Journal of Economic Structures

RESEARCH **Open Access**

The impact of digital financial inclusion on household carbon emissions: evidence from China

Yu Zhou*, Caijiang Zhang and Zhangwen Li

*Correspondence: eczhouyu@mail.scut.edu.cn

School of Economics and Finance, South China University of Technology, Guangzhou 510006, People's Republic of China

Abstract

The role of digital financial inclusion in economic development has been widely appreciated, and its carbon emission mitigating effect on the household sector needs to be noticed. This study investigates the impact of digital financial inclusion on household carbon emissions based on panel data for 30 Chinese provinces from 2011 to 2020. The results show that digital financial inclusion has a significant and robust mitigation effect on household carbon emissions and that digital financial inclusion impacts mainly from the breadth of coverage and the degree of digitization. The heterogeneity test results show that this mitigation effect is mainly found in the central and western inland regions as well as in the northern regions with high winter heating demand. In addition, this mitigation effect is mainly found in urban rather than rural areas. The results of the mechanism analysis show that digital financial inclusion reduces household carbon emissions through two pathways, electricity consumption and natural gas consumption share, and no significant mediating effect is observed for residential consumption share. The results of this study shed light on the relationship between digital financial inclusion and carbon emissions in the household sector and provide a reference for decision-making to address household carbon emission mitigation in China.

Keywords: Digital financial inclusion, Carbon emissions, Household carbon emissions, China, Mechanism

JEL Classification: G50, Q54, Q57

1 Introduction

Promoting sustainable economic development and addressing climate change are important issues facing countries around the world today. The reality that temperatures could rise by about 1.5 °C between 2030 and 2050 at the current rate of increase is making an aggressive response to climate change the consensus of the world (Valérie et al. 2018). The majority of countries have signed the Kyoto Protocol and the Paris Climate Agreement, which means that these countries have an incentive to control CO_2 emissions. Based on the realities of the country, different economies have announced their own carbon reduction or carbon neutrality schedules. As the developing country with the highest carbon emissions, China has proposed a 30–60 target of peaking its carbon emissions by 2030 and achieving carbon neutrality by 2060. However, what makes different countries decrease their carbon emissions while not harming economics remains an open question.

Household carbon emissions are an essential aspect of carbon emissions because they are a major source of GHG. Household carbon emissions refer to the carbon emissions of household products and services. According to Wilson et al. (2013), household carbon emissions account for 72% of total emissions in Canada. However, policies on carbon mitigation have mainly targeted carbon emissions in the industrial sector and less in the household sector, which has hindered the process of carbon emission reduction to some extent (Shi et al. 2020). Understanding household behavior, including how households make energy use decisions, is important not only for researchers, but also for policymakers aiming to promote efficient and sustainable energy use through different policies (Borozan 2018).

The intention of financial inclusion is to improve the accessibility of financial services, especially for the low-income in less-developed regions. The rapid development of fintech innovations has changed the global financial industry and the household sector (Banna et al. 2021). Through rapid digital infrastructure development, China is proliferating in the digital and fintech sectors, and digital financial inclusion is one of the construction results. Digital financial inclusion is a new area of financial inclusion which carries out financial services in digital form. Traditional financial institutions promote financial accessibility mainly through the establishment of institutional branches. Digital financial inclusion, on the other hand, lowers the barrier of entry for customers and penetrates areas that are beyond the reach of traditional finance through digitization, eliminating the previous regional restrictions on financial inclusion and reducing the cost of financing for small firms and households (Geng and He 2021). Traditional financial institutions promote financial accessibility mainly by setting up institutional branches. Digital financial inclusion, on the other hand, lowers the entry barrier for customers through digitization and penetrates areas beyond the reach of traditional finance.

As a result, several questions have aroused our interest. (1) How does digital financial inclusion affect household carbon emissions in China? (2) Is there any regional heterogeneity in these effects? (3) Does digital financial inclusion interact with other influencing factors in influencing household carbon emissions? Existing studies have focused on the impact of digital financial inclusion on carbon emissions (Shahbaz et al. 2022; Wang et al. 2022). However, to our knowledge, no studies have analyzed the regional differences and mechanisms of action regarding the impact of digital financial inclusion on household carbon emissions. To address this issue, we systematically study the impact of digital financial inclusion, population, income, and technology level on household carbon emissions using panel data from 2011 to 2020 for 30 Chinese provinces.

More specifically, our contribution is threefold: first, and perhaps most importantly, we systematically explored the role of digital financial inclusion on household carbon emissions, which has important implications for enhancing the contribution of financial inclusion to CO_2 mitigation in the household sector. As far as we know, this topic has not received attention in the existing research. Second, we discussed the regional and urban–rural heterogeneity of the role of digital financial inclusion on household carbon emissions across regions, which provides a vital reference for policymakers to develop locally adapted and efficient solutions to household carbon emissions. Third, we discussed clean energy, electricity, and dwelling consumption and whether it is a valid influencing pathway for digital financial inclusion to affect household carbon emissions. It helps us to understand the changes in household consumption caused by digital financial inclusion to release household credit constraints and its impact on household carbon emissions, which is conducive to achieving household-level carbon emission reductions.

The rest of this manuscript is organized as follows. In the following section, we provide a brief review of the existing literature. Then the theoretical framework and methodology are presented in Sect. 3. Section 4 illustrates the empirical results and discussions. Finally, Sect. 5 summarizes the empirical findings and concludes with policy implications.

2 Literature review

2.1 The influence of financial development on carbon emissions

Existing research on the relationship between financial development and carbon emissions mainly focused on whether financial development can mitigate carbon emissions. Although the importance of financial development has been confirmed, no consensus has been reached on how financial development impacts carbon emissions.

Most studies found that financial development mitigates carbon emissions (Jalil and Feridun 2011; Kim et al. 2020; Tamazian et al. 2009; Tamazian and Bhaskara Rao 2010). The reason may be that financial investments in new technologies give rise to green products, the widespread use of green products improves the global environment, i.e., the technology effect, and financial development reduces carbon emissions by promoting technological innovation (Bekhet et al. 2017; Paramati et al. 2017). For example, Khan and Ozturk (2021) studied the impact of financial development on carbon emissions for 88 developing countries from 2000 to 2014. They found that financial development can reduce carbon emissions, which they attribute to the fact that financial development helps to provide credit for environmentally friendly energy technologies, leading to the improvement of the energy sector's overall efficiency.

