The Dynamic Variation of Digital Inclusive Finance's Carbon Effect and the Conditional Moderating Role of Energy Consumption Structure

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Abstract. There is disagreement over the carbon footprint of digital inclusive finance. Panel data at the provincial level of China from 2011 to 2022 were used in this paper to study how and in what way the energy structure affects carbon emissions. Instead of the above-mentioned stable non-linear path, this paper found that different periods have different dynamics; at first, due to scaling expansion, digital finance emissions rose; However, this increase did not continue for a long time. The interaction coefficient of digital finance and coal dependence is positive and statistically significant, but how differently this impact affects different parts of the energy structure is not yet known. Therefore, based on the above results, it is determined that digital inclusive finance does not directly promote the reduction of carbon emissions, and the scale rebound is still relatively large compared with technological offsetting. Energy Structure is a constraint that inhibits rather than drives, and it is not the primary cause. Policies should aim to change the structure of energy and not assume that digitalisation will reduce greenhouse gas emissions.

Keywords: Digital Inclusive Finance, Carbon Emission Intensity, Energy Consumption Structure, Rebound Effect, Conditional Moderation.

1 Introduction

In September 2020, China officially set its goals for carbon peak and carbon neutrality, and as a result, the green and low-carbon transition of the economy and society has become a main national policy. At the same time, China's digital inclusive finance industry has been developing well. The annual growth rate of the provincial index for digital inclusive finance has been more than 26 per cent [1]. In light of the goal of carbon neutrality, it is currently unknown whether digital inclusive finance will help reduce carbon emissions or, on the contrary, due to an increase in the scale of economic activity, lead to higher emissions. It has laid a certain foundation and will be used to some extent. The environmental impact of digital inclusive finance on carbon has not yet been agreed upon by scholars at present, and thus, the research results are all different.

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Most of the current studies have shown that digital inclusive finance is negatively associated with carbon emissions. Based on the data of A-share listed companies, Zhang and others have found that digital inclusive finance can lower the carbon emission intensity of enterprises through the promotion of green technological innovation and improvement in operating cost efficiency [2]. Jia and others have also found that the green credit mechanism is a typical link in this process [3].

There are many problems with these optimistic views. Through some research, although digital finance is low-cost, it may also promote the general development of the economy to a certain extent. Although there have been some improvements in the energy efficiency of new energy and other sources of new energy, the expansion and deepening of inclusive finance also stimulate consumption and economic activities in the grey-coal production sector, and many new low-carbon products will be needed. The rapid expansion of the economy will increase the total amount of energy consumption and thus reduce the carbon mitigation effect of technological progress [4, 5]. Zhou and others believe that digital finance will reduce carbon emissions in a non-linear manner; it will fall initially and then rise [6]. Research has found that areas with a large number of traditional manufacturing enterprises will be less affected by the green advantages of digital finance [7].

As noted by van der Ploeg and Withagen, the theoretical green paradox suggests that anticipated climate policies may accelerate resource extraction and temporarily increase emissions, which implies that the emission-reduction benefits of digital inclusive finance may be weakened in carbon-locked regions [8]. Based on the above evidence, digital inclusive finance is not a natural green catalyst. Ultimately, its ecological footprint reflects the net outcome of technological progress and scale-driven rebound effects, and thus remains contingent upon the evolving economic structure.

Moreover, the effectiveness of digital finance in reducing emissions is constrained by the existing energy consumption mix. Zhang and Chu have found that optimising the energy consumption structure can facilitate pollution reduction and greenhouse gas mitigation in the process of financial digitalisation [9, 10].

Although the earlier studies have often considered the energy structure as a medium, there is a lack of analysis of its changes in times of crisis and the problem of high-carbon inertia has been largely overlooked. China has big regional differences in energy resources, and the northern provinces and the northeast will be required to use more coal in the future [11, 12]. Due to the lack of support from green policies, the funds obtained through digital finance may be allocated to older, high-emission industries because there are few green investment projects. Improving the operating efficiency of polluting enterprises will lead to an increase in brown digitalisation and thus will not reduce total pollution [13]. No empirical studies have found that the constraints mentioned above can change the trend of carbon emissions and affect the development path of this phenomenon in practice.

To address the problems in the above research by current scholars, this paper takes provincial panel data from the 30 Chinese provinces in 2011-2022 as its basis. A two-way fixed-effects and interaction model will be employed in the empirical study of the effect of digital inclusive finance on carbon emission intensity to examine how it works, and at the same time, the moderating effect of energy structure will also be investigated.

