Digital Financial Inclusion, Household Financial Participation and Well-being: Micro-Evidence from China

Qunyang Du[a], Fangxing Zhou[a]*, Tianle Yang[a] and Min Du[b]

[a]*School of Economics, Zhejiang University of Technology, Hangzhou, China;* [b]*The Business School, Edinburgh Napier University, Edinburgh, UK*

*corresponding author: Fangxing Zhou

School of Economics, Zhejiang University of Technology, No. 288 Liuhe Road, Hangzhou, 310023, China

E-mail addresses: Zhoufangxing1997@163.com

Digital Financial Inclusion, Household Financial Participation and Well-being: Micro-Evidence from China

Though financial inclusion has drawn a lot of attention lately, especially in emerging markets, it remains unclear how it affects household well-being. This study investigates the connection between digital financial inclusion (DFI) and household well-being using two databases in China. The findings suggest that DFI is positively associated with household well-being. Mechanism analysis reveals that a rise in DFI facilitates household financial participation, thereby increasing the probability of household well-being. Our further empirical analysis demonstrates that groups with lower education and income levels are more significantly affected by DFI regarding household well-being. Overall, the research provides empirical evidence for the assertion that expanding financial inclusion in the digital economy era can promote social fairness and provide a basis for a vigorous expansion of financial inclusion in emerging economies.

1. Introduction

Since the 21st century, the World Bank has vigorously emphasised "financial inclusion", that is, fair and accessible financial services. Because of the underdevelopment of the capital market, the overall financing needs of Chinese households have not been met. Financial inclusion has flourished in recent years, benefiting from the high utilisation rate of financial technology, high fintech adoption rates and the digital technology linked to financial technology advances. According to the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), the average value of the Digital Inclusive Finance (DFI) Index at the municipal level in China was 155.35 in 2013, and the index rose to 220.01 in 2015 and then to 271.98 in 2017, making DFI a rapid development in just a few years. Financing has become easier

for people to acquire, afford, and sustain because of the rapid growth of financial services like mobile payments and internet lending. This has sparked a broad research interest in fintech and financial inclusion among many scholars. For example, economic growth (Stein and Yannelis, 2020; Van et al., 2021), information asymmetry problems between firms and financial institutions (Dupas and Robinson, 2013; Lee and Deng, 2017; Makina, 2019; Pagano, 1993) and households and financial institutions information asymmetry problems between (Jack and Suri, 2014; Pierrakis and Collins, 2013).

Although fintech and financial inclusion attract considerable attention from government authorities and academia in various countries, the relevant research is concentrated in the fields of household finance, corporate finance, and economic growth, and digital finance has received very little attention from researchers in welfare economics. For economists, well-being, despite being one of the most important characteristics of welfare economics, is a novel topic (Graham, 2009). Many studies have examined well-being in an economic context since Easterlin (1974) introduced the analysis of well-being into economics. According to the World Happiness Report[1] published by UN Sustainable Development Solutions Network (SDSN) and Earth Institute of Columbia University in 2012, 2013, 2015, 2016 and 2017, China ranked 112th, 93rd, 84th, 83rd and 79th among more than 150 happy countries in the world, respectively. In a vertical comparison, the happiness of Chinese residents has been on an upward trend. However, compared to other countries, the happiness of Chinese people is at a relatively low level. Combined with the latest release of the UN World Happiness Report in 2022, China's average global happiness ranking has risen to 72nd. Although this is a substantial increase, the demand for a better life remains unsatisfactory. Some researchers point out that despite the economic growth and increase in China's Gross

National Well-being, household well-being has not improved in China (Easterlin et al., 2012; Li and Raine, 2014). Therefore, with the developments in fintech and digital finance, what effect does DFI have on household well-being? What is the logic behind it? Which groups will benefit more? This study seeks to answer these questions.

We use China as the empirical context for our research because, over the last decade or so, the government has committed itself to promote financial innovation and deepening the structural reforms of the financial markets. China has made considerable progress in financial inclusion, and its leading role in the field of fintech is reflected in a high rate of fintech adoption, several world-leading fintech companies, and fintech centres (Amstad et al., 2020).

We combine data from China Household Finance Survey (CHFS) and the PKU-DFIIC, conducted in 2013, 2015, and 2017, to investigate the impact of DFI on household well-being. This research shows that the probability of household well-being rises by 16.74% for every unit (i.e., 100) increase in the DFI. Furthermore, a mediating effect test shows that growth in DFI facilitates household financial participation, thereby increasing the likelihood of household well-being. Lastly, we find that the effect of DFI on household well-being is significantly influenced by education and income levels. The well-being of households with lower income and education levels is more affected by an increase in DFI than those with higher income and education levels. Our findings provide empirical evidence supporting the claim that social equity is enhanced by greater financial inclusion.

Our study contributes to the related literature from several aspects. First, we employ large-scale household survey data to explore the factors that affect household well-being. Earlier studies attribute factors affecting well-being to individual characteristics, such as marriage (Gove et al., 1990), age (Diener and Suh, 1997), trust

(Guven, 2011), health (Bernanke, 2010), and education and gender (Gerdtham and Johannesson, 2001); macroeconomic variables, such as employment (Gielen and Van Ours, 2014; Tella et al., 2003); and social environment, such as housing and wealth inequality (Cheng et al. (2020) and air pollution (Cuñado and Gracia, 2013; Luechinger, 2010; etc.). This research investigates the causal relationship between DFI and household well-being in light of the rising levels of both in China. This study broadens the research boundaries of fintech and financial inclusion and helps to understand some of the reasons for the rise in Chinese household well-being. It also provides empirical evidence for developing countries to vigorously develop fintech and financial inclusion.

Second, we contribute to the literature by examining how an increase in DFI affects household well-being. To this end, we evaluate the channel via which financial inclusion affects household well-being and the impact of household financial involvement on wealth accumulation using the mediating effect test model. Furthermore, this research investigates the mechanisms through which DFI impacts household well-being based on the individual characteristics of household members, regional and geographic information, and income distribution. This research has significant ramifications for increasing social equity and promoting prosperity.

