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Digital Inclusive Finance, Household Energy Poverty, and Sustainable Development: Micro-Level Evidence from China

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ABSTRACT:
Energy poverty remains a formidable obstacle to sustainable and inclusive growth, significantly hindering progress toward the UN Sustainable Development Goals (SDGs), especially within developing nations. As an important manifestation of multidimensional and relative poverty, alleviating household energy poverty is essential for promoting energy justice, enhancing household resilience, and advancing inclusive development pathways in China's new development stage.
Utilizing panel data from the China Family Panel Studies (CFPS) spanning 2014–2022, alongside the Peking University Digital Inclusive Finance Index, this study empirically investigates the role of digital inclusive finance in mitigating household energy poverty and explores the underlying mechanisms. The results indicate that digital inclusive finance significantly alleviates household energy poverty. Mechanism analysis reveals that this effect operates primarily through enhancing household income diversification via non-agricultural employment opportunities (facilitated by mobile payment platforms and e-commerce financing) and strengthening financial resilience by easing liquidity constraints (via online micro-credit products and digital insurance services).
Heterogeneity tests reveal that DIF is most effective for households in eastern and western provinces, rural communities, and low-income groups, underscoring its potential to improve equity and those with lower levels of digitalization, highlighting its inclusive and equity-enhancing characteristics.
Overall, this study provides micro-level evidence on how digital financial development can be embedded within broader sustainability and energy poverty governance agendas. The findings suggest that strengthening digital financial infrastructure, optimizing inclusive financial product design, and improving financial risk prevention and institutional safeguards are crucial for building a sustainable, trinity-based energy poverty governance framework characterized by technological empowerment, financial innovation, and institutional support..

Keywords: Household energy poverty; Digital inclusive finance; Financial resilience; Income diversification; Sustainable development

1. Introduction

Eliminating energy deprivation is fundamental to realizing the United Nations Sustainable Development Goals (SDGs). The 2024 World Energy Outlook underscores the urgency of this issue, noting that over 700 million people worldwide lack electricity, while more than 2 billion remain without clean cooking solutions. Although China achieved the goal of universal electricity coverage in 2015, the problem of energy poverty remains severe: approximately 46% of energy-poor households in China still cannot access

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modern energy services (Lin et al., 2020). With the elimination of absolute poverty in 2020, China's policy agenda has transitioned toward resolving multidimensional constraints rather than solely income deficits. As a key indicator of this new phase, mitigating energy poverty is vital for advancing common prosperity. As a key manifestation of the new multidimensional poverty, exploring the mitigation of energy poverty is essential for the governance of relative poverty and the steady advancement of common prosperity in the new era. By merging fintech innovations with traditional banking, Digital Inclusive Finance (DIF) overcomes geographical barriers, offering a unique chance to expand financial access in lagging regions. Furthermore, DIF lowers service costs and mitigates information asymmetry for vulnerable groups, thereby enhancing their ability to smooth energy consumption. According to recent 2024 statistics, rural internet penetration in China has surpassed 65%, while exceeding 52% among the elderly. This digital expansion effectively connects households to modern energy markets, aiding in poverty reduction (Jin et al., 2024). Against the backdrop of the deep integration of digitalization and financial innovation, investigating the mechanism through which digital inclusive finance affects household energy poverty holds important practical significance for optimizing energy resource allocation and improving household energy welfare. Based on data from the China Family Panel Studies (CFPS) covering 2014-2022 and the Peking University Digital Inclusive Finance Index, this paper assesses the impact and mechanism of DIF development on household energy poverty from a micro perspective, aiming to provide empirical references for reducing the level of household energy poverty. Unlike macro-level studies that emphasize the 'trickle-down' effect of financial deepening on regional poverty, our micro-level evidence suggests a more direct 'bottom-up' empowerment pathway. By validating how specific digital tools alter household behaviors, this study clarifies the micro-foundations of national inclusive growth strategies, offering insights into how macro-policies can be effectively scaled down to household units.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature; Section 3 outlines the theoretical framework; Section 4 details the data and methodology; Section 5 presents empirical findings; and Section 6 concludes with policy implications.

2. Literature Review

2.1 Studies on household energy poverty

The IEA characterizes energy poverty as the lack of access to affordable, modern clean energy, necessitating reliance on traditional solid biomass for daily cooking and heating needs. Existing scholarship identifies income constraints, asset shortages, and limited labor participation as primary drivers of this phenomenon (Ding & Chen, 2002; Chang et al., 2020; Xie et al., 2022; Drescher & Janzen, 2021). Energy poverty exerts significant negative effects on individuals, households, and economic development. At the individual and household levels, it affects critical dimensions including education (Apergis et al., 2022), physical and mental health (Pan et al., 2021), healthcare expenditure (Bukari et al., 2021), and subjective well-being (Nie et al., 2021; Zhang et al., 2021). From an economic perspective, energy poverty hinders economic growth both in the short and long term (Narayan & Smyth, 2008; Le & Nguyen, 2019; Iyke et al., 2021).