Theoretically, there will be a scale-induced rebound effect and green empowerment by technology in digital inclusive finance; at the same time, there will be a trade-off between the two, and various carbon performances will occur under the constraints of the energy structure. Do not need to assume that it is a deterministic non-linearity or strong moderation, so in this study will empirically test whether digital finance has phase-dependent carbon emissions and a noticeable but statistically insignificant conditional effect on the structure of energy consumption.

2 Research Design

2.1 Econometric Model Specification

To know if digital inclusive finance directly affects carbon intensity, a two-way fixed-effects panel model is used in this paper, and it is shown in Equation (1).

$$\ln CEI_{it}=\alpha_0+\alpha_1 \ln DIF_{it}+\lambda_t+\gamma X_{it}+\mu_i+\varepsilon_{it} \quad (1)$$

As shown in Equation (1), indices i and t are the dimensions of provinces and time, respectively. $lnCEI_{it}$ is the main dependent variable, which is the natural logarithm of carbon emission intensity in province i during year t, and $lnDIF_{it}$ is the central explanatory variable. X_{it} is the vector of control indicators, which includes logged per capita GDP, urbanisation rate, openness degree, environmental governance, industrial structure, R&D investment, etc.; μ_i is the provincial-specific bias, and λ_t is the annual fixed effect term to account for macroeconomic fluctuations that affect all areas. ε_{it} is the residual error term, and the standard deviations are grouped at the provincial level.

To determine if the composition of energy use restricts the emission reduction effect of digital inclusive finance, add the structure of energy use (ECS) and its interaction coefficient with digital inclusive finance to Equation (1) to construct a moderating-effect model in Equation (2):

$$\ln CEI_{it}=\beta_0+\beta_1 c_\ln DIF_{it} +\beta_2 c_ECS_{it}+\beta_3(c_\ln DIF_{it}\times c_\ln ECS_{it})+\gamma X_{it}+\mu_i+\varepsilon_{it} \quad (2)$$

ECS_{it} in Equation (2) is a moderator that represents the proportion of coal use in the total primary energy supply of province i at time t; c_lnDIF_{it} and c_ECS_{it} are the mean-centred values of the digital inclusive finance index and energy consumption structure, respectively; $c_lnDIF_{it}\times c_ECS_{it}$ is the interaction term of the main explanatory variable and the moderator.

2.2 Selection of Variables and Data Sources

The dependent variable is carbon emission intensity (CEI), which is adopted to measure regional carbon emission levels. Its calculation formula is specified as: $CEI_{it} = CO2_{it}/GDP_{it}$. Specifically, CO2it denotes the total provincial carbon emissions, and

GDPit represents the nominal gross domestic product. The fundamental data are collected from the China Statistical Yearbook and the National Bureau of Statistics of China. To mitigate heteroscedasticity and obtain elastic coefficients, carbon emission intensity is logarithmically transformed and denoted as $lnCEI_{it}$. Carbon emission data are derived from the China Emission Accounts and Datasets (CEADs), which are calculated based on the IPCC accounting framework and widely recognised in existing academic research.

The core explanatory variable is the development level of digital inclusive finance, measured by the aggregate digital inclusive finance index compiled by Peking University. Considering the skewed distribution and wide value range of the raw index, apply a natural logarithmic transformation to construct $lnDIF_{it}$ for regression estimation, which facilitates interpreting the marginal effect of digital inclusive finance.

The previous research used the proportion of coal consumption as a substitute for energy consumption; now, use the ratio of coal-based carbon emissions to total carbon emissions. This former way is more representative of the carbon intensity of the energy mix. The Range of the Metric is 0 to 1. A relatively large number indicates that a considerable amount of coal has been used in the past, promoting carbon lock-in. The CEADs publish the fuel-specific emission inventories, and this information can be obtained from the Internet.

Based on the current primary academic sources, some additional control factors have been added to address the problem of omitted variable bias, and the original dataset is from the China Statistical Yearbook. The control indicators are per capita GDP (to measure the level of economic development in a certain region), urbanization rate (the proportion of urban residents), trade openness (the ratio of total trade with GDP), strength of environmental regulation (the share of investment in pollution control), industrial structure (the proportion of output by the secondary sector) and technological innovation ability (the share of government expenditure on scientific research).