Finally, we also relate to the substantial growth of the Chinese financial inclusion literature in recent years. Liu et al. (2021) empirically found that DFI can significantly contribute to economic growth in China. Using survey data from the Qinba region, Han et al. (2019) find that financial inclusion affects poverty vulnerability by influencing farmers' risk coping capacity. Similarly, Wang and Fu (2021) analyze the connection between DFI and rural poverty vulnerability in China. They find that DFI reduces poverty vulnerability by increasing agricultural productivity, encouraging entrepreneurship, and encouraging off-farm employment. Huang and Zhang (2020) use

province data from 1985 to 2013 in China to conduct a panel cointegration approach and found that financial inclusion reduces the urban-rural income gap over the long term but widens it over the short term. Wang et al. (2022) investigated the effect of DFI on CO_2 emissions in Chinese cities using a spatial Durbin model. They found that industrial structure and economic growth are two ways that DFI can influence CO_2 emissions. Further study found that DFI benefits the poor and those lacking economic opportunities. In contrast to this literature, we use data from a representative microsample of Chinese households to study the effect of DFI on household well-being, particularly from the perspective of household financial participation. Our findings suggest that a rise in DFI facilitates household financial participation, thereby increasing the probability of household well-being.

The remainder of this research is divided into the following sections. The research hypotheses are presented in Section 2. Our sample and model setting are described in Section 3. The effect of DFI on household well-being is examined in Section 4 of this report. Section 5 describes the mediating effect test. Section 6 further analyses the variation in how DFI impacts different groups. Section 7 details the robustness tests. Section 8 concludes the paper.

2. Research hypotheses

The degree of financial inclusion has a feature known as financial availability, which represents the difficulties faced by individuals and businesses in a region in obtaining formal financial resources (Sarma, 2012). Thus, as financial inclusion rises, so does the financial resource availability of households, thereby increasing the likelihood that households will participate in the financial markets (Yue et al.，2022). The developments in digital finance have increased consumer choice, consumer

participation in financial activities, and household credit availability (Rajan et al., 2010). Investment income influences consumer spending through the income effect, which affects household well-being, much as financial assets assist investors in meeting their consumption needs.

Dupas and Robinson (2013) and Karlan and Zinman (2010) show that low-income individuals typically have higher incomes and consumption when they open accounts at financial institutions and utilise them more regularly. Li et al. (2020) also show that the rise in DFI in China has greatly increased household consumption. With an increase in consumption, household members obtain more material or spiritual satisfaction, thereby increasing household well-being (Guillen-Royo, 2008).

A decrease in income in comparison to social groups can make people unhappy (Luttmer, 2005; McBride, 2001), and a widening of the income gap lowers subjective well-being of households as a whole (Graham and Felton, 2006). Additionally, the growing wealth inequality has several detrimental repercussions (such as slower economic growth, a rise in crime, etc.), which lower subjective well-being (Jiang et al., 2012). According to Brockmann et al. (2009), during the period of strong economic growth in China, the income gap widened further, preventing a rise in people's subjective well-being. Conversely, an increase in relative income improves individual well-being (Easterlin, 1974). Furthermore, digital technology lowers the barriers to entry into the financial market, encourages low-income groups to start their businesses, boosts the creation of human capital, and eventually closes the income gap. Meanwhile, by lowering the cost of financial services, enabling rural inhabitants to use banking services (Burgess and Pande, 2005), and enhancing their well-being, an increase in financial inclusion dramatically reduces the income gap between urban and rural populations. Therefore, it is proposed that:

H1: Digital financial inclusion is positively associated with household well-being.

H2: Digital financial inclusion facilitates household participation in financial markets, thereby increasing household well-being.

Education is an important investment in household's human capital. However, households with tighter credit constraints and less wealth and income spend less on education (Becker and Tomes, 1979; Lochner and Monge-Naranjo, 2011). DFI greatly simplifies people's participation in financial markets without the need for very complex financial calculations, planning, and choices (Torres and Augusto, 2020). For those who are more educated, financial literacy is generally higher, so DFI helps them less. In contrast, those with less educated levels are at a loss for conducting financial markets due to weak financial literacy. As a result, DFI can significantly increase the financial participation of this group. Therefore, it is proposed that:

H3a: The well-being of households with lower education levels is more affected by a rise in digital financial inclusion than is the well-being of households with higher education levels.

The absence of reputable financial services in economically disadvantaged areas is one of the major causes of financial poverty (Beck et al., 2007; Khaki, 2017). Corrado and Corrado (2017) find that financial inclusion gives all households access to inexpensive and equitable financial products, particularly the most marginalised ones. Therefore, farmers' vulnerability to poverty and poverty alleviation are both positively impacted by financial inclusion (Han et al., 2019; Peng et al., 2022). Aisaiti et al. (2019) use a structured questionnaire to investigate Chinese rural farmers' financing intention and its factors, such as financial inclusion, financial knowledge, and the perceived benefits and risks of subscription finance. They show that promoting the participation of

social enterprises and developing digital finance in rural China can considerably reduce the transaction costs for farmers.

Traditional financial institutions do not focus on doing business with the poor. In contrast, financial inclusion uses financial technology to close the digital divide between the haves and have-nots, thereby addressing the impediments that prevent the poor from accessing financial services, such as high service costs, an imbalance between service efficiency and safety, and insufficient personal income (Hannig and Jansen, 2010). Thus, financial inclusion helps financial institutions lower the costs of their services and the obstacles to entry that often prevent low-income and disadvantaged populations from accessing financial resources (Demirgüç-Kunt and Klapper, 2012). In addition, financial inclusion can help the poor transfer funds over time to alleviate poverty (Mader, 2018). The main beneficiaries of financial inclusion are low-income groups/communities, rural economic entities, and small and medium-sized enterprises (Kapoor, 2014). These groups are relatively small in size, large in number, geographically dispersed, and vary widely in composition. In addition, they lack basic financial knowledge, such as an understanding of financial data or collateral assets. Therefore, the development of DFI helps low-income groups acquire financial knowledge, which aids in better pension planning, eases household credit obligations, and lessens the likelihood of poverty among households (Lusardi and Mitchell, 2014; Van Rooij et al., 2011). Therefore, it is proposed that:

H3b: The well-being of low-income households benefits more from digital financial inclusion than the well-being of high-income households.

3. Sample selection, descriptive statistics and model setting

3.1. *Sample selection*

The PKU-DFIIC data span three levels (province, city, and district/county) and cover the period 2011–2018. It is widely used in Chinese financial inclusion research (Guo et al., 2020; Huang and Chen, 2016; Xie et al., 2018).

We perform an empirical analysis of a combination of 2013, 2015, and 2017 CHFS and PKU-DFIIC data. The CHFS data come from the Southwestern University of Finance and Economics' Survey and Research Center for China Household Finance, which started conducting a biennial random sampling survey of Chinese household finances in 2009[2]. PKU-DFIIC database started in 2011[3]. This index allows for the analysis of digital financial innovation trends in China by quantifying the level of financial inclusion in the digital age, reflecting the level of service development, and considering regional balance. By quantifying the degree of financial inclusion in the digital age, reflecting the level of service development, and taking regional balance into account, this index enables the analysis of digital financial innovation trends in China.