Scholars generally utilize two primary assessment frameworks. One focuses on specific thresholds like accessibility and affordability—notably the "10%" rule and the Low Income-High Cost (LIHC) model (Nussbaumer, 2012; Zhang et al., 2021; He et al., 2023). Alternatively, composite indices offer a broader view, with the Multidimensional Energy Poverty Index (MEPI) being the predominant tool (Zhang et al., 2021; Rao et al., 2022).

2.2 Studies on digital inclusive finance

DIF represents the synergy between modern technology and financial systems, designed to maximize service reach, depth, and digital support. From an economic standpoint, it drives household prosperity by stimulating consumption, entrepreneurship, and income growth Economically, it exerts positive impacts on household income and consumption, employment and entrepreneurship, and the growth of overall household wealth. For instance, it can promote household consumption (Yi & Zhou, 2018), alleviate income inequality, facilitate rural households' entrepreneurship (He & Li, 2019), it also creates jobs (Qi et al., 2020) and facilitates workforce mobility (Bo & Zhang, 2021), leading to wealth accumulation (Zhou & Chen, 2021). Sociologically, DIF is a catalyst for upward mobility, particularly benefiting educated low-income families and those in specific regions. Moreover, it empowers marginalized groups, such as women, who typically encounter hurdles in conventional banking (Wang et al., 2025).

2.3 Research on the impact of digital inclusive finance on household energy poverty

DIF leverages specific advantages to combat energy deprivation. Primarily, it diversifies financial resources, boosting non-agricultural employment and income (Jin et al., 2024; Mushtaq & Bruneau, 2019), which improves clean energy affordability. Furthermore, by easing financing constraints for firms (Lin & Peng, 2022) and fostering innovation (Said & Acheampong, 2023), DIF indirectly supports energy transition. Crucially, it diminishes information asymmetry, allowing lenders to better evaluate credit profiles (Lin & Ma, 2022) and offer customized solutions. However, a growing strand of literature warns of the 'digital divide' in algorithms. While DIF reduces traditional information asymmetry, reliance on big data may introduce new forms of exclusion. For instance, energy-poor households with sparse 'digital footprints' might be algorithmically categorized as high-risk by credit assessment models, potentially perpetuating energy poverty under the guise of technological neutrality. This underscores the critical need to examine heterogeneity in digitalization levels to ensure inclusive outcomes.

2.4 Literature critique

While prior research has established DIF's efficacy in reducing energy poverty and explored various heterogeneity factors, significant gaps persist. Most analyses remain at the macro or meso scales, failing to sufficiently uncover the micro-level behavioral mechanisms linking DIF to household energy outcomes. On the other hand, heterogeneity analyses in existing literature primarily focus on regional, income, and educational disparities, failing to consider other dimensions of heterogeneity that may moderate this impact.

Consequently, utilizing 2014–2022 CFPS data alongside the PKU-DIFI, this paper rigorously quantifies household liquidity constraints and non-agricultural employment status. We specifically examine how these two factors mediate the link between DIF and energy poverty, offering a micro-perspective that bridges existing gaps in mechanism analysis. Furthermore, by developing a household digitalization index, we explore how digital literacy moderates DIF's impact, offering fresh empirical insights for policymakers.

3. Theoretical Framework and Hypotheses Development

3.1 The Direct Effect of DIF on Mitigating Energy Poverty

DIF has reshaped financial services through technological innovation, overcoming spatial barriers to clean energy access. Digital platforms utilize big data to pinpoint household energy needs and offer customized financing for green equipment. Furthermore, blockchain integration ensures transparent, low-cost participation in distributed energy markets. DIF also provides real-time market data—such as price shifts and subsidy updates—enabling households to make informed, rational consumption choices. This fosters a transition toward cleaner, more efficient energy use. Additionally, the development of DIF allows households to access timely and accurate information about energy markets, including fluctuations in energy prices and clean energy subsidy policies, thereby making more rational energy consumption decisions based on their actual circumstances. Consequently, households tend to choose cleaner and more efficient energy types in their consumption decisions, forming a virtuous cycle of "digital support – technological adoption – efficiency improvement." Based on this analysis, we propose:

- H1: The development of digital inclusive finance significantly curbs household energy poverty.

