China Economic Review 94 (2025) 102556

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

The nexus between digital finance and household consumption-based carbon emissions: Evidence from China

Yong Yu[a], Chenzhe Zhai[b], Debao Hu[c,*], Zicun Wang[d]

[a] School of Finance, Guangdong University of Finance and Economics, Guangzhou 510320, China
[b] School of Finance, Renmin University of China, Beijing 100872, China
[c] International College, Renmin University of China, Beijing 100872, China
[d] Sino-French Institute, Renmin University of China, Beijing 100872, China

ARTICLE INFO

JEL classification:
D12
G50
Q56

Keywords:
Digital finance
Household consumption carbon emission
China family panel studies

ABSTRACT

While identifying the sources of carbon emissions has long been a critical focus for researchers and policymakers, there remains a notable gap in understanding micro-level drivers, particularly the relationship between digital finance and household consumption-based carbon emissions. Existing literature has paid limited attention to how digital finance influences this issue. To address this gap, this study investigates the effect of digital finance on household consumption-based carbon emissions and its underlying mechanisms, using Chinese household data. Our analysis reveals that the development of digital finance significantly increases household consumption-based carbon emissions, and this positive effect remains robust even after addressing potential endogeneity concerns. Furthermore, the impact of digital finance on household consumption-based carbon emissions is more prominent in China's eastern region and rural areas. These findings provide valuable insights for formulating targeted carbon emission reduction policies in the context of digital financial development

1. Introduction

Escalating emissions of greenhouse gases—mainly carbon dioxide—have precipitated grave environmental concerns. As indicated by the Copernicus Climate Change Service, July 2023 witnessed the highest global temperatures ever recorded, underscoring the immediacy of the challenges posed by climate change. Growing environmental issues such as global warming and the accelerating recession of glaciers have become relentless reminders of the critical imperative to address carbon emissions. Notably, carbon emissions can be delineated according to their origin and categorized into emissions generated from the household and production sectors. On the one hand, carbon emissions from the household sector have already surpassed those originating from the industrial sector (Reinders et al., 2003). A report issued by the Chinese Academy of Sciences shows that residential consumption is responsible for 53 % of the total carbon emissions, while the United Nations Intergovernmental Panel on Climate Change attests that residential consumption contributes to approximately 72 % of total global carbon emissions. On the other hand, the purpose of all human production is to meet our needs, whereby production ultimately serves consumption. Hence, there is a close relationship between carbon emissions and household consumption. Nowadays, increased household consumption engenders augmented production, thereby escalating carbon emissions. In a context where governments are committed to enhancing the quality of life for their citizens and

* Corresponding author.
E-mail addresses: yu.yong@live.com (Y. Yu), hdb@ruc.edu.cn (D. Hu).

https://doi.org/10.1016/j.chieco.2025.102556
Received 1 December 2024; Received in revised form 20 August 2025; Accepted 7 September 2025
Available online 11 September 2025
1043-951X/

promoting economic development, the issue of household-related carbon emissions warrants heightened scrutiny.

Meanwhile, digital finance has undergone a remarkable evolution within China since 2013, often regarded as the inaugural year of digital finance in China. The scope and coverage of digital financial services have experienced sustained expansion, including third-party payment systems, online credit services, and internet-based wealth management. For instance, the behemoth of Chinese digital finance—Ant Group—has cumulatively extended unsecured digital loans to an astounding 86 million micro-enterprises and micro-operators. Prior research demonstrates that digital finance promotes household consumption expenditure (Yue et al., 2022) and facilitates consumption upgrading (Hu et al., 2023).

In the context of the burgeoning development of digital finance and the concurrent surge in household-related carbon emissions, several questions naturally emerge: First, does digital financial development increase household carbon emissions? If so, what are the underlying mechanisms driving this phenomenon? Additionally, is there any heterogeneity in the impact of digital finance on household carbon emissions?

This study derives its motivation from several critical considerations. First, household consumption-induced carbon emissions represent a focal point within the field of energy consumption. Carbon emissions attributable to household consumption have assumed a pivotal role in shaping global carbon emissions trends. Nations worldwide have embarked on initiatives aimed at achieving carbon peaking and carbon neutrality, accentuating the importance of environmental and climatic considerations in economic development. The Paris Agreement further underscores the necessity of international collaboration in addressing the climate change challenge. Second, numerous countries—including China—are resolutely committed to expanding domestic demand to stimulate economic growth while promoting green development, whereby the role of household consumption in driving economic development has gained increasing significance. Amplified household consumption concurrently exerts an impact on carbon emissions. Third, the ascendancy of digital finance has brought transformative changes in consumer behavior and catalyzed increased consumption. Digital finance has facilitated more secure and efficient consumption approaches through electronic and mobile payments, reducing wait times and enhancing the consumption experience. Furthermore, digital channels such as the internet and e-commerce platforms enable the ability to shop without time and location limitations.

In this paper, we use Chinese household survey data from China Family Panel Studies (CFPS) and the Digital Financial Inclusion Index (DFII) to investigate the relationship between digital financial development and household consumption carbon emissions in China. We conduct a baseline regression analysis using panel data spanning 2014, 2016, 2018, and 2020. An instrumental variable (IV) and lagged core variables are used to detect potential endogeneity concerns. Furthermore, we explore several plausible mechanisms influencing this relationship, including liquidity constraints easing, household entrepreneurship, and payment convenience. Heterogeneity analyses are developed across urban-rural divides and city-level variations. We also seek to reveal the impact of digital finance using the sub-indicators of digital financial development. Finally, we propose several implications based on our findings.

By synthesizing and analyzing relevant literature and data, this paper aims to establish the mechanisms through which digital finance modulates the level of household carbon emissions. Given the incessant innovation of digital financial instruments and changes in household financial behaviors, comprehending the impact of digital finance on carbon emissions assumes pivotal importance in formulating precise and sustainable policies.

Following this introduction, Section 2 conducts a review of pertinent literature. Section 3 comprises the quantitative and theoretical analyses, expounding on our research hypotheses. Section 4 delves into the data, models, and variables employed in our study. Section 5 offers a comprehensive exposition of our empirical findings and their interpretation, and finally, Section 6 concludes.

2. Literature review

2.1. Digital financial development

Digital finance has been subject to significant scholarly inquiry, yielding insights across various dimensions. At the macro level, Moraes et al. (2023) find that accessing digital finance contributes to mitigating income inequality. Ozili (2018) corroborates these findings, highlighting the crucial role of financial service availability. Ren et al. (2023) argue that digital finance promotes industrial structure upgrading in China, with innovation emerging as a prominent mechanism. Wang et al. (2021) provide empirical evidence that digital finance positively influences employment, suggesting that governments can harness this development to stimulate industrial growth and job creation. Digital finance can also stimulate investment (Yilmaz et al., 2002), promoting a more transparent and stable financial system (Yang et al., 2025). Furthermore, digital finance influences the reduction of sulfur dioxide emissions, as illustrated by Cao et al. (2021) and Lv et al. (2024). Despite these positive attributes, it is essential to acknowledge that digital finance also prompts a digital divide, potentially exacerbating income inequality (Molero-Simarro, 2017; Yao & Ma, 2022).

At the micro level, digital finance has been found to promote households' inclination toward entrepreneurship, which can be attributed to its positive effect in providing liquidity and improving household financial literacy (Rajkhowa & Qaim, 2022). Ozili (2021) offers insights into how digital finance promotes both green and social financing, and its impact on farmer household consumption decisions is also demonstrated (Zhang & Zhou, 2025). Moreover, digital finance stimulates household expenditure (Li et al., 2020; Yue et al., 2022) and structure (He & Song, 2020), and has an income-increasing effect (Zhan et al., 2025). Some scholars also focus on the effect of digital finance on the over-indebtedness of households (Wang et al., 2022, b).

2.2. Household consumption-based carbon emissions

With the increasing global interest in carbon peaking and carbon neutrality, an intense focus has been placed on household consumption-based carbon emissions, as the summation of both emissions directly produced by households and those indirectly linked to them. These emissions encompass not only the release of CO_2 resulting from energy consumption (i.e., direct carbon emissions) but also emissions related to the needs of other products and services (i.e., indirect carbon emissions). Relevant research can be broadly categorized into measuring carbon emissions generated by households and identifying their influencing factors.

For direct carbon emissions, it is customary to convert the amount of energy consumed by a household into standard coal (Lyu et al., 2023), and data related to this category mainly relate to demands for fuel, coal, electricity, etc. The consumer lifestyle approach (CLA) is a popular method of converting the amount of expenditure into carbon emissions. CLA calculates carbon emissions by dividing the household's consumption expenditure into several categories, and multiplying the amount consumed by the carbon emission intensity of each category (Fan et al., 2021; Li et al., 2019; Wei et al., 2007). CLA is particularly suitable for household-level studies since it provides a framework to convert consumption expenditure to energy use. Some scholars use the input-output method proposed by Leontief, which comprehensively analyzes the link between production and consumption in every sector of the national economy to estimate carbon emissions (Kizilaslan, 2009).

Some research investigates—mainly traditional—factors that affect carbon emissions, with Sun & Shen (2024) finding that the Low-Carbon City Pilot reduced household energy consumption. Zhang et al. (2023) demonstrated that income growth is the primary catalyst for household carbon emissions, whereby increased income prompts the consumption of clean energy and thus reduces household carbon emissions. Aging populations and family size are proven to have explanatory power concerning household carbon emissions (Pais-Magalhaes et al., 2022). Consumption patterns (Duarte et al., 2010), population aging (Fan et al., 2021), education level (Andersson et al., 2014), household average weekly non-working time (Zhang et al., 2023), financial development (Khan et al., 2019), urbanization level (Zhou et al., 2025), and online shopping behavior (Xu et al., 2025) also influence household carbon emissions.

