Can the Digital Economy Promote Green Household Consumption? —Evidence Based on Empirical Data from the China Household Finance Survey

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Abstract: Greenhouse gas (GHG) emissions generated by household consumption currently account for approximately two-thirds of total global emissions. Accelerating the transformation of public lifestyles is thus essential to mitigating climate change and realizing sustainable development. Using China Household Finance Survey (CHFS) data from 2013-2019, this study conducted a quasi-natural experiment based on the "Broadband China" pilot city policy and employed a multi-period difference-in-differences(DID) model to explore the mechanism behind and the heterogeneous effects of the digital economy on household green consumption. The results obtained demonstrate that the digital economy significantly reduces the scale of household carbon consumption and promotes low-carbon consumption by improving residents' digital literacy. The digital economy is also more likely to reduce carbon emissions in rural areas as well as the consumption of water, electricity, fuel, transportation, and communication.

1. Introduction

The global digital economy is developing at an unprecedented pace. Countries worldwide are accelerating the development of key areas of the digital. As of March 2023, 30.6% of the global population had 5G network coverage, demonstrating the rapid development of this sector. Digital transformation of global industries has entered the stage of scale expansion and deep application, extending from production and R&D to supply chain synergy, green and low-carbon directives, and the development of high-end, intelligent, green, and integrated industries.

Ecological and environmental issues have become important topics for global environmental governance and sustainable development. Green low-carbon transformation is key to reducing social emissions, realizing global greenhouse gas emission quotas, and applying emission reduction credits. As an end-use link in industrial production processes, residential consumption is also an important source of carbon emissions. Approximately 70% of total global greenhouse gas emissions come from household consumption, making the transition to residential green consumption a clear priority. Green consumption choices directly affect the structure of energy demand; raising demand for green production and forcing enterprises to engage in more green innovation and industrial upgrading.

The digital economy provides a potential solution for promoting residential green consumption. This study utilized data from the biennial China Household Finance Survey (CHFS) from 2013–2019, viewing the "Broadband China" pilot city policy as a quasi-natural experiment. A difference-in-differences model was adopted to compare changes in carbon emissions attributable to household consumption in the pilot cities before and after the implementation of the policy, and in the pilot cities relative to the non-pilot cities. We assessed the impact of the digital economy on residents' low-carbon consumption and its internal mechanism; analyzed the heterogeneity of regions and sectors. This analysis was performed to provide a theoretical basis for achieving a definitive transition to low-carbon household consumption in the context of the digital economy.

2. Literature review

The Organisation for Economic Co-operation and Development (OECD) (2017) stated that in its

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current state, the size of the digital economy can be captured by the value-added by digital economy industries.[1] Eurostat (2017) focused on measuring digital economic development in terms of the total economic outputs resulting from digital inputs, including digital skills, digital devices, and digitized intermediate products or services.[2] There is currently no accounting system with a unified form for measuring the digital economy. This remains an important issue that needs to be resolved on a unified basis.The rapid recent development of the Internet and big data technology has meant that researchers have begun to focus on new types of green consumption behaviors triggered by the digital economy. Examples include shared car and bicycle schemes, and real-time feedback information designed to conserve water and electricity based on usage levels.[3]

Most existing literature on how the digital economy affects carbon emissions has focused on the city and enterprise level and studied the carbon reduction effect via the promotion of green technology innovation and industrial structure optimization and upgrading.[4] However, few researchers have studied how the digital economy influences green consumption at the micro-household level. Furthermore, the relationship between the digital economy and low-carbon consumption, and the mechanism through which the digital and economic characteristics of the digital economy drive residents to consume in a low-carbon manner has not yet been made clear. Some researchers believe that digital literacy promotes a cleaner energy consumption structure by increasing nonfarm income, and that convenient mobile payment significantly reduces household carbon emissions and promotes the adoption of green lifestyles.[5] Conversely, others have found that digital finance increases household carbon emissions by expanding the scale of consumption and raising individuals' propensity to consume.[6]

The marginal contributions of this study are as follows. First, it helps to determine whether the development of the digital economy can reduce carbon emissions and promote green household consumption; providing empirical evidence. Second, it comprehensively examines the mechanism behind and the multidimensional heterogeneity of the digital economy's effect on green household consumption. Existing studies have primarily taken a demand-based perspective, whereas this study examines both the supply and demand side. We also analyze the heterogeneity of the digital economy to promote household green consumption from three dimensions: urban and rural households and type of consumption; providing theoretical guidance for the formulation of differentiated emission reduction policies.