3 Results and Discussion

3.1 Descriptive Statistics

Table 1 is the description of the main variables. Finally, based on the data of the 30 Chinese provinces over the past 12 years, an unbalanced panel data framework has been built, and there are a total of 360 observations. The average value of the main explanatory factor, digital inclusive finance, is 5.338 and its standard deviation is 0.663. The above results show that the development trend of China's digital financial services has been gradually increasing over the study period, and there are still many differences among provinces. In addition, the statistical characteristics of all the control variables are the same as in the previous studies; all figures are in a reasonable range, and no significant outliers have been found in the dataset.

Table 1. Descriptive Statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
lnCEI	360	0.337	0.671	-1.443	1.807

Variable	Observations	Mean	Std. Dev.	Min	Max
lnDIF	360	5.338	0.663	3.013	6.099
ECS	360	0.654	0.148	0.033	0.903
lnPGDP	360	1.674	0.461	0.738	2.939
URB	360	0.601	0.120	0.373	0.893
OPEN	360	0.265	0.273	0.012	1.303
ER	360	0.008	0.005	0.002	0.030
IND	360	0.396	0.079	0.156	0.541
lnRD	360	4.537	0.591	2.80	5.78

3.2 Benchmark Regression Results Sample

Table 2. Baseline Regression Results.

Variable	Pooled OLS	Prov FE	TWFE
lnDIF	-0.024	0.012	0.186*
	(0.096)	(0.023)	(0.107)
lnPGDP	-1.421***	-0.997***	-1.217***
	(0.261)	(0.109)	(0.223)
URB	5.971***	1.476**	1.677*
	(1.228)	(0.711)	(0.872)
OPEN	-1.233***	0.168	-0.012
	(0.382)	(0.106)	(0.157)
ER	10.800	1.223	3.689
	(14.040)	(3.496)	(3.095)
IND	3.802***	0.585	0.580
	(1.174)	(0.363)	(0.530)
lnRD	-0.295	-0.091	-0.070
	(0.238)	(0.056)	(0.065)
_cons	-0.671	1.181**	0.433
	(0.718)	(0.443)	(0.672)
Prov FE	No	Yes	Yes
Year FE	Yes	No	Yes
Observations	360	360	360
Adj. R-squared	0.677		
Within R-squared		0.900	0.397

Note: Robust standard errors clustered at the level of provinces are provided in parentheses. ***p<0.01, **p<0.05, *p<0.10. All the models are the same regarding control variables. Column (1) is the pooled OLS estimate with province and year dummies. Column (2) is only the province fixed effects. Column (3) is the combined effect of province and year.

Table 2 presents the baseline regression results of the three types of models. Column (1) is the result of pooled OLS without fixed effects, and the coefficient of digital inclusive finance (*lnDIF*) is not statistically significant. Column (2) is the provincial fixed effect, and Column (3) is a two-way fixed effect. All the above estimates are with robust

standard errors and have dealt with the problems of serial correlation and cross-sectional dependence at the provincial level.

The coefficient for *lnDIF* is 0.186; it is positive and statistically significant at the 5% level in the two-way fixed-effects model, so it can be concluded that there is a scale-rebound effect. It indicates that, at present, the economic development driven by digital inclusive finance is the main cause of increased carbon emissions from technological progress and thus raises carbon intensity.

3.3 Moderator Analysis

Table 3 shows the moderation effect of energy consumption structure (ECS) on the carbon emission impact of digital inclusive finance. Column (1) is the base regression without the interaction term, and Column (2) shows the full model with the added interaction term. In all the specifications, two-way fixed effects are employed for the provincial and annual data, and the standard errors are clustered at the level of provinces.

Table 3. Moderating Effect of Energy Consumption Structure.

Variable	Main Effect	Moderation Model
c_lnDIF	0.172*	0.120
	(0.096)	(0.105)
c_ECS	1.138***	1.055***
	(0.242)	(0.243)
lnPGDP	-0.988***	-0.895***
	(0.168)	(0.187)
URB	1.066	0.843
	(0.781)	(0.812)
OPEN	-0.193	-0.216
	(0.139)	(0.137)
ER	3.490	3.411
	(2.878)	(2.706)
IND	0.541	0.471
	(0.397)	(0.371)
lnRD	-0.020	-0.035
	(0.060)	(0.057)
Interact_DIF		0.187**
		(0.087)
_cons	1.247***	1.338***
	(0.439)	(0.436)
Observations	360	360
Within R-squared	0.546	0.560

Robust standard errors clustered at the provincial level are in parentheses. ***p<0.01, **p<0.05, *p<0.10. All the models use fixed effects for both provinces and years, *c_lnDIF* and *c_ECS* are mean-centered values, and the interaction term *Interact_DIF* is built from these centred metrics.Multicollinearity diagnostics show that all variance inflation factors (VIFs) are below 10, with a mean VIF of 4.55, indicating no severe multicollinearity.

