R^2	0.718	0.718	0.707	0.707	0.734	0.734

Note: *, **, and *** respectively represent significance at the level of 10%, 5%, and 1%.

5.2. Robustness Tests

We employed four methods for robustness testing and are depicted in Table 5. First, the outliers were excluded. To prevent outlier-induced bias in the estimation results, we used a reduced tail treatment at the 2.5% and 97.5% levels for the explained variable. The second was the instrumental variable (IV) method. Endogeneity problems often arise in econometric models due to omitted variables, measurement errors, and two-way causality, leading to biased estimation results. Therefore, we estimated the core explanatory variable with a one-period lag as an instrumental variable and used the two-stage least squares (2SLS) equation. Finally, we introduced the impact of macroeconomic policies into the model. In October 2017, the 19th National Congress of the Communist Party of China first proposed a new expression for high-quality development, and China's economic development focus shifted from speed to quality. To consider this "economic growth target constraint" of China, we constructed a corresponding time dummy variable (year_2018: takes the value of 1 between 2011 and 2017 and takes the value of 0 between 2018 and 2019) and established interaction terms between the dummy and main explanatory variables. The results of these robustness tests indicate that the findings of the previous section of the study are more reliable. In the various robustness tests mentioned above, Digi and the interaction terms of Digi and FD are significantly negative, thereby indicating that the findings of the previous section are reliable.

Table 5. Robustness Tests.

	Robustness Tests of the Baseline Regression Model			Robustness Tests of the Moderating Effect Model		
	Exclude the Outliers	**IV**	**Macro Factor**	**Exclude the Outliers**	**IV**	**Macro Factor**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Digi	−0.115 *** (0.024)	−0.238 *** (0.077)	−0.132 *** (0.025)	−0.091 *** (0.025)	−0.185 ** (0.074)	−0.107 *** (0.025)
FD	−6.141 * (3.145)	−5.269 (4.850)	−7.687 ** (3.150)	−7.239 ** (3.075)	−4.092 (5.091)	−9.142 *** (3.076)
Digi × FD				−1.422 *** (0.379)	−2.062 ** (0.859)	−1.524 *** (0.407)
Digi × FD × year_2018						−7.919 * (4.308)
year_2018			−1.764 *** (0.643)			−0.691 *** (0.229)
Digi × year_2018			0.458 *** (0.163)			0.675 *** (0.200)
FD × year_2018						10.036 * (5.242)
IND	0.745 (0.674)	−0.232 (1.456)	0.844 (0.680)	0.468 (0.660)	−0.507 (1.538)	0.715 (0.661)
EDU	−0.147 (0.099)	−0.059 (0.099)	−0.173 * (0.099)	−0.063 (0.099)	0.017 (0.112)	−0.086 (0.099)
GOV	3.031 *** (0.891)	3.744 * (1.911)	3.304 *** (0.890)	2.702 *** (0.872)	2.978 ** (1.442)	3.542 *** (0.913)
FDI	3.265 ** (1.488)	2.345 (1.797)	3.259 ** (1.467)	3.336 ** (1.448)	2.134 (1.664)	3.141 ** (1.424)
URB	−6.423 *** (0.948)	−5.009 ** (2.012)	−5.783 *** (1.027)	−8.251 *** (1.043)	−7.427 *** (2.161)	−7.925 *** (1.137)
_cons	11.952 *** (2.464)		13.074 *** (2.462)	6.845 *** (1.253)		6.524 *** (1.256)
N	270	240	270	270	240	270
Adjusted_R^2	0.674	0.578	0.683	0.691	0.618	0.704

Note: *, **, and *** respectively represent significance at the level of 10%, 5%, and 1%.

5.3. Heterogeneity Analysis

According to the findings, FD amplifies the disincentive effect of Digi on CEI. Higher the degree of FD, stronger is the disincentive effect of Digi on CEI. To further confirm the validity of this view, we conducted a regional heterogeneity test by dividing the sample into three groups of eastern, central, and western regions. Table 6 reports the regression results. According to the regression results in columns (1)–(3) of the baseline regression model, Digi has a significant negative effect on CEI in the eastern, central, and western regions, and this effect is more prominent in the central and western regions. The regression results in columns (4)–(6) show that in the moderating effect model, the negative moderating effect of FD is greater in Digi reducing CEI in the central region, followed by the western region. Notably, in the eastern region, FD had little impact on Digi curbing CEI. The main reason for these findings is that the eastern region is more industrialized compared to the central and western regions, and in turn, has a higher share of green and low-carbon energy consumption, which weakens the impact of Digi on CEI and the regulating effect of FD.