2.3. Digital finance and household consumption-based carbon emissions

As digital finance continues to rapidly advance, some scholars are concerned about how it affects the carbon emissions induced by household consumption. The most notable research by Qin et al. (2022) who use micro-level data from China to find that digital finance leads to increased carbon emissions due to household consumption. This increasing effect is caused by the combined impact of increased consumption expenditure and the development of green consumption patterns, both of which are stimulated by the progress of digital finance. Since the former leads to a greater increase in carbon emissions than the latter leads to a decrease, the synergy of the two mechanisms is reflected in rising carbon emissions induced by household consumption. The authors focus on theoretical analysis but do not propose a quantitative analytical framework. Ma et al. (2022) discuss the impact of financial development and digitalization on CO_2 emissions, suggesting that financial development and digitalization contribute to reduced CO_2 emissions in the long term. However, this study is based on Chinese provincial-level data from 2006 to 2017 and does not analyze data at the household level. Other researchers (Sheraz et al., 2021) prove that digital financial development leads to an evident decrease in carbon emissions from household consumption, while Charfeddine and Ben Khediri (2016) found a bell-shaped relationship.

While some scholars have focused on the influence of digital financial development on household carbon emissions, relevant research remains sparse and lacking consensus. Compared to extant studies, this paper makes several incremental contributions. First, it proposes a quantitative framework to describe how digital financial development affects household consumption-induced carbon emissions. Second, our empirical investigation relies on household-level panel data, diverging from prior research that predominantly employs macro-level datasets, such as regional and provincial statistics. Finally, we highlight the impact of digital finance, as an aspect that has traditionally received less attention in existing literature.

3. Hypotheses development and theoretical analysis

3.1. Theoretical analysis

Digital finance involves a combination of information technology and conventional financial systems. It serves a dual role, encompassing the functions of traditional finance—such as capital financing, payment, and settlement—while also addressing the issue of financial exclusion through the efficient utilization of digital technology, characterized by its cost-effectiveness and high efficiency. Consequently, the impact of digital finance on household consumption carbon emissions can be regarded as an incremental effect, whereby the impact of digital financial development superimposes itself upon a backdrop of pre-existing factors. In line with this perspective, we propose a quantitative framework to deduce the impact of digital finance development.

3.1.1. Basic model

We construct a basic model to describe how digital finance influences households' carbon emissions.

Let w—a one-dimensional variable—be the potential carbon emission caused by households. This impact is innate and derived from basic survival needs. The variable w follows a normal distribution with a mean of $\overline{w}$ and a variance of $\overline{\sigma}^2$. For simplicity, we define a new notation $\overline{\tau}$, which represents the precision of the variable:

$$\overline{\tau} = \frac{1}{\overline{\sigma}^2} \tag{1}$$

As shown above, $\overline{\tau}$ is the reciprocal of the distribution variance σ^2. Now, let us focus on the case before households are influenced by financial services, both traditional and digital finance. To sustain themselves, households require a certain amount of food and energy, which equates to a minimum carbon emission. This minimum level of carbon emissions is influenced by factors such as the endowment of resources and the economic development level of the household's location. In sum, a household's ownership of resources is ultimately reflected by its minimum carbon emission. Therefore, we define y_1 as the minimum carbon emission of a household before they engage with financial services, which can be written as:

$$y_1 = w + \epsilon_1 \tag{2}$$

In Eq. (2), ϵ_1 is normal with a mean of zero and precision of τ_1. Although households lack access to financial services, their carbon emissions can still be influenced by the environment, family circumstances, education, or other factors. Thus, we can express the conditional distribution of w, which is also a normal distribution, albeit with a mean of $\mathbb{E}[wy_1]$ and precision of $\overline{\tau} + \tau_1$:

$$\mathbb{E}[w \mid y_1] = \frac{\overline{\tau}\overline{w} + \tau_1 y_1}{\overline{\tau} + \tau_1} \tag{3}$$

For proof of Eq. (3), see the Appendix.

Furthermore, we divide the entire population into two subsets (Z) in our research based on their minimum carbon emission, namely the high-emission group (Z = H) and the low-emission group (Z = L).[1] We then assume that people in group H have a higher average emission than those in subset L, i.e., $\overline{w}_L \leq \overline{w}_H$. For the convenience of the following research, we also assume that $\overline{\tau}_H = \overline{\tau}_L$, $\tau_{1L} < \tau_{1H}$. It is reasonable to assume that subset H has a higher precision and subset L has a lower precision. For the low-emission group, the situation considerably varies among regions, with households in less economically developed regions having significantly lower emissions than those in economically developed regions. For example, households in large cities have higher levels of carbon emissions due to their lifestyle, given that they are typically more inclined to travel and drive their own car. By contrast, there is little intra-group variability in the case of the high-emission group, and households in the high-consumption carbon emission group are likely to own cars and larger houses.

3.1.2. *Traditional scenario*

For the convenience of the analysis, in this section, we elaborate on the traditional scenario in which households can only obtain traditional financial assistance. Financial services can help households ease liquidity constraints and facilitate payments, thereby increasing their willingness to consume. In turn, this leads to an increase in household carbon emissions, i.e., increased consumption expenditure, more goods and services obtained, and more carbon emissions induced. Therefore, we define $u = w + \epsilon_u$ as the carbon emission of a household under the traditional scenario, and its precision is τ_u. The conditional distribution of w conditioned on u and y_1 also follows a normal distribution as well, with a mean of

$$\mathbb{E}[w \mid y_1, u, z] = \frac{\overline{\tau}\overline{w}_z + \tau_u u + \tau_{1z} y_1}{\overline{\tau} + \tau_u + \tau_{1z}} \tag{4}$$

and the precision of the conditional distribution can be expressed as $\overline{\tau} + \tau_1 + \tau_u$. According to the self-fulfilling prophecy theory in psychology, one's views and opinions are self-reinforcing, whereby the frugal man is more frugal and the extravagant man is more extravagant. Consequently, households with low carbon emissions are more likely to maintain their low-carbon lifestyle and leverage the positive effects of financial assistance. Thus, we define $\widehat{w}_L = \overline{w}_L - \delta_t$ as the average willingness for people in subset L where δ_t can be regarded as a penalty for them. Now, we can rewrite the conditional expectation as:

$$\widehat{\mathbb{E}}[w \mid y_1, u, L] = \frac{\overline{\tau}\widehat{w}_L + \tau_u u + \tau_{1L} y_1}{\overline{\tau} + \tau_u + \tau_{1L}} = \frac{\overline{\tau}(\overline{w}_L - \delta_t) + \tau_u u + \tau_{1L} y_1}{\overline{\tau} + \tau_u + \tau_{1L}} \tag{5}$$

3.1.3. *Incremental impacts of digital finance*

Digital finance has rapidly grown, taking advantage of the increasing penetration of the internet and mobile devices. We define the household carbon emission after households engage in digital financial development as

$$y_2 = w + \epsilon_2 \tag{6}$$

where ϵ_2 is normal with a mean of zero and a precision of τ_2. For households in subsets H and L, there is no difference in enjoying the benefits of digital finance due to its inclusiveness, and thus, we assume that $\tau_{2L} = \tau_{2H}$. It is obvious that the conditional distribution of w—which is conditioned on y_1 and y_2—is also normally distributed with a mean of

$$\mathbb{E}[w \mid y_1, y_2] = \frac{\overline{\tau}\overline{w} + \tau_1 y_1 + \tau_2 y_2}{\overline{\tau} + \tau_1 + \tau_2} \tag{7}$$

and a precision of y_2 is $\overline{\tau} + \tau_1 + \tau_2$. For people in subset L, the conditional expectation can be expressed as:

[1] In this paper, it is assumed that the classification criteria is given, so we will not deliberate on how to distinguish between high and low carbon emission groups.

$$\mathbb{E}[w \quad y_1, y_2; L] = \frac{\overline{\tau}\overline{w}_L + \tau_1 y_1 + \tau_2 y_2}{\overline{\tau} + \tau_1 + \tau_2} \tag{8}$$

Considering the self-fulfilling prophecy theory

$$\widehat{\mathbb{E}}[w \quad y_1, y_2, L] = \frac{\overline{\tau}\left(\overline{w}_L - \delta_f\right) + \tau_1 y_1 + \tau_2 y_2}{\overline{\tau} + \tau_1 + \tau_2} \tag{9}$$

δ_f can be regarded as a penalty for households that have low carbon emissions.

3.1.4. Compound scenario

A compound scenario refers to the situation in which people have access to both traditional and digital financial services. According to the previous analysis, we can conclude:

$$\widehat{\mathbb{E}}[w \quad y_1, y_2, u, L] = \frac{\overline{\tau}\left(\overline{w}_L - \delta_f - \delta_t\right) + \tau_1 y_1 + \tau_2 y_2 + \tau_u u}{\overline{\tau} + \tau_1 + \tau_2 + \tau_u} \tag{10}$$

For proof, refer to the Appendix.

Widely developed digital finance requires several preconditions. First, the high penetration of mobile phones and computers is necessary because it ensures that people have the tools to obtain financial services online. Second, it requires effective cable broadband, wireless network coverage, and other network infrastructure, and households have a sufficient level of awareness to choose the proper financial support. Thus, we have the following lemma:

Lemma. When certain preconditions are met and digital finance is widely developed, the impact of digital financial development is positive compared with the traditional scenario.

This lemma can be expressed by the following formula:

$$\mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1, y_2, L] \,|L] > \mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1, u, L] \,|L] \tag{11}$$

Eq. (11) can be further simplified to obtain the following equivalent form:

$$\delta_t(\overline{\tau} + \tau_1 + \tau_2) > \delta_f(\overline{\tau} + \tau_u + \tau_1) \tag{12}$$

The proof of Eqs. (11) and (12) is provided in the Appendix.

Thus, we propose the following hypothesis:

Hypothesis 1. The development of digital finance leads to an increase in household consumption carbon emissions if digital finance is widely developed.

The above assumptions are based on the results derived from the scaling of inequalities with the lemma as the condition. We obtain:

$$\mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1, y_2, u, L] \,|L] > \mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1, y_2, L] \,|L] \tag{13}$$

Proof of Eq. (13) can be found in the Appendix.