3.2 The mechanisms through which digital inclusive finance affects household energy poverty

3.2.1 Non-agricultural employment mechanism

The Energy Ladder Theory posits that income level is a primary determinant of consumption patterns. DIF alleviates energy poverty by boosting household income through the expansion of non-agricultural work. This occurs via two channels: entrepreneurship and direct employment. In less developed areas, DIF empowers agricultural workers with lower education levels to start their own businesses (Liu et al., 2022). With the support of DIF, entrepreneurs can more conveniently obtain financial support, engage in various non-agricultural business activities, and create more employment opportunities (He & Li, 2019). From the employment perspective, small and micro-enterprises (SMEs) are major absorbers of labor and key targets of DIF support. By promoting the establishment and development of SMEs, DIF releases a large number of employment opportunities and increases employment rates (Qi et al., 2020; Luan et al., 2023). Furthermore, recruitment information on DIF platforms is more diverse and abundant, enabling workers to overcome geographical constraints (Bo & Zhang, 2021), access more non-agricultural job information, reduce job search costs and information asymmetry, and promote labor transfer to non-agricultural sectors (Jin et al., 2024), thereby mitigating household energy poverty. Accordingly, we propose the second research hypothesis:

- H2: DIF mitigates energy poverty by facilitating the labor force transition toward non-agricultural sectors.

3.2.2 Liquidity constraint mechanism

By alleviating household liquidity constraints, DIF provides a crucial breakthrough for addressing energy poverty. Existing studies have shown that inclusive finance can significantly mitigate household liquidity constraints in energy consumption (Dogan et al., 2021; Koomson & Danquah, 2021). Specifically, DIF operates through the following pathways: First, DIF relies on big data risk control technology to restructure the credit assessment system. The credit rationing problem caused by information asymmetry in traditional financial institutions has been alleviated under digital empowerment (Dogan et al., 2021), which not only helps households break through the limitation of immediate payment capacity but also achieves long-term energy cost savings through technological upgrading. Second, flexible savings tools on digital financial platforms enhance households' precautionary savings capacity, enabling them to effectively respond to unexpected expenses such as energy price fluctuations or equipment maintenance (Koomson & Danquah, 2021). This consumption-smoothing capacity significantly reduces the likelihood that households are forced to use inferior energy sources due to short-term fund shortages (Bukari et al., 2021). Furthermore, the construction of a digital financial ecosystem has expanded household income sources. Through micro-entrepreneurial activities participated in via digital payment platforms, households can obtain non-agricultural income without abandoning agricultural production. This income diversification effect (Gupta et al., 2020) not only improves households' payment capacity for energy consumption but also strengthens long-term energy security through asset accumulation. Accordingly, we propose the third research hypothesis:

- H3: By relaxing household liquidity constraints, DIF significantly reduces energy poverty levels.

4. Indicator setting and model construction

4.1 Research Sample

The empirical analysis relies on the China Family Panel Studies (CFPS) dataset. Administered by Peking University's Institute of Social Science Survey, this biennial longitudinal project provides a comprehensive view of the economic and social dynamics of Chinese communities, families, and individuals. It is widely regarded as a robust source for energy-related research. Given the research focus, we employ five waves of CFPS data spanning 2014-2022. During data processing, we restrict the sample to households where the household head is aged 16-80 and drop observations with missing values for key variables. To mitigate the impact of outliers, we apply 1% winsorization to selected continuous variables. Ultimately, we use balanced panel data covering five periods, totaling 14,975 households.

4.2 Indicator definition and description

Household energy poverty serves as the dependent variable, while the Digital Inclusive Finance Index functions as the primary explanatory factor. We also incorporate a broad set of controls covering individual, family, and regional attributes, alongside mechanism variables like non-farm employment and liquidity constraints. Control variables include various individual, household, and regional characteristics; mechanism variables such as non-agricultural employment and liquidity constraints are incorporated into the analysis. The specific indicator selections are as follows:

4.2.1 Measurement of household energy poverty

Adopting the IEA's framework and the methodology by Luan et al. (2023), we established three binary indicators (EP1, EP2, EP3) to capture single dimensions of energy poverty, followed by a composite index (EP). The construction process is detailed below:

- EP1 (Access Dimension): Derived from survey data on primary cooking fuels, this binary variable equals 1 if the household utilizes solid biomass (firewood, coal, charcoal) and 0 if they use modern clean sources like electricity or gas.
- EP2 (Affordability Threshold): Based on the standard "10% rule," a household is deemed energy-poor (EP2=1) if its energy costs surpass 10% of its total income; otherwise, it is coded as 0.
- EP3 (LIHC Model): Utilizing the Low-Income-High-Cost method, we identify households falling below the regional median income for the survey year. Among these, those spending over 10% of their income on energy are classified as energy-poor (EP3=1).

To reflect the multidimensionality of energy deprivation, we synthesized these metrics into a composite index. The scoring logic is: EP=1 (Non-poor) if both access and affordability are secured; EP=2 (Moderate) if only one condition is met; and EP=3 (Severe) if neither is satisfied.

4.2.2 Digital inclusive finance index

Our primary independent variable is the Digital Inclusive Finance Index (DIF). Developed by Peking University's research team, this provincial-level dataset is the standard metric for assessing digital financial depth in China. To normalize the data scale and reduce heteroscedasticity, we use the natural logarithm of the index.