The value of the interaction coefficient for digital inclusive finance and the structure of energy consumption in column (2) is 0.187, and it is still statistically significant at the 5% level. The results show that the patterns of energy consumption have an effect, but it is not statistically significant. Since the main effect coefficient (*c_lnDIF*) is not statistically significant, the carbon footprint of digital finance can only be determined by the interaction term. With the increase in the proportion of coal, the marginal reduction in emissions from digital inclusive finance has been declining gradually and is currently positive.

The reason for this moderation in economic terms is that resources are limited. In areas with relatively scarce coal reserves, the effect of digital finance is close to zero and may even be slightly negative; at the same time, the resource reorganisation function of digital finance is still able to promote the spread of green technologies to some extent. In the area where there are many coal-fired enterprises, convenient funds and payment systems in digital finance are used to support or increase the scale of high-emission production. Therefore, there will be a scale-up and rebound effect, and thus some expected technological emission reduction benefits will be lost.

As a result, the structure of power supply will be a certain constraint. Although the direction of the effect in terms of theory is consistent, it is not significant in terms of statistics; therefore, such a conditional function should be treated cautiously.

Therefore, it can be seen that the development of digital finance itself will not reduce carbon emissions naturally. Only by altering the energy system and abandoning the high-carbon path of reliance can digital monetary assets be used to advance the development of an economy that is sustainable and environmentally friendly. To show how the pattern of energy consumption is related, Figure 1 presents the portion of the impact of digital inclusive finance on carbon emission intensity. The x-axis is the energy consumption composition index, which is based on the coal consumption ratio, and the y-axis is the marginal effect of digital inclusive finance on carbon emission intensity; the coloured area shows the 95% confidence interval.

As shown in Figure 1, with an increase in the coal ratio, the marginal effect is still increasing and the interaction coefficient is positive and statistically significant (Table 3, Column 2). Therefore, there will be a change in the proportion of energy. Nonetheless, the 95% confidence bounds for the marginal effect are all negative for every coal proportion in the data. The reason for this is that the first one. At first, the main effect of digital inclusive finance on carbon emission density was not significant in any region according to the energy structure.

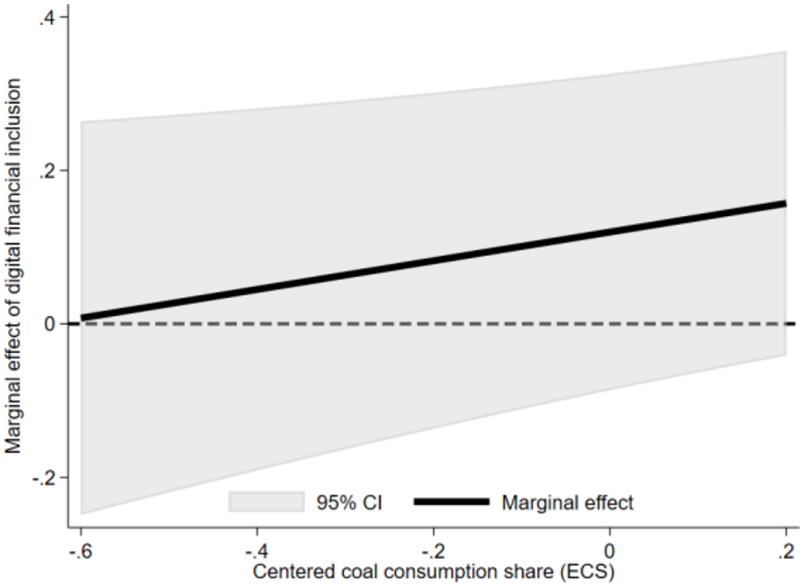


Fig 1: Marginal Effect Diagram

Despite a significant interaction term, the marginal effect remains statistically indistinguishable from zero across all observed coal shares, indicating a theoretically consistent but empirically weak conditional role

3.4 Heterogeneity Analysis

Based on the previous examination of moderating effects, the framework of energy use is positively associated, but its statistical significance is weak (Figure 1). It is not known whether this moderating effect changes with time or is different in various areas due to different reasons for the resource gap. Therefore, heterogeneity tests are conducted at both the level of time and at different times.