3.2. Mechanism analyses

3.2.1. Liquidity constraints easing

Household liquidity constraints refer to the limitations on households' ability to allocate income and savings for consumption. According to Maslow's hierarchy of needs, households prioritize fundamental subsistence consumption—such as food and clothing—before considering high-end products. The amount of disposable income—whether derived from current earnings or past savings—often directly determines households' consumption. In contrast to the exclusionary nature of traditional financial services, digital finance has emerged as an inclusive force, offering households access to financial support—particularly consumer loans—that can alleviate liquidity constraints. This has dramatically changed as a result of the rapid growth of digital finance, which leverages tools such as big data and artificial intelligence to create detailed customer profiles, enabling accurate and differentiated consumer credit solutions to ease the tight liquidity constraints faced by households. Rapid approvals, substantial credit limits, and flexible repayment options characterize these consumer credit products. Borrowers can conveniently submit their documents via mobile devices, with financial institutions' scoring models providing approval results and credit amounts within minutes. High-quality customers might even enjoy interest rate discounts. As households' consumption demand grows, carbon emissions from production, transportation, and packaging also tend to rise. Increasing consumption places additional demands on resources such as energy, water, and raw materials, potentially impacting ecosystems. The spread of digital finance can also encourage households to strongly engage in carbon-emitting activities, such as long-distance travel, online shopping, and fast delivery services. While digital finance enhances the convenience of these activities, it can also lead to higher carbon emissions. As household consumption increases, liquidity constraints relax, contributing to a rise in carbon emissions from household consumption.

Hence, we propose the following hypothesis:

Hypothesis 2. Easing households' liquidity constraints is a mechanism through which digital financial development affects household consumption carbon emissions.

3.2.2. Household entrepreneurship

Digital finance fosters household entrepreneurship (Hu, Guo, & Zhai, 2023), stimulating households' willingness to start businesses by providing initial capital and easy access to business loans at a reasonable cost. Digital financial institutions can extend promotional services to micro, small, and medium-sized enterprises (MSMEs) through digital infrastructure such as mobile apps and online banking. Additionally, digital financial platforms offer real-time data on markets and industries, empowering households to make more informed business decisions. These factors encourage more households to try their hand at entrepreneurship, thereby increasing their willingness to start a business.

Motivated by demonstration effects, entrepreneurial households might employ signals of capability to attract partners or gain a competitive edge in the business world. These signals include renting larger offices or acquiring high-end vehicles and clothing. Moreover, starting a business often necessitates substantial resources, including office space, equipment, and transportation, which can contribute to higher carbon emissions. Regular entrepreneurial activities might require frequent business travel, logistics and transportation, and energy consumption, all of which are closely linked to carbon emissions. While the development of digital finance might prompt households to prefer asset-light entrepreneurship, it is reasonable to argue that digital financial development increases household consumption carbon emissions through the mechanism of entrepreneurship. As mentioned earlier, the demonstration effect remains, with the purchase of more upscale goods hinting at entrepreneurial success and providing a sign that the business is operating effectively. While people are now thinking more about environmental issues such as carbon emissions, this is not yet at the forefront of shopping decisions, especially for successful entrepreneurial families, who have considerable wealth and not only enjoy themselves to improve their quality of life but also have a stronger incentive to flaunt their wealth. Thus, the elevated expenditures resulting from entrepreneurial motivation lead to increased carbon emissions. Successful entrepreneurial ventures typically result in a significant income boost, further contributing to higher household carbon emissions. Thus, we propose the following hypothesis:

Hypothesis 3. Improving household entrepreneurship is a mechanism through which digital financial development affects households' consumption of carbon emissions.

3.2.3. Payment convenience

The evolution of digital finance has simplified transactions, transferring from traditional cash transactions to online payments. This evolution includes enhanced transaction speed and security. Furthermore, online payment has strongly facilitated the development of online shopping. Convenient payment options enhance consumers' shopping experience, prompting consumers to increase both the frequency and magnitude of shopping. Digital financial tools such as mobile payments, online shopping platforms, and virtual credit cards have streamlined the shopping and payment process for households. Households can now purchase goods and services online anytime, anywhere, without the need for physical store visits or cash transactions. This convenience bolsters the efficiency of households' spending, potentially leading to more consumer activities. As households increase their consumption, carbon emissions tied to production, packaging, and transportation are likely to grow. In addition, families can choose from a wide range of domestic and worldwide products via shopping apps, facilitating increased consumer spending and access to more sophisticated products. Cross-border logistics and transportation—driven by globalized shopping trends—can further escalate carbon emissions. In turn, the increased availability of goods and products with more complex and energy-intensive production processes points toward higher carbon emissions from household consumption. A case in point is China's Ant Group, with its Tmall App offering consumers access to a diverse array of products, from basic agricultural products to cutting-edge electronic devices, all available for purchase via smartphone. Alipay—the Ant Group's app, which provides transaction and payment services—streamlines the payment process, allowing consumers to complete transactions immediately when they confirm the order. Consumers complete the entire payment process by simply verifying their face, fingerprint, or password, and the service also offers consumers short-term, interest-free consumer credit.

Here, we would like to clarify and emphasize that while both the improvement of payment convenience and the relaxing of liquidity constraints are closely linked to households' spending behavior, they are different channels, each with its own focus. The relaxation of liquidity constraints emphasizes the increase in household budgets, enabling access to sufficient money to purchase necessary goods and services. Having an adequate budget is a prerequisite for all consumption behaviors, and the transaction behavior can only be successfully completed when funds are matched with the price of the target good. The sources of an adequate budget can be diversified, such as wage income and consumer credit, which can provide households with sufficient disposable funds. Increased payment convenience focuses on facilitating transactions, making it easier for households to complete the payment process to obtain the necessary goods and services. Adequate budgeting is only a prerequisite for consumption, while ease of payment is a "catalyst" for consumption. Thus, the two mechanisms described above are not different expressions of the same mechanism but rather emphasize two separate benefits of digital financial development, which in turn significantly influence household energy consumption.

Thus, we propose the following hypothesis:

Hypothesis 4. Increasing payment convenience is a mechanism through which digital financial development affects household consumption carbon emissions.

4. Empirical study design

4.1. Data source

As this is an empirical study focusing on households in China, we chose the Chinese households' micro-level database as the data source. China Family Panel Studies (CFPS) is a tracking survey initiated by Peking University in 2011, with six waves of data released thus far, and the latest data collected in 2020. CFPS covers Chinese households correlated with consumption, income, work, and education, with a sample of households spread across 25 provinces. The CFPS data has been used extensively in micro-level studies related to China due to its excellent representativeness and extensive coverage. We use the Digital Finance Inclusion Index (DFII)—jointly compiled by Peking University and Ant Group—as a measure of the level of development of digital finance. DFII is released annually, covering 31 provinces in China, with the most recent data released in 2020 (Guo et al., 2020).

4.2. Variables

4.2.1. Household consumption carbon emission

Household consumption carbon emission (*HCCE*) is the core dependent variable. Referring to previous studies (Li et al., 2019; Wei et al., 2007), we employ CLA to estimate this variable. The CLA method has clear advantages in measuring the amount of carbon emissions caused by household consumption for several reasons. First, the CLA method takes into account both direct (from fuel consumption) and indirect carbon emissions (from consumption of products and services other than fuel), making it a more comprehensive measure of carbon emissions from household consumption (Zhang et al., 2015). Second, CLA integrates external environmental variables, individual determinants, household characteristics, and consumer choices and consequences into a unified framework (Bin & Dowlatabadi, 2005). Third, CLA uses both macro and micro data in its calculations, improving the accuracy and robustness of carbon emissions from household consumption. Naturally, there are also some shortcomings of the CLA approach that have drawn criticism. First, it is built on the assumption of constant carbon intensity across different regions and periods. We use a shorter data period from 2014 to 2020, which reduces the impact of the time span. At the same time, we chose the Energy Statistics Yearbook data from the same year as the household survey data to eliminate this effect as much as possible. The second widely discussed drawback is that CLA requires a large amount of microdata to support it, although fortunately CFPS provides reliable and rich household data for our work. Thus, although CLA is not a flawless method, we decided to employ this approach considering its clear advantages and its applicability to research at the micro level.

According to CLA, this indicator is calculated by converting household consumption into carbon emissions using the following equation:

$$CCE_{i,j} = Coeff_i \times Consumption_{i,j} \tag{14}$$

where $CCE_{i,j}$ refers to the carbon emission of household j in consumption category i. $Consumption_{i,j}$ is the consumption expenditure on consumption category i of household j. $Coeff_i$ denotes the carbon intensity of consumption category i, which can be calculated as:

$$Coeff_i = \frac{\sum_n Emission_{i,n}}{\sum_n Output_{i,n}} \tag{15}$$

where $Emission_{i,n}$ is the carbon emissions of the n_{th} industrial sector corresponding to expenditure on consumption category i (unit: 10^4 tce), with data collected from the China Energy Statistical Yearbook. $Output_{i,n}$ is the output value of the n_{th} industrial sector corresponding to the i_{th} category of consumer spending items (unit: 10^4 RMB), obtained from the China Statistical Yearbook. However, as household consumption expenditures are categorized into several categories in the CFPS, which are different from the industrial sectors in the China Energy Statistics Yearbook, we match the CFPS classifications to the industrial production sectors based on their detailed definitions, as shown in Table 1.

The household total carbon emission (unit: tce) released by the consumption of household j can be denoted as:

$$HCCE_j = \sum_i CCE_{i,j} \tag{16}$$

Table 1
Matching of CFPS consumption categories to industrial sectors.

Consumption Categories (CFPS)	Industrial Sectors (China Energy Statistical Yearbook)
Food	Food processing; food manufacturing; beverage manufacturing; agriculture; forestry; livestock; fishing; water conservation
Clothing	Textile industry; textile clothing, shoes and hats manufacturing; leather, fur, and down manufacturing
Transportation and communications	Electronic and communications equipment manufacturing; transportation equipment manufacturing
Medical care	Pharmaceutical manufacturing
Household equipment and daily needs	Electrical machinery and equipment manufacturing; wood processing and bamboo, rattan, palm, and straw products; furniture manufacturing; plastic products; metal products
Culture, education, and entertainment	Paper and paper products industry; reproduction of recording media in the printing industry; manufacture of educational and sporting goods
Residence	Construction; non-metallic mineral products; electricity, steam and hot water production and supply; gas production and supply; water production and supply

4.2.2. Digital financial development

Digital financial development is the core independent variable, for which we used DFII as a proxy. DFII is an important indicator to measure the development level of digital inclusive finance in China, compiled by the Digital Finance Research Center of Peking University in cooperation with Ant Group Research Institute. This index is obtained by adopting the indicator dimensionless and hierarchical analysis method, and assigning different weights to a total of 33 specific indicators in three major categories, namely the breadth of digital financial coverage, the depth of digital financial use, and the degree of digitalization of inclusive finance. The index has excellent representativeness and persuasive power, covering 31 provinces, 337 cities above prefecture level, and around 2800 counties in mainland China.