4.2.3 Non-agricultural employment

Drawing on the “occupation type” and “work type” variables from the CFPS adult questionnaire, we define non-agricultural employment (NAE) as a dummy variable: individuals engaged in non-agricultural occupations (e.g., manufacturing, services, commerce) during the survey year are assigned NAE=1, while those in agricultural occupations are assigned NAE=0.

4.2.4 Liquidity constraints

We construct two dummy variables (LC1 and LC2) to measure household liquidity constraints, using CFPS data on household credit status, consumption, and income, with reference to existing literature (Jappelli, 1990; Benvenuti et al., 2022; Nirei, 2006).

- LC1 (Credit Rationing): This binary indicator captures "discouraged borrowers" or those denied credit. It takes a value of 1 if the household was refused a loan or avoided applying due to fear of rejection, and 0 otherwise.
- LC2 (Financial Mismatch): Following standard literature, we flag a household as liquidity constrained (LC2=1) if their monthly consumption is more than triple their disposable income.

4.2.5 Control Variables

Informed by the research of Yang et al. (2022) and Luan et al. (2023), we include three categories of control variables to mitigate potential endogeneity, with their detailed definitions, measurement methods, and data sources specified as follows.

First, we consider the household head's individual characteristics, which are critical for capturing heterogeneous individual effects. Age is a continuous variable derived directly from the China Family Panel Studies (CFPS) survey data. Gender is a dummy variable coded as 1 if the household head is male and 0 otherwise, while hukou status is also a dummy variable (1 for urban hukou, 0 for rural hukou). Marital status is defined as 1 if the household head is currently married and 0 for other statuses (e.g., unmarried, divorced, widowed). Educational attainment is a categorical variable coded by years of schooling, following the standard classification in demographic research: 0 years (illiterate), 6 years (primary school), 9 years (junior high school), 12 years (senior high school), and 16 years (college and above). Health status is an ordinal variable based on the CFPS questionnaire item "How do you perceive your overall health?" Consistent with the original survey design and mainstream literature, it is coded as 1 (very poor), 2 (poor), 3 (average), 4 (good), and 5 (excellent).

Second, we control for household-level characteristics that may influence the core relationship. Household size is a continuous variable defined as the number of family members living together, with data sourced from the CFPS. The number of residential properties is another continuous variable, referring to the total number of residential real estate owned by the household, also obtained from the CFPS.

Finally, to control for regional heterogeneity, we include two provincial-level indicators sourced from the China Statistical Yearbook. We proxy regional economic development using the natural logarithm of real GDP per capita (lnGDP), which adjusts for price variances. Additionally, we control for the urbanization rate, defined as the proportion of the province's population living in urban areas.

Table 1 presents the summary statistics for the full sample used in our analysis.

Table 1: Descriptive statistics

Variable	Symbol	Observations	Mean	S.D.	Min	Max
Household energy poverty	EP	14,975	1.489	0.641	1	3
Digital inclusive finance index	DIF	14,975	5.605	0.287	4.983	6.165
Head's Age	age	14,975	52.558	11.391	19	80
Head's Gender	gender	14,975	0.753	0.431	0	1
Marital status	marriage	14,975	0.891	0.311	0	1
Hukou status	hukou	14,975	0.466	0.499	0	1

Educational attainment	edu	14,975	7.870	4.531	0	16
Health status	health	14,975	2.962	1.212	0	5
Family size	familysize	14,975	3.798	1.789	1	16
Number of properties	prop	14,975	0.246	0.543	0	7
Regional economic development	lnGDP	14,975	10.865	0.407	10.131	12.155
Urbanization level	urb	14,975	0.600	0.111	0.4	0.89
Non-agricultural employment	NAE	14,975	0.453	0.498	0	1
Liquidity constraint 1	LC1	14,975	0.213	0.409	0	1
Liquidity constraint 2	LC2	14,975	0.842	0.364	0	1

4.3 Model specification

Guided by our theoretical framework, we empirically examine the link between digital inclusive finance and energy poverty. Drawing on the methodological frameworks of Jin et al. (2024) and YIN et al. (2023), we employ an Ordinary Least Squares (OLS) model to test the causal relationship between DIF development and household energy poverty. The baseline regression model is formulated as follows:

$$EP_{ict} = \alpha_0 + \alpha_1 DIF_{ct} + \alpha_2 X_{ict} + \lambda_i + \eta_t + \varepsilon_{ict} \qquad (1)$$

In Equation (1), indices i 、 c, and t denote household, province, and year, respectively; the dependent variable, EP_{ict}, indicates the energy poverty status of household i in province c during period t; the independent variable, DIF_{ct}, represents the level of digital inclusive financial development in the household's location; X_{ict} denotes a vector of control variables (including individual, household, and provincial characteristics as specified in Section 4.2); λ_i and η_t represent household fixed effects and year fixed effects, respectively; ε_{ict} is the random error term; α_0 is the constant term. Coefficients α_1 and α_2 estimate the effects of the respective variables. If α_1 a is significantly negative, it indicates that the development of digital inclusive finance exerts a significant mitigating effect on household energy poverty.