The questions in CHFS questionnaire regarding respondents' subjective well-being were used to determine the explained variable in this research: household well-being. Measuring individual well-being by directly asking respondents whether they are satisfied with their lives is both traditional and reasonable in economics (Frey, 2010). The possible responses to the question 'Overall, are you happy?' are Answer 1: "very happy", answer 2: "happy", answer 3: "neutral", answer 4: "unhappy", and answer 2: "very unhappy". We set a dummy variable for household well-being that is equal to 1 if the response to the above question is answer 1 or answer 2, and 0 otherwise. Then, we calculate the relative size of happy households to unhappy households to obtain the annual household well-being in China. Household well-being in China increased from

1.309 in 2013 to 1.915 in 2017, and digital finance also developed rapidly in China during this period. This leads to the question: will the further increase in DFI significantly improve household well-being?

This research has three categories of control variables: personal information, household information, and provincial characteristics. Personal information includes age, (age)2/100, education level, marital status, and endowment insurance status. Age is calculated from the year of birth to the sample year. Education level is determined as follows: (1) no schooling is counted as 1 year; (2) primary school education is counted as 6 years; (3) junior high school education is counted as 9 years; (4) senior high, technical secondary, or vocational high school education is counted as 12 years; (5) an undergraduate degree at a university, junior college, or higher vocational education is counted as 16 years; (6) a master's degree is counted as 19 years; and (7) a doctoral degree is counted as 22 years. Household information comprises whether respondents own a car and/or a house, household size, and their total assets, income, consumption expenditure, and liabilities (all in yuan). The province characteristics are regional GDP (in yuan) and degree of environmental pollution, which is denoted by total wastewater discharged (in multiples of 10,000 tons) and is determined using resources and environment data from the National Bureau of Statistics.

3.2. *Descriptive statistics*

We excluded samples in which respondents were younger than 16 years and did not provide complete information in the well-being interview. In addition, we exclude samples in which the total assets, total income, and consumption expenditure are less than zero, as well as samples with missing three-year interviews. Table 1 gives the variables' descriptive statistics. The means of the respondents' subjective well-being during the sampling period is 0.620, indicating that people are generally happy. The

average educational level of the respondents is 8.784 years, which is slightly higher than junior high school level, 32.9% of the respondents have endowment insurance, and 86.3% are married. The average household size is 3.643 people, which is in line with the current national household size, 17.7% of the respondents own cars, and 93.2% of the households own a house.

3.3. *Model setting*

We adopt a logit panel binary selection model to analyse the impact of an increase in DFI on household well-being. We also adopt a linear probability model (LPM) as a reference, as the panel logit model tends to drop samples with unchanged outcomes. The core independent variable in the baseline model, i.e. DFI, is lagged by one because there can be reverse causality between the variables, which can lead to endogeneity, and obtain the following model setting:

$$Pr\ (Well-being_{ijt} = 1) = \Lambda(\alpha_0 + \alpha_1 \times DFI_{jt-1} + X_{ijt}\beta) \qquad (1)$$

where the ith household's subjective well-being in the jth province at time t is represented by the dependent variable $Well-being_{ijt}$, with a value of 1 indicating well-being and 0 indicating no well-being, and the independent variable DFI_{ijt} denotes the DFI of the jth province at time $t-1$. Finally, we divide the index by 100 in the empirical procedure based on the magnitude of the dependent variable. X_{ijt} is the control variable. The logical distribution's cumulative function is represented by $\Lambda(\cdot)$.

We use the mediating effect test to investigate whether an increase in DFI affects subjective well-being through increased household financial participation (HFP), where HFP indicates whether the household owns risk assets in the formal financial market. HFP is equal to 1 if the household owns demand deposits, time deposits, stocks,

funds, financial products, bonds, derivatives, non-RMB assets, precious metals, other financial assets or loans, otherwise it is equal to 0.

There are many methods for testing mediating effects, and each has its own advantages and disadvantages in terms of statistical test error and test power. The general applicability of any one method is low (MacKinnon et al., 2002). Based on test methodologies suggested by Baron and Kenny (1986), Judd and Kenny (1981), and Sobel (1982), the new comprehensive mediating effect test by Yan et al. (2021) can adjust for the likelihood of type-I and type-II mistakes due to its high statistical power. Therefore, we use this procedure to test the mediating effect in Equations (2), (3), and (4), and Figure 1 shows the verification procedure.

$$Well - being_{ijt} = a_0 + a_1 DFI_{jt-1} + a_2 X_{ijt} \tag{2}$$

$$Mediator_{ijt} = b_0 + b_1 DFI_{jt-1} + b_2 X_{ijt} \tag{3}$$

$$Well - being_{ijt} = c_0 + c_1 DFI_{jt-1} + c_2 Mediator_{ijt} + c_3 X_{ijt} \tag{4}$$

where $Mediator$ represents the intermediary variable, namely household financial participation.

4. Digital Financial Inclusion and Household Well-being

Table 2 presents the panel logit regression results estimated using Equation (1), where column (1) displays the fixed-effect regression findings. The DFI has a 0.8925 marginal effect on household well-being, and the significance level is 5%. This finding demonstrates that increasing DFI significantly increases the probability of household well-being. According to the LPM (column 4) results, each additional unit (i.e., 100) of the DFI increases the probability of household well-being by 16.74%. This result confirms H1. At the 1% level, *age* and *(Age)2/100* have marginal effects on household

well-being that are significant and are -0.0238 and 0.0261, respectively. In other words, age and household well-being have a U-shaped relationship: it first decreases and then increases after the age of 45.59. Household well-being is significantly impacted by marital status, and the magnitude of the coefficient of *Married* shows that marriage significantly improves household well-being.

The results of the panel binary fixed effect regression show that household size generally does not change over time, so there is no intra-group variance in the household size variable. Therefore, it is deleted from the fixed-effect model. As we hypothesised, the probability of a household's well-being in good shape is increased by higher total household assets and income. Similarly, an increase in total household debt decreases the probability of household well-being. Regional GDP per-capita growth significantly increases the probability of household well-being.