4.2.3. Control variables

Referring to previous studies (Han et al., 2015; Meng et al., 2023; Qin et al., 2022; Sager, 2019; Zhang et al., 2015), household-, individual-, and regional-level variables also have explanatory power and thus are included in the regression as control variables. Specifically, household-related variables comprise total income, net assets, family size, proportion of elderly members, proportion of children, housing area, and ownership of cars. Individual-level variables reflect the characteristics of the household head, including age, gender, marital status, and education level. Regional economic and financial development are taken into consideration as the regional-related factors. Heads of households are usually the elders of the family, with managerial and decision-making roles, and the responsibility of being the economic breadwinner. Given that they are usually responsible for managing the household's income and expenditure, they enjoy a high degree of respect and authority in family affairs and decision-making. They are usually responsible for deciding major matters, which have a profound impact on the life of the family. Therefore, head-of-household-related variables are included in the empirical analysis.

4.3. Regression model

Ordinary least squares (OLS) regression is the appropriate model, whereby the basic regression model is set up as follows:

$$HCCE_{ijt} = \alpha + \beta_1 \bullet DF_{ijt} + \beta_2 \bullet Controls_{ijt} + \theta_i + \delta_j + \gamma_t + \varepsilon_{ijt} \tag{17}$$

In Eq. (17), *HCCE* denotes household consumption carbon emission, while *DF* refers to DFII. *Controls* represents control variables, and θ, δ and γ represent household-, region-, and year-fixed effects. The subscripts i, j, and t represent household i, region j, and year t, respectively.

Table 2 summarizes the details and descriptive statistics of the above indicators.

Fig. 1 presents detailed information on carbon emissions due to various types of household consumption in CFPS. From 2014 to 2020, household consumption carbon emissions exhibited an upward trend, with a notable increase of about 22 % from 2018 to 2020. We will find that carbon emissions from food and residence consumption consistently account for the majority of carbon emissions from household consumption, at more than 90 % per year. Among these, the contribution of food consumption exceeded 60 % in 2020, marking a significant increase from the previous three years. In contrast, the contribution of residential consumption declined to about 31 %.

5. Empirical results and discussion

In this section, we present the results and interpretations of our analysis, beginning with an overview of the baseline regression. We

Table 2
Details of variables.

Variable	Notation	Definition	Obs.	Mean	Std.
Household consumption-based carbon emissions	*HCCE*	See Section 4.2.1	13,112	13.1212	17.3972
Digital financial development	*DF*	Digital Financial Inclusion Index	13,112	259.9008	66.9383
Total income	*Income*	$Ln\,(Total\ household\ income + 1)$	13,112	10.6418	1.2362
Net asset	*NetAsset*	$Ln\,(Net\ household\ asset + 1)$	13,112	12.4949	1.4332
Family size	*FamSize*	Number of family members	13,112	3.9444	1.7677
Elder ratio	*Elder*	$(Number\ of\ households\ over\ the\ age\ of\ 65)/FamilySize$	13,112	0.1171	0.2023
Children ratio	*Child*	$(Number\ of\ households\ under\ the\ age\ of\ 16)/FamilySize$	13,112	0.1558	0.1734
Housing size	*HousingSize*	Size of current housing	13,112	18.8833	67.7568
Car ownership	*Car*	If the household owns a ca, 1; else, 0	13,112	0.2843	0.4511
Education	*Edu*	Household head years of education	13,112	7.6972	4.3767
Marital status	*Marriage*	If the head of the household is married, 1; else, 0	13,112	0.8803	0.3247
Gender	*Gender*	Male, 1; else, 0	13,112	0.5799	0.4936
Economic development	*Econ*	Per capita GDP	13,112	52,994.9300	25,580.5700
Financial development	*Fin*	*Outstanding loans in RMB of financial institutions/GDP*	13,112	1.5625	0.4520
Easing of liquidity constraints	*Liquidity*	Amount of money owed by households to banks	13,112	1.1247	3.2051
Household entrepreneurship	*Entrepre*	If any members of the household self-employed or owners of a private business, 1; else. 0	13,112	0.1157	0.3199
Payment convenience	*Payment*	If the household shopped online in the past week,1; else, o	13,112	0.2479	0.4318

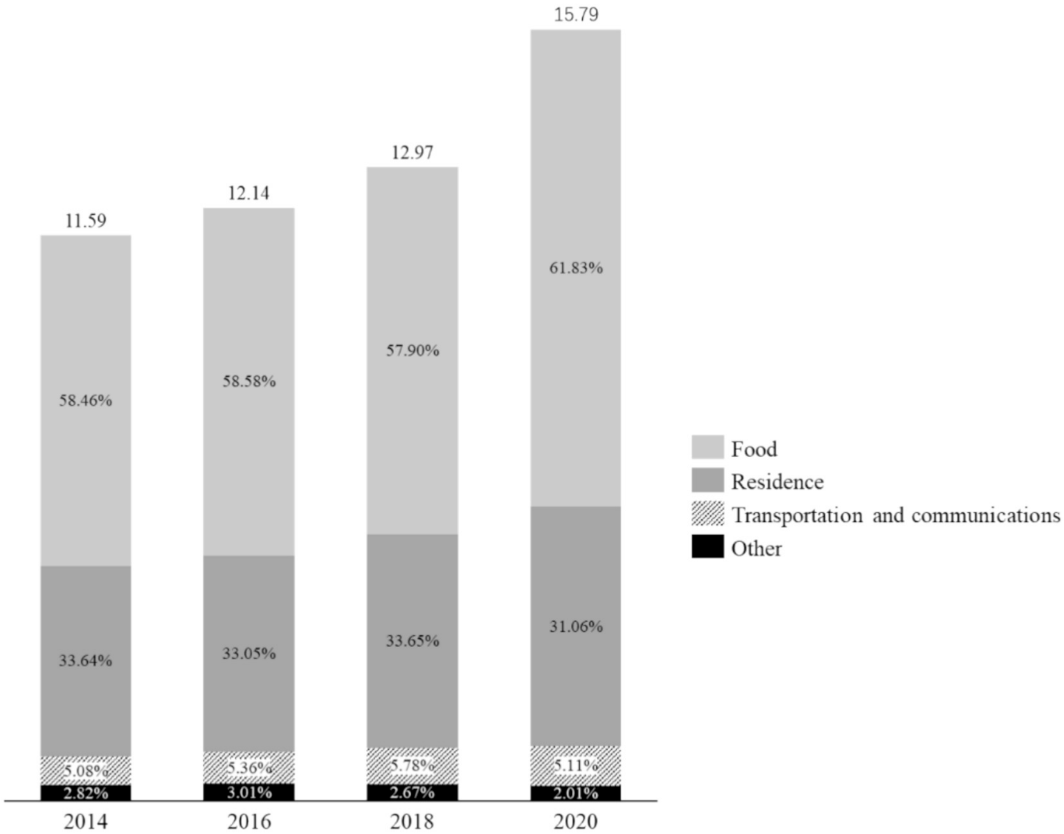

Fig. 1. Household consumption carbon emissions based on CFPS consumption categories.

will address potential endogeneity concerns through the IV method, which is discussed in Section 5.2. Section 5.3 delves into the results of the tests regarding the influencing mechanisms and the responses to the research hypotheses. We examine heterogeneity in Section 5.4, and finally, we provide additional discussion in Section 5.5.

5.1. Baseline regression

Table 3 presents the OLS regression result for the baseline model. We find that the core dependent variable (*DF*) has a statistically significant positive coefficient of 0.9993 without control variables, as shown in Column (1). When control variables are considered, the coefficient is 0.1043 and is still positive at the 1 % significance level. These findings support Hypothesis 1 and confirm a positive relationship between digital finance and household consumption-induced carbon emissions, which aligns with our intuitive expectations. The rationale behind this result is grounded in the transformative influence of digital finance. As digital finance proliferates, previously excluded households can gain access to a wider array of financial services at reduced costs. These digital advancements facilitate an expansion in the volume and diversity (in other words, the upsurge in consumption expenditure and the upgrading of the consumption structure) of household spending, which in turn leads to increased carbon emissions.

Digital finance results in increased household spending. Assuming that households maintain a consistent consumption structure (in which the distribution of consumption and the ratio of subsistence to non-subsistence consumption remain constant), the added consumption expenditure creates a heightened production demand, contributing to increased carbon emissions. However, the progress of digital finance promotes the upgrading of consumption structures, enabling households to opt for more non-subsistence consumption, including a greater inclination toward developmental consumption, such as cultural and educational expenditures, as well as hedonic consumption. Since the production of one unit of developmental and hedonic consumption produces significantly higher carbon emissions than subsistence consumption, the consumption structure upgrading—prompted by digital finance development—explains the increase in carbon emissions.

In our regression analysis, several control variables emerge as significant explanatory factors. Specifically, as shown in Column (2) of Table 3, household income (*Income*) and net assets (*NetAsset*) exhibit a notable and statistically significant positive correlation. The income and asset levels of households reflect their economic standing and play a critical role in shaping lifestyle choices. Households with higher incomes tend to adopt (whether intentionally or unintentionally) carbon-emitting lifestyles, such as owning larger vehicles and luxury residences and engaging in frequent international travel. These preferences for high-carbon-emitting lifestyles substantially contribute to elevated carbon emissions from household consumption.

Table 3
Baseline regression results.

Variables	*HCCE*	*HCCE*
	(1)	(2)
DF	0.0993***	0.1043***
	(3.4447)	(2.9640)
Income		0.5706***
		(3.3062)
NetAsset		0.7859***
		(4.3906)
FamSize		0.1866
		(0.7611)
Elder		−1.8491**
		(−2.3344)
Child		2.0024
		(1.0733)
HousingArea		0.0419***
		(5.8189)
Car		3.1711***
		(6.3406)
Edu		0.1339**
		(1.9641)
Marriage		0.8687
		(1.4580)
Gender		−0.4886
		(−0.8403)
Econ		−0.0001
		(−0.7129)
Fin		0.4306
		(0.2432)
Constant	−12.6906*	−31.8004***
	(−1.6984)	(−3.5868)
Household	Yes	Yes
Region	Yes	Yes
Year	Yes	Yes
R^2	0.1895	0.2268
Observations	13,112	13,112

Note: This table shows OLS regression results of the baseline model. Household consumption carbon emission (*HCCE*) is the core dependent variable, and digital financial development (*DF*) is the core independent variable. Statistics in parentheses are t-statistics. *, **, and *** denote significance at the 10 %, 5 % and 1 % levels, respectively.