Some studies argue the opposite, suggesting that financial development is exactly the main driver of increasing carbon emissions (Abbasi and Riaz 2016; Al-Mulali et al. 2016). Zhang (2011) attributes the above phenomenon to the scale effect of financial development on carbon emissions, i.e., the increase in the size of loans and the size of equity financing boosted China's carbon emissions. Financial development reduces the financial constraints of firms. On the one hand, bank loans provide a solid support for Chinese firms to obtain external financing and expand their investments; on the other hand, the hotness of the stock market further enhances firms' external financing. As a result, firms boosted productive capacity and energy consumption through reinvestment, especially for countries in the initial stages of financial development (Haseeb et al. 2018).

It should be noted that a few empirical studies yielded statistically insignificant or nonlinear results due to the heterogeneity in the role of technology and scale effects across regions and over time. For example, Ozturk and Acaravci (2013) pointed out that there is no significant relationship between financial development and carbon emissions. In the study of Kim et al. (2020) for a sample of 86 developed and developing countries from 1989 to 2013, a threshold effect on carbon emissions was found for some sub-indicators of financial development, such as loan volume.

In summary, the impact of financial development on carbon emissions has two main paths: (1) the scale effect, as demonstrated by financial development increasing carbon emissions by easing financing constraints and increasing output, and (2) the technology effect, as demonstrated by financial development reducing carbon emissions by promoting green innovation.

2.2 The influence of financial inclusion on carbon emissions

The concepts of financial inclusion and financial development are similar in that both include the provision of financial services by financial institutions to individuals. However, the difference is that financial development is more oriented to the industry's overall development, and large enterprises tend to obtain the majority of financial services while neglecting small enterprises and individuals who dominate in number. It is these individuals who are served by financial accessibility. Financial inclusion eases financing constraints for households and small enterprises and incentivizes households to participate more in financial markets and allocate assets.

An inconclusive linkage between financial and carbon emissions is evident in the literature. Existing studies on the relationship between financial inclusion and carbon emissions have mainly used national cross-sectional data (Le et al. 2020; Qin et al. 2021; Usman et al. 2021). However, the results are conflicted due to the heterogeneity between different countries. For instance, Usman et al. (2021) found that financial inclusion overcomes environmental degradation based on the data of the 15 highest emitting countries from 1990 to 2017. They attribute the mitigation effect of financial inclusion on carbon emissions to the that a developed financial sector helps institutions, organizations, and industrial units utilize modern and eco-friendly technologies and allocate financial assets to protect and control environmental degradation. Shahbaz (2022) studied the synergistic reduction of CO_2 and SO_2 by digital financial inclusion. They found that increased financial inclusion can enable more energy-intensive individuals to receive financial support to improve energy efficiency and reduce total energy consumption; in addition, it can enable more households and individuals who previously could not afford clean energy to receive financial support to replace energy-consuming equipment. Thus, a synergistic reduction in pollutants and carbon emissions can be achieved.

Conversely, opponents claim that the financial policies in less polluted countries are not aligned with environmental goals. With an improved financial inclusion situation, on the one hand, the development of pollution-intensive industries leads to an increase in carbon emissions (Qin et al. 2021). On the other hand, big-ticket items are more affordable for citizens, and the widespread use of big-ticket items leads to higher domestic fossil-fuel energy consumption, leading to a higher emission level (Le et al. 2020; Zaidi et al. 2021). For example, based on the dataset of 31 Asian countries over the period 2004–2014, Le et al. (2020) constructed a composite indicator of financial inclusion using five variables: number of automatic teller machines per capita, commercial bank branches per capita, commercial bank institutions, commercial bank outstanding deposits, and commercial bank outstanding loans through principal component analysis, and found that there is a facilitative effect of financial inclusion on carbon emissions. They suggest that the mechanism of this contribution is that with the widespread adoption of financial inclusion, Asian citizens can afford to purchase more big-ticket items such as cars, refrigerators, air conditioners, and televisions, boosting the regional energy demand and thus leading to an increase in CO2 emissions in countries. Zaidi et al. (2021) constructed financial inclusion indicators and studied 23 OECD countries from 2004 to 2017 using the panel mean group model. The results indicate a positive relationship between financial inclusion and carbon emissions. The explanation is that OECD economies are at an early stage of development of their resources and are developing and transforming their financial resources according to the objectives. Financial inclusion enables consumers to consume high-energy consumer goods, such as cars and air conditioners; on the other hand, the financial system drives carbon emissions from energy consumption by promoting economic development and increasing energy demand.

Based on conflicting results from previous empirical studies, Renzhi and Baek (2020) combined the previous studies and claimed a two-stage model based on the dataset of 103 countries from 2000 to 2017. In the early stage, residents promote consumption level, and enterprises expand their production scale; in the later stage, corporate social responsibility is emphasized, strict investment decision-making policies are introduced, and enterprises have to low-carbon innovation, leading to a lower carbon-emitting level. Therefore, an inverted U-relationship between financial inclusion and carbon emissions emerges.

To conclude, a few studies on the impact of financial inclusion on carbon emissions have emerged in recent years. However, the aforementioned studies have some limitations in terms of perspective. For example, in the analysis of mechanisms, the household sector, as the main object of the role of financial inclusion, is often passed over, and the household level is not taken out of consideration, which is very important.

2.3 The other impact factor of household carbon emissions

The number of existing studies on household carbon emissions is limited, and the relevant studies mainly focus on identifying the influencing factors of household carbon emissions. To summarize, the main influencing factors of household carbon emissions are as follows.

First, several studies point out that disposable income contributes significantly to household carbon emissions. Grossman and Krueger (1995) proposed an inverted U-shaped relationship between income and environmental stress, i.e., the environmental Kuznets curve (EKC). According to this theory, environmental stress increases with income at lower incomes, and decreases with higher incomes after incomes exceed a certain threshold. As Lévay et al. (2021) and Shi et al. (2020) found, the main influencing factor of household carbon emissions is income. Second, population level is also regarded as an impact factor on household carbon emissions. For example, Li et al. (2015) used cointegration and Granger causality tests for Chinese data from 1996 to 2012 and found a unidirectional causal relationship between urbanization and household carbon emissions. Household size is also one of the population-level indicators (Shirley et al. 2012; Underwood and Zahran 2015). Finally, consumption factors also play a vital role in household carbon emissions, such as dwelling, food, and energy consumption

(Shi et al. 2020; Zhang et al. 2021). People with larger dwellings will produce more emissions because heating requires more fuel (Li et al. 2019). Households that use natural gas or liquefied natural gas as their primary energy source emit less CO_2 than those that use coal or straw as their primary energy source (Shi et al. 2020).