3. Theoretical mechanisms and research hypotheses

3.1. Direct effects of the digital economy on residents' green consumption

Internet of Things technology, artificial intelligence, and other technological assets enable individuals and enterprises to monitor production and energy consumption more accurately, analyze consumption behavior, improve the transparency of carbon consumption. They can correct the degree of resource mismatch in the manufacturing industry by promoting industrial restructuring, technological innovation, and upgrading.[7]This can help to optimize the economic structure so that economic resources can flow more freely to industries and sectors that can provide the greatest economic returns, which is beneficial to the sustainability and green development of the overall economy.On the other hand,personalized intelligent recommendations (such as information presentation, system interaction, and community influence) and product involvement through e-commerce platforms have positive impacts on consumers' purchasing decisions.[8] Based on these observations, the following hypothesis is proposed:

H1: The digital economy can reduce the scale of residential carbon consumption.

China's urban-rural dichotomous economic structure may produce heterogeneous impacts in terms of the low-carbon transition to green consumption. These differences are likely to be based on the development level of the digital economy and differences in Internet use.[9] Urban residents are more likely to enjoy the benefits of digital technology in terms of energy saving and emission reduction, while rural areas will likely benefit less owing to their weaker foundations in terms of digital infrastructure. From the industrial structure perspective, the carbon emission reduction effect of the digital economy varies across different consumption types. Regarding high-energy-consuming industries, residents can effectively adjust their consumption choices according to their level of environmental awareness. For food and other forms of spontaneous consumption for which carbon content is low, it is difficult to significantly reduce carbon emissions through individual efforts. Accordingly, the following hypothesis is proposed:

H2: The impact of the digital economy on residential carbon consumption is characterized by heterogeneity in terms of urban-rural settings and consumption types.

3.2. Indirect effects of the digital economy on residential green consumption

Residents' digital literacy has been improved by access to diversified information accessible via multiple channels. As digital literacy improves, consumers are increasingly inclined to choose low-carbon consumption behaviors such as online shopping and digital payments,[10] with these green lifestyle practices further limiting carbon emissions and promoting sustainable development. It is worth noting that the economic impact of the digital economy tends to be somewhat masked in mediating effect studies. Specifically, the economic effect likely outweighs the digital effect in certain situations. Accordingly, the following hypothesis is proposed:

H3: The digital economy can have a dampening effect on the scale of residential carbon consumption by improving consumers' digital literacy; that is, digital literacy plays a mediating effect in the digital economy's influence on the scale of residential carbon consumption.

4. Research Design

4.1. Variable Selection

The data in this study was obtained from the biannual CHFS questionnaire statistics released by the Southwestern University of Finance and Economics, which detail the consumption expenditure of households in all provinces and cities across China. This study aims to explore the impact of the digital economy on green household consumption. This is measured by the impact of the "Broadband China" policy on the construction of public infrastructure for broadband networks and the level of residential green consumption, which is itself measured by the carbon emissions generated by household consumption. To reduce the influence of extreme values and outliers and eliminate the influence of scale, a 1% shrinkage was applied to all continuous variables, and logarithmic treatment was applied to the total household income and household carbon emission indexes belonging to the household head. Finally, 120,286 valid data points were obtained for the analysis.

4.1.1. Explained variable: Household carbon emissions ($AllCO_{2_i}$)

As this study used micro survey data to study the relationship between digital economic policies and green household consumption, it is reasonable to calculate household carbon emissions using micro household consumption pattern analysis.[11,12] The specific steps taken were as follows.

First, using the energy consumption by industry published in the China Energy Statistics Yearbook for each year and the carbon emission coefficients issued by the IPCC, the following formula was adopted from Dulimin to calculate the CO2 emissions of different industries:[13]

$$CO_{2_j} = \sum_{k=1}^{7} E_k \times CF_k \times CC_k \times COF_k \times 44/12$$

where, CO_{2_j} denotes the industrial CO2 emissions; E_k is the kth energy consumption; CF_k denotes the heat value corresponding to the kth energy source; CC_k is the carbon content of the kth energy source; COF_k denotes the oxidation factor of the kth energy source. According to the carbon content (CC) and other related values, the formula $CF_k \times CC_k \times COF_k \times 44/12$ can be used to calculate kth CO2 emission factor of the specific kind of energy. Specifically, the CO2 emission factors of the seven fossil fuels, namely, coke, coal, kerosene, diesel, gasoline, fuel oil, and natural gas, were 2.8481, 1.6470, 3.1742, 3.1500, 3.0451, 3.0642, and 21.6704, respectively.