The random-effects regression results and mixed regression analysis are displayed in columns (2) and (3), respectively. We show that higher levels of education boost the probability of household well-being, whereas increasing household size negatively affects the probability of household well-being. In addition, we find that owning a house or a car significantly increases the probability of household well-being, which is related to wealth and household values in China. In contrast, we find that environmental pollution has a detrimental impact on mental and physical health, greatly reducing the probability of household well-being. Regression coefficients for the mixed regression and random-effects models have values and degrees of significance comparable to those for the fixed-effect model's regression coefficients. Therefore, we adopt the fixed-effect model in the subsequent regression analysis based on the Hausman test's findings.

5. Mediating effect test

Digital finance facilitates user payment for goods and services and encourages involvement in household finances. Moreover, as the digital economy has grown, customers can now buy high-risk funds and bank financial products without opening an account. Instead, they can earn money by investing a portion of their assets in money market funds that are extremely low-risk and easy to operate. Therefore, we posit that promoting household engagement in the financial market through increased DFI fosters household well-being.

We conduct a regression analysis of Equations (2), (3), and (4) to verify that the hypothetical increase in DFI does have a mediating impact on household well-being through household financial participation. According to Column 1 in Table 3, the DFI has a regression coefficient of 0.8925, and its significance level is 1%. The next step is a regression analysis according to the mediation test process. Column (2) shows the effect of the DFI on household financial participation. The DFI coefficient's value is substantial and positive, indicating that the DFI enhances the probability that households will participate in the financial market. Column (3) shows the effect of the DFI and household financial participation on household well-being. The effect of household financial participation and the DFI on household well-being is seen in column (3). Despite being significant and positive, the DFI coefficient value is smaller than the coefficient in column (1). At the 1% level, the effect of household financial participation on household well-being is also significant and positive, indicating that household financial participation mediates the effect of the DFI on household well-being. Similarly, columns (4) to (6) of Table 3 also show that household financial participation has a mediating role in the effect of DFI on household well-being.

6. Discussion of sample heterogeneity

6.1. *Heterogeneity analysis based on individual information classification*

We perform a regression analysis of heterogeneity according to political status and educational attainment. Although in the benchmark results, we do not find that an increase in educational attainment significantly brings well-being, educational attainment may be a mechanism through which increased DFI affects well-being. In China, Communist Party members are usually highly educated and are selected through various tests. Therefore, Party members are on average better educated than non-Party members. The corresponding outcomes are revealed in Table 4's Columns (1) and (2). In the two models, the interaction term between DFI and Party members has regression coefficients of -0.1083 and -0.0375, which, at the 10% and 1% levels, respectively, are significant. It demonstrates that the well-being of Party members is less affected by increasing DFI than non-Party members. We set the dummy variable *High education* according to the median value to reveal the moderating effect of education level on increased DFI and well-being. Its value is 1 when education level is higher than the median, and 0 otherwise. The corresponding outcomes are revealed in Table 4's Columns (3) and (4). In the two models, the DFI and education level dummy variables had regression coefficients of -0.1910 and -0.0454, which, at the 1% level, respectively, are both significant. It means the higher the level of education, the lower the impact of increased DFI on well-being. The above results empirically support education level as a mechanism for the impact of increased DFI on well-being, confirming H3a.

6.2. *Heterogeneity analysis based on regional information and income level classification*

We perform heterogeneity regression analyses by region, geography, and income level.

In the benchmark results, we find that increasing household income levels significantly improve household well-being. However, it can be inferred from the hypothesis section that income level has a moderating effect on increased DFI and household well-being. We first present the mechanism of income level through two indirect income classifications and verify it further through direct income level. First, households in rural areas have lower incomes than urban households. The corresponding outcomes are revealed in Table 5's Columns (1) and (2). In the two models, the interaction term between DFI and dummy variables in rural areas has regression coefficients of 0.0752 and 0.0288, which, at the 10% and 1% levels, respectively, are significant. This finding indicates that the well-being of rural households is more affected by the growth in DFI than urban households' well-being. Thus, H2a is supported. The western region of China is economically less developed than the eastern and central regions. The corresponding outcomes are revealed in Table 5's Columns (3) and (4). In the two models, the interaction term between DFI and dummy variables for the western region has regression coefficients of 0.3455 and 0.0657, which, at the 1% level, respectively, are both significant. This finding demonstrates that increasing DFI benefits households in the western region more than those in the eastern and central regions. Last, we set the dummy variable *High income* according to the median value to reveal the moderating effect of income level on increases in DFI and well-being. Its value is 1 when the income level is higher than the median, and 0 otherwise. The corresponding outcomes are revealed in Table 5's Columns (5) and (6). In the two models, the interaction term between DFI and dummy variables for income level has regression coefficients of -0.2137 and -0.0522, which, at the 10% and 1% levels, respectively, are significant. This finding suggests that the impact of growing DFI on well-being decreases as income level increases. The above results empirically support income level as a channel for an

impact of increased DFI on well-being, confirming H3b.

7. Robustness

We conduct two robustness tests. On the one hand, although we adopt the lagged first-order term of DFI as the explained variable to alleviate endogeneity in the benchmark model, the DFI may be affected by a household's desire for a better life and pursuit of well-being. In addition, DFI may be related to regional economic and social conditions, and its growth may be an indicator of the strength of the local economy. The probability of household well-being rises in proportion to locations with rapid economic development. Therefore, reverse causality could exist between household well-being and DFI. Further, there might be missing variable bias since several variables influence household well-being, even after accounting for unobservable factors such as regional economic and social disparities. Therefore, we adopt the instrumental variable (IV) method to overcome possible endogeneity. As an IV, we adopt the spherical distance between the capital cities of each province and Hangzhou, Zhejiang province. This approach mainly considers the following factors. First, distance will affect economic behaviour, but it will not change with economic development. Second, the distance between the respondent's city and Hangzhou is closely correlated with the amount of urban digital finance development, and it has no bearing on the locals' financial needs, thereby satisfying the two requirements of IV. As distances are cross-sectional and are not available in the panel data, we define a 'generalised distance' over time by multiplying the distance by the year. Table 6's Column (1) lists the results. In the correlation test of the IV, the Kleibergen-Paap rk LM statistic has P-values that are all less than 0.1, rejecting the null hypothesis that the IVs were not sufficiently identified. The Cragg–Donald Wald F statistic is greater than the empirical judgement value of 10, rejecting the null hypothesis of weak IV and indicating that the selection of IV is

appropriate. An increase in DFI significantly increases the probability of household well-being, suggesting that our results are robust.