2.4 Research gap

In summary, existing studies on household carbon emissions have focused on the drivers of household carbon emissions. Only a few studies have been conducted on the impact of financial inclusion on carbon emissions, and even fewer studies on digital financial inclusion. Digital financial inclusion, with the help of new digital financial services represented by Internet technology companies providing financial services, is better able to meet the needs of micro, small and medium-sized enterprises and low-income people who usually have difficulty accessing financial services than financial inclusion services relying on banking institutions, and also has a closer relationship with Chinese households. Therefore, digital financial inclusion can better portray the impact on households. However, to our best knowledge, there are no studies on the impact of digital financial inclusion on household carbon emissions. Considering this issue is very important, this study fills the gap in the literature on the impact and mechanism of action of digital financial inclusion and household carbon emissions.

3 Theoretical framework and methodology

3.1 Theoretical framework

Digital financial inclusion targets households and small businesses. For households, the liquidity released by digital financial inclusion allows them to have more money at their disposal over time. Previous studies have often argued that providing financial products to households tends to stimulate the consumption of bulky goods, which in turn leads to high energy consumption and, thus to increased carbon emissions (Le et al. 2020). However, the consumption of bulky products does not necessarily lead to large consumption of energy but may crowd out previously inefficient energy consumption. In the case of China, for example, the population involves a choice of fuel before coal, liquefied petroleum gas, and natural gas, and China is a coal-rich, gas-poor, oil-poor country where the use of coal is less costly. However, the heavy use of coal inevitably brings high pollution and carbon emissions. When making energy consumption choices, it is often considered what energy consumption devices are available in the residential environment. When energy consumption devices are identified, there is generally no incentive to replace them, even if doing so would lead to a lower carbon lifestyle. The growth of digital financial inclusion may enable households to purchase energy-consuming devices that were previously unaffordable and squeeze out inefficient energy use. The energy consumption mix of households has the potential to shift both to clean energy and to secondary energy sources, such as electricity. Therefore, we propose hypothesis 1 to hypothesis 3.

Hypothesis 1: Digital financial inclusion negatively impacts household carbon emissions.

Hypothesis 2: Digital financial inclusion reduces household carbon emissions by increasing the share of clean energy consumption.

Hypothesis 3: Digital financial inclusion reduces household carbon emissions by increasing the share of electricity consumption.

However, existing studies also point out that households may boost residential consumption as liquidity on hand increases. This may create resistance to a reduction in household carbon emissions. This is because, on average, the larger the dwelling, the higher the energy needed to keep it warm (Shi et al. 2020). We, therefore, propose hypothesis 4:

Hypothesis 4: Digital financial inclusion increases carbon emissions by increasing the share of dwelling consumption.

3.2 Model

Taking into account the above discussion, we mainly focus on the impact of digital financial inclusion on household carbon emissions. We draw on the Stochastic Impacts by Regression on Population, Affluence, and Technology model proposed by Dietz and Rosa (1997) to introduce digital financial inclusion based on population, income, and technology level. The empirical model is presented as Eq. (1):

$$\ln HCE_{it} = \beta_1 + \beta_2 DFI_{it} + \beta_3 \ln POP_{it} + \beta_4 \ln INC_{it} + \beta_5 \ln TEC + \varepsilon_{it}, \tag{1}$$

where the subscripts i and t indicate the province and year, respectively. HCE, DFI, POP, INC, and TEC denote household carbon emissions, digital financial inclusion, income level, population level, and technology level, respectively. ε_{it} denotes the error term.

3.3 Data and variables

To explore the impact of digital financial inclusion on household carbon emissions, this study utilizes the balanced annual dataset of thirty Chinese provinces from 2011 to 2020 for empirical analysis. Since the earliest data on the explanatory variable digital financial inclusion were generated in 2011 and the latest data available are up to 2020, the data set in this study is from 2011 to 2020. Hong Kong, Macaw, Taiwan, and Tibet are not included in the dataset because of the incomplete data.

The dependent variable is household carbon emission, denoted as HCE, which is estimated by the consumption of fossil fuels derived from China Energy Statistical Yearbook (2008–2021). This study uses the IPCC (Intergovernmental Panel on Climate Change) recommended method to estimate household carbon emissions:

$$HCE = \sum_{j=1}^{17} EC_j \times NCV_j \times CC_j \times O_j \times \frac{44}{12}, \tag{2}$$

where EC_j is the j th type of fossil fuel consumption, NCV_j is the net calorific value of the j th type of fossil fuel, and CC_j represents the carbon content of the unit heating value of the j types of energy. O_j is the carbon oxidation rate of the jth fossil fuel, and $\frac{44}{12}$ is the ratio of the molecular weight of carbon dioxide to the carbon atom.

Furthermore, digital financial inclusion is proxied by the digital financial inclusion index. The data on DFI is from The Peking University Digital Financial Inclusion Index of China (Guo et al. 2020). The index covers three sub-indicators, which are the breadth of coverage (COV), depth of use (DEP), and degree of digitization (DIG). The breadth of

Table 1 Descriptive statistics of variables

Variable name	Units	Mean	SD	Min	Median	Max
HCE	Million ton	13.609	8.920	0.962	11.754	42.871
DFI	–	217.246	96.968	18.330	224.105	431.930
COV	–	198.010	96.334	1.960	198.495	397.000
DEP	–	212.036	98.106	6.760	203.655	488.680
DIG	–	290.238	117.644	7.580	323.250	462.230
POP	Million	4599.783	2837.845	568.000	3917.500	12624.000
INC	CNY	23531.626	11158.386	8028.907	21070.719	72232.398
TEC	pcs	2210.227	2789.244	23.000	1106.500	15222.000
DC	%	0.217	0.072	0.096	0.190	0.379
NC	%	0.211	0.146	0.000	0.184	0.979
EC	10^8 kWh	267.998	203.545	14.950	215.470	1179.470

coverage refers to the comprehensive degree of financial services covering the population; the depth of use refers to the diversity of financial products used by the population; the degree of digitalization refers to the convenience, cost, and creditability of the population using digital financial products.