Table 6. Heterogeneity Analysis.

	Baseline Regression Model			Moderating Effect Model		
	Eastern Sample	Central Sample	Western Sample	Eastern Sample	Central Sample	Western Sample
	(1)	(2)	(3)	(4)	(5)	(6)
Digi	−0.035 **	−0.162 **	−0.158 ***	−0.034 *	−0.257 ***	−0.100 *
	(0.016)	(0.064)	(0.050)	(0.018)	(0.073)	(0.056)
FD	4.733 **	−12.895 *	−17.858 **	4.658 **	−17.007 **	−23.657 ***
	(2.258)	(7.259)	(8.456)	(2.294)	(7.213)	(8.680)
Digi × FD				−0.070	−3.835 **	−2.106 **
				(0.299)	(1.598)	(0.977)
IND	1.835 ***	0.563	1.310	1.826 ***	0.426	0.990
	(0.592)	(1.668)	(1.426)	(0.596)	(1.611)	(1.400)
EDU	−0.216 ***	0.009	−0.196	−0.210 ***	0.054	−0.216
	(0.064)	(0.263)	(0.212)	(0.070)	(0.254)	(0.207)
GOV	−3.493 ***	0.628	4.376 ***	−3.451 ***	2.347	4.334 ***
	(1.109)	(3.079)	(1.353)	(1.129)	(3.057)	(1.321)
FDI	1.554 **	11.352	−7.916	1.560 **	11.718	−5.342
	(0.751)	(8.883)	(9.131)	(0.756)	(8.576)	(8.991)
URB	−5.021 ***	−2.988	−7.694 ***	−5.160 ***	−4.763 *	−8.953 ***
	(0.617)	(2.815)	(2.091)	(0.858)	(2.816)	(2.123)
_cons	3.122 *	14.357 **	23.060 ***	7.124 ***	2.870	8.295 ***
	(1.739)	(5.721)	(7.060)	(0.992)	(3.341)	(2.103)
N	99	81	90	99	81	90
Adjusted_R^2	0.891	0.526	0.744	0.890	0.559	0.756

Note: *, **, and *** respectively represent significance at the level of 10%, 5%, and 1%.

5.4. Threshold Effect Analysis

This analysis reveals that FD plays a positive moderating role in the Digi-reducing CEI process. What level of FD can achieve this effect? This question is worth analyzing, and clarifying the impact of Digi on FD under different levels of FD is conducive to proposing corresponding policy measures and providing a reference for decision-making for China's low-carbon economic development. Therefore, we used FD as a threshold variable combined with panel threshold regression models for testing. Subsequently, the model was tested using the hypotheses of "no threshold", "single threshold", and "double thresholds". Table 7 presents the results. FD passes the single-threshold effect test at the 5% significance level with a specific threshold value of 0.840, which is consistent with the conclusion drawn from Figure 1. As of 2019, only eight provinces (Hebei, Shanxi, Anhui, Shandong, Henan, Hunan, Guangxi, and Sichuan) have not crossed the FD threshold level. We then conducted a threshold regression model and test based on the threshold numbers determined in Table 7, and the results are presented in Table 8.

Table 7. Results of the Threshold Effect Test.

Threshold Variables	Single Threshold Model		Double Threshold Model		Threshold Value	95% Confidence Interval
	F-Value	*p*-Value	F-Value	*p*-Value		
FD	21.75 **	0.0380	8.720	0.220	0.840	[0.794,0.867]

Note: ** represent significance at the level of 5%.

Table 8. Regression Analysis of Threshold Effects.

Variables	FD as the Threshold Variable
Digi (FD $\leq$ 0.61)	−0.036 *** (0.008)
Digi (FD > 0.61)	−0.052 *** (0.008)
IND	0.557 *** (0.186)
EDU	−0.513 ** (0.241)
GOV	0.909 *** (0.254)
FDI	0.479 (0.337)
URB	−3.378 *** (0.293)
_cons	3.680 *** (0.573)
N	270
Adjusted_R^2	0.808

Note: **, and *** respectively represent significance at the level of 5%, and 1%.

According to the results in Table 8, the effect of Digi on CEI is not significant when the fiscal share is below the threshold value of 0.84. When the fiscal share is above the threshold value of 0.84, the coefficient of Digi is −0.131 and passes the 1% significance test. This result indicates that the effect of Digi on CEI is constrained by FD. Specifically, Digi significantly reduces CEI only when the degree of FD crosses the threshold value, thus verifying Hypothesis 3.

