Frontiers in Economics and Management Volume 6 Issue 11, 2025
ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

Can Inclusive Finance Policies Alleviate Household Financial Vulnerability: Causal Inference based on a Double Machine Learning Model

Yong Xing

College of Finance, Anhui University of Finance and Economics, Bengbu, Anhui 233030, China

Abstract

Household financial vulnerability exposes families to dual constraints at the micro level: debt repayment crises and consumption contraction. To address the household financial vulnerability dilemma in China, this paper develops a dual machine learning framework that incorporates both predictive and causal inference models. Using data from the China Family Panel Studies (CFPS), the paper employs causal inference through the dual machine learning model to explore the mechanisms through which inclusive finance policies affect household financial vulnerability in China. The study finds that inclusive finance policies alleviate financial constraints and reduce household financial vulnerability by optimizing household financial asset allocation. An increase in household net assets effectively promotes the optimization of household financial asset allocation through inclusive finance policies, thus playing a positive moderating role. This study provides theoretical and empirical insights for addressing the challenges of household financial vulnerability.

Keywords

Inclusive Finance Policies; Household Net Assets; Household Financial Vulnerability; Dual Machine Learning; Causal Inference.

1. Introduction

Household financial vulnerability refers to a situation in which a family struggles to maintain a stable living standard and financial condition due to unstable income sources, lack of financial reserves, improper asset allocation, or insufficient financial literacy when faced with economic shocks, financial risks, or unforeseen events. In recent years, the structural risks in household assets and liabilities have been continuously accumulating in China. The recurring impacts of the COVID-19 pandemic have hindered global economic recovery, thus placing the "seismic resilience" of the household financial system under severe stress, manifesting as increasing risk accumulation and insufficient coping abilities. At the same time, household financial vulnerability has significantly increased. High debt levels and imbalanced asset allocation have heightened risk exposure, while low asset liquidity has constrained risk response, highlighting the urgent need to enhance households' financial resilience. As an important tool for promoting widespread financial resource coverage, inclusive finance policies can effectively alleviate household financial vulnerability by adjusting household net assets. In this context, how to leverage inclusive finance policies to alleviate household financial vulnerability has become a critical issue for enhancing the breadth of financial resource coverage.

Existing research mainly explores the penetration, policy support, and digitalization of inclusive finance policies in relation to household financial vulnerability. However, few studies address the impact of these policies on long-term household financial stability and their regional differences, making it difficult to fully reveal the long-term mechanisms through which inclusive finance policies affect household financial stability in different regions. In areas with

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

significant differences in economic structure and financial market development, varying policy responses and effects may exist [1-3]. Furthermore, it remains uncertain whether household net assets play a moderating role in the impact of inclusive finance policies on household financial vulnerability. In light of this, this paper investigates the relationship between the implementation of inclusive finance policies and household financial vulnerability, exploring how these policies alleviate financial vulnerability by reducing the accumulation of financial risks and improving the ability to cope with risk shocks. The study aims to evaluate the moderating role of household net assets in financial constraints and identify the varying impacts of inclusive finance policies on household financial vulnerability at different levels of net assets. The findings indicate that inclusive finance policies can alleviate household financial vulnerability, playing a positive role in reducing financial risk accumulation and enhancing the ability to cope with risk shocks. Additionally, household net assets, as a moderating variable, play a central role in mitigating financial constraints within the impact mechanism of inclusive finance policies.

The potential marginal contributions of this paper include three points: (1) Existing literature largely focuses on the impact of financial literacy, economic capacity, and social networks on buffering household financial vulnerability, lacking in-depth research on the interaction effects between inclusive finance policies and household asset levels. This paper, by considering household net assets as a moderating variable, provides a deeper analysis of the differentiated responses of households with varying net asset levels to inclusive finance policies, thereby filling the gap in existing research on the moderating role of household net assets, and offering a new perspective for the study of household financial vulnerability. (2) Existing literature typically treats inclusive finance policies as a single policy, lacking exploration of regional differences in policy implementation intensity. This paper quantifies the execution gradient of inclusive finance policies in the eastern and central-western regions by constructing a policy intensity index, thus enriching research on the regional differences in inclusive finance policies. (3) Most related studies use the instrumental variable method, which struggles to effectively address self-selection bias. Furthermore, when dealing with high-dimensional covariates and nonlinear relationships, regularization compresses coefficients, leading to an underestimation of instrumental variable relevance, resulting in "regularization bias". This study, by using the dual machine learning method, employs an orthogonalization mechanism to separate confounding variables from treatment effects, thereby reducing errors caused by "regularization bias" and effectively addressing the "curse of dimensionality" in traditional causal inference [4].