Second, the CO2 emission intensity per unit of subindustry, that is, CO2 emissions per unit of GDP, was calculated based on the value-added of each industry published in the China Statistical Yearbook of the given year using the formula:

$$CO_2pergdp_j = {CO_2}_j/GDP_j$$

where, $CO_2pergdp_j$ denotes the jth emission intensity per unit of GDP for the industry in question, CO_2, GDP_j is the jth GDP scale of the industry, and ${CO_2}_j$ denotes the jth CO_2 emission of the industry.

Finally, households' consumption expenditure items were categorized by industry. The amount of household expenditure for each item was then multiplied by the CO_2 emission intensity per unit of GDP of that industry to obtain the CO_2 emission indexes generated by each type of household consumption expenditure: Agriculture, forestry, animal husbandry and fishery (ACO2), manufacturing (CCO2), electricity, heat, gas and water production and supply (DCO2), construction (ECO2), transportation, storage and postal (GCO2), and other industries (OthersCO2). The value of each of these industries was then summed to measure the total CO_2 emissions of an individual household (${AllCO_2}_i$). The specific formula used was:

$$AllCO_{2_i} = \sum_{j=1}^{6}\sum_{m=1}^{13} CO_2pergdp_j \times consu_m$$

where, $AllCO_{2_i}$ denotes the CO_2 emissions of the ith household; and $CO_2pergdp_j$ is the GDPCO2 emission intensity of the jth unit of industry; and $consu_m$e denotes the amount of annual household consumption expenditure for 13 different measures. This process was repeated to obtain the data for carbon emissions from household consumption every two years from 2013-2019.

4.1.2. Core explanatory variable: Digital Economy

Network infrastructure construction is an important indicator of the digital economy's level of development. Since pilot cities implementing the "Broadband China" policy are more advanced than non-pilot cities in terms of network infrastructure construction, urban informatization development, and industrial science and technology innovation, the "Broadband China" policy provides a decent measure of the impact of the digital economy. In this study, we used the product of whether a city was one of the three "Broadband China" pilot cities and whether it had become a pilot city in that year (did) to measure the digital economy.

4.1.3. Control variables

Referring to existing studies, this study focused on controlling for the factors that may affect the green energy consumption of residential households at the individual and household levels. At the individual level, we chose the age of the household head (age), sex (sex), education level ($education$), and health degree ($health$). At the household level, we chose the number of household members ($household\_size$), household debt ratio ($debt\_ratio$), total household income ($total\_income$), elderly dependency ratio ($old\_dependency\_ratio$) and child dependency ratio ($child\_dependency\_ratio$).

4.1.4. Mediating variables

Referring to existing studies, this study used residents' digital literacy as a mediating variable to explore the mediating role it played in the impact of the digital economy on green household consumption. Drawing on the works of researchers such as Yin Zhichao[14] and Wang Qiankun,[15] digital literacy was defined in terms of accessibility and usage. Owning a smartphone (mob) and having access to a third-party payment account (tp_pmt) were selected from the CHFS 2019 questionnaires to measure "accessibility". The amount spent on online shopping (es_exs) and communication network fee ($netcom\_exs$) were selected to measure the "degree of use," and these four indicators were subjected to principal component analysis to generate the composite variable Digital Literacy Index (dig). The Kaiser–Meyer–Olkin (KMO) test showed that the sample was suitable for principal component analysis.

The variable definition criteria are presented in Table 1.