It is essential to acknowledge the influence of societal pressures and norms, which might exert additional pressure on high-income families. In certain societies and cultural contexts, affluent households often face heightened social pressure to exude dignity, prompting them to demonstrate their wealth and social status. Consequently, a propensity exists for such households to engage in behaviors associated with higher carbon emissions, driven by the need to deal with social pressures and meet social expectations.

The coefficient of *Elder* is negative, implying that having a higher proportion of older individuals within a household corresponds to lower levels of carbon emissions. This phenomenon can be attributed to shifting consumption patterns as a person ages. Older individuals typically curtail carbon-emitting activities such as long-distance travel and major home renovations, in favor of priorities centered around health, safety, and comfort. This shift in focus reduces the demand for high-carbon-emitting products. Furthermore, some older individuals maintain long-term frugal habits characterized by a reduction in waste and unnecessary consumption. Their emphasis on financial prudence and savings over excessive consumption contributes to reduced carbon emissions.

We also find that increased housing size (*HousingSize*) and car ownership (*Car*) are associated with increased household carbon emissions, underscoring the carbon-intensive nature of larger living spaces and increased car ownership.

An interesting observation is the positive relationship between education level (*Edu*) and household carbon emissions, as greater educational attainment appears to influence individual lifestyle choices. Some individuals with higher levels of education might gravitate toward activities such as international travel, fine dining, and luxury purchases, all of which typically entail higher carbon emissions. They might also exhibit a preference for high-tech, energy-intensive household appliances, leading to boosted energy consumption within the family.

5.2. Endogeneity concern and robustness check

5.2.1. Endogeneity

There might be endogeneity concerns in the benchmark regression that reduce the credibility of the regression results, mainly arising due to the omission of significant explanatory variables and reciprocal causality. For the former, we refer to the existing literature to include three levels of control variables in the regression equation, namely household, individual (head of household), and regional levels. For the latter, we choose the IV approach, using the spherical distance from the household's location to Hangzhou. The IV meets two crucial requirements. In terms of the correlation between the IV and DFII, Hangzhou serves as the "birthplace" and core hub of China's digital finance development, hosting leading digital financial institutions such as Ant Group. It has taken an early lead in innovation and adoption across sectors such as digital payments, internet lending, and smart wealth management, with widespread coverage. Under this "center-periphery" structure, the technological diffusion, business expansion, and infrastructure coverage of digital financial services exhibit a "radiation effect" centered on Hangzhou, whereby regions closer to Hangzhou enjoy higher service accessibility and information transmission efficiency in digital finance. In terms of exogeneity, the spherical distance between the household's location and Hangzhou is a geographical endowment variable determined by natural geographical conditions. It is not affected by the economic behavior of individuals or households, nor the use of digital finance itself or the explanatory variables. For example, a household will not actively move closer to Hangzhou because it "wants to use digital finance more." Furthermore, its value will not change due to other variables in the model, thus avoiding "endogeneity interference."

Thus, we believe that this is a suitable IV. The first two columns in Table 4 detail the results, showing that both the first- and second-stage coefficients are significantly positive and the F value is sufficiently large (with $F = 39.46 > 10$), thus providing convincing evidence that the baseline regression results are robust.

5.2.2. Robustness check

Considering the lagged effects of digital financial development and the problem of reciprocal causality (Wang et al., 2022, b), we include one-period lagged *DF* in the regression, with the third column presenting the results. The coefficient of $DF(-1)$ in Table 5 remains positive (with $0.0786 > 0$) and significant at the 5 % level. This result is also in line with the baseline effect and further supports our findings.

In addition to the lagged variable method, following Wang, Zhou, & Wan (2025), we use the wild bootstrap method to support the robustness of our results. The wild bootstrap method simulates the distribution of resampled data to approximate the true distribution of the original data. It uses known information to infer the accuracy of the estimate, thereby improving the accuracy of the inference. Table 5 shows the results of conducting a wild bootstrap analysis with 5000 samples and a 95 % confidence interval, which supports our baseline finding.

5.3. Mechanisms

We next examine the influencing mechanisms illustrated in Section 3.2 and employ the corresponding channel variables, with Table 6 summarizing the results.

For the first mechanism—easing of liquidity constraints—the responses to the question "*Excluding banks and relatives/friends, how much does your family owe to other institutions?*" are used as the channel variable (*Liquidity*). If digital finance can help alleviate the liquidity constraints that a household faces, the amount of informal loans it can receive will increase. Column (1) of Table 6 reports the analysis results, whereby the significant positive coefficient of the $DFII \times Liquidity$ interaction term validates Hypothesis 2. With increased liquidity, households are able to purchase more goods and services, increasing the carbon emissions induced by consumption.

The second mechanism is household entrepreneurship. As described in Hypothesis 3, we believe that digital financial development increases carbon emissions by promoting households' willingness to start a business. The responses to the question "*Are any members of your household self-employed or owners of a private business?*" are used as the channel variable (*Entrepre*) to examine the second mechanism. If any members of the household are self-employed or owners of a private business, *Entrepre* equals 1, and otherwise zero. The results are reported in Column (2) of Table 6, whereby the significant positive coefficient of the interaction term ($0.0139 > 0$) verifies Hypothesis 3, showing that household entrepreneurship is an effective mechanism. The spread of digital finance increases the willingness to be an entrepreneur among households and encourages more individuals to start their own businesses, triggering higher levels of carbon emissions.

For Hypothesis 4, we use the responses to the question "*Have you shopped online in the past week*" as the channel variable (*Payment*). If the household shopped online in the past week, *Payment* equals 1, and otherwise zero. Column (3) of Table 6 reports the results and shows that Hypothesis 4 is validated, indicating that the progression of digital financial services contributes to increased carbon emissions through the payment convenience of the household. Digital finance has simplified the payment process, provided ease of payment, increased incentives to consume, and contributed to increased consumption and carbon emissions.

5.4. Heterogeneity discussion

5.4.1. Analysis of heterogeneity across regions[2]

The discussion of regional heterogeneity stems from several realities, including China's geographic and economic heterogeneity.

[2] The eastern region comprises ten provinces: Hebei, Liaoning, Tianjin, Beijing, Shanghai, Guangdong, Shandong, Jiangsu, Fujian and Zhejiang. The central region comprises eight provinces: Henan, Jiangxi, Hunan, Shanxi, Anhui, Jilin, Hubei and Heilongjiang. Finally, the western region comprises seven provinces: Shaanxi, Yunnan, Gansu, Sichuan, Guizhou, Guangxi and Chongqing.

Table 4
Endogeneity concerns.

Variables	*DF* (First stage)	*HCCE* (Second stage)
	(1)	(2)
IV	0.0099***	
	(7.0800)	
DF		0.9376***
		(2.3056)
Controls	Yes	Yes
R^2	0.4222	0.4863
Observations	13,112	13,112
Cragg-Donald Wald F-statistic	39.4632	–

Note: Table 4 reports the results of the endogeneity and robustness check. We use the spherical distance from the household's location to Hangzhou as the IV. $DF(-1)$ represents the first-order lag of the variable *DF*. *Controls* denotes control variables as well as fixed effects (household, region, and year). Statistics in parentheses are robust to standard errors. *, **, and *** denote significance at the 10 %, 5 % and 1 % levels, respectively.

Table 5
Robustness check.

Variables	HCCE	Wild bootstrap
	(1)	(2)
$DF(-1)$	0.0786**	
	(2.1865)	
DF		0.0912***
		[0.0095]
Controls	Yes	Yes
R^2	0.2259	0.4798
Observations	13,112	13,112

Note: Table 5 reports the wild bootstrap result. Statistics in parentheses and bracket are t-statistics and *p*-value, respectively. *, **, and *** are significant at the levels of 10 %, 5 % and 1 %, respectively.

China is a vast country with unbalanced economic development. The eastern region is gently sloping, densely populated, and economically developed, while the central and western regions are relatively sparsely populated and less economically developed. Moreover, another relevant factor is policy differences, as the Chinese government implements different policies in various regions to address the diverse challenges and needs of each place. Development strategies tailored to local conditions maximize the region's strengths to promote economic development and improve household living standards. The classification of east, central, and west is adopted to highlight the economic, social, and cultural characteristics of different regions, which contributes to a better understanding of the variability within China. The entire sample of households is divided into three subsets based on the location of the province in which they reside, with the results of subset regressions reported in Table 7. We find regional heterogeneity in the impact of digital finance on household consumption carbon emissions. First, the contribution of digital financial development to household consumption carbon emissions is significantly positive in all three regions, although the level of significance varies, with the central region being less significant than the other two regions. Second, the regression coefficients by region decrease in the order of eastern, central, and western regions, implying that the role of digital finance in promoting carbon emissions from household consumption is most obvious in the east, and weaker in the center and west.

This regional heterogeneity can be explained by the significant geographic differences in China's economy and infrastructure. Eastern regions have higher levels of economic development and higher average household income levels than households in other regions, enabling them to easily enjoy the digital dividend. People in the eastern region are more able and motivated to purchase electronic devices, cars, and household appliances. Digital finance has made it easier for households to shop online and use e-payments, although this comes with increased energy consumption and carbon emissions. In contrast, for the central provinces, although the digital financial infrastructure covers the main prefecture-level cities, the mobile payment penetration rate and logistics efficiency are lower than in the east, and the frequency of consumption and the scale of cross-regional consumption are relatively limited. Household consumption is mainly "improved", and the proportion of high-carbon consumption is lower than in the east. Moreover, the stimulation of digital finance is more reflected in the expansion of the scale of consumption than in structural upgrading, and industrial chain integrity is insufficient. Some commodities need to be transferred from the east, the logistics radius is longer, incremental carbon emissions from production and transportation exist, although the scale is smaller than that in the east. Therefore, the promotion effect of digital finance on the carbon emission of consumption is weaker than in the east. For western provinces, the digital financial

Table 6
Inspecting the mechanisms.