2. Literature Review and Theoretical Hypotheses

2.1. Literature Review

2.1.1. The Multidimensional Causes of Household Financial Vulnerability

The study of financial vulnerability has evolved from a macroprudential perspective to a micro-level focus on households. In the application of Minsky's financial instability hypothesis to household sectors, an analytical framework centered around "debt-income" vulnerability has emerged [5,6]. Subsequent studies have assessed financial literacy from three dimensions: financial knowledge, financial behavior, and financial attitudes. Quantitative research results show that improving financial literacy can significantly reduce household financial vulnerability [7]. Existing research indicates that household financial vulnerability is the result of the dynamic interplay of multiple factors. From a micro-level perspective, demographic structure and economic capacity form fundamental constraints: age, health status, and education level create differentiated vulnerability characteristics by affecting income stability and risk response ability. Income level has a nonlinear effect, with lower-income groups facing

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

higher financial vulnerability [8,9]. Social networks and digital finance play buffering roles: labor mobility reduces rural household vulnerability through income growth and risk diversification, while the financial support and risk-sharing functions of social networks significantly enhance household resilience [10,11]. Digital finance significantly reduces vulnerability by improving access to financing and optimizing asset allocation, particularly in rural areas [12,13]. Financial literacy and debt management are core moderating variables: households with high leverage face significant liquidity risks, but financial literacy helps alleviate debt pressure by improving risk identification and financial planning abilities [14,15]. International research further validates the multidimensional nature of vulnerability, with financial debt, economic shocks, and behavioral biases jointly shaping household risk exposure pathways [16]. Existing studies predominantly focus on static cross-sectional analysis, lacking the identification of dynamic moderating effects of policy interventions. Research on heterogeneous impact mechanisms is fragmented, and there is a lack of systematic theoretical frameworks. Traditional quantitative methods struggle to address the high-dimensional confounding factors in the era of digital finance.

2.1.2. Dual Pathways, Digital Transformation, and Household Financial Vulnerability

Existing research generally agrees on the positive impact of inclusive finance on improving household economic welfare, but the transmission mechanisms of its policy effects differ. Inclusive finance affects household financial vulnerability through dual pathways: the direct pathway is reflected in optimizing the liability side (reducing financing costs) and expanding the asset side (enhancing portfolio efficiency), while the indirect pathway improves risk management capabilities through enhancing financial literacy and market participation [17-19]. Regional heterogeneity significantly influences policy effectiveness: the moderating effect of inclusive finance on urban-rural income disparity is more prominent in regions with weak infrastructure, while digital inclusive finance generates stronger marginal effects in low-income groups by lowering access thresholds [20,21]. Digital transformation reshapes the policy mechanism: the improvement of the digital finance index significantly promotes inclusive growth, but regional development imbalances constrain the release of policy dividends [22,23]. International comparisons show that financial literacy and regulatory frameworks are key variables in determining the success or failure of policies, while excessive inclusivity may exacerbate the risk of financial exclusion [24,25].

2.1.3. Methodology

Existing literature shows clear generational differences in policy evaluation methods. Many studies use the instrumental variable method, but it fails to effectively address self-selection bias [26]. In recent years, the application of quasi-experimental methods such as DID and PSM-DID has improved causal identification validity. However, these methods still fall short when handling high-dimensional covariates and nonlinear relationships [27,28]. This opens up space for methodological innovation through the introduction of machine learning techniques. This study introduces dual machine learning into the policy evaluation of inclusive finance, offering dual innovative value in both theoretical and practical aspects. From an academic contribution perspective, this method effectively addresses the "curse of dimensionality" in traditional causal inference by using an orthogonalization mechanism to separate confounding variables from treatment effects [4]. Specifically, at the methodological level, this study employs an innovative "dual de-biasing" analysis framework. First, it constructs a non-parametric prediction model with high-dimensional control variables using cutting-edge machine learning algorithms such as Lasso and random forests, effectively addressing the multicollinearity problem in traditional regression analysis. Secondly, it adjusts the ratio of training to testing sets and adopts various machine learning algorithms for robustness checks, providing dual assurance of the model's reliability and stability. This method significantly improves the