Temporal Heterogeneity. To know whether the effect has changed, all the samples were split into three groups according to the different stages of development of digital inclusive finance: the initial period (2011-2014), the development period (2015-2018), and the mature period (2019-2022). Next, the moderation effect regression for each subgroup will be calculated, and the results will be shown in Table 4.

The regression results of the sub-periods show different moderation at different times. In the first stage, digital inclusive finance has increased carbon emissions slightly and is thus in line with the Jevons Paradox [14]. In the beginning of the digital economy, most of the productivity increases caused by innovation were in the form of expanded scale of production. The increase in carbon emissions from more production exceeds the decrease in emissions due to technological progress.

During the development period, the interaction coefficient is positive and statistically significant; at the same time, the main effect coefficient is negative and not statistically significant. With the development of digital financial services in the actual economy, the rigid industrial and energy systems of high-carbon areas will be unfavorable and reduce the emission reduction effect of digital finance.

At the stage of maturity, the main effect coefficient continues to rise and is even negative, but it does not have statistical significance. Given that the size of the interaction coefficient is different in different intervals, it is possible that the range of the conditional effect of energy composition expands gradually over time.

As there is no general method for sample marginal effect statistical analysis, it should be used cautiously.

Table 4. Sub-Period Regression Results.

Variable	Initial Stage	Growth Stage	Mature Stage
c_lnDIF	0.258***	-0.308	-1.149
	(0.071)	(0.304)	(0.996)
Interact_DIF	-0.281***	0.743***	1.512***
	(0.077)	(0.260)	(0.547)
c_ECS	0.131	0.600*	-0.696
	(0.471)	(0.310)	(0.663)
lnPGDP	-1.169***	-0.710***	-0.814**
	(0.418)	(0.228)	(0.306)
URB	4.136**	-2.315**	3.140*
	(2.015)	(0.996)	(1.695)
OPEN	-0.371*	0.226	0.195
	(0.198)	(0.194)	(0.212)
ER	2.635	1.318	0.612
	(3.032)	(2.580)	(4.201)
IND	-1.018	1.269**	0.463
	(0.888)	(0.555)	(0.574)
lnRD	0.027	0.129***	0.177
	(0.113)	(0.036)	(0.136)
Observations	120	120	120

Note: Robust standard errors are clustered at the provincial level and shown in parentheses. *** indicates significance at the 0.01 level, ** at the 0.05 level, and * at the 0.10 level. All the model have a fixed-effects term for both provinces and years, and *c_lnDIF* and *c_ECS* are mean-centred indicators; the interaction term *Interact_DIF* is calculated from centred data. The first period is from 2011 to 2014; the growth period is from 2015 to 2018; the maturity period is 2019-2022.

Heterogeneity in Economic Development. To explore how the uneven distribution of energy resources affects the carbon emissions from digital inclusive finance, the whole dataset is divided into high-income and low-income groups based on the median of

lnPGDP, and then subgroup regressions are carried out. The results of the above estimations are shown in Table 5.

The extent of the effect varies in different areas and at different times of the economy. The interaction coefficient of the high-income group is 0.780 and still exceeds the 1% significance level. Therefore, the coal-intensive energy system is one of the main reasons for the lack of green development in digital finance. The coefficient for the low-income group is -0.211, and considering that it has a 10% significance level, a high proportion of coal suggests that there is an increase in the carbon-intensification effect of digital finance in underdeveloped areas, which is consistent with the characteristic of scale-rebound at the beginning of development. On the other hand, there is little positive moderating effect of energy structure.

Therefore, it can be concluded that the moderating effect of high-carbon lock-in is mainly in the economically developed areas.

Table 5. Moderating Effect of Economic Development Level.