Variables	*HCCE*	*HCCE*	*HCCE*
	(1)	(2)	(3)
DFII	0.1021***	0.1126***	0.1246***
	(2.9405)	(2.9378)	(2.9631)
DFII × *Liquidity*	0.0009***		
	(−0.0004)		
Liquidity	−0.0078***		
	(−00024)		
DFII × *Entrepre*		0.0139***	
		(2.3470)	
Entrepre		1.3609**	
		(2.1406)	
DFII × *Payment*			0.0932***
			(2.5644)
Payment			0.0166
			(1.2470)
Controls	Yes	Yes	Yes
R^2	0.2361	0.2582	0.2459
Observations	13,112	13,112	13,112

Note: This table reports the results of the influencing mechanisms. Column (1) reports the results of the mechanism of liquidity constraints easing and the responses to the question "*Excluding banks and relatives/friends, how much does your family owe to other institutions?*" (*Liquidity*). Column (2) reports the result of the mechanism of household entrepreneurship, whereby the responses to the question "*Do any members of your household who are self-employed or own a private business*" are used as the channel variable (*Entrepre*). Column (3) reports the result of the mechanism of payment convenience, using responses to the question "*Have you shopped online in the past week*" as the channel variable (*Payment*). *Controls* denotes control variables as well as fixed effects (household, region, and year). T-statistics are listed in parentheses. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 7
Comparisons between households in different regions.

Variables	Eastern	Central	Western
	(1)	(2)	(3)
DF	0.1613***	0.1241**	0.1157***
	(2.8970)	(2.0382)	(2.5902)
Controls	Yes	Yes	Yes
R^2	0.2405	0.2067	0.2158
Observations	5346	3845	3766
Suest test			
Diff	0.0337***		
P-value	0.0058		

Note: Table 7 reports the result of comparisons between different regions. T-statistics are listed in the parentheses. *, **, and *** are significant at the levels of 10 %, 5 % and 1 %, respectively.

infrastructure is limited to major cities, characterized by low reliance on mobile payments, high logistics costs, and long cycles. Consequently, household consumption relies more on local brick-and-mortar stores. Accordingly, the "expansion" of digital finance on consumption is limited, whereby household consumption is "survival-oriented" and dominated by the ability and willingness to pay for high-carbon consumption, and it is difficult to significantly increase high-carbon consumption through digital finance. At the same time, the industrial chain in the western region is weak, most commodities rely on external inputs, and the logistics network is sparse. Therefore, carbon emissions brought by the growth of consumption are more generated externally and the part borne by the local community is smaller, meaning that the promotion of the role of digital finance on the carbon emissions of consumption is the weakest among the three regions.

5.4.2. Analysis of heterogeneity between urban and rural areas

Unbalanced development between urban and rural areas is another feature of China's economic development. There is a wide gap between urban and rural development in China, with cities usually having richer resources, higher living standards, and more opportunities. As the level of urbanization increases, the number of people and resources occupied by cities is growing. Meanwhile, the Chinese government has adopted many policies to promote the balanced development of urban and rural areas. Taking urban and rural areas as the dimension of analysis helps to more comprehensively understand the diversity and problems within China. Table 8 reports the results of heterogeneity tests between urban and rural areas. We notice that the coefficients of *DF* are both positive, while only the rural group has a significant result. Both rural and urban households can enjoy the digital dividend of digital financial development, although the marginal effect is larger in urban areas compared to rural households.

There are several possible reasons for urban-rural heterogeneity. First, differences in lifestyle and consumption habits exist, whereby urban residents usually have more disposable income and are more inclined to use services such as online shopping and takeaway food delivery. These convenient services lead to more parcel deliveries, resulting in increased energy consumption and carbon emissions. In contrast, rural residents rely more on traditional self-sufficient lifestyles and consumption patterns. A second factor is differences in transportation needs. Compared to rural areas, urban areas have a large number of public transportation and car-hailing services, and the development of digital finance has made it easier to use these services. On the other hand, transportation demand in rural areas is relatively low, relying mainly on individual transportation. Consequently, the development of digital finance has a less significant impact on rural transportation demand.

5.4.3. Analysis of heterogeneity between households with different leverages

The third heterogeneity analysis starts with the degree of leverage of households, defined as total liabilities divided by total assets. We use the median level of leverage of the sample households as the criterion to categorize households into two groups. Table 9 shows the results.

We find that for households with low levels of leverage, the development of digital finance increases their carbon emissions from consumption, reflecting a statistically significant result. For the other group, households with high leverage levels, the development of digital finance has a reducing effect, although it is not statistically significant. Low-leverage households usually have low indebtedness, low debt-servicing pressure, relatively abundant disposable income, and looser budget constraints. The development of digital finance will significantly reduce transaction costs and credit constraints on consumption, stimulating such households to unleash their potential consumption demand. In terms of consumption structure, low-leveraged households are more likely to increase high-carbon consumption; for example, by purchasing large home appliances through online platforms or utilizing the convenience of digital finance to increase the consumption of services such as takeaways. This expansion of consumption under the “income effect” directly pushes up carbon emissions, and the effect is statistically more pronounced due to the greater consumption elasticity of low-leveraged households. Highly leveraged households face stronger debt-servicing pressures, with a larger proportion of their disposable income going to debt repayment and tighter budgetary constraints. Although digital finance can enhance the convenience of consumption, the core constraint of such households is “repayment pressure” rather than “transaction costs,” meaning that digital finance has a weaker stimulus effect on their consumption. In contrast, it might strengthen their behavior of “compressing non-essential consumption” due to the convenience of fund management brought by digital finance. Instead, the ease of managing money brought by digital finance might reinforce their behavior of “compressing non-essential consumption.”

5.5. Further study

In order to further investigate the impact of digital financial development on carbon emissions from household consumption, we examined the case of DFII’s segmented indicators. According to DFII, in addition to the aggregate digital finance development index used in the baseline regressions, it provides sub-indicators for measuring the coverage breadth (*Coverage*), depth of use (*Depth*), and degree of digitization of finance (*Digitization*).[3] Table 10 shows the results.

In Table 10, we replace the aggregate digital financial development index (DF) in the baseline regression with Coverage, Depth, and Digitization, respectively, and the remaining variables are consistent with the baseline regression. The regression coefficients for Coverage, Depth, and Digitization are all significantly positive, implying that digital finance explains the increase in household carbon emissions by increasing the breadth of coverage and depth of use of financial services, as well as increasing the digitization of financial services. In Column (Andersson et al., 2014), the results indicate that digital finance promotes household consumption of carbon emissions through increased financial account coverage. The depth of digital financial service use also has a positive effect by facilitating households’ payment, investment, and credit operations. Finally, the development of digital finance has strongly contributed to the mobility, inclusion, and accessibility of financial services, which have helped to increase carbon emissions resulting from household consumption.

6. Conclusions

We have investigated the impact of digital financial development on household consumption carbon emission using Chinese household-level data, proposing a quantitative framework to deduce the basic effect of digital finance, and identifying three potential influencing mechanisms. The empirical results show that the development of digital finance increases carbon emissions induced by household consumption, whereby our findings are robust to endogeneity checks. Liquidity constraints easing, household

[3] The breadth of digital financial coverage focuses on the horizontal expansion of financial services and products, measuring the accessibility of digital inclusive finance, with account coverage serving as the metric. The depth of digital financial usage focuses on users’ actual use of digital financial services, reflecting their level of engagement, and is measured across various aspects such as payment services, money market fund services, credit services, insurance services, investment services, and credit services. The assessment of the digitalization level of inclusive financial services evaluates the digitalization level of inclusive financial services, reflecting the modernization and convenience of financial services. It primarily includes the mobile, affordable, credit-based, and convenient aspects of digital finance.

Table 8
Comparisons between urban and rural households.

Variables	Urban	Rural
	(1)	(2)
DF	0.0955	0.0910***
	(1.4058)	(2.6009)
Controls	Yes	Yes
R^2	0.1716	0.2217
Observations	1092	9393
Suest test		
Diff	0.0216***	
P-value	0.0032	

Note: This table reports the results of comparisons between urban and rural households. T-statistics are listed in parentheses. *, **, and *** denote significance at the 10 %, 5 % and 1 % levels, respectively.

Table 9
Comparisons between households with different leverages.

Variables	High	Low
	(1)	(2)
DF	−0.3367	0.0867***
	(0.2727)	(0.0311)
Controls	Yes	Yes
R^2	0.5898	0.4678
Observations	4430	4429

Note: This table reports the results of comparisons between urban and rural households. T-statistics are listed in parentheses. *, **, and *** denote significance at the 10 %, 5 % and 1 % levels, respectively.

Table 10
Further discussion results.

Variables	*Coverage*	*Depth*	*Digitization*
	(1)	(2)	(3)
DF	0.0834***	0.0913***	0.0360***
	(2.6297)	(3.5592)	(2.8779)
Controls	Yes	Yes	Yes
R^2	0.2265	0.2279	0.2266
Observations	13,112	13,112	13,112

Note: Table 10 reports the regression results of further discussion using OLS regression. We replace the aggregate digital financial development index (DF) in the baseline regression with Coverage, Depth, and Digitization, respectively, and the remaining variables are consistent with the baseline regression. T-statistics are listed in parentheses. *, **, and *** denote significance at the 10 %, 5 % and 1 % levels, respectively.

entrepreneurship, and payment convenience are proven to be effective mechanisms verified by the channel variable method. In the heterogeneity discussion section, we find regional and urban-rural heterogeneity in the contribution of digital financial development to the increase in household carbon emissions. The effect of digital finance decreases in the order of east, central, and west regions, and shows a significant facilitating effect in rural areas. Finally, we further use segmented indicators of DFII to discuss the impact of digital finance.

Our study unveils several meaningful implications. First, our research demonstrates that digital finance exerts a promoting effect on increased household consumption carbon emissions. In light of this finding, governments must pay more attention to the impact of digital finance on carbon emissions when promoting its development. Policymakers should prioritize green finance practices, utilize the inclusive nature of digital finance to concurrently reduce carbon emissions, foster convenience for economic agents, and promote the development of a sustainable economy. One promising policy avenue is introducing a carbon tax or emissions rights market, in which the cost of carbon emissions is integrated into digital financial transactions and consumption. This mechanism would elevate the price associated with carbon emissions, prompting households to curtail high-carbon consumption. Simultaneously, it would encourage digital financial platforms to diversify their offerings by incorporating more low-carbon financial products. Furthermore, governments could embark on comprehensive public awareness campaigns and educational initiatives to elevate households' consciousness regarding carbon footprints and sustainable consumption. Moreover, they could provide tax incentives to encourage environmentally friendly and sustainable investments.