We follow the previous empiricalF literature to use the control variables illustrated as follows: (1) population (denoted as POP) is measured by the number of residents population, which is collected from the China Statistical Yearbook (2012–2021). (2) Income level (denoted as INC) is proxied by the real income per capita, with data obtained from the official website of the Chinese National Bureau of Statistics. (3) Technology level (denoted as TEC) is proxied by the count of low-carbon innovation, which is collected from China National Intellectual Property Administration. (4) Dwelling consumption (denoted as DC) is proxied by the share of residential consumption in total income. The data are collected from China Statistical Yearbook (2012–2021). (5) Electricity consumption (denoted as EC) is proxied by electricity consumption, which is collected from China Energy Statistical Yearbook (2012–2021). (6) Natural gas consumption (denoted as NC) is the share of natural gas consumption in total energy consumption. The data can be obtained from China Energy Statistical Yearbook (2012–2021). We take logarithms for all variables except DFI, COV, DEP, DIG, DC, and NC, for which their units are proportional or null. Table 1 presents the summary statistics for the variables.

3.4 Estimation methodology

In the baseline model, the two-way fixed effect panel estimation approach is applied. It is also applied in heterogeneity tests. The two-way fixed effect estimator includes individual fixed effect and time fixed effect, see Eq. (3):

$$y_{it} = x'_{\mathbf{it}}\boldsymbol{\beta} + z'_{\mathbf{it}}\boldsymbol{\delta} + u_i + \lambda_t + \varepsilon_{it}, \tag{3}$$

where u_i and λ_t denote individual fixed effect and time fixed effect, respectively. $\boldsymbol{x}_{it}^{'}$ is a vector of explanatory variables, and $\boldsymbol{z}_{it}^{'}$ is a vector of control variables.

Furthermore, considering the endogenous, system generalized method-of-moments (GMM) approach with the instrument is provided. System GMM is proposed by Blundell and Bond (1998), which is the combination of level GMM and

Table 2 The results of the panel unit root test

		LLC	IPS	HT
lnHCE	Level	− 9.9238***	− 0.4482	− 1.4846*
	1st difference	− 9.7875***	− 5.3041***	− 18.4294***
lnINC	Level	− 4.2123***	− 6.2775***	3.7780
	1st difference	− 3.5933***	− 3.1060***	− 9.4231***
lnPOP	Level	− 5.0399***	2.7286	4.2002
	1st difference	− 15.2341***	− 1.8525**	− 2.7125***
lnTEC	Level	2.0619	1.1000	-0.1151
	1st difference	− 8.5451***	-2.6118***	-5.3882***
DFI	Level	− 17.5407***	− 6.2949***	2.6322
	1st difference	− 2.2705**	− 4.7776***	− 11.1512***
DEP	Level	− 19.9730***	0.0760	1.7683
	1st difference	− 5.8271***	− 5.1003***	− 12.3590***
BRE	Level	− 9.4077***	− 2.0724**	3.9586
	1st difference	− 15.8632***	− 3.2678***	− 8.2381***
DIG	Level	− 22.6952***	− 5.0498***	0.6283
	1st difference	− 4.2767***	− 4.1945***	− 10.6416***
DC	Level	− 5.2699***	0.1837	− 2.8878***
	1st difference	− 7.1261***	− 4.6668***	− 12.5719***
NC	Level	− 0.8790	3.8136	− 5.8995***
	1st difference	− 30.3398***	− 4.1173***	− 20.8027***
lnEC	Level	2.2456	6.7486	− 1.8607**
	1st difference	− 7.0054***	− 5.4796***	− 21.2291***

*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively

difference GMM. The application of system GMM estimation requires the data is a short panel, which means that the number of individuals (N) should be greater than the number of observations (T). The dynamic panel model is presented in Eq. (4):

$$y_{it} = \alpha + \rho_1 y_{i,t-1} + \rho_2 y_{i,t-2} + \cdots + \rho_p y_{i,t-p} + \mathbf{x'}_{\mathbf{it}}\boldsymbol{\beta} + \mathbf{z'}_{\mathbf{it}}\boldsymbol{\delta} + u_i + \lambda_t + \varepsilon_{it}. \qquad (4)$$

4 Empirical results

4.1 Stationarity and cointegration test

Verifying the stationarity of the variables and the existence of cointegration is necessary to avoid spurious regression (Beenstock and Felsenstein 2015; Chica-Olmo et al. 2020; You and Lv 2018). First, we verify whether the variables are stationary by LLC (Levin et al. 2002), IPS (Im et al. 2003), and HT (Harris and Tzavalis 1999) panel unit root tests. The results in Table 2 indicate that all the variables are stationary after the first-order differencing.

The long-term relationship exists when all the variables are cointegrated. The result of the Pedroni cointegration test is presented in Table 3 (Pedroni 2004). The within-dimensional (ν, ρ, PP, ADF) and between-dimensional (ρ, PP, ADF) statistics indicated that all variables were cointegrated, which supported the long-term relationship between our focused variables.

Table 3 The results of Pedroni cointegration test

	χ^2	Prob
Within-dimension cointegration test		
Panel ν statistic	− 8.5314***	0.0000
Panel ρ statistic	5.5501***	0.0000
Panel *PP* statistic	− 8.0800***	0.0000
Panel *ADF* − statistic	− 9.6247***	0.0000
Between-dimension cointegration test		
Group ρ statistic	8.5226***	0.0000
Group *PP* statistic	− 7.9337***	0.0000
Group *ADF* statistic	− 12.8089***	0.0000

*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively

Table 4 The results of baseline model

	(1) Pooled OLS	(2) RE	(3) Two-way FE	(4) FGLS
DFI	− 0.105*** (− 2.669)	− 0.105** (− 2.223)	− 0.130** (− 2.205)	− 1.089*** (− 12.524)
lnPOP	0.532*** (5.781)	0.593*** (3.441)	0.606*** (2.791)	1.257*** (17.043)
lnINC	0.861*** (26.640)	0.952*** (10.222)	2.471*** (6.591)	0.887*** (67.979)
lnTEC	0.040 (0.874)	0.084*** (2.678)	0.084*** (2.698)	0.049* (1.829)
Constant	− 9.787*** (− 10.975)	− 11.133*** (− 6.269)	− 23.677*** (− 6.583)	− 16.590*** (− 23.446)
Obs	300	300	300	300
Adj. R^2	0.718		0.701	
F statistics			34.99***	
Wald		167.47***		4910.25***
Xttest3_Chi2				14286.08***
Hausman			17.37***	