On the other hand, in the average household, total assets, total income, and consumer spending should be greater than zero. Therefore, we exclude samples in which total assets, total income, and consumer spending are equal to zero and re-estimate the effect of DFI on household well-being through panel logit and LPM models. Columns (2) and (3) in Table 6 present the results of the logit and LPM model regression, which indicate that our baselines are robust. Last, as most households have zero or less debt, we run the regression again after removing the top and bottom 1% of the debt sample. The logit model's and the LPM model's corresponding regression outcomes are shown in columns (4) and (5). The findings demonstrate that, at the 10% and 5% levels, an increase in DFI significantly boosts the probability of household well-being. The above tests confirm that our findings are reliable.

8. Conclusion

We employ a panel binary choice model and a linear probability model, combining the CHFS and PKU-DFIC databases of 2013, 2015, and 2017, to study the causal effects of DFI on household well-being. Our findings suggest that DFI significantly increases the probability of household well-being. Specifically, if DFI increases by one unit (i.e. 100), the probability of household well-being will increase by 16.74%. Furthermore, a mediating effect test suggests that DFI facilitates household participation in financial markets, thereby increasing the likelihood of household well-being. Lastly, we find that education and income levels are how DFI affects household well-being. The well-being of households with lower education and income levels is more affected by DFI than the well-being of households with higher education and income levels. Overall, our findings provide empirical evidence that financial inclusion improves social equity.

According to the results of our empirical analysis, the probability of household well-being increases dramatically as DFI rises. However, studies find that participation in risky financial investments has a negative effect on household well-being. Therefore, regulators should strengthen the management of digital finance, evaluate the risk tolerance of investors and borrowing ability of entrepreneurs strictly, and prevent digital fraud. Our findings imply that higher DFI has a greater welfare benefit in rural areas, even though the pace of development of the DFI in rural areas is relatively modest. Hence, the government needs to aggressively encourage the development of rural digital finance and attend to concentrate on the financial requirements of rural households. The finding that greater DFI benefits low-income households more than high-income households demonstrates that DFI reduces inequities in financial development.

China's digital economy is growing rapidly. As digital finance continues to advance, it will help rural areas' access to credit, make it handier for micro and SMEs to obtain funding, and support the financial sector's sustainable and balanced growth. An increase in financial inclusion will assist the developing country to build a moderately prosperous society and win the battle against poverty. Our findings also imply that social justice will rise as inclusive finance develops in the age of the digital economy and build a more harmonious society by further improving and managing societal imbalances.

Declaration of Competing Interest

None.

Notes

References:

Aisaiti, G., L. Liu, J. Xie, and J. Yang. 2019. An empirical analysis of rural farmers' financing intention of inclusive finance in China: The moderating role of digital finance and social enterprise embeddedness. *Industrial Management and Data Systems* 119 (7):1535-1563. doi:10.1108/IMDS-08-2018-0374.

Amstad, M., G. Sun, and W. Xiong. 2020. The handbook of China's financial system. In The Handbook of China's Financial System. Princeton University Press.

Amstad, M., G. Sun, and W. Xiong. 2020. *The Handbook of China's Financial System.* Amstad, Marlene, Sun, Guofeng and Xiong, Wei, Princeton: Princeton University Press. https://doi.org/10.1515/9780691205847.

Baron, R. M., and D. A. Kenny.1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology* 51 (6):1173-1182. doi:10.1037/0022-3514.51.6.1173.

Beck, T., A. Demirgüç-Kunt, and R. Levine. 2007. Finance, inequality and the poor. *Journal of Economic Growth* 12 (1):27-49. doi:10.1007/s10887-007-9010-6.

Beck, T., R. Levine, and N. Loayza. 2000. Finance and the sources of growth. *Journal of Financial Economics* 58 (1-2):261-300. doi:10.1016/S0304-405X(00)00072-6.

Becker, G. S., and B. R. Chiswick. 1966. Education and the distribution of earnings. *American Economic Review* 56 (1/2):358-369.

Becker, G. S., and N. Tomes. 1979. An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy* 87 (6):1153-1189. doi:10.1086/260831.

Bernanke, B. S. 2010. The economics of happiness. Commencement address: Remarks by Ben S. Bernanke, Chairman, Board of Governors of the Federal Reserve System, at the University of South Carolina Columbia, South Carolina, 8.

Brockmann, H., J. Delhey, C. Welzel, and H. Yuan. 2009. The China puzzle: Falling happiness in a rising economy. *Journal of Happiness Studies* 10 (4):387-405. doi:10.1007/s10902-008-9095-4.

Burgess, R., and R. Pande. 2005. Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review* 95 (3):780-795. doi:10.1257/0002828054201242.

Cheng, Z., K. Prakash, R. Smyth, and H. Wang. 2020. Housing wealth and happiness in urban China. *Cities* 96:102470. doi:10.1016/j.cities.2019.102470.

Corrado, G., and L. Corrado. 2017. Inclusive finance for inclusive growth and development. *Current Opinion in Environmental Sustainability* 24:19-23. doi:10.1016/j.cosust.2017.01.013.

Cuñado, J., and F. P. De Gracia. 2013. Environment and happiness: New evidence for Spain. *Social Indicators Research* 112 (3):549-567. doi:10.1007/s11205-012-0038-4.

Demirgüç-Kunt, A., and L. F. Klapper. 2012. Measuring financial inclusion: The global findex database. World Bank Policy Research Working Paper, (6025).

Diener, E. D., and M. E. Suh. 1997. Subjective well-being and age: An international analysis. *Annual Review of Gerontology and Geriatrics* 17 (1):304-324. doi: 10.1891/0198-8794.17.1.304.

Dupas, P., and J. Robinson. 2013. Why don't the poor save more? Evidence from health savings experiments. *American Economic Review* 103 (4):1138-71. doi:10.1257/aer.103.4.1138.

Easterlin, R. A. 1974. Does economic growth improve the human lot? Some empirical evidence. In Nations and Households in Economic Growth (pp. 89-125). Academic Press.

Easterlin, R. A. 1974. Does Economic Growth Improve the Human Lot? Some Empirical Evidence. Paul A. David, Melvin W. Reder, Nations and Households in Economic Growth, Academic Press, Pages 89-125. https://doi.org/10.1016/B978-0-12-205050-3.50008-7.

Easterlin, R. A., R. Morgan, M. Switek, and F. Wang. 2012. China's life satisfaction, 1990–2010. *Proceedings of the National Academy of Sciences* 109 (25):9775-9780. doi:10.1073/pnas.1205672109.

Frey, B. S. 2010. Happiness: A revolution in economics. Frey, Bruno S. Cambridge. MA: MIT press.

Levinson, A. (2010), Happiness: A Revolution in Economics, by Bruno S. Frey. *Journal of Regional Science*, 50: 1015-1017. https://doi.org/10.1111/j.1467-9787.2010.00709_8.x.