Second, the study underscores that household consumption behaviors directly determine the extent of household-related carbon emissions. Households stand to benefit from the digital dividends ushered in by digital financial development, which alleviate liquidity constraints and simplify payment processes, thereby bolstering household consumption expenditure. From the perspective of carbon emissions, households should proactively embrace an environmental, social, and governance-conscious approach to consumption. Households should allocate the additional consumption facilitated by digital finance toward low-carbon products while upgrading their consumption structures to mitigate carbon emissions. Households could take proactive steps, such as participating in educational programs on sustainable consumption, which governmental bodies and social organizations could offer. These programs could equip individuals with the knowledge to learn how to reduce their carbon footprint, including choosing environmentally friendly products and reducing energy consumption. In addition, households could explore investment opportunities in sustainable projects and green financial products to support the development of a low-carbon economy.

Third, financial institutions such as banks serve as providers of financial services and play a significant role in guiding households toward low-carbon lifestyles. A practical strategy for financial institutions is to offer differentiated interest rates, aligning them with carbon emissions considerations. For example, banks could offer varying interest rates for car loans, levying high interest rates on car loans for high-carbon-emitting vehicles while reducing interest rates for loans aimed at acquiring new energy vehicles. Financial institutions could also introduce green financial products—including environmentally friendly loans and green savings accounts—to attract households to invest in environmentally conscious endeavors. Furthermore, institutions could invest in training their staff, equipping them with a nuanced understanding of sustainable investment and environmentally friendly financial products to empower financial professionals to advise clients on low-carbon choices.

Fourth, the findings of this paper are also applicable beyond the Chinese context. Digitization is becoming increasingly significant in terms of its role in economic development and improving the lives of residents, and it can be expected that countries with less-developed digital finance will usher in their own equivalents of Alipay and WeChat Pay. China's practice provides a valuable reference for these countries in promoting the development of digital finance, with our study providing several crucial findings. First, the development of digital finance can indeed bring positive impacts, but it also has possible negative environmental impacts that should be noted, such as increased carbon emissions. At the early stage of digital finance development, timely attention to these negative effects can prevent them from occurring. Second, this paper reveals the heterogeneous impacts of digital finance development between urban and rural areas and regions, whereby other governments might consider adopting more policies that contribute to equitable development when designing policies. Third, this study verifies the important role of mechanisms such as liquidity constraint relaxing, household entrepreneurship, and payment convenience in digital financial development. Policymakers could lower the threshold of financial services and improve their accessibility through developing new types of financial instruments, such as mobile payments and internet finance, thus enabling more residents to enjoy the digital dividend.

One limitation of this paper is that, due to data availability constraints, we used some macro data to construct the indicators, rather than relying solely on survey data at the household level. We hope that we will be able to construct more comprehensive indicators to measure household carbon emissions when more data becomes available.

Funding

This work was supported by the Major Program of National Fund of Philosophy and Social Science of China (24&ZD286).

Declaration of competing interest

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 paper.

Appendix A. Appendix

1. Proof of Eq. (3)

First, suppose there are y_1 and w that obey the following distribution:

$$y_1 = w + \epsilon_1 \tag{A-1}$$

$$w \sim N\left(\overline{q}, \overline{\sigma}^2\right) \tag{A-2}$$

$$\epsilon_1 \sim N\left(0, \overline{\sigma}_1^2\right) \tag{A-3}$$

$$y_1 \sim N\left(\overline{w}, \overline{\sigma}^2 + \overline{\sigma}_1^2\right) \tag{A-4}$$

Secondly, the covariances of y_1 and w (is)

$$\sigma_{y_1,w} = \mathbb{E}(y_1 - \overline{w})(w - \overline{w})$$

$$= \mathbb{E}(w - \overline{w} + \epsilon_1)(w - \overline{w})$$

$$= \mathbb{E}(w-\overline{w})^2 + \mathbb{E}(\epsilon_1)(w-\overline{w})$$

$$= \overline{\sigma}^2 \tag{A-5}$$

Finally, by introducing the expression of covariance (Eq. (5)), it can be deduced that the conditional expectation of w (is)

$$\mathbb{E}[wy_1] = \mathbb{E}[w] + \frac{\sigma_{y_1,w}}{\sigma_{y_1}^2}(y_1-\overline{w})$$

$$= \overline{w} + \frac{\overline{\sigma}^2}{\overline{\sigma}^2+\overline{\sigma}_1^2}(y_1-\overline{w})$$

$$= \overline{w} + \frac{\tau_1}{\overline{\tau}+\tau_1}(y_1-\overline{w})$$

$$= \frac{\tau_1 y_1 + \overline{\tau}\overline{w}}{\overline{\tau}+\tau_1} \tag{A-6}$$

Thus, Eq. (3) has been proved.

2. Proof of Eq. (10)

y_2, w and u have the following assumptions:

$$y_2 = w + \epsilon_2 \tag{A-7}$$

$$\epsilon_2 \sim N\left(0,\overline{\sigma}_2^2\right) \tag{A-8}$$

$$u = w + \epsilon_u \tag{A-9}$$

$$\epsilon_u \sim N\left(0,\overline{\sigma}_u^2\right) \tag{A-10}$$

$$\widehat{\mathbb{E}}[wy_1,y_2,u] = \overline{w} + \begin{pmatrix}\overline{\sigma}^2 & \overline{\sigma}^2 & \overline{\sigma}^2\end{pmatrix}\begin{pmatrix}\overline{\sigma}^2+\overline{\sigma}_1^2 & \overline{\sigma}^2 & \overline{\sigma}^2\\ \overline{\sigma}^2 & \overline{\sigma}^2+\overline{\sigma}_2^2 & \overline{\sigma}^2\\ \overline{\sigma}^2 & \overline{\sigma}^2 & \overline{\sigma}^2+\overline{\sigma}_u^2\end{pmatrix}^{-1}\left(\begin{pmatrix}y_1\\ y_2\\ u\end{pmatrix}-\begin{pmatrix}\overline{w}\\ \overline{w}\\ \overline{w}\end{pmatrix}\right)$$

Let $D = \overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_2^2 + \overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_u^2 + \overline{\sigma}^2\overline{\sigma}_2^2\overline{\sigma}_u^2 + \overline{\sigma}_1^2\overline{\sigma}_2^2\overline{\sigma}_u^2$, the above equation can be denoted as:

$$\overline{w} + \frac{\begin{pmatrix}\overline{\sigma}^2 & \overline{\sigma}^2 & \overline{\sigma}^2\end{pmatrix}}{\mathrm{D}}\begin{pmatrix}\overline{\sigma}^2\left(\overline{\sigma}_2^2+\overline{\sigma}_u^2\right)+\overline{\sigma}_2^2\overline{\sigma}_u^2 & -\overline{\sigma}^2\overline{\sigma}_u^2 & -\overline{\sigma}^2\overline{\sigma}_2^2\\ -\overline{\sigma}^2\overline{\sigma}_u^2 & \overline{\sigma}^2\left(\overline{\sigma}_1^2+\overline{\sigma}_u^2\right)+\overline{\sigma}_1^2\overline{\sigma}_u^2 & -\overline{\sigma}^2\overline{\sigma}_1^2\\ -\overline{\sigma}^2\overline{\sigma}_2^2 & -\overline{\sigma}^2\overline{\sigma}_1^2 & \overline{\sigma}^2\left(\overline{\sigma}_1^2+\overline{\sigma}_2^2\right)+\overline{\sigma}_1^2\overline{\sigma}_2^2\end{pmatrix}\begin{pmatrix}y_1-\overline{w}\\ y_2-\overline{w}\\ u-\overline{w}\end{pmatrix}$$

$$= \overline{w} + \frac{1}{\mathrm{D}}\begin{pmatrix}\overline{\sigma}^2\overline{\sigma}_2^2\overline{\sigma}_u^2\\ \overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_u^2\\ \overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_2^2\end{pmatrix}'\begin{pmatrix}y_1-\overline{w}\\ y_2-\overline{w}\\ u-\overline{w}\end{pmatrix} = \overline{w}\bullet D + \overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_2^2 u + \overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_u^2 y_2 + \overline{\sigma}^2\overline{\sigma}_2^2\overline{\sigma}_u^2 y_1 - \frac{\overline{w}\left(\overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_2^2+\overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_u^2+\overline{\sigma}^2\overline{\sigma}_2^2\overline{\sigma}_u^2\right)}{\mathrm{D}}$$

$$= \frac{\overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_2^2 u + \overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_u^2 y_2 + \overline{\sigma}^2\overline{\sigma}_2^2\overline{\sigma}_u^2 y_1 + \overline{\sigma}_1^2\overline{\sigma}_2^2\overline{\sigma}_u^2\overline{w}}{\overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_2^2+\overline{\sigma}^2\overline{\sigma}_1^2\overline{\sigma}_u^2+\overline{\sigma}^2\overline{\sigma}_2^2\overline{\sigma}_u^2+\overline{\sigma}_1^2\overline{\sigma}_2^2\overline{\sigma}_u^2} = \frac{\frac{1}{\overline{\sigma}_1^2}y_1+\frac{1}{\overline{\sigma}_2^2}y_2+\frac{1}{\overline{\sigma}_u^2}u+\frac{1}{\overline{\sigma}^2}\overline{w}}{\frac{1}{\overline{\sigma}_1^2}+\frac{1}{\overline{\sigma}_2^2}+\frac{1}{\overline{\sigma}_u^2}+\frac{1}{\overline{\sigma}^2}} = \frac{\tau_1 y_1+\tau_2 y_2+\tau_u u+\tau\overline{w}}{\tau_1+\tau_2+\tau_u+\tau} \tag{A-11}$$

In Eq. (A-11), let $\overline{w} = w_L - \delta_f - \delta_t$ and Eq. (10) is derived.