The values in parentheses represent the t-statistics. *, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent the t-statistics

4.2 Baseline model

In order to consider the impact of digital financial inclusion on household carbon emissions, it is necessary to carry out an empirical test using a suitable methodology. We started by introducing a baseline model (see Table 4), including digital financial inclusion (DFI), the primary explanatory variable, and the other variables, namely population (POP), disposable income per capita (INC), and technology level (TEC). Columns (1)–(3) are the pooled OLS model, random effects model, two-way fixed effects model, and feasible generalized least squares model, respectively. The results of Chi-square statistics from the Hausman test reject the null hypothesis, so applying the fixed effects model is reasonable.

The estimated coefficient of digital financial inclusion on household carbon emissions is negative and significant at the 1% level, as seen in the OLS regression, which is consistent in the random effects model, the two-way fixed effects model, and the generalized least squares model. Over the sample period, improving digital financial inclusion helps decrease household carbon emissions. Therefore, Hypothesis 1 is verified. The results differ from the current research on the existence of an enhanced effect of financial inclusion on carbon emissions. Zaidi et al. (2021) observed a positive relationship between financial inclusion and carbon emissions in OECD countries, which they suggest are in the early part of the environmental Kuznets curve, where residents acquire more cars, refrigerators, air conditioners, and televisions after receiving financial inclusion, leading to higher carbon emissions. We believe that the different results may stem from the differences between financial inclusion and digital financial inclusion. In general, the "low credit limit and wide coverage" feature of digital financial inclusion suggests that its average credit limit is lower than that of financial inclusion,[1] which prevents most households from acquiring large and expensive goods such as cars through digital financial inclusion, making residents more likely to consume necessities such as appliances and energy equipment, and new high-efficiency equipment to replace old inefficient ones. New energy-efficient equipment replaces inefficient energy consumption, which in turn may reduce carbon emissions in total.

Furthermore, our findings within the baseline model show that the population, income, and technology level significantly impact household carbon emissions. The carbon emissions-population elasticity is 1.257, indicating that for every 1% increase in population, the household carbon emissions will increase by 1.257% on average, which is consistent with the findings of Anser et al. (2020) and Qi and Li (2020), more population corresponds to greater energy demand, which leads to higher carbon emissions. On the one hand, for the developed countries, the carbon emissions-population elasticity tends to be below 1, while China is well above this level. On the other hand, fertility rates in developed countries tend to be lower, which indicates that population growth rates are maintained at lower levels. The growth rate of fertility in China is slowing down, but the population is still on an upward trend. Therefore, carbon emissions in the household sector will remain under tremendous pressure in the future.

For income, the estimated coefficient of carbon emission-income elasticity is 0.887, indicating that for every 1% increase in income, carbon emissions from the household sector increase by 0.887% on average. Similar findings can be found in Shi et al. (2020) and Saidi and Mbarek (2017). For households with a constant marginal propensity to consume, an increase in income will lead them to spend more on energy consumption, leading to higher levels of carbon emissions.

In addition, the estimates show that each 1% increase in technology will result in an average 0.049% increase in household carbon emissions. However, this effect only holds at the 10% significance level.

4.3 Robustness test

Due to the possible bidirectional causality problem caused by endogenous of the digital financial inclusion index, the conclusions obtained in the baseline model may be unreliable. Therefore, we discuss the endogeneity issue in this section. We estimate the baseline model through system GMM by taking lagged explanatory variables into the equation and introducing internet broadband penetration rate (IBP) as instrumental variables. IBP is measured by the number of Internet broadband per

[1] According to the < Prospectus for Initial Public Offering of Shares and Listing on the Growth Enterprise Market (Registration Draft) > of Ant Group Technology Co., Ltd. (currently the largest fintech company in China), the company facilitated a consumer credit balance of 1,732 billion yuan as of June 30, 2020, and the company has over 1 billion users with an average consumer credit balance of less than 1,700 yuan per person.

Table 5 The results of system GMM estimation

	(1) lnHCE	(2) lnHCE
lnHCE(− 1)	0.923*** (6.949)	0.920*** (4.162)
DFI	− 0.255** (− 2.731)	− 0.251** (− 2.147)
lnPOP	0.003 (0.020)	0.153 (0.844)
lnINC	0.387* (1.741)	0.192 (1.630)
lnTEC	0.119 (1.286)	0.083 (0.877)
Constant	− 3.346* (− 1.710)	− 2.708 (− 1.640)
Obs	270	270
F statistics	5004.670***	7689.521***
Hansen	20.216 (0.164)	21.914 (0.289)
AR(1)	− 3.599 (0.000)	− 3.356 (0.001)
AR(2)	− 0.591 (0.555)	− 0.206 (0.837)

The values in parentheses represent the t-statistics

*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively

capita, reflecting the regional digital infrastructure level and impacting the development of digital financial inclusion. On the other hand, its impact on household carbon emissions is weak. Therefore, IBP is an ideal instrumental variable. The results of the system GMM estimation are presented in Table 5, where the first column is the estimation using only the lagged explanatory variables as instrumental variables; the second column is the estimation using IBP as instrumental variables.

The results in Table 5 show that digital financial inclusion still shows a mitigating effect on household carbon emissions under the system GMM estimation. Further, each 1% increase in the digital financial inclusion index will result in an average 0.349% decrease in household carbon emissions. This estimation result is even higher than that of the benchmark regression, indicating that the carbon mitigation effect of digital financial inclusion is robust when endogeneity is taken into account.

To confirm the reasonableness of the system GMM usage, we apply the over-identifying restrictions test to verify the exogeneity of instrument variables. Hansen J statistic cannot reject the null hypothesis that the instrument variables are exogenous as a group. Thus, all the instruments are efficient. The Hansen J statistic of both two GMM approaches indicates no over-identification problem. Therefore, the application of the system GMM setting is reasonable.