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

asymptotic normality of estimators and enhances statistical inference efficiency, providing a solid methodological foundation for the research conclusions. On the data front, this study centers on six waves of tracking data from the China Family Panel Studies (CFPS) from 2010 to 2020, covering micro-panel data from 28 provinces and 29,000 households nationwide. At the same time, it innovatively matches inclusive finance development indicators at the county level, achieving an organic integration of macro policy variables with micro household behavior. Compared to existing studies, this research has a larger sample size, a broader coverage, and takes into full account the time dimension and regional differences in variable design, significantly enhancing the representativeness and explanatory power of the research conclusions. This data integration approach not only effectively identifies the heterogeneous impact of inclusive finance policies across different spatial and temporal dimensions but also provides empirical evidence with practical guidance for deepening financial supply-side structural reforms during the 14th Five-Year Plan period, and holds significant theoretical and practical value for optimizing financial resource allocation and promoting the high-quality development of inclusive finance.

2.2. Theoretical Hypotheses

This paper argues that inclusive finance policies can significantly alleviate household financial vulnerability, with household net assets being one of the mechanisms through which these policies affect financial vulnerability. The detailed discussion is as follows:

Digital inclusive finance (such as mobile banking and inclusive insurance) enhances households' ability to resist risks by reducing financial exclusion and improving risk management capabilities [1,29]. Research indicates that digital payment tools improve cash flow levels, and inclusive credit alleviates liquidity constraints, thus reducing the risk of debt defaults caused by income shocks [30,31]. These policy combinations aim to enhance the accessibility, convenience, and cost-effectiveness of financial services, helping households establish financial buffer mechanisms, thereby reducing the risk of worsened repayment ability due to income disruption or unexpected expenditures. At the same time, based on resource-based theory, high-net-worth households strengthen productive investments through inclusive financial tools, forming a cycle of "asset appreciation—credit expansion". However, low-net-worth households may experience the "Matthew effect", where policy benefits are crowded out by emergency expenditures, exhibiting "diminishing marginal returns" [32-34]. Differences in net assets affect the efficiency of converting financial resources, leading to heterogeneous policy effects. Based on this, the paper proposes the following hypothesis:

Hypothesis 1: Inclusive finance policies can alleviate household financial vulnerability.

Hypothesis 2: The moderating effect of household net assets is one of the mechanisms through which inclusive finance policies influence household financial vulnerability.

3. Research Design

3.1. Sample Data

The sample data is sourced from the China Family Panel Studies (CFPS) conducted by Peking University. As a nationwide and comprehensive social tracking survey, the project aims to track and collect data across three levels: individual, household, and regional, providing a detailed and accurate reflection of the current state of household financial vulnerability in China. Based on the CFPS data from 2010 to 2020, this paper explores the effects of inclusive finance policies on household financial vulnerability. In order to ensure the reliability of the empirical results, this paper excludes missing and outlier values, ultimately selecting a sample of 29,526 households from 2010 to 2020.

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

3.2. Variable Description

3.2.1. Dependent Variable

Table 1. Description of Control Variables

Variable Type	Variable Name	Variable Name	Variable Description
Household Head's Personal Characteristics Variables	Age	Household Head's Age	Represented by the actual age of the respondent in the survey year
	Gen	Household Head's Gender	Male = 1, Female = 0
	Edu	Household Head's Education Level	Education Level: 0 = Illiterate/semi-illiterate, 1 = Primary school, 2 = Middle school, 4 = High school/secondary technical school/vocational high school, 5 = College diploma, 6 = Bachelor's degree, 7 = Master's degree, 8 = Doctorate
	Health	Household Head's Health Status	Assigned values from 1 to 5, with higher values indicating better health
	Medsure_dum	Whether the Household Head Has Health Insurance	Whether the household head has purchased health insurance
Household Overall Characteristics Variables	Mar	Marital Status	Marital Status: 1 = Married, 0 = Unmarried
	Fml	Household Size	Household Size
	Weak	Number of Unhealthy Household Members	Number of Unhealthy Household Members
	Rural	Household Registration Type	Household Registration Type: 1 = Agricultural household registration, 0 = Non-agricultural household registration
	Old	Elderly Population Size	Elderly Population Size
	Exp	Logarithm of Total Household Expenditure in the Past 12 Months	The logarithm of total household expenditure in the past 12 months
Regional Characteristics Variables	Uois	Industrial Structure Upgrading	Overall Upgrading of the Industrial Structure
	Ais	Advanced Industrial Structure	Advancement of the Industrial Structure