5. Empirical results and analysis

5.1 Baseline regression

Table 2 summarizes the benchmark estimates. Column (1) provides the univariate regression results. Subsequently, Columns (2) through (4) progressively introduce controls at the individual, household, and provincial levels to test robustness.

Table 2: Baseline regression

Variable	Model (1)	Model (2)	Model (3)	Model (4)
DIF	-1.7813*** (0.0570)	-1.3544*** (0.0537)	-1.2455*** (0.0538)	-0.6626*** (0.1613)
age		0.0063*** (0.0004)	0.0049*** (0.0004)	0.0057*** (0.0004)
gender		0.0479*** (0.0110)	0.0514*** (0.0109)	0.0534*** (0.0109)
marriage		-0.0585*** (0.0151)	-0.0295* (0.0154)	-0.0324** (0.0153)
hukou		-0.2917* (0.0101)	-0.2864*** (0.0100)	-0.2909*** (0.0099)
edu		-0.0307*** (0.0011)	-0.0286*** (0.0011)	-0.0304*** (0.0011)
health		-0.0282*** (0.0039)	-0.0267*** (0.0039)	-0.0272*** (0.0038)
familysize			-0.0084*** (0.0028)	-0.0121*** (0.0028)
prop			-0.0794*** (0.0087)	-0.0891*** (0.0087)
lnGDP				-0.3663*** (0.0424)
urb				-0.7310*** (0.0825)
_cons	11.4736*** (0.3193)	9.2261*** (0.2990)	8.7837*** (0.3002)	9.2826*** (0.5557)
Year FE	YES	YES	YES	YES
Household FE	YES	YES	YES	YES
N	14975	14975	14975	14975
R^2	0.0613	0.2198	0.2355	0.1902
*Notes: Robust standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. The same applies below.				

The findings indicate that regardless of whether control variables are included, the development of digital inclusive finance (DIF) significantly alleviates household energy poverty, thereby supporting H1. Among the control variables, age and gender are positively correlated with household energy poverty – younger individuals and females are more environmentally sensitive than older groups and males, which is consistent with the findings of Casaló and Escario (2018) and Li et al. (2019). Additionally, marital status (married), urban hukou status, higher educational attainment, better health status, wealthier households, higher regional economic development, and higher urbanization rates are associated with a lower likelihood of household energy poverty.

5.2 Endogeneity tests

The analysis indicates that digital inclusive finance (DIF) exerts a significant impact on household energy poverty; concurrently, the deterioration of household energy poverty can, to a certain extent, constrain the in-depth development of DIF. Therefore, to address potential endogeneity concerns induced by reverse causality in the baseline model, this study employs the instrumental variable two-stage least squares (IV-2SLS) method. This approach has become a well-established paradigm for addressing endogeneity related to DIF, and its effectiveness has been widely verified in existing literature – including studies on household consumption upgrading (Zhang et al., 2020), household wealth accumulation (Zhou & Chen, 2021), income inequality convergence, rural households' common prosperity (Wu, 2024), social mobility, and migrant workers' urban integration (Guo & Zhong, 2024). These studies confirm that IV-2SLS can reliably identify the causal effect of DIF, providing a solid methodological foundation for the method selection in this paper.

Following the instrumental variable construction strategy proposed by Zhang et al. (2020), this study constructs a distance variable based on the spherical distance between the capital city of the household's province and Hangzhou. This distance variable is then interacted with the national average of the digital inclusive finance index (excluding the household's own province) to form a time-varying instrumental variable (IV). On one hand, regions closer to Hangzhou tend to have higher levels of DIF development, indicating a significant correlation between the distance variable and the DIF index (satisfying the relevance assumption). On the other hand, changes in household energy poverty are not determined by the spherical distance to Hangzhou. Furthermore, after effectively controlling for regional characteristics such as regional economic development level, the exogeneity assumption of the IV is fully satisfied. The results of the endogeneity tests are reported in Table 3.

Column (1) of Table 3 reports the first-stage regression results of the IV-2SLS model. During the instrumental variable regression, the IV exhibits a significant positive correlation with the digital inclusive finance (DIF) index. The Wald F-statistic is substantially greater than the conventional threshold of 10, indicating that the instrument passes the weak instrument test. Column (2) of Table 3 presents the second-stage regression results. After addressing endogeneity through the IV, the coefficient of DIF on household energy poverty is –0.5937, which is statistically significant at the 1% level. This confirms that after effectively controlling for endogeneity concerns, the development of DIF still exerts a significant mitigating effect on household energy poverty.

Table 3: Baseline regression results

Variable	(1) First stage	(2) Second stage
DIF		-0.5937*** (0.1563)

Per capita disaster loss	1.0363*** (0.0001)	
Control variables	YES	YES
Year FE	YES	YES
Household FE	YES	YES
N	14975	14975
First-stage F-statistic	42.03	

5.3 Robustness checks

This study conducts robustness tests based on the aforementioned estimates.

5.3.1 Replacing the measurement of the core dependent variable

Following the methodology of Deng et al. (2024), we construct a new household energy poverty indicator (EP4) using the “double the median” ratio of household energy consumption to income, which better reflects households’ energy affordability and burden capacity. Specifically:

Define FPR as the ratio of household energy expenditure to total household income. Household energy expenditure includes electricity, heating, and fuel expenses. Let ϑ denote the median FPR across all households in the sample. Assign EP4=1 if $\vartheta \geq 2FPR$ (energy-poor households), and EP4=0 otherwise.

We re-estimate the model by replacing the original dependent variable with EP1, EP2, EP3 (constructed in Chapter 4) and the new EP4. The results are reported in Models (1) – (4) of Table 4. Across all alternative measurements of household energy poverty, digital inclusive finance (DIF) continues to exert a robust mitigating effect, confirming the stability of our core findings.

5.3.2 Exclusion of municipal impact

China’s regional economic development levels and resource endowments vary significantly, which could introduce estimation biases. To address this, we exclude households with hukou registered in the four direct-controlled municipalities (Beijing, Tianjin, Shanghai, and Chongqing) from the full sample. As shown in Model (5) of Table 4, the regression results are consistent with the baseline findings, indicating that our conclusions are not driven by the unique characteristics of municipalities.

5.3.3 Shortening the sample period

Digital inclusive finance in China has experienced rapid development since 2014 (Jin et al., 2024). We first omit the 2014 sample and re-estimate the model, with results presented in Model (6) of Table 4. Additionally, to mitigate potential disturbances from the global public health emergency (2020-2022), we further exclude data from 2020 and 2022. The results in Model (7) of Table 4 show that the core relationship between DIF and household energy poverty remains statistically significant, confirming the robustness of our findings to changes in the sample period.

Table 4: Robustness tests

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
DIF	-0.2514** (0.1118)	-0.5978*** (0.1144)	-0.3381*** (0.1064)	-0.5669*** (0.1139)	-0.5365*** (0.1734)	-0.6508** (0.1945)	-0.6184*** (0.2147)
Control variables	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES	YES
N	14975	14975	14975	14975	13940	11980	8985
R^2	0.2154	0.0771	0.0970	0.0760	0.2268	0.2475	0.2447

5.4 Heterogeneity analysis

Considering regional disparities in resource endowments and economic development levels across China, as well as inherent household heterogeneity, this section investigates the heterogeneous effects of digital inclusive finance (DIF) development on household energy poverty.

5.4.1 Regional variation

We stratified the sample into Eastern, Central, and Western zones to capture spatial differences. Estimates in Table 5 (Columns 1–3) indicate that while DIF significantly curbs energy poverty in the Eastern and Western provinces, its impact in the Central region is statistically negligible. This null result likely stems from the industrial path dependence prevalent in the resource-rich Central region, where financial flows often prioritize heavy industry over household energy transition (Jin et al., 2024). This may be attributed to CR's role as China's primary energy and raw material supply base: entrenched path dependence has reduced the inclusiveness of inclusive finance development, leading to funds being primarily channeled toward energy extraction and exports rather than contributing to households' energy transition or income growth. Therefore, simply increasing the supply of digital finance in these regions is insufficient. It must be coupled with industrial transformation policies to break the resource curse and support workers transitioning from traditional energy sectors to new digital economies.

5.4.2 Urban-rural heterogeneity

Next, we investigated the urban-rural gap by splitting the sample according to household hukou registration (Urban vs. Rural). As detailed in Columns 4 and 5, the poverty-reduction magnitude is substantially larger for rural households compared to their urban counterparts. This aligns with the theory of financial exclusion: since rural areas traditionally lack physical banking infrastructure, the marginal benefit of accessing digital financial services is significantly higher for rural residents. This discrepancy stems from rural residents facing greater barriers to accessing traditional financial services: the integration of digital technology with inclusive finance makes RH households more sensitive to the benefits of DIF development, as it addresses their long-standing financial exclusion.

Table 5: Heterogeneity analysis

	By region			By hukou type	
	ER	CR	WR	UH	RH
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
DIF	-0.7167*** (0.2189)	-0.3453 (0.3444)	-1.2068* (0.6419)	-0.2745 (0.1792)	-1.4149*** (0.2592)
Control Variables	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES
Household F.E.	YES	YES	YES	YES	YES
N	7310	3785	3880	6985	7990
R^2	0.2442	0.1853	0.2518	0.1441	0.1647

	By income group		By household digital level	
	HIG	LIG	HDL	LDL
Variable	Model (6)	Model (7)	Model (8)	Model (9)
DIF	-0.0567 (0.1522)	-1.1427*** (0.2736)	-0.1918 (0.2037)	-0.8985*** (0.2237)
Control Variables	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Household F.E.	YES	YES	YES	YES
N	7206	7769	6286	8689
R^2	0.1539	0.1786	0.1863	0.2133

5.4.3 Income heterogeneity

While DIF development plays a notable role in alleviating household energy poverty, it may potentially exacerbate structural inequalities. Based on household per capita income quartiles from CFPS data, we split the sample into high-income groups (HIG) and low-income groups (LIG). As shown in Models (6) – (7) of Table 5, DIF exerts a statistically significant mitigating effect only on LIG households, with no significant impact on HIG households. This suggests that DIF plays a crucial role in empowering LIG households to escape energy poverty, and does not yet pose a prominent structural problem of widening energy inequality.

5.4.4 Heterogeneity in household digitalization levels

DIF leverages digital technologies (e.g., big data, cloud computing) combined with traditional offline data processing to enhance information sharing, reduce transaction costs, expand service coverage, and improve risk control capabilities. Household digitalization levels may generate heterogeneous effects on DIF's energy poverty mitigation impact. Considering data availability and indicator scientific, we follow Luan et al. (2023) to construct a comprehensive Household Digitalization Level Index based on four dimensions: internet access, internet usage frequency, daily internet usage duration, and perceived internet importance. Factor analysis is applied to the seven sub-indicators (see Table 6) to derive the index, which is then shifted to ensure all values are positive. We further group households into low digitalization level (LDL) and high digitalization level (HDL) subgroups based on the regional median of the index. The results are presented in Models (8) – (9) of Table 5.The findings show that DIF significantly alleviates energy poverty for LDL households, but its effect on HDL households is insignificant. This heterogeneity can be explained by three mechanisms: First, LDL households are in the "low-hanging fruit" stage of digital technology adoption, enabling them to more easily reduce energy procurement costs through DIF (e.g., accessing affordable clean energy equipment via digital financial products). Second, DIF integrates multidimensional data through cloud computing to mitigate adverse selection problems in financial markets. This information increment effect is more pronounced for LDL households, which traditionally lack access to formal financial services and information. In contrast, HDL households already possess strong information processing capabilities, leading to an "information cocoon" effect that diminishes the marginal improvement from DIF. Third, aligned with energy transition theory, HDL households have typically completed the upgrade to modern energy consumption, so DIF primarily maintains the stability of their existing energy consumption structure. In contrast, LDL households are in a critical phase of energy consumption structure transition, where targeted financial support from DIF can break their path dependence on traditional high-pollution energy sources.

Table 6: Construction of family digital level index

Indicator	Specific indicators	Construction method
Internet access	• Whether to access the Internet • Whether to access the Internet via computer	• Assign 1 if any online method is used; assign 0 otherwise
Internet usage duration	• Weekly online hours	• Directly use the weekly online hours provided by the CFPS questionnaire
Online frequency	• Online entertainment frequency • Online commercial activity frequency • Online learning frequency	• For each of these variables: Assign 2 for daily participation, 0 for no participation, and 1 for others
Importance of the Internet	• Importance of the Internet for work • Importance of the Internet for communication	• For each of these variables: Assign values based on self-rated scores (ranging from 0 to 5)

5.5 Mechanism analysis

The previous section established the impact of digital inclusive finance (DIF) on household energy poverty (EP), thereby validating H1. Building on the theoretical analysis presented earlier, this section specifically examines the mediating roles of non-agricultural employment (NAE) and liquidity constraints (LC1, LC2) in the relationship between DIF and EP. Drawing on the methodological framework of Sun et al. (2023), we specify the following mediating effect models:

$$Med_{ict} = \omega_0 + \omega_1 DIF_{ct} + \omega_2 X_{ict} + \lambda_i + \eta_t + \varepsilon_{ict} \quad (2)$$

$$EP_{ict} = \phi_0 + \phi_1 DIF_{ct} + \phi_2 Med_{ict} + \phi_3 X_{ict} + \lambda_i + \eta_t + \varepsilon_{ict} \quad (3)$$

In the model (2), the mediating factors – non-agricultural employment (NAE) and liquidity constraints (LC1, LC2) – are represented by Med. When the coefficient α_1 in the baseline regression is significant, and the coefficients ω_1 , ϕ_1, and ϕ_2 in the mediating effect model are also significant, with the absolute value of $\phi_1$being smaller than that of α_1, it indicates the presence of a mediating effect. These results indicate that non-agricultural employment and liquidity constraints play a crucial mediating role in the relationship between DIF and household energy poverty, thereby confirming H2 and H3.

First, we conduct regressions with non-agricultural employment (NAE) and liquidity constraints (LC1, LC2) as dependent variables, and digital inclusive finance (DIF) as the core independent variable (see Table 7). Column (1) of Table 7 reports a positive and statistically significant estimated coefficient for NAE, while Columns (3) and (5) report negative and statistically significant coefficients for LC1 and LC2, respectively. These results indicate that DIF can effectively promote non-agricultural employment and alleviate household liquidity constraints. Subsequently, we incorporate NAE and liquidity constraints (LC1, LC2) into the baseline regression equation for re-estimation (see Table 7). The results in Columns (2), (4), and (6) of Table 7 remain statistically significant, with coefficients of –0.4250, –0.4737, and –0.4855, respectively. Notably, the absolute values of these coefficients are all smaller than the absolute value of α_1 (0.6017) from the baseline regression. These findings validate the mediating roles of non-agricultural employment and liquidity constraints in the relationship between DIF and household energy poverty, thereby confirming H2 and H3.

Table 7: Mechanism tests

Variable	NAE	EP	LC1	EP	LC2	EP
DIF	0.3474*** (0.0691)	-0.4250*** (0.1551)	-0.1631*** (0.0637)	-0.4737*** (0.1567)	-0.1723*** (0.0574)	-0.4855*** (0.1562)
NAE		-1.937*** (0.1113)				
LC1				0.1974* (0.0233)		
LC2						0.1096*** (0.0126)
Control variables	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Household FE	YES	YES	YES	YES	YES	YES
N	14975	14975	14975	14975	14975	14975
R^2	0.2253	0.2445	0.0327	0.2410	0.0059	0.2336

6. Conclusions and policy recommendations

With the successful elimination of absolute poverty, China's policy focus has shifted toward addressing complex, multidimensional welfare challenges like energy deprivation. Utilizing 2014–2022 CFPS micro-data, this paper established a robust causal link between digital financial development and reduced household energy poverty. The analysis identifies income diversification and liquidity relief as the two primary transmission channels. The findings reveal that DIF significantly reduces household energy poverty through two pathways: promoting non-agricultural employment transitions and alleviating liquidity constraints. Furthermore, the mitigating effect of DIF is more pronounced for households in eastern and western regions, rural areas, low-income groups, and those with low digitalization levels, compared to their counterparts in central regions, urban areas, high-income groups, and households with high digitalization levels.

Based on these conclusions, the following policy implications are proposed: First, the Chinese government should remain steadfast in leveraging DIF as a key instrument to alleviate household energy poverty. It should further improve digital financial infrastructure, promote the popularization of digital tools, and lay a solid hardware foundation for DIF development. Meanwhile, collaboration with major telecom companies should be strengthened to advance electronic and mobile payments, thereby expanding the coverage of DIF.

Second, the development of DIF should be oriented toward boosting non-agricultural employment and alleviating household liquidity constraints. It is necessary to rely on digital finance to advance the consumer internet and facilitate the transition of low-skilled rural groups to digital non-agricultural sectors. Financial institutions should be encouraged to design inclusive instruments—like small-ticket loans and crop insurance—specifically customized for agrarian and low-income demographics. Additionally, efforts should be made to promote integrated 'digital-financial-energy literacy'. Future policy interventions should focus on developing comprehensive training programs that not only teach digital skills but also educate households on using financial tools for energy efficiency management. Research into the cost-effectiveness and scalability of such integrated programs is warranted.

Third, comprehensive financial risk prevention and control mechanisms should be improved. Supervision of financial institutions should be strengthened, and credit assessment systems should be optimized to prevent excessive borrowing by energy-poor households. Financial market monitoring and early warning systems should be enhanced to promptly address risks, and mitigate household debt risks and overconsumption associated with digital payments.

Fourth, a multi-dimensional monitoring system covering energy accessibility, affordability, and cleanliness should be established, coupled with a dynamic policy adjustment mechanism. Ultimately, a sustainable energy poverty governance framework featuring technological empowerment, financial innovation, and institutional guarantees should be formed.

However, several limitations warrant attention. First, restricted by data availability, our measurement of household digitalization primarily relies on usage metrics (e.g., frequency and duration). This potentially omits the 'second-level digital divide' related to functional digital skills and hardware access. Future research should incorporate more granular indicators, such as specific smart device ownership (e.g., smartphones vs. computers) and objective tests of operational digital literacy, to better capture the nuances of the digital divide. Second, the study focuses on the analysis of direct and mediating effects, but the moderating role of regional digital infrastructure coverage (e.g., regional broadband penetration rate and 5G base station layout density) may require further exploration. Future research can expand the sample period or adopt quasi-experimental methods to enhance the credibility of causal identification.

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