Furthermore, The Arellano–Bond test results are presented in Table 5. The AR(1) test rejects the hypothesis that the first-order autocorrelation coefficient of the difference of the disturbance term is zero. The AR(2) test accepts the hypothesis that the second-order autocorrelation coefficient of the difference of the disturbance term is 0. The results indicate that there is first-order autocorrelation in the difference of the perturbation terms, but not second-order autocorrelation. Therefore, the null hypothesis of no autocorrelation in the error terms is accepted. The AR(1) and AR(2) tests demonstrate the appropriateness of using lagged explanatory variables as instrumental variables in the GMM model.

Table 6 The results of the sub-indicators estimation

	(1) lnHCE	(2) lnHCE	(3) lnHCE
BRE	− 0.319*** (− 3.277)		
DEP		− 0.018 (− 0.486)	
DIG			− 0.052** (− 2.042)
lnPOP	2.248*** (5.307)	2.048*** (4.780)	2.072*** (4.880)
lnINC	1.126*** (3.356)	0.584* (1.965)	0.789** (2.525)
lnTEC	0.078** (2.043)	0.083** (2.131)	0.087** (2.244)
Constant	− 27.246*** (− 5.963)	− 20.553*** (− 4.932)	− 22.688*** (− 5.317)
Obs	300	300	300
Wald	2802.98***	2234.84***	1876.95***
Xttest3_chi2	96253.75***	65888.27***	21798.70***

The values in parentheses represent the t-statistics

*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively

4.4 Heterogeneity test

4.4.1 Sub-indicators estimation

Digital financial inclusion indicators include multiple dimensions, and in the process of policy formulation, it is necessary to promote the development of digital financial inclusion in a focused manner. Therefore, in this section, we first carry out the analysis from the perspective of sub-indicators. We draw on the approach of Guo et al. (2020) to divide digital financial inclusion into three dimensions of sub-indicators: breadth of coverage, depth of usage, and degree of digitization, where the breadth of coverage refers to the coverage of digital accounts, depth of use refers to the frequency and amount of digital financial inclusion services such as payments, money funds, and credit operations used by residents, and the digitalization rate refers to the frequency and amount of offline payments and microfinance on mobile.

Further, we replaced the DFI with a subindex and re-estimated the model shown in Eq. (1). The estimation results are presented in Table 6. The results indicate that both breadth of coverage and degree of digitization significantly reduce household carbon emissions. However, the impact of depth of usage on household carbon emissions is not statistically significant.

The above results indicate that the most significant pathway through which digital financial inclusion affects household carbon emissions is the breadth of coverage, followed by the degree of digitization.

In summary, the development of digital financial inclusion can reduce carbon emissions in the household sector, but there is heterogeneity in the sub-indicators. Among them, the reduction of household carbon emissions mainly relies on the breadth of coverage and the degree of digitalization. On the one hand, broader coverage will allow more people to access credit products; on the other hand, higher digitalization broadens the usage scenarios and increases the frequency of usage in the daily lives of residents. Therefore, the household sector has a higher probability of accessing credit, expanding the household consumption set, which leads residents to consume newly introduced energy-efficient products with a higher probability, leading to a decrease in household carbon emissions. It should be noted that the effect of the indicator of usage depth of

Table 7 The results of the sub-sample estimation

	(1) Eastern	(2) Central	(3) Western	(4) Coastal	(5) Inland	(6) Heating	(7) Unheating
DFI	0.024 (0.275)	− 0.418** (− 2.533)	− 0.201* (− 1.874)	0.025 (0.271)	− 0.224** (− 2.469)	− 0.193** (− 2.067)	0.015 (0.171)
lnPOP	− 0.152 (− 0.206)	4.031*** (4.521)	3.566*** (4.393)	− 0.308 (− 0.399)	2.727*** (5.303)	3.748*** (7.206)	− 1.373 (− 1.434)
lnINC	− 0.386 (− 0.792)	2.393** (2.584)	1.599*** (2.824)	− 0.434 (− 0.771)	1.249** (2.598)	0.603 (1.394)	0.203 (0.376)
lnTEC	0.100** (2.146)	0.163** (2.308)	− 0.048 (-0.933)	0.089* (1.764)	0.115*** (2.704)	− 0.097 (− 1.315)	0.172*** (3.961)
Constant	− 0.311 (-0.044)	− 61.442*** (− 7.747)	− 37.929*** (− 4.672)	8.491 (0.988)	− 32.113*** (− 7.369)	− 32.260*** (− 6.983)	10.838 (0.954)
Obs	120	90	90	110	190	130	170
Wald	48.80***	81.03***	21.97**	5591.21***	745.77***	663.11***	2607.25***
Xttest3_chi2	74078.53***	1487.45***	4.9e + 05***	10862.85***	2247.31***	54862.78***	4.9e + 05***
Permutation test	0.050	0.020	0.075	0.042		0.040	

The values in parentheses represent the t-statistics

*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively. The number of bootstraps is 1000

digital financial inclusion is not significant, indicating that the diversified use of digital financial inclusion does not affect household carbon emissions during the sample period.

4.4.2 Sub-sample estimation

China is a vast country with large differences between the resource endowments of different regions, which has led to the unbalanced and insufficient characteristics of regional development. There are differences in the level of digital financial inclusion in different regions, such as the eastern region has a significantly higher level of digital financial inclusion than the western region. In the estimation of the baseline model, we obtained the average treatment effect of digital financial inclusion on household carbon emissions. However, based on the intra-regional differences in China, the emission reduction effect of digital financial inclusion may be heterogeneous across regions. Therefore, heterogeneity tests are necessary.

Sub-sample regression is a common method for diagnosing heterogeneity. Table 7 presents the impact of digital financial inclusion on household carbon emissions by different sub-samples. In columns (1)–(3) of Table 7, the sample is divided into three parts, East, Central, and West, where the division is based on the China Statistical Yearbook. In columns (4) and (5), the sample is divided into coastal and inland parts, where the division is based on the China Marine Statistical Yearbook. In columns (6) and (7), the sample is divided into heated and unheated areas.

Digital financial inclusion in eastern China showed an insignificant impact on household carbon emissions, while this effect is significantly negative in the central and western provinces. Among them, the effect is greater in the central region.

