DIGITAL FINANCE AND FARMER CREDIT: EVIDENCE FROM RURAL CHINA

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ABSTRACT

Effectively addressing the financial development dilemma faced by rural areas has been a worldwide challenge. Based on the China Household Finance Survey (CHFS) and the Digital Inclusive Finance Index database, this paper investigates the impact of digital finance on farmers' productive formal credit demand and consumer formal credit demand by establishing a panel Probit model and an IV-Probit model with the introduction of instrumental variables to control for endogeneity. The results show that the development of digital finance has a significant dampening effect on farmers' productive formal credit demand and a significant promoting impact on farmers' consumer legal credit demand. Furthermore, the results of the robustness test also confirm the stability and reliability of the findings. At the same time, the heterogeneity of the two types of formal credit demand of farmers is further explored in this paper.

Keywords: Digital Finance, Farm Credit, Panel Probit Model.

INTRODUCTION