Table 1. Variable definitions

Variable type	variable name	variable symbol	Variable Meaning
Explained variable	household consumption carbon emissions	$lnAllCO_2$	Logarithm of carbon emissions from household consumption
Core explanatory variable	digital economy	did	Whether the household's city has become a pilot city in the current year, yes = 1, no = 0
Control variables	(a person's) age	age	Actual age in the year of the questionnaire
	(a person's) sex	$gender$	Male = 1, Female = 0
	educational attainment	$education$	Educational level of the head of the household (no schooling = 1, elementary school = 2, junior high school = 3, high school = 4, secondary school = 5, college=6, bachelor's degree = 7, master's degree = 8, doctorate = 9)
	healthiness	$health$	Physical condition of the head of household (very good = 1, good = 2, fair = 3, bad = 4, very bad = 5)
	number of family members	$household\_size$	Household size in the year of the questionnaire
	household indebtedness	$debt\_ratio$	Total household liabilities as a proportion of total household assets
	gross household income	$lntotal\_income$	Logarithm of total annual household income in the year of the questionnaire
	elderly dependency ratio	$old\_dependency\_ratio$	Proportion of persons under 15 years of age in total household population
	Child dependency ratio	$child\_dependency\_ratio$	Percentage of population over 64 years of age in total household population
Mechanism variables	digital literacy	dig	Comprehensive Measurement Indicators of Digital Literacy of the Population

4.2. Model Design

To accelerate the process of broadband construction, on August 17, 2013, the State Council of China published the implementation plan for the "Broadband China" strategy. This strategy involved deploying broadband development goals and paths over the following eight years and selecting 117 "Broadband China" demonstration cities (clusters) across three phases, namely, 2014, 2015 and 2016. Changes in Chinese household green consumption are primarily driven by two separate effects. One is the time effect generated by the passage of time; the other is the policy effect driven by the implementation of the "Broadband China" policy. In this study, the phased implementation of the "Broadband China" pilot program is regarded as a quasi-natural experiment that is exogenous to the level of household green consumption, which is estimated with the help of the multi-temporal difference-in-differences method. The control and treatment groups were divided based on whether or not households in the pilot cities responded to the implementation of this program. Households that never became pilot cities during the sample examination period were set as the control group for all study participants. A multi-temporal DID benchmark regression model was constructed, and the specific expressions were:

$$lnAllCO_{2_{it}} = \alpha_0 + \alpha_1 did_{it} + \alpha_2 Control_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

where, the explained variable $lnAllCO_{2_{it}}$ refers to the logarithm of household ith's consumption carbon emissions in year tth, and the core explanatory variable did_{it} describes whether the city where household ith is located has become a pilot implementation of the "Broadband China" policy in year tth. This took the value of 1 if the city had become a pilot city in tth, otherwise it took the value of 0. μ_i and η_t denote individual fixed effects and time fixed effects, respectively; ε_{it} is a random perturbation term that affects carbon emissions from household consumption; α_1 is the estimator; $Control_{it}$ represents a series of control variables that affected carbon emissions from household consumption in tth years.

5. Research Results

5.1. Descriptive Statistics

Table 2 presents the descriptive statistical characteristics of the variables. All continuous variables are presented at the 1% level. To conduct the empirical test, natural logarithms were taken for the scale variables of total household income and consumption carbon emissions to attenuate the heteroscedasticity of the data.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max.
AllCO2	120286	143691.46	193917.24	2559.642	1174644.1
did	120286	0.403	0.49	0	1
age	120286	54.209	14.265	24	85
sex	120286	0.757	0.429	0	1
education	120286	3.436	1.687	1	9
health	120286	2.772	1.064	1	5
household_size	120286	3.234	1.536	1	8
debt_ratio	120286	0.105	0.379	0	2.946
total_income	120286	74486.488	95198.097	-5313	601800.5
old_dependency_ratio	120286	0.346	0.4	0	1
child_dependency_ratio	120286	0.051	0.113	0	.5

5.2. Baseline Regression Analysis

Table 3. Benchmark regression results

VARIABLES	(1)	(2)
	did1	did2
did	-0.0431***	-0.0551***
	(0.0129)	(0.0128)
age		-0.00365***
		(0.000641)
sex		0.0424***
		(0.0123)
education		0.0254***
		(0.00569)
health		-0.0100**
		(0.00408)
household_size		0.101***
		(0.00456)
debt_ratio		-0.0421***
		(0.00963)
lntotal_income		0.0769***
		(0.00311)
old_dependency_ratio		-0.410***
		(0.0280)
child_dependency_ratio		0.338***
		(0.0637)
year	yes	yes
hhid	yes	yes
Constant	11.22***	10.33***
	(0.00689)	(0.0557)
Observations	120,286	116,054
R-squared	0.103	0.164
F	35.78***	267.97***
Number of hhid	66,102	64,776

Note: *** indicates the presence of a correlation at a significance level of 0.01.
The t-value is inside the parenthesis.