Galor, O., and J. Zeira. 1993. Income distribution and macroeconomics. *Review of Economic Studies* 60 (1):35-52. doi:10.2307/2297811.

Gerdtham, U. G., and M. Johannesson. 2001. The relationship between happiness, health, and socio-economic factors: results based on Swedish microdata. *Journal of Socio-Economics* 30 (6):553-557. doi:10.1016/S1053-5357(01)00118-4.

Gielen, A. C., and J. C. Van Ours. 2014. Unhappiness and job finding. *Economica* 81 (323):544-565. doi:10.1111/ecca.12089.

Gove, W. R., C. B. Style, and M. Hughes. 1990. The effect of marriage on the well-being of adults: A theoretical analysis. *Journal of Family Issues* 11 (1):4-35. doi:10.1177/019251390011001002.

Graham, C. 2009. Why Societies Stay Stuck in Bad Equilibrium: Insights from Happiness Studies amidst Prosperity and Adversity. In IZA Conference on Frontiers in Labor Economics: Economics of Well-Being and Happiness, Washington, DC.

Graham, C., and A. Felton. 2006. Inequality and happiness: insights from Latin America. *Journal of Economic Inequality* 4 (1):107-122. doi:10.1007/s10888-005-9009-1.

Guillen-Royo, M. 2008. Consumption and subjective well-being: Exploring basic needs, social comparison, social integration and hedonism in Peru. *Social Indicators Research* 89 (3):535-555. doi:10.1007/s11205-008-9248-1

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

Guven, C. 2011. Are happier people better citizens?. *Kyklos* 64 (2):178-192. doi:10.1111/j.1467-6435.2011.00501.x.

Han, J., J. Wang, and X. Ma. 2019. Effects of farmers' participation in inclusive finance on their vulnerability to poverty: Evidence from Qinba poverty-stricken area in China. *Emerging Markets Finance and Trade* 55 (5):998-1013. doi:10.1080/1540496X.2018.1523789.

Hannig, A., and S. Jansen. 2010. Financial inclusion and financial stability: Current policy issues. ADBI Working Paper, Available at SSRN 259.

Huang, Y., and L. Chen. 2016. Digital financial inclusion index by Peking university. Beijing: Institute of Digital Finance, Peking University.

Huang, Y., and Y. Zhang. 2020. Financial inclusion and urban–rural income inequality: Long-run and short-run relationships. *Emerging Markets Finance and Trade* 56 (2):457-471. doi:10.1080/1540496X.2018.1562896.

Jack, W., and T. Suri. 2014. Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review* 104 (1):183-223. doi:10.1257/aer.104.1.183.

Jiang, S., M. Lu, and H. Sato. 2012. Identity, inequality, and happiness: Evidence from urban China. *World Development* 40 (6):1190-1200. doi:10.1016/j.worlddev.2011.11.002

Judd, C. M., and D. A. Kenny. 1981. Process analysis: Estimating mediation in treatment evaluations. *Evaluation Review* 5 (5):602-619. doi:10.1177/0193841X81005005.

Kapoor, A. 2014. Financial inclusion and the future of the Indian economy. *Futures* 56:35-42. doi:10.1016/j.futures.2013.10.007.

Karlan, D., and J. Zinman. 2010. Expanding credit access: Using randomised supply decisions to estimate the impacts. *Review of Financial Studies* 23 (1):433-464. doi:10.1093/rfs/hhp092.

Khaki, A. R. 2017. Does access to finance alleviate poverty? A case study of SGSY beneficiaries in Kashmir Valley. *International Journal of Social Economics* 44 (8):1032-1045. doi:10.1108/IJSE-10-2015-0277

King, R. G., and R. Levine. 1993. Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics* 108 (3):717-737. doi:10.2307/2118406.

Lee, D., and R. H. Deng. 2017. Handbook of Blockchain, Digital Finance, and Inclusion: Cryptocurrency, FinTech, InsurTech, Regulation, ChinaTech, Mobile Security, and Distributed Ledger. David Lee Kuo Chuen, Robert H. Deng. Academic Press. Pages 1000.

Li, J., and J. W. Raine. 2014. The time trend of life satisfaction in China. *Social Indicators Research* 116 (2):409-427. doi:10.1007/s11205-013-0300-4.

Li, J., Y. Wu, and J. J. Xiao. 2020. The impact of digital finance on household consumption: Evidence from China. *Economic Modelling* 86:317-326. doi:10.1016/j.econmod.2019.09.027.

Liu, Y., L. Luan, W. Wu, Z. Zhang, and Y. Hsu. 2021. Can digital financial inclusion promote China's economic growth?. *International Review of Financial Analysis* 78:101889. doi:10.1016/j.irfa.2021.101889.

Lochner, L., and A. Monge-Naranjo. 2012. Credit constraints in education. *Annual Review of Economics* 4 (1):225-256. doi:10.1146/annurev-economics-080511-110920.

Luechinger, S. 2010. Life satisfaction and transboundary air pollution. *Economics Letters* 107 (1):4-6. doi:10.1016/j.econlet.2009.07.007.

Lusardi, A., and O. S. Mitchell. 2014. The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature* 52 (1):5-44. doi:10.1257/jel.52.1.5.

Luttmer, E. F. 2005. Neighbors as negatives: Relative earnings and well-being. *Quarterly Journal of Economics* 120 (3):963-1002. doi:10.1162/003355305774268255.

MacKinnon, D. P., C. M. Lockwood, J. M. Hoffman, S. G. West, and V. Sheets. 2002. A comparison of methods to test mediation and other intervening variable effects. *Psychological Methods* 7 (1):83. doi:10.1037/1082-989x.7.1.83.

Mader, P. 2018. Contesting financial inclusion, *Development and Change* 49 (2):461-483. doi:10.1111/dech.12368.

Makina, D. 2019. The potential of FinTech in enabling financial inclusion. In Extending Financial Inclusion in Africa (pp. 299-318). Academic Press.

Makina, D. 2019. The Potential of FinTech in Enabling Financial Inclusion. Daniel Makina, Extending Financial Inclusion in Africa, Academic Press, Pages 299-318,https://doi.org/10.1016/B978-0-12-814164-9.00014-1.

Maldonado, J. H., and C. González-Vega. 2008. Impact of microfinance on schooling: Evidence from poor rural households in Bolivia. *World Development* 36 (11):2440-2455. doi:10.1016/j.worlddev.2008.04.004.