The dependent variable, HFV_{it}, represents "Household Financial Vulnerability". Following the approach of Zhang Ji et al., it is assigned values based on the household's accumulation of financial risks and its ability to respond to risk shocks [35]. The specific calculation steps are as follows: A comprehensive measurement system for household financial vulnerability is constructed from two perspectives: financial safety margin and repayment ability. First, based on the principle of dynamic cash flow balance, the household financial safety margin (*HFMit*) is defined as the difference between pure income (*INCit*) and basic expenditures and liabilities (*EXPit*), i.e., *HFMit* = *INCit* - *EXPit*. Where *INCit* includes all types of income, such as wage, business, and property income, and *EXPit* includes consumption expenditures, transfer payments, and fixed debt repayments (such as housing loans and financial liabilities). This indicator reveals the degree of household risk accumulation by quantifying the current income-

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

expenditure gap. Secondly, the repayment ability indicator (*HSit*) is introduced to represent risk response resilience, defined as *HSit* = (*INCit* + *LAit*) / *EXPit*, where LAit represents liquid assets (cash, deposits, and highly liquid financial assets), reflecting the household's ability to cope with risk shocks through asset liquidation. Finally, based on the dual-threshold cross-determination rule, household vulnerability is classified into three levels: When $HFMit \geq 0$, it is assigned a value of 0 (no vulnerability, income covers expenditures); when $HFMit < 0$ and $1 \leq HSit < (1 + LAit/EXPit)$, it is assigned a value of 1 (low vulnerability, assets partially mitigate risk); When $HFMit < 0$ and $HSit < 1$, it is assigned a value of 2 (high vulnerability, dual imbalance in income-expenditure and assets). This classification standard, by coupling flow-type (*HFM*) and stock-type (*HS*) indicators, overcomes the limitations of a single-dimensional measurement and more accurately identifies the dynamic evolution path of household financial crises.

3.2.2. Key Explanatory Variables

The penetration of inclusive finance policies in eastern regions (such as digital financial service coverage and inclusive credit issuance density) is significantly higher than in the western regions. Furthermore, policy tools (such as mobile payment pilots and microfinance innovations) are first piloted in the east, thus the eastern region can be considered the "high-intensity intervention group" and the western region the "low-intensity control group". Additionally, following the approaches of Li Jianjun et al. and Qian Haizhang et al., the policy implementation time is treated as an exogenous shock. Given the uneven regional economic development in China, there is significant heterogeneity in the impact of inclusive finance policies on the developed eastern regions versus the underdeveloped central and western regions [27,36]. Therefore, core explanatory variables are constructed by setting regional dummy variable "*Treat*" and time dummy variable "*Time*" Specifically, eastern provinces such as Beijing, Tianjin, Hebei, Shandong, Jiangsu, Zhejiang, Shanghai, Fujian, Guangdong, and Hainan are designated as the experimental group (*Treat*=1), while other regions in the central and western areas are the control group (*Treat*=0); In terms of the time dimension, 2010, 2012, and 2014 are set as the pre-policy implementation period (*Time*=0), and 2016, 2018, and 2020 as the post-policy implementation period (*Time*=1). The interaction term of *Treat* and *Time*, *Treat* × *Time*, serves as the core explanatory variable to identify the differentiated implementation effects of inclusive finance policies across regions. This variable setting takes into account both the time dimension of the policy shock and the regional heterogeneity characteristics, effectively controlling for potential confounding factors, thus providing a scientific basis for the evaluation of policy effects.

3.2.3. Moderating Variables

Household net assets (*Ta*) are defined as total assets (including financial assets, real estate, and other physical assets) minus total liabilities. The data is sourced from micro-level household financial survey data, and logarithmic transformation is applied to eliminate heteroscedasticity.

3.2.4. Control Variables

The control variables in this study will be selected from three dimensions: individual characteristics, family characteristics, and regional characteristics.. Household head's personal characteristics include age, gender, education level, health status, and health insurance purchase status; Household characteristics include marital status, household size, number of unhealthy household members, household registration type, elderly population size, and the logarithm of total household expenditure in the past 12 months; Regional characteristics include industrial structure upgrading (*Uois*) and advancement of the industrial structure (*Ais*). The specific setting of the variables is shown in Table 1.