To test the impact of the digital economy on household green consumption, we first estimated equation (1) using a two-way fixed-effects DID approach. The estimation results of the reported baseline regression are presented in Table 3. In column (1), only the "Broadband China" pilot policy was used as an explanatory variable for the regression, without controlling other variables. The estimated coefficient was significantly negative at the 1% level, which indicated that the implementation of the "Broadband China" pilot policy significantly reduced the carbon emissions from household consumption. Column (2) added a series of control variables based on column (1) and found that the regression coefficient was further reduced and that the digital economy reduced household carbon emissions significantly by 5.5%. The results of the benchmark regression support Hypothesis 1; that is, the digital economy can promote green household consumption and reduce the scale of residents' carbon consumption.

5.3. Robustness Test

5.3.1. Parallel trend test

The prerequisite assumption for the validity of the difference-in-differences method is the convergence assumption; that is, if the Broadband China pilot policy had not been implemented, the trends regarding carbon emissions from household consumption in the pilot and non-pilot cities should have been parallel. Beck's (2010)[16] event analysis method was thus adopted to conduct the parallel trend test. The results of the parallel trend test, depicted in Figure 1, demonstrate that the regression coefficients exhibited a significant decrease in the year of policy implementation that continued for two periods after implementation. This indicates that while the implementation of the Broadband China policy significantly reduced carbon emissions from household consumption in pilot cities, the economic marginal effect meant that the carbon emissions from consumption increased slightly but remained lower than the pre-policy level. The regression satisfied the parallel trend assumption, and the policy identification results were relatively reliable.

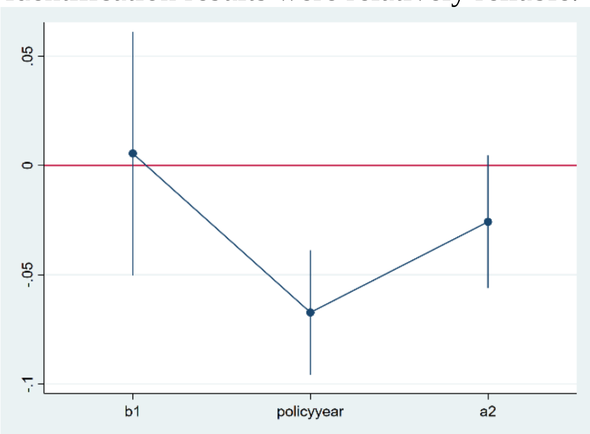

Figure 1. Parallel trend test

5.3.2. Placebo test

Another concern regarding the identification assumption of the difference-in-differences method is the impact on the estimation results of other unobservable urban characteristics that change over time. This study employed an indirect placebo test, which has been widely employed in the existing literature (Chetty et al., 2009; Ferrara et al., 2012)[17,18]. Specifically, we randomly generated a list of pilot cities for the Broadband China policy, generating an incorrect estimate and repeating this process 500 times to create 500 estimates. Figure 2 depicts the distribution of these estimates. The estimates followed a normal distribution, as expected, and were distributed around zero.

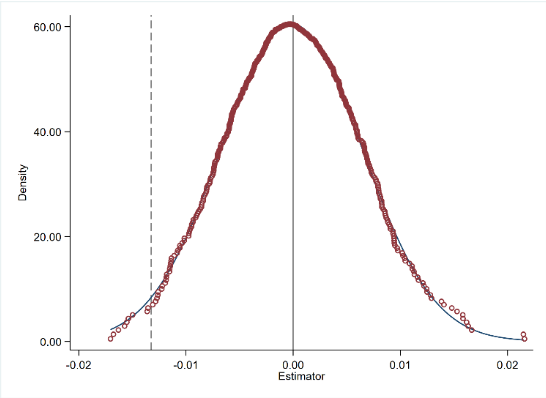

Figure 2. Distribution of regression coefficients

5.3.3. Propensity score matching and difference-in-differences (PSM-DID) test

Although the Broadband China pilot policy is considered exogenous as a government-led policy, the government may tend to select Broadband China city pilots, for example, by selecting cities with strong economic development and high levels of innovation and entrepreneurship. To make the pilot cities comparable with non-pilot cities, this study adopted the PSM-DID method to test the benchmark regression. The results showed no significant differences between the treatment and control groups and the sample data were balanced. Based on the matched samples and difference-in-differences estimation (the regression results are presented in Table 4), the estimated coefficients obtained using the PSM-DID method showed a slight decrease. However, the impact of broadband network construction on household green consumption was significantly negative at the 1% level, meaning the results of the PSM-DID test supported the conclusion of the benchmark regression.