McBride, M. 2001. Relative-income effects on subjective well-being in the cross-section. *Journal of Economic Behavior and Organization* 45 (3):251-278. doi:10.1016/s0167-2681(01)00145-7.

Pagano, M. 1993. Financial markets and growth: an overview. *European Economic Review* 37 (2-3):613-622. doi:10.1016/0014-2921(93)90051-b.

Peng, H., J. Wang, L. Wen, P. Ding, and Y. Zhu. 2022. Is the Development of Inclusive Finance Truly Able to Alleviate Poverty?——an Empirical Study Based on

Spatial Effect and Threshold Effect. *Emerging Markets Finance and Trade* 58 (9):2505-2521. doi:10.1080/1540496x.2021.2002141.

Pierrakis, Y., and L. Collins. 2013. Crowdfunding: A new innovative model of providing funding to projects and businesses. Available at SSRN 2395226.

Rajan, R. G., and F. Lines. 2010. How hidden fractures still threaten the world economy. Princeton, New Jersey.

Sarma, M. 2012. Index of Financial Inclusion–A measure of financial sector inclusiveness. Centre for International Trade and Development, School of International Studies Working Paper Jawaharlal Nehru University. Delhi, India.

Sobel, M. E. 1982. Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology* 13:290-312. doi:10.2307/270723.

Stein, L. C., and C. Yannelis. 2020. Financial inclusion, human capital, and wealth accumulation: Evidence from the freedman's savings bank. *Review of Financial Studies* 33 (11):5333-5377. doi:10.1093/rfs/hhaa013.

Tella, R. D., R. J. MacCulloch, and A. J. Oswald. 2003. The macroeconomics of happiness. *Review of Economics and Statistics* 85 (4):809-827. doi:10.1162/003465303772815745.

Torres, P. and M. Augusto. 2020. Digitalisation, social entrepreneurship and national well-being. *Technological Forecasting and Social Change* 161:120279. doi:10.1016/j.techfore.2020.120279.

Van Rooij, M., A. Lusardi, and R. Alessie. 2011. Financial literacy and stock market participation. *Journal of Financial Economics* 101 (2):449-472. doi:10.1016/j.jfineco.2011.03.006.

Van, L. T. H., A. T. Vo, N. T. Nguyen, and D. H. Vo. 2021. Financial inclusion and economic growth: An international evidence. *Emerging Markets Finance and Trade* 57 (1):239-263. doi:10.1080/1540496x.2019.1697672.

Wang, X., and Y. Fu. 2021. Digital financial inclusion and vulnerability to poverty: evidence from Chinese rural households. *China Agricultural Economic Review* 14 (1):64-83. doi:10.1108/caer-08-2020-0189.

Wang, X., X. Wang, X. Ren, and F. Wen. 2022. Can digital financial inclusion affect CO2 emissions of China at the prefecture level? Evidence from a spatial econometric approach. *Energy Economics* 109:105966. doi:10.1016/j.eneco.2022.105966.

Xie, X., Y. Shen, H. Zhang, and F. Guo. 2018. Can digital finance promote entrepreneurship? Evidence from China. *China Economic Quarterly* 17 (4):1157-1180.

Yan, G., Y. Peng, Y. Hao, M. Irfan, and H. Wu. 2021. Household head's educational level and household education expenditure in China: The mediating effect of social class identification. *International Journal of Educational Development* 83:102400. doi:10.1016/j.ijedudev.2021.102400.

Yue, P., A. G. Korkmaz, Z. Yin, and H. Zhou. 2022. The rise of digital finance: Financial inclusion or debt trap?. *Finance Research Letters* 47:102604. doi:10.1016/j.frl.2021.102604.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Well-being	45720	0.620	0.485	0	1
DFI/100	45720	1.739	0.582	0.615	2.864
Age	45720	53.832	13.965	16	113
Age^2/100	45720	30.929	15.079	2.560	127.690
Education	45720	8.784	4.107	1	22
Endowment insurance	45720	0.329	0.470	0	1
Household size	45720	3.643	1.681	1	19
Cars	45720	0.177	0.382	0	1
Houses	45720	0.932	0.251	0	1
Married	45720	0.863	0.344	0	1
Log(Total assets)	45720	12.442	1.724	0	17.217
Log(Total income)	45720	10.190	1.964	0	15.425
Log(Nonproductive expenditure)	45720	10.357	0.930	0	14.215
Log(Total liability)	45720	2.686	4.675	0	18.603
Log(GDP per capita)	45720	10.854	0.407	10.050	11.768
Environmental pollution	45720	2.723	1.936	0.220	9.115

DFI data from PKU-DFIIC, household micro data from CHFS, and macro data from the National Bureau of Statistics of China.

Table 2. Digital financial inclusion and household well-being

	(1)	(2)	(3)	(4)
Well-being	FE	RE	POOLED	LPM
DFI	0.8925**	0.6114***	0.4309***	0.1674**
	(0.4301)	(0.0349)	(0.0277)	(0.0731)
Age	-0.1403***	-0.1518***	-0.1191***	-0.0238***
	(0.0122)	(0.0071)	(0.0050)	(0.0022)
Age^2/100	0.1533***	0.1651***	0.1298***	0.0261***
	(0.0124)	(0.0067)	(0.0048)	(0.0022)
Education	0.0082	0.0053	0.0028	0.0009
	(0.0086)	(0.0044)	(0.0030)	(0.0015)
Married	0.4008***	0.5474***	0.4502***	0.0659***
	(0.0693)	(0.0442)	(0.0311)	(0.0128)

Endowment insurance	0.0488	0.1822***	0.1146***	0.0052
	(0.0489)	(0.0368)	(0.0289)	(0.0082)
Total assets	0.0772***	0.1009***	0.0856***	0.0132***
	(0.0146)	(0.0108)	(0.0082)	(0.0026)
Total income	0.0333***	0.0559***	0.0468***	0.0063***
	(0.0085)	(0.0072)	(0.0057)	(0.0015)
Nonproductive expenditure	0.0520**	0.0237	0.0066	0.0095**
	(0.0228)	(0.0185)	(0.0142)	(0.0042)
Total liability	-0.0195***	-0.0292***	-0.0248***	-0.0031***
	(0.0037)	(0.0029)	(0.0022)	(0.0007)
Household size		-0.0111	-0.0104	
		(0.0100)	(0.0064)	
Cars	0.0569	0.3064***	0.3028***	0.0077
	(0.0539)	(0.0397)	(0.0297)	(0.0090)
Houses	-0.0194	0.1275**	0.1234***	-0.0009
	(0.0785)	(0.0584)	(0.0435)	(0.0132)
GDP per capita	0.1856	-0.1788***	-0.1518***	0.0681*
	(0.2290)	(0.0504)	(0.0337)	(0.0351)
Environmental pollution	-0.0031	-0.0168**	-0.0105*	0.0059
	(0.0901)	(0.0085)	(0.0055)	(0.0149)
Constant		1.9736***	1.7269***	-0.3378
		(0.5514)	(0.3707)	(0.3896)
Household FE	Yes			Yes
Year FE	Yes			Yes
N	24321	45720	45720	45720
R^2	0.066		0.045	0.517