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

3.3. Descriptive Statistics

Descriptive statistics for each variable are detailed in Table 2. The data shows that the mean of household financial vulnerability is 0.099, with most households falling under the categories of no financial vulnerability or low financial vulnerability. The mean of inclusive finance policies is 0.164, with the control group comprising the majority of the experiment. The average age of the household head is 51.311 years, with the oldest being 95 years and the youngest being 14 years. Most household heads are male, with an average education level of 1.619. The general education level is relatively low, and there is limited knowledge and attention to financial matters. The average health status of household heads in the sample is 3.027. Most households have purchased health insurance and are married. The average household size is 3.863, with an average of 0.455 unhealthy household members and 0.403 elderly members. Most households have agricultural household registration.

Table 2. Descriptive Statistics of Variables

Variable	N	Mean	SD	Min	Max
HFV	29520	0.099	0.422	0.000	2.000
DID	29526	0.164	0.370	0.000	1.000
Age	29516	51.310	13.030	14.000	95.000
Gen	29526	0.586	0.493	0.000	1.000
Edu	19656	1.619	1.279	0.000	7.000
Health	29479	3.027	1.280	1.000	5.000
Medsure dum	29526	0.930	0.255	0.000	1.000
Mar	29390	0.887	0.316	0.000	1.000
Fml	29526	3.863	1.804	1.000	16.000
Weak	14763	0.455	0.670	0.000	4.000
Rural	14647	0.765	0.424	0.000	1.000
Old	14763	0.403	0.690	0.000	3.000
Exp	28414	10.490	0.974	5.193	15.460
Ta	27812	12.153	1.567	0.000	18.199
Uois	29526	2.365	0.122	2.145	2.836
Ais	29526	1.125	0.490	0.500	5.297

3.4. Econometric Model

This paper aims to explore the impact of inclusive finance policies on household financial vulnerability in China. Currently, such studies typically use traditional causal inference models for policy empirical evaluation, but these models have many drawbacks. Therefore, this paper adopts a dual machine learning model to investigate the impact of inclusive finance policies on household financial vulnerability in China.

Based on this, the paper uses a dual machine learning model to evaluate the effects of inclusive finance policies.

First, we construct the following partially linear dual machine learning model:

$$HFV_{it} = \theta_0 Treat \times Time_{it} + g(X_{it}) + U_{it} \quad (1)$$

$$E(U_{it} | Treat \times Time_{it}, X_{it}) = 0 \quad (2)$$

Here, iii represents the city, and ttt represents the year. HFV_{it} denotes the dependent variable, which is household financial vulnerability; $Treat \times Time_{it}$represents the treatment variable, which is the inclusive finance policy variable. The experimental group is 1, and the control

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

group is 0. θ0 is the key treatment coefficient of interest. X_{it} is the set of high-dimensional control variables, and the specific form $g(X_{it})$ must be estimated using machine learning algorithms. U_{it} is the error term, with a conditional mean of 0. Estimating equations (1) and (2), the treatment coefficient estimator is obtained as:

$$\theta_0 = (\frac{1}{n}\sum_{i\in I,t\in T} Treat \times Time_{it}^2)^{-1}\frac{1}{n}\sum_{i\in I,t\in T} Treat \times Time_{it}[HFV_{it} - g(X_{it})] \quad (3)$$

4. Empirical Analysis

4.1. Baseline Regression

This paper uses a dual machine learning model to assess the impact of inclusive finance policies on household financial vulnerability, with a sample split ratio of 1:4. The Lassocv algorithm is used to predict and solve the main and auxiliary regressions, with the regression results detailed in Table 1. Model (1) controls for time fixed effects and individual fixed effects across the full sample period. The results show that the regression coefficient of inclusive finance policies on household financial vulnerability is significantly negative and holds at the 10% statistical significance level, indicating that inclusive finance policies can alleviate household financial vulnerability. Building on model (1), model (2) further controls for the quadratic terms of the control variables. The introduction of quadratic terms captures the nonlinear interaction between covariates and policy effects (such as the diminishing marginal effect of income growth on vulnerability), correcting the underestimation bias in the base model. The empirical regression coefficient remains significantly negative and significant at the 1% level.

Table 3. Baseline Regression Results

Variable	(1)	(2)
	HFV	HFV
DID	-0.027*	-0.047***
	(0.016)	(0.018)
Constant	-0.000	-0.000
	(0.003)	(0.003)
Sample Size	13,509	13,509
Control Variables (Linear Terms)	Yes	Yes
Control Variables (Quadratic Terms)	No	Yes
Time Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes

Note: *** p<0.01; values in parentheses are t-values, and the same applies hereafter.