3. Proof of Eq. (11) and (12)

$$\mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1,y_2,L] \quad L] - \mathbb{E}[\widehat{\mathbb{E}}(w|y_1,u,L)\,|L]$$

$$= -\frac{\overline{\tau}\delta_f}{\overline{\tau}+\tau_1+\tau_2} + \frac{\overline{\tau}\delta_t}{\overline{\tau}+\tau_u+\tau_1} = \overline{\tau}\frac{-\delta_f(\overline{\tau}+\tau_u+\tau_1)+\delta_t(\overline{\tau}+\tau_1+\tau_2)}{(\overline{\tau}+\tau_1+\tau_2)(\overline{\tau}+\tau_u+\tau_1)} > 0 \tag{A-12}$$

Thus, Eq. (11) and (12) has been proved.

Proof of Eq. (13):

$$\mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1,y_2,u,L]\,|L] - \mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1,y_2,L] \quad L] = -\frac{\overline{\tau}\left(\delta_f+\delta_t\right)}{\overline{\tau}+\tau_1+\tau_2+\tau_u} + \frac{\overline{\tau}\delta_t}{\overline{\tau}+\tau_1+\tau_u} \tag{A-13}$$

From the lemma, we can then conclude that

$$\delta_t\tau_2 > \delta_t(\overline{\tau}+\tau_1+\tau_2) > \delta_f(\overline{\tau}+\tau_u+\tau_1) \tag{A-14}$$

Thus, we get:

$$\mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1, y_2, u, L] \, |L] - \mathbb{E}[\widehat{\mathbb{E}}[w \quad y_1, y_2, L] \quad L] = \overline{\tau}\frac{-\delta_f(\overline{\tau} + \tau_1 + \tau_u) + \delta_t\tau_2}{\overline{\tau} + \tau_1 + \tau_2 + \tau_u} > 0 \tag{A-15}$$

Thus, Eq. (13) has been proved.

Data availability

Data will be made available on request.

References

Andersson, D., Nässén, J., Larsson, J., & Holmberg, J. (2014). Greenhouse gas emissions and subjective well-being: An analysis of Swedish households. *Ecological Economics, 102*, 75–82.

Bin, S., & Dowlatabadi, H. (2005). Consumer lifestyle approach to US energy use and the related CO2 emissions. *Energ Policy, 33*(2), 197–208.

Cao, S., Nie, L., Sun, H., Sun, W., & Taghizadeh-Hesary, F. (2021). Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *Journal of Cleaner Production, 327*, Article 129458.

Charfeddine, L., & Ben Khediri, K. (2016). Financial development and environmental quality in UAE: Cointegration with structural breaks. *Renewable and Sustainable Energy Reviews, 55*, 1322–1335.

Duarte, R., Mainar, A., & Sánchez-Chóliz, J. (2010). The impact of household consumption patterns on emissions in Spain. *Energy Economics, 32*(1), 176–185.

Fan, J., Zhou, L., Zhang, Y., Shao, S., & Ma, M. (2021). How does population aging affect household carbon emissions? Evidence from Chinese urban and rural areas. *Energy Economics, 100*, Article 105356.

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., & Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Quarterly, 19*(4), 1401–1418.

Han, L. Y., Xu, X. K., & Han, L. (2015). Applying quantile regression and Shapley decomposition to analyzing the determinants of household embedded carbon emissions: Evidence from urban China. *Journal of Cleaner Production, 103*, 219–230.

He, Z. Y., & Song, X. G. (2020). How does digital finance promote household consumption. *Financ. Trade Econ., 41*(8), 65–79.

Hu, D., Guo, F., & Zhai, C. (2023). Digital finance, entrepreneurship and the household income gap: Evidence from China. *Information Processing & Management, 60*(5), 103478.

Hu, D., Zhai, C., & Zhao, S. (2023). Does digital finance promote household consumption upgrading? An analysis based on data from the China family panel studies. *Economic Modelling, 125*, Article 106377.

Khan, Z., Sisi, Z., & Siqun, Y. (2019). Environmental regulations an option: Asymmetry effect of environmental regulations on carbon emissions using non-linear ARDL. *Energy Sources Part A-Recovery Utilization and Environmental Effects, 41*, 137–155.

Kizilaslan, H. (2009). Input–output energy analysis of cherries production in Tokat Province of Turkey. *Applied Energy, 86*(7), 1354–1358.

Li, J., Wu, Y., & Xiao, J. J. (2020). The impact of digital finance on household consumption: Evidence from China. *Economic Modelling, 86*, 317–326.

Li, J., Zhang, D. Y., & Su, B. (2019). The impact of social awareness and lifestyles on household carbon emissions in China. *Ecological Economics, 160*, 145–155.

Lv, Y., Jia, Y., Sang, C., & Sun, X. (2024). Carbon reduction effect of digital finance in China: Based on household micro data and input-output model. *China Finance Review International, 15*(2), 363–388.

Lyu, K., Yang, S., Zheng, K., & Zhang, Y. (2023). How does the digital economy affect carbon emission efficiency? Evidence from energy consumption and industrial value chain. *Energies, 16*, 761.

Ma, Q., Tariq, M., Mahmood, H., & Khan, Z. (2022). The nexus between digital economy and carbon dioxide emissions in China: The moderating role of investments in research and development. *Technology in Society, 68*, Article 101910.

Meng, W. L., Yuan, G. C., & Sun, Y. P. (2023). Expansion of social networks and household carbon emissions: Evidence from household survey in China. *Energ Policy, 174*, Article 113460.

Molero-Simarro, R. (2017). Inequality in China revisited. The effect of functional distribution of income on urban top incomes, the urban–rural gap and the Gini index, 1978–2015. *China Economic Review, 42*, 101–117.

Moraes, C. O., Roquete, R. M., & Gawryszewski, G. (2023). Who needs cash? Digital finance and income inequality. *The Quarterly Review of Economics and Finance, 91*, 84–93.

Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review, 18*(4), 329–340.

Ozili, P. K. (2021). Digital finance, green finance and social finance: Is there a link? *Financial Internet Quarterly, 17*(1), 1–7.

Pais-Magalhaes, V., Moutinho, V., & Robaina, M. (2022). Is an ageing population impacting energy use in the European Union? Drivers, lifestyles, and consumption patterns of elderly households. *Energy Research and Social Science, 85*, Article 102443.

Qin, X. D., Wu, H. T., & Li, R. R. (2022). Digital finance and household carbon emissions in China. *China Econometric Reviews, 76*, Article 101872.

Rajkhowa, P., & Qaim, M. (2022). Mobile phones, off-farm employment and household income in rural India. *Journal of Agricultural Economics, 73*(3), 789–805.

Reinders, A. H. M. E., Vringer, K., & Blok, K. (2003). The direct and indirect energy requirement of households in the European Union. *Energ Policy, 31*(2), 139–153.

Ren, X. H., Zeng, G. D., & Gozgor, G. (2023). How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *Journal of Environmental Management, 330*, Article 117125.

Sager, L. (2019). Income inequality and carbon consumption: Evidence from environmental Engel curves. *Energy Economics, 84*.

Sheraz, M., Xu, D., Ahmed, J., Ullah, S., & Ullah, A. (2021). Moderating the effect of globalization on financial development, energy consumption, human capital, and carbon emissions: Evidence from G20 countries. *Environemental Science and Pollution Research, 28*(26), 35126–35144.

Sun, W., & Shen, J. (2024). The impact of low-carbon city pilot on carbon emissions of high-polluting enterprises – Based on financing constraint perspective. *Energy Reports, 12*, 762–774.

Wang, D., Ren, C. R., & Zhou, T. (2021). Understanding the impact of land finance on industrial structure change in China: Insights from a spatial econometric analysis. *Land Use Policy, 103*, Article 105323.

Wang, J., Wang, J., & Li, Z. G. (2022). Development of digital finance and carbon emission of household consumption. *Finance & Economics, 4*, 118–132.

Wang, L., Zhou, H., & Wan, G. (2025). The impact of robots on unemployment duration: Evidence from the Chinese General Social Survey. *China Economic Review, 89*, 102305.

Wang, Z., Zhang, D., & Wang, J. (2022). How does digital finance impact the leverage of Chinese households? *Applied Economics Letters, 29*(6), 555–558.

Wei, Y. M., Liu, L. C., Fan, Y., & Wu, G. (2007). The impact of lifestyle on energy use and CO2 emission: An empirical analysis of China's residents. *Energ Policy, 35*(1), 247–257.

Xu, Z. C., Yu, J. Y., Zhang, D. Y., & Xie, K. (2025). Shopping online: E-commerce and household carbon emissions in China. *Journal of Environmental Management, 373*, Article 123621.

Yang, R., Li, R., & Ge, X. (2025). Digital finance development, financial mismatches, and corporate shadow banking activities. *China Economic Review, 93*, Article 102495.

Yao, L., & Ma, X. (2022). Has digital finance widened the income gap? *PLoS ONE, 17*(2), Article e0263915.

Yilmaz, S., Haynes, K. E., & Dine, M. (2002). Geographic and network neighbors: Spillover effects of telecommunications infrastructure. *Journal of Regional Science, 42*(2), 339–360.

Yue, P., Korkmaz, A. G., Yin, Z., & Zhou, H. (2022). The rise of digital finance: Financial inclusion or debt trap? *Finance Research Letters, 47*, Article 102604.

Zhan, Y. Q., Gao, D. F., Feng, M. Z., & Yan, S. (2025). Digital finance, non-agricultural employment, and the income-increasing effect on rural households. *International Review of Financial Analysis, 98*, Article 103897.

Zhang, S. B., Shi, B. F., & Ji, H. (2023). How to decouple income growth from household carbon emissions: A perspective based on urban-rural differences in China. *Energy Economics, 125*, Article 106816.

Zhang, S. J., & Zhou, Q. (2025). The impact of digital finance on farmers' consumption decisions: An analysis based on the moderating effect of risk preference. *International Review of Financial Analysis, 99*, Article 103928.

Zhang, X. L., Luo, L. Z., & Skitmore, M. (2015). Household carbon emission research: An analytical review of measurement, influencing factors and mitigation prospects. *Journal of Cleaner Production, 103*, 873–883.

Zhou, J. B., Ma, H. T., & Wang, S. J. (2025). Household consumption carbon emissions under different urbanization levels-a study based on micro-survey data. *Cities, 158*, Article 105630.