The provinces in eastern China are averagely more developed, and the alleviation of residents financing constraints by digital financial inclusion does not affect the energy decisions of households in these developed regions. On the other hand, for households in western and central China, improved financing constraints will allow those more expensive and energy-efficient products to enter their consumption set. For these regions with much lower per capita income, digital financial inclusion helps them have more consumption options, which happens to be one of the goals of financial inclusion development. The development of digital financial inclusion helps people in these areas have better development prospects and creates conditions for them to have a more energy-efficient lifestyle.

Furthermore, the sub-sample estimated results in the coastal and inland are similar to those in the East–Central–West sub-sample. In the coastal regions, the effect of digital financial inclusion on household carbon emissions is not significant, while this effect is significantly negative in the inland regions, which suggests that the impact of digital financial inclusion is greater in inland regions where economic development is weaker relative to coastal regions.

Referring to the study by Fan et al. (2021), winter heating policies in northern China may affect household carbon emissions by changing the consumption decisions of households. Further, we estimate the sub-sample by dividing the regions into two categories based on the presence or absence of heating in winter. The results show that digital financial inclusion statistically significantly reduces carbon emissions in heated regions, while no significant effect can be observed in non-heated regions.

In order to verify whether the difference between the coefficients is significant, we apply the approach proposed by Cleary (1999), which is called the Fisher permutation test. The test results (see the last row of Table 7) reject the null hypothesis, in which the coefficients of the two estimations are the same. In other words, the results indicate that the regional heterogeneity of the impact of digital financial inclusion on household carbon emissions is significant.

Living in urban or rural areas may impact carbon emissions (Liu et al. 2011). China has a long-standing urban–rural dichotomy, with a large development gap between urban and rural areas, in addition to significant differences in urban and rural lifestyles. This study further discusses how urban and rural household carbon emissions are affected by digital financial inclusion through sub-sample estimation.

The regression results for the urban and rural subsamples are presented in Table 8. The estimation results show that the mitigation effect of digital financial inclusion on household carbon emissions occurs mainly in urban areas, while this effect is not significant in the rural sample. The urban–rural heterogeneity exists. This heterogeneity may result in the particular situation of rural areas. First, the urban–rural dichotomy in China leads to significant differences in income, demographic structure, and available consumer goods between rural and urban areas. During the sample period, the digital infrastructure in rural areas was slow to advance, and there was a lag in the development of digital financial inclusion. However, digital financial inclusion relies mainly on smartphone Internet promotion and implementation. Therefore, digital financial inclusion did not play a significant role in rural areas for the time being during the examination period. Even if the digital financial inclusion index is high on a regional basis, it may only represent urban development rather than rural areas.

Table 8 The results of urban and rural sample estimation

	(1) Urban	(2) Rural
DFI	−0.154* (− 1.743)	− 0.017 (− 0.083)
lnPOP	1.116 (1.393)	− 0.013 (− 0.165)
lnINC	1.945** (2.621)	− 0.477 (− 0.389)
lnTEC	− 0.112** (− 2.219)	− 0.003 (− 0.042)
Constant	− 25.851*** (− 2.874)	2.708 (0.240)
Obs	300	300
Wald	1350.46***	953.98***
Xttest3_chi2	1.2e+05***	1.4e+05***

The values in parentheses represent the t-statistics

*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively

In summary, the results of the sub-sample estimation show the heterogeneity of the impact of digital financial inclusion on household carbon emissions across regions. Specifically, the mitigating effect of digital financial inclusion is observed on household carbon emissions in central and western regions, inland regions, and heating regions of China, while the results are not significant in other regions. Moreover, the permutation test results indicate that the differences between regions are statistically significant.

4.5 Mechanism analysis

So far, we have investigated the causal relationship between digital financial inclusion and household carbon emissions. The above results corroborate the inhibitory effect of digital financial inclusion on household carbon emissions. However, the underlying causal channel between the two is unclear. This study further employs the mediating effect models to further test the mechanism of the effect of digital financial inclusion on household carbon emissions. In this model, electricity consumption, clean energy consumption, and residential consumption shares are included as mediating variables to assess whether digital financial inclusion affects household carbon emissions through these factors. The estimated model is defined as follows:

$$\ln HCE_{it} = \alpha_1 DFI_{it} + \beta_1' X_{it} + \varepsilon_{it}, \tag{5}$$

$$M_{it} = \alpha_2 DFI_{it} + \beta_2' X_{it} + \phi_{it}, \tag{6}$$

$$\ln HCE_{it} = \alpha_3 DFI_{it} + \alpha_4 M_{it} + \beta_3' X_{it} + \gamma_{it}, \tag{7}$$

where lnHCE and DFI represent household carbon emissions and the digital financial inclusion index, respectively. X_{it} is the control variable, which includes income level, population level, and technology level M_{it} is the mediating variable, which includes electricity consumption, natural gas consumption share, and dwelling consumption share.ε_{it} ,ϕ_{it} ,γ_{it} and denote the residuals of the three estimated equations, respectively.

The results of the mechanism analysis are shown in Table 9, where column (1) is the estimated results of Eq. (4), which is the same as column (4) in Table 4, columns (2)–(4) are the estimated results of Eq. (5), and column (5) is the estimated result of Eq. (6). First,

Table 9 The results of mechianism analysis

	(1) lnHCE	(2) DC	(3) lnEC	(4) NC	(5) lnHCE
DFI	− 1.089*** (− 12.524)	0.096*** (8.282)	0.211*** (4.249)	0.080* (1.898)	− 0.131** (− 2.242)
EC					− 0.176*** (− 2.685)
DC					0.146 (1.101)
NC					− 0.747*** (− 5.747)
lnINC	1.257*** (17.043)	− 0.083*** (− 9.518)	0.490*** (12.655)	− 0.018 (− 0.550)	0.899*** (4.108)
lnPOP	0.887*** (67.979)	− 0.002 (− 1.445)	1.058*** (119.366)	− 0.039*** (− 5.389)	2.383*** (6.675)
lnTEC	0.049* (1.829)	0.004* (1.677)	− 0.016 (− 1.546)	0.067*** (6.895)	0.037 (1.179)
Constant	− 16.590*** (− 23.446)	0.947*** (11.076)	− 8.482*** (− 22.798)	0.591* (1.786)	− 24.813*** (− 7.247)
Obs	300	300	300	300	300
Wald	4910.25***	4209.95***	20585.41***	202.15***	2758.14***
Xttest3_chi2	14286.08***	4395.53***	54243.97***	6515.38***	31204.35***

The values in parentheses represent the t-statistics

*, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent the t-statistics

as can be seen from columns (2)–(4) of Table 9, the estimated coefficients of the mediating factors, i.e., electricity consumption, dwelling consumption share, and natural gas consumption share, are statistically significant. Furthermore, the coefficients are 0.096, 0.211, and 0.080, respectively, indicating that digital financial inclusion promotes the use of natural gas, boosting electricity consumption and boosting residential consumption share of expenditure to different degrees. Meanwhile, column (5) of Table 9 shows that the use of natural gas and the increase in electricity consumption can reduce household carbon emissions, while the effect of the share of residential consumption on household carbon emissions is not significant. In other words, this study shows that electricity consumption and dwelling consumption play a mediating role in mitigating household carbon emissions by digital financial inclusion. However, the mediating role of residential consumption share is not significant.