4.2. Robustness Check

4.2.1. Change of Split Ratio (Cross-Validation)

To prevent bias in the dual machine learning setup from affecting the conclusions, this paper takes an approach of adjusting the split ratio to validate the robustness of the results. In the dual machine learning model, changing the split ratio allows for training and validating the model on different data subsets, which helps more accurately assess the model's performance on unseen data and enhance the model's generalization ability. Through multiple rounds of training and validation, changing the split ratio helps identify models that perform well on specific datasets but poorly on others, reducing the risk of overfitting. This paper adjusts the sample split ratio from 1:4 to 1:2 and 1:7, reducing selection bias and taking into account different parts of the sample household data, rather than relying solely on a single training split, thereby optimizing the overall estimation process.

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

Table 4. Change of Split Ratio

Variable	(1) Three-Fold Cross-Validation	(2) Eight-Fold Cross-Validation
	HFV	HFV
DID	-0.047***	-0.047**
	(0.018)	(0.018)
Constant	0.000	0.000
	(0.003)	(0.003)
Sample Size	13,509	13,509
Control Variables (Linear Terms)	Yes	Yes
Control Variables (Quadratic Terms)	Yes	Yes
Time Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes

Table 5. Change of Machine Learning Algorithm

Variables	(1) Random Forest	(2) Gradient Boosting	(3) Linear Support Vector Machine
	HFV	HFV	HFV
DID	-0.013***	-0.104*	-0.056***
	(0.003)	(0.054)	(0.010)
Constant	-0.007***	-0.000	0.163***
	(0.003)	(0.003)	(0.005)
Sample Size	13,509	13,509	13,509
Control Variables (Linear Terms)	Yes	Yes	Yes
Control Variables (Quadratic Terms)	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes

4.2.2. Modify the Machine Learning Algorithms

Algorithms such as Random Forest (RF) and Gradient Boosting Decision Trees (GBDT) can automatically select important covariates, thereby reducing omitted variable bias. For example, Wager S proposed the "Causal Forest" algorithm, which uses recursive partitioning to identify heterogeneous treatment effects (HTE), improving prediction accuracy by over 30% in policy evaluation compared to traditional methods. Support Vector Machines (SVM) can capture complex interaction effects between variables [37]. The Double Machine Learning (DML) framework, for instance, achieves nonlinear causal estimation through orthogonalization, significantly reducing the risk of model mis-specification [4]. Therefore, the previously used LassoCV algorithm for prediction is replaced with Random Forest, Gradient Boosting, and Linear Support Vector Machine.

After resetting the Double Machine Learning model, the regression results are detailed in Table 5. Clearly, neither the sample split ratio, prediction algorithm, model estimation form, nor endogeneity issues affect the conclusion that inclusive finance policies mitigate household financial vulnerability. These factors only slightly alter the magnitude of the policy effect, sufficiently confirming the robustness of the original conclusion. Therefore, Hypothesis 1 is confirmed.

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

5. Mechanism Analysis

In the aforementioned related studies, this research, through systematic theoretical and empirical analysis, has revealed the effect of inclusive finance policies in alleviating household financial vulnerability. However, the formation mechanism of household financial vulnerability is highly complex. Household net wealth, as a key factor reflecting the level of wealth accumulation and risk resilience, may play a crucial mediating or moderating role in the process through which inclusive finance policies impact household financial vulnerability. To analyze this complex relationship network and accurately identify the role of household net wealth in the transmission path of inclusive finance policies, this study will construct a moderation effect model. Through theoretical derivation and econometric analysis, it will delve into the mechanism by which household net wealth affects the impact of inclusive finance policies on household financial vulnerability. The model setup is outlined as follows:

$$HFV_{it} = \theta_0 Treat \times Time_{it} + \beta Ta_{it} + \gamma(Treat \times Time_{it} \times Ta_{it}) + g(X_{it}) + \varepsilon_{it} \quad (4)$$

$$E(\varepsilon_{it}|Treat \times Time_{it}, X_{it}) = 0 \quad (5)$$

Here, HFV_{it} represents household financial vulnerability; $Treat \times Time_{it}$ and $g(X_{it})$ are set as described above; Ta_{it} represents household net wealth, which is the selected moderating variable; $Treat \times Time_{it} \times Ta_{it}$ is the interaction term. The results of the moderation effect test in Table 6 show that household net wealth is one of the mechanisms through which inclusive finance policies alleviate household financial vulnerability. Therefore, Hypothesis 2 is confirmed.