Variable	High PGDP	Low PGDP
c_lnDIF	-0.420	0.284**
	(0.383)	(0.115)
c_ECS	-0.005	0.923**
	(0.264)	(0.402)
Interact_DIF	0.780***	-0.211*
	(0.167)	(0.114)
URB	1.394	0.652
	(0.830)	(1.201)
OPEN	-0.293***	0.082
	(0.057)	(0.229)
ER	-1.055	2.710
	(2.821)	(2.897)
IND	0.107	-0.277
	(0.463)	(0.423)
lnRD	-0.092	0.084
	(0.057)	(0.055)
_cons	0.812	1.472***
	(0.548)	(0.463)
Obs	178	177

Note: Robust standard errors clustered by province are in parentheses. ***p<0.01, **p<0.05, *p<0.10. All the models have fixed effects for both provinces and years. Mean-center the *c_lnDIF* and *c_ECS* variables, and then build the interaction term Interact_DIF. Grouping is done by means of the median of *lnPGDP*.

3.5 Robustness Test

The four robustness tests of the stability are presented in Table 6 below. First, substituting the CEADs' information with that in the EDGAR database is consistent with the initial results. Next, there is a good correlation with the depth of use sub-index. Thirdly,

in the addition of regulation on the impact of carbon trading policy shocks (DID), it is found that this effect is not due to external factors. Lastly, to solve the problem of endogeneity, a lagged explanatory variable is employed.

Table 6. Robustness Test.

Variable	EDGAR-based Carbon Emission	Usage Depth of Digital Finance	Carbon Trading Pilot (DID)	One-period Lagged Specification
c_lnDIF	0.025		0.103	
	(0.041)		(0.107)	
c_ECS	0.355**	1.022***	1.012***	0.918***
	(0.131)	(0.251)	(0.246)	(0.213)
Interact_DIF	0.212***		0.189**	
	(0.064)		(0.088)	
lnPGDP	-0.840***	-0.835***	-0.870***	-0.845***
	(0.068)	(0.167)	(0.188)	(0.187)
URB	0.152	0.850	0.650	0.389
	(0.282)	(0.830)	(0.852)	(0.810)
OPEN	-0.039	-0.185	-0.245*	-0.149
	(0.081)	(0.134)	(0.130)	(0.122)
ER	-2.246	3.566	3.326	3.622
	(1.549)	(2.675)	(2.680)	(2.343)
IND	0.029	0.440	0.455	0.760*
	(0.211)	(0.368)	(0.375)	(0.376)
lnRD	-0.089**	-0.033	-0.030	-0.020
	(0.039)	(0.053)	(0.058)	(0.053)
c_lnDepth		0.073		
		(0.048)		
Interact_Depth		0.211**		
		(0.077)		
DID			-0.057**	
			(0.027)	
c_L_lnDIF				0.003
				(0.088)
Interact_Lag				0.303***
				(0.073)
_cons	15.726***	1.225***	1.410***	1.329***
	(0.231)	(0.420)	(0.444)	(0.451)
Obs	360	360	360	330

Note:Robust standard errors clustered by province are given in parentheses. *** p<0.01, ** p<0.05, * p<0.10. There is a fixed effect for each province and year. Variables marked with "c_" are mean-centered before creating the corresponding interaction terms. Column (1) is the

carbon emission intensity from EDGAR and uses it as a proxy for CEADs. Column (2) is a measure of the level of digital inclusive finance. Column (3) is the DID estimator, and at the same time, the effect of China's carbon trading pilot program is controlled for. Column (4) is a one-period lag of the predictor to address the problem of endogeneity, and thus the size of the dataset is reduced to 330.

Generally speaking, the first few results of the moderation effects in terms of energy use patterns are reliable and consistent.

4 Conclusion

It has been found in this paper that digital inclusive finance is not directly correlated with the reduction of carbon emissions. Based on the above results, an expansion of scale has not led to significant technological progress; therefore, it is currently only a matter of scale rebound. The composition of energy utilisation has a small but essential conditional effect; that is to say, an increase in the proportion of coal will raise the marginal effect of emissions in a specific area or at a particular time, but this is not uniformly the case everywhere and at all times.

Therefore, digital finance is not good for the environment in nature. In line with the goal of carbon neutrality, it need to make all-round changes to the energy system and not only focus on financial digitalisation. The carbon-reduction effects of digital innovation should not be considered too important; at the same time, digital finance needs to be included in the first round of restructuring of energy.

In the future, more information and various indicators from small and micro enterprises on the scope and use of electronic finance will be introduced to determine the direction of green innovation and whether digital banking can help achieve the "dual-carbon" goals by reducing greenhouse gas emissions.

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