Standard errors in parentheses. R2 is pseudo R-squared. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 3. Mediating effect test – household financial participation

	(1)	(2)	(3)	(4)	(5)	(6)
Model		Logit			LPM	
Dependent	Well-being	Household financial participation	Well-being	Well-being	Household financial participation	Well-being

DFI	0.8925**	3.0956***	0.8445**	0.1674**	0.5985***	0.1517**
	(0.4301)	(0.5332)	(0.4306)	(0.0731)	(0.0645)	(0.0733)
Household financial participation			0.1047***			0.0263***
			(0.0369)			(0.0067)
Controls	Yes	Yes	Yes			
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	24321	21243	24321	45720	45720	45720
R^2	0.066	0.247	0.067	0.517	0.534	0.518

Standard errors in parentheses. R2 is pseudo R-squared. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

Table 4. Digital financial inclusion and household well-being: heterogeneity by political status and education level

	(1)	(2)	(3)	(4)
Model	Logit	LPM	Logit	LPM
Well-being	Political status		Education level	
DFI	0.9040**	0.1719**	0.9395**	0.1819**
	(0.4303)	(0.0731)	(0.4306)	(0.0732)
Party member	0.1543	0.0578**		
	(0.1399)	(0.0228)		
DFI * Party member	-0.1083*	-0.0375***		
	(0.0649)	(0.0098)		
High education			0.3828***	0.0917***
			(0.1256)	(0.0213)
DFI * High education			-0.1910***	-0.0454***
			(0.0505)	(0.0081)
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24321	45720	24321	45720
R^2	0.066	0.518	0.067	0.518

Standard errors in parentheses. R2 is pseudo R-squared. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

Table 5. Digital financial inclusion and household well-being: Heterogeneity by region, geography, and income level

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Logit	LPM	Logit	LPM	Logit	LPM
Well-being	Region		Geography		Income level	
DFI	0.8785**	0.1585**	0.4746	0.0876	0.9505**	0.1811**
	(0.4304)	(0.0732)	(0.4355)	(0.0741)	(0.4308)	(0.0731)
Rural	0.0146	-0.0209				
	(0.2069)	(0.0348)				
DFI * Rural	0.0752*	0.0288***				
	(0.0445)	(0.0077)				
West			-0.6066***	-0.1084***		
			(0.1566)	(0.0274)		
DFI * West			0.3455***	0.0657***		
			(0.0561)	(0.0097)		
High income					0.4858***	0.1104***
					(0.0917)	(0.0153)
DFI * High income					-0.2137***	-0.0522***
					(0.0485)	(0.0080)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	24321	45720	24321	45720	24321	45720
R^2	0.066	0.518	0.068	0.518	0.068	0.518

Standard errors in parentheses. R2 is pseudo R-squared. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Digital financial inclusion and household well-being: Heterogeneity in effects due to income level

	(1)	(2)	(3)	(4)	(5)
Well-being	IV	Logit	LPM	Logit	LPM
DFI	1.1866***	0.8405*	0.1626**	0.8305*	0.1597**
	(0.3075)	(0.4365)	(0.0739)	(0.4400)	(0.0743)
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes

Year FE	Yes	Yes	Yes	Yes	Yes
Kleibergen–Paap rk LM statistic	1433.364				
P-value	(0.0000)				
Cragg–Donald Wald F statistic	2773.554				
Kleibergen–Paap rk Wald F statistic	2631.624				
N	45720	23532	44899	23175	44445
R^2	0.003	0.066	0.038	0.068	0.038

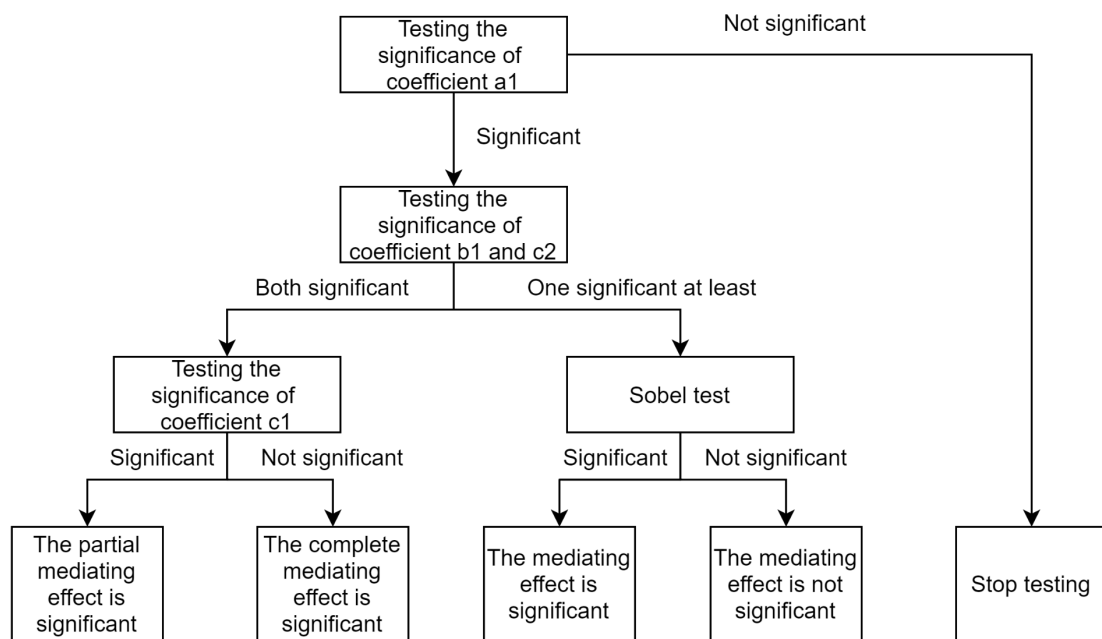Standard errors in parentheses. R2 is pseudo R-squared. * p < 0.10, ** p < 0.05, *** p < 0.01

<mark>Figure 1. Mediating effect test process</mark>