Table 6. Mechanism Analysis Results

Variables	(1)	(2)	(3)
	HFV	HFV	HFV
DID	-0.027*	-0.047***	-0.220***
	(0.016)	(0.018)	(0.063)
Interaction Term			0.014**
			(0.005)
Constant	-0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.003)
Sample Size	13,509	13,509	12,802
Control Variables (Linear Terms)	Yes	Yes	Yes
Control Variables (Quadratic Terms)	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes

6. Conclusion and Recommendations

This paper employs the causal inference method of double machine learning to analyze in detail the impact of inclusive finance policies on household financial vulnerability and its underlying mechanisms. The conclusions of this study are as follows: First, inclusive finance policies can alleviate household financial vulnerability. This conclusion holds even after robustness checks with changes in the split ratio and machine learning algorithms, including adjustments to the training and test set ratios. Cross-validation using algorithms such as Random Forest and Support Vector Machines further supports a stable positive relationship between policy implementation and reduced household financial vulnerability. Second, household net wealth plays a positive moderating role in the impact of inclusive finance policies on household

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

financial vulnerability. Specifically, inclusive finance policies can optimize household financial asset allocation structures, alleviate liquidity constraints and credit threshold limitations, thereby enhancing households' ability to cope with sudden economic shocks and ultimately reducing financial vulnerability.

Based on the above conclusions, this paper proposes the following policy recommendations:

First, the government should implement differentiated inclusive finance policies based on the economic conditions and financial needs of different households. For low-income households and vulnerable groups, the focus should be on providing low-interest loans, financial literacy programs, and risk protection services to reduce their financial vulnerability. At the same time, the monitoring and evaluation of the implementation effectiveness of inclusive finance policies should be strengthened to ensure that the policies accurately benefit the target groups.

Second, the government should guide households in reasonably allocating their assets. Households should be encouraged to increase investments in stable financial instruments such as government bonds and funds, thereby optimizing household financial asset allocation and enhancing asset stability. At the same time, supervision of household investment behavior should be strengthened. The risk investment threshold for low-net-worth households should be raised, and high-net-worth households' risky investment behavior should be restricted to alleviate household financial vulnerability.

References

[1] Liu J, Chen Y, Chen X, et al. Digital financial inclusion and household financial vulnerability: An empirical analysis of rural and urban disparities in China[J]. Heliyon, 2024, 10(15).

[2] Yin Z, Zhang D. Financial inclusion, household poverty and vulnerability[J]. China Econ. Q, 2020, 20: 153-172.

[3] Chen S, Liang M, Yang W. Does digital financial inclusion reduce China's rural household vulnerability to poverty: An empirical analysis from the perspective of household entrepreneurship[J]. Sage Open, 2022, 12(2): 21582440221102423.

[4] Chernozhukov V, Chetverikov D, Demirer M, et al.Double/debiased machine learning for treatment and structural parameters[J]. The Econometrics Journal,2018,21(1):C1-C68.

[5] Minsky H P, Kaufman H. Stabilizing an unstable economy[M]. New York: McGraw-Hill, 2008.

[6] Atif M, Amir S. House of Debt:How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again[M]. University of Chicago Press:2020-05-20.

[7] Sabri M F, Abd Rahim H, Wijekoon R, et al. The mediating effect of money attitude on association between financial literacy, financial behaviour, and financial vulnerability[J]. International Journal of Academic Research in Business and Social Sciences, 2020, 10(15): 340-358.

[8] He L, Zhou S. Household financial vulnerability to income and medical expenditure shocks: measurement and determinants[J]. International journal of environmental research and public health, 2022, 19(8): 4480.

[9] Lei H,Shuyi Z .Household Financial Vulnerability to Income and Medical Expenditure Shocks: Measurement and Determinants[J].International Journal of Environmental Research and Public Health,2022,19(8):4480-4480.

[10] Jiang M, Sun R, Zhang B. Social networks and household financial decisions: evidence from China[J]. Journal of Applied Economics, 2022, 25(1): 58-92.

[11] Chen B, Zeng N, Tam K P. Do social networks affect household financial vulnerability? Evidence from China[J]. Finance Research Letters, 2024, 59: 104710.

[12] Wang Z. Digital finance, financing constraint and enterprise financial risk[J]. Journal of Mathematics, 2022, 2022(1): 2882113.

[13] Xu G, Feng L, Wang W, et al. Digital financial literacy and rural income inequality[J]. Sage Open, 2024, 14(3): 21582440241275642.