Table 4. PSM-DID test

Variable	$lnAllCO_2$
did	-0.0552***
	(0.0128)
Control	yes
year	yes
hhid	yes
Observations	116,038
R-squared	0.164
F	268.30***

Note: *** indicates the presence of a correlation at a significance level of 0.01.
The t-value is inside the parenthesis.

5.4. Mechanism analysis

The empirical results show that the digital economy drives green household consumption and effectively utilizes the low-carbon consumption governance dividends of the digital economy. There are several channels through which the "Broadband China" pilot affects green household consumption, with residents' digital literacy undoubtedly having a direct and significant impact on household consumption choices. To test this, a mediation effect model was constructed to assess residents' digital literacy. The model was designed as follows:

$$dig_{it} = \beta_0 + \beta_1 did_{it} + \beta_2 Control_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

$$lnAllCO_{2it} = \gamma_0 + \gamma_1 did_{it} + \gamma_2 dig_{it} + \gamma_3 Control_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

where, dig_{it} denotes the digital literacy index. Considering that the relevant issues involving digital literacy variables were reflected only in the CHFS 2019 data, only these data were selected for this study.

The results of the two-step regression are provided in Table 5, where the digital literacy index passed the mediation effect test. The coefficient of the digital economy on the residents' digital literacy index was significantly positive at the 1% level, and the coefficient of the digital literacy index on the carbon emissions from household consumption was significantly positive at the 1% level. This may be because digital literacy provides a digital foundation and support for economic activities, while economic forces allow the Digital Economy to generate economic growth and development. With both items jointly promoting the rapid development of the digital economy, the economy can play a greater role, thus interfering with the exploration of the "Digital Economy → Digital Literacy → Green Consumption" impact path. In this regard, this study split the comprehensive indicator of digital literacy and conducted a two-step regression on four indicators: Whether to use smartphones, whether to open a third-party account, online shopping expenses (logarithmic treatment), and communication network expenses (logarithmic treatment). The results show that only whether to open a third-party account was dominated by digitality. The coefficient of the digital economy on this variable was -0.0338 at the 1% significance level, and the coefficient of this variable on carbon emissions from household consumption was -0.429 at the 1% significance level. The estimated coefficients of the rest of the variables were significantly positive because of the dominance of economic forces.

Table 5. Intermediation effect regression results

VARIABLES	Combined impacts		Digital impact		Economic impact					
	dig		tp_pmt		mob		es_exs		netcom_exs	
	step1	step2	step1	step2	step1	step2	step1	step2	step1	step2
did	0.102***	0.171***	-0.0338***	0.192***	0.0537***	0.191***	0.227***	0.109***	0.0566***	0.177***
	(0.00927)	(0.0112)	(0.00497)	(0.0114)	(0.00540)	(0.0115)	(0.0250)	(0.0169)	(0.0102)	(0.0108)
dig		0.385***								
		(0.00758)								
mob						0.300***				
						(0.0131)				
tp_pmt				-0.429***						
				(0.0140)						
lnes_exs								0.211***		
								(0.00659)		
lnnetcom_exs										0.421***
										(0.00660)
Control	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
year	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
hhid	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	25,532	25,532	26,447	26,447	26,389	26,389	10,409	10,409	25,641	25,641
R-squared	0.490	0.452	0.390	0.415	0.307	0.406	0.233	0.289	0.339	0.465
F	2452.10***	1915.97***	1689.39***	1705.60***	1167.22***	1641.83***	316.46***	384.84***	1311.71***	2021.43***

Note: *** indicates the presence of a correlation at a significance level of 0.01.
The t-value is inside the parenthesis.

5.5. Heterogeneity analysis

5.5.1. Urban-rural heterogeneity

The digital economy may have different degrees of impact on residents of towns or villages in terms of green household consumption. The heterogeneity test was conducted according to whether the sample households were located in the countryside or not, with the test structure presented in Table 6. The results show that the development of the digital economy had a significant effect on urban and rural households' green consumption. The estimated coefficient of carbon emission reduction of rural households was -0.0878 at the 1% significance level, and the estimated coefficient of carbon emission reduction of urban households was -0.0302 at the 10% significance level, demonstrating a more significant effect for rural households. The primary reason for this is that the advancement of digital technology has made electronic devices more popular, and urban households are usually more likely to buy and use these devices. The manufacturing, use, and disposal of these devices generate a certain amount of carbon emissions, while the charging of electronic devices and the use of the electricity network also increase household energy consumption.

Table 6. Results of the test for urban-rural heterogeneity

VARIABLES	(1)	(2)
	rural	urban
did	-0.0878***	-0.0302*
	(0.0236)	(0.0159)
year	yes	yes
hhid	yes	yes
Constant	9.971***	10.44***
	(0.0876)	(0.0727)
Observations	36,525	79,529
R-squared	0.173	0.160
F	114.56***	155.71***
Number of hhid	17,568	47,719

Note: *** indicates the presence of a correlation at a significance level of 0.01.
The t-value is inside the parenthesis.

5.5.2. Heterogeneity of consumption types

This study sought to verify the extent to which the digital economy can promote green household consumption and reduce consumption-based carbon emissions. It primarily manifests in terms of high energy consumption and fixed asset procurement, which also affects the production and supply of electricity, heat, gas, and water (industry code D), transportation, storage, and postal industry (industry code G). Other industries were selected as the classification objects of consumption-type heterogeneity.

The test results are listed in Table 7. The results show that the digital economy significantly reduced carbon emissions from household consumption in industries D and G. The digital economy produced the most obvious carbon emission reduction effect on household expenditures on water, electricity, fuel, and property heating, producing a coefficient of -0.0656 at the 1% significant level. This was followed by the emission reduction effect on residents' local transportation and communication network expenses of -0.0360 at the 5% significant level. This shows that the development of the digital economy has prompted residents to consciously control the frequency and intensity of their use of water, electricity, fuel, and heating and to select low-carbon travel modes more often.

Table 7. Consumption type heterogeneity test results

VARIABLES	(1)	(2)	(3)
	DCO2	GCO2	OthersCO2
did	-0.0656***	-0.0360**	-0.00120
	(0.0122)	(0.0147)	(0.0233)
year	yes	yes	yes
hhid	yes	yes	yes
Constant	10.42***	7.813***	4.714***
	(0.0540)	(0.0646)	(0.103)
Observations	110,956	111,269	106,915
R-squared	0.126	0.197	0.215
F	100.86***	399.87***	454.03***
Number of hhid	62,646	63,111	61,576

Note: *** indicates the presence of a correlation at a significance level of 0.01.
The t-value is inside the parenthesis.

6. Conclusion

6.1. Research Findings

The conclusions of this study are as follows: (1) The digital economy can reduce the scale of residents' carbon consumption; (2) the digital economy can inhibit the scale of residents' carbon consumption by improving their digital literacy; that is, digital literacy has a mediating effect on the digital economy's influence on the scale of residents' carbon consumption; (3) the digital economy has a significant impact on the scale of green household consumption. Furthermore, green consumption exhibits heterogeneous influence characteristics, with the digital economy having a more obvious effect on carbon reduction in rural households. It also has a greater impact on the decarbonization of the electric power, heat, gas, and water production and supply industries, as well as the transportation, warehousing, and postal industries.

6.2. Research Recommendations

This study proposes the following policy recommendations: (1) The construction of the digital economy should be accelerated and the number and scale of "Broadband China" pilot cities continuously expanded. (2) Personal digital skills and digital literacy should be cultivated. (3) The scale of residents' carbon consumption should be continuously reduced and environmental protection differentiation should be promoted for households in different regions and with differing levels of consumption. (4) Low-carbon production processes in high-energy-consuming industries must be continuously improved alongside the full implementation of the dual-carbon policy. Advanced low-carbon technologies and management experience must also be introduced and promoted through international cooperation projects, and dual-carbon policies must be fully implemented to promote the realization of global carbon reduction targets.

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