First, from the estimation results, it can be concluded that increasing digital financial inclusion enables more households to access financial support, allowing households that previously could not afford clean energy to access financial support, replace existing energy consumption devices, optimize the energy consumption mix of households, and direct households to consume more clean energy as well as secondary energy, thus increasing energy use efficiency. The result is in line with Shahbaz et al. (2022), who argue that the development of financial inclusion can help shift coal to gas-based consumption. Therefore, Hypothesis 2 is verified. Second, increasing digital financial inclusion will boost electricity consumption in households but will reduce carbon emissions in the household sector. It may seem counterintuitive, but it is also explainable in that the development of digital inclusion not only leads households to upgrade their energy consumption devices, but may also lead them to upgrade from energy consumption devices to more energy-efficient appliances, which has not been observed in previous studies. Therefore, Hypothesis 3 is verified. Finally, digital financial inclusion raises the share of housing consumption in total consumption but does not raise household carbon emissions as a result. Thus, the pathway that digital financial inclusion boosts the share of housing expenditure and increases heating demand, leading to higher household carbon emissions, is not corroborated.

5 Conclusion and policy implications

Our study analyzed the effects of digital financial inclusion on carbon emissions in the household. To do so, we employ a balanced data set on 30 Chinese provinces from 2011 to 2020 to evaluate the effect of digital financial inclusion on household carbon emissions. Our conclusions include the following main points. First, at the national level, there is a significant mitigating effect of digital financial inclusion on household carbon emissions. The robustness of this finding has also been verified. Then we carried out heterogeneity tests in two steps, including (i) estimating the effect of sub-indicators of digital financial inclusion on household carbon emissions; and (ii) estimating the effect of digital financial inclusion on carbon emissions in a sub-sample. Finally, this study introduces electricity consumption, clean energy use, and residential consumption ratios to investigate the mechanism of the effect of digital financial inclusion on household carbon emissions. The estimation results indicate a statistically significant mitigating effect of digital financial inclusion on household carbon emissions, which remains significant when considering endogeneity in the robustness test. The results of sub-indicator estimation show that the breadth of coverage and degree of digitalization effectively reduce household carbon emissions, while the effect of depth of use is not significant. The subsample results indicate that the mitigation level of digital financial inclusion is significant in central and western China but not in the east; significant in the inland regions but not in the coastal regions; and significant in the heating regions but not in the non-heating regions. The mechanism analysis results suggest that digital financial inclusion reduces household carbon emissions through two pathways: electricity consumption and the share of natural gas consumption, while dwelling consumption cannot mediate.

China's economy is shifting from high growth to high-quality development. The combination of economic growth and green development has become the core objective of economic transformation. Based on the above research findings, we propose several policy implications.

First, the benchmark model in this study shows that digital financial inclusion helps to reduce carbon emissions from the household sector. Therefore, in order to achieve CO_2 reductions in the household sector, policies that encourage the development of digital financial inclusion are needed, i.e., building digital infrastructure or encouraging digital financial inclusion product innovation.

Second, the results of the heterogeneity analysis show that policies to encourage the development of digital financial inclusion need to be formulated according to the characteristics of different regions. For example, the future development of digital financial inclusion should be focused on residents of less developed regions and rural areas to cultivate digital financial knowledge among local households, and encourage them to upgrade their existing inefficient energy consumption tools; in addition, subsidies for energy-efficient fuel-consuming equipment and appliances entering these regions can be considered so that residents can enjoy the convenience of digital financial inclusion.

Third, the focus of digital financial inclusion development can be on the breadth of coverage and digitalization. Specifically, the breadth of coverage requires more households to be facilitated by digital financial inclusion, which requires digital financial inclusion operators to develop more promotional tools and tap more new users; the degree of digitization requires a higher level of mobility and convenience, i.e., mobile payment and payment through QR code. The government needs to implement the laying of communication infrastructure., targeting subsidies to low-cost communication devices that can meet the basic network requirements and lowering the threshold of Internet access for less developed areas and low-income people.

Finally, returning to the issue of household carbon emissions, Chinese households should cultivate a low-carbon lifestyle, consciously conserve energy in general, actively use digital financial inclusion products when needed, and obtain energy-efficient products.

Abbreviations

IPCC	Intergovernmental Panel on Climate Change
EKC	Environmental Kuznets Curve
CEADs	Carbon Emission Accounts & Datasets
OECD	Organisation for Economic Cooperation and Development
HCE	Household carbon emissions
DFI	Digital financial inclusion
COV	Breadth of coverage
DEP	Depth of use
DIG	Degree of digitization
POP	Population
INC	Income
DC	Dwelling consumption
NC	Natural gas consumption
EC	Electricity consumption
IBP	Internet broadband penetration

Acknowledgements
The Article Processing Charge was covered by the funds of PAPAIOS and JSPS (KAKENHI Grant Number JP 21HP2002). We acknowledge the editor and two anonymous reviewers for their constructive and insightful comments and suggestions.

Author contributions
YZ: conceptualization, investigation, methodology, software, formal analysis, writing—original draft, visualization. CZ: supervision, project administration, funding acquisition. ZL: investigation, data curation, writing—review and editing. All authors read and approved the final manuscript.

Funding
This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Availability of data and materials
The data that support the findings of this study are available in China Statistical Yearbook, and Institute of Digital Finance Peking University at https://idf.pku.edu.cn/.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

Received: 4 June 2022 Revised: 4 February 2023 Accepted: 6 February 2023
Published online: 16 February 2023

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