6. Conclusions and Insights

6.1. Conclusions and Discussion

Digi is an important way to transform technological tools into regional development advantages [61] and is closely related to China's green economic transformation, industrial structure upgrading, and high-quality development [62–64]. The results of this study confirm that Digi is an important factor in the impact of CEI; in other words, Digi has a significant inhibitory effect on CEI, and this relationship is largely influenced by the degree of FD.

First, by building a basic regression model, we explore the relationship between Digi and CEI at the national and regional levels and find that Digi significantly reduces overall CEI, but there are significant differences in the intensity of its reduction effect between different regions; that is, the inhibitory effect of Digi on CEI is stronger in the central and western regions of China than in the eastern region. The existing studies generally agree that digital empowerment has significant regional heterogeneity [63], thereby suggesting that it is necessary to explore regional heterogeneity, which provides new ideas and directions to solve the current problem of improving the efficiency of digital emissions reduction.

Second, by constructing a moderating effect model, we find that the degree of FD affects the potential of Digi to reduce CEI. China adopts a "central–local" decentralization model, which gives a distinct institutional character to its fiscal development and is described in the 2023 study by He and Hou [65]. Under FD, local governments are better able to enhance the supply of public goods in the market through fiscal support and provide basic support for the Digi of industries [66,67]. Therefore, it is important to introduce moderating variables, such as FD, in the study of the relationship between Digi and CEI [68]; however, there is a lack of research in this area. This study introduces the role of FD in the relationship between Digi and CEI and finds that FD strengthens the inhibitory effect of Digi on CEI. Interestingly, a threshold effect of FD is related to this inhibitory effect, that is, when the degree of FD is higher than 0.84. This result suggests that the carbon-reduction benefits of Digi play different roles and has variable potentials in different FD environments. The conclusion of the threshold effect of different degrees of FD provides empirical support for the existence of an optimal FD value, which is an important contribution to the theoretical hypothesis of the optimal degree of FD [69].

6.2. Theoretical Contributions and Practical Insights

In terms of theoretical value, based on a comprehensive review of the existing research results, we systematically constructed a theoretical framework of FD, Digi, and CEI, and empirically tested the impact of Digi on CEI and the moderating effect of FD to not only expand the existing research results on FD, Digi, and CEI but also provide strong theoretical support to promote low-carbon production and reduce CEI.

From a practical perspective, in China's push to shift from quantitative to qualitative economic development, reducing CEI and improving carbon production efficiency are China's best strategies to promote sustainable economic growth. A systematic study of the current situation, and the problems associated with FD and Digi with respect to CEI can help provide scientific theoretical guidance and a realistic basis for central and local governments to formulate energy conservation and emission reduction policies and measures, thereby promoting the sustainable development of China's economy.

6.3. Policy Recommendations

This study makes certain recommendations regarding policy.

First, the Chinese authorities should strive to reduce regional disparities in Digi levels to promote the coordinated advancement of CEI in different regions. On the one hand, they should increase support for Digi to improve digital infrastructure in the central and western regions. Local governments should fully combine local resource endowment and development needs to cultivate digital industries, and simultaneously, should gradually guide Digi in the direction of intelligence to strengthen the management of digital carbon emission reduction. On the other hand, the Chinese authorities should accelerate the process of national coordination of Digi and continuously narrow the Digi gap between regions by building an information-sharing platform to efficiently link carbon emission reduction developments in different regions.

Second, the Chinese authorities should further deepen the "delegating power, improving regulation, and optimizing service" reform and give local governments fiscal freedom to take advantage of local government information to meet the needs of regional Digi, especially in the central and western regions, while strictly enforcing a performance assessment based on green development requirements to ensure the quality and efficiency of FD.

6.4. Limitations and Future Research Directions

The limitations of this study are as follows: first, this study discusses only the influence of Digi on CEI through technological innovation and lifestyle of residents on a theoretical level, but there is a lack of empirical data required for a robust evaluation. Analysis of the intermediate mechanism by which Digi affects CEI can be further refined when more data are available. However, this study mainly focuses on the impact of Digi on CEI and that is the primary research objective. Future research can explore the efficiency of carbon emissions [70] and decipher the role of Digi in environmental improvement. Moreover, further research is needed to identify the heterogeneity of Digi at multidimensional levels, such as resource- and non-resource-based regions and coastal and non-coastal regions, and to explore its relationship with strategic choices and carbon emissions [71].

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