ISSN: 2692-7608 DOI: 10.6981/FEM.202511_6(11).0009

[14] Li B, Zhu T. Debt leverage, financial literacy and household financial fragility-an empirical investigation based on CFPS 2014 data[J]. Studies of International Finance, 2020, 7: 25-34.

[15] Lusardi A, Tufano P. Debt literacy, financial experiences, and overindebtedness[J]. Journal of pension economics & finance, 2015, 14(4): 332-368.

[16] Anderloni L, Bacchiocchi E, Vandone D. Household financial vulnerability: An empirical analysis[J]. Research in Economics, 2012, 66(3): 284-296.

[17] Jiang Y, Liu Y. Does financial inclusion help alleviate household poverty and vulnerability in China?[J]. Plos one, 2022, 17(10): e0275577.

[18] Li K, Mengmeng H, Huo J. Digital inclusive finance and asset allocation of Chinese residents: Evidence from the China Household Finance Survey[J]. Plos one, 2022, 17(5): e0267055.

[19] Van Rooij M, Lusardi A, Alessie R. Financial literacy and stock market participation[J]. Journal of Financial economics, 2011, 101(2): 449-472.

[20] Li J J, Peng Y C, Ma S C. Inclusive finance and economic development in China: Multidimensional connotation and empirical analysis[J]. Economic Research Journal, 2020, 55(4): 37-52.

[21] Ozili P K. Impact of digital finance on financial inclusion and stability[J]. Borsa istanbul review, 2018, 18(4): 329-340.

[22] Xun Z, Guanghua W, Jiajia Z, et al. Digital economy, financial inclusion and inclusive growth[J]. China Economist, 2020, 15(3): 92-105.

[23] Guo F, Wang J, Wang F, et al. Measuring China's digital financial inclusion: Index compilation and spatial characteristics[J]. China economic quarterly, 2020, 19(4): 1401-1418.

[24] Arun T, Kamath R. Financial inclusion: Policies and practices[J]. IIMB Management Review, 2015, 27(4): 267-287.

[25] Ozili P K .Financial inclusion research around the world: a review[J].MPRA Paper, 2020.

[26] Huang Z H, Song W H, Ye C H. The Impact and Mechanism of Digital Inclusive Finance on the Establishment of New Agricultural Operators-Evidence from 1845 Counties in China[J]. Financ. Res, 2023, 4: 92-110.

[27] Yang B, Wang X, Wu T, et al. Reducing farmers' poverty vulnerability in China: The role of digital financial inclusion[J]. Review of Development Economics, 2023, 27(3): 1445-1480.

[28] Song W, Huang Z, Ye C. The impact of digital finance use on rural household livelihood strategy selection: evidence from the China Rural Household Panel Survey[J]. 2023.

[29] Wang X, Mao Z. Research on the impact of digital inclusive finance on the financial vulnerability of aging families[J]. Risks, 2023, 11(12): 209.

[30] Kasri R A, Indrastomo B S, Hendranastiti N D, et al. Digital payment and banking stability in emerging economy with dual banking system. Heliyon, 8 (11), e11198[EB/OL].(2022)

[31] Wang Y Z, Lin X, Li Z H, et al. Digital financial inclusion facilitates common prosperity: From the perspective of liquidity constraint[J]. Economic Research Journal, 2024, 59(6): 49-68.

[32] Barney J. Firm resources and sustained competitive advantage[J]. Journal of management, 1991, 17(1): 99-120.

[33] Schularick M, Taylor A M. Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008[J]. American Economic Review, 2012, 102(2): 1029-1061.

[34] Jinlin Z, Xiaofan D, Jian L. Can digital inclusive finance promote common prosperity? An empirical study based on micro household data[J]. Journal of Finance and Economics, 2022, 48(07): 4-17.

[35] Ji Z, Xiao S, Yang C. Financial Risk Assessment of Middle-aged and Elderly Families under Dynamic Health Shocks[J]. Journal of Finance and Economics, 2022, 48(02): 153-168.

[36] Qian H, Tao Y, Cao S, et al. Theoretical and empirical analysis on the development of digital finance and economic growth in China[J]. The Journal of Quantitative & Technical Economics, 2020, 37(06): 26-46.

[37] Wager S, Athey S. Estimation and inference of heterogeneous treatment effects using random forests[J]. Journal of the American Statistical Association, 2018, 113(523): 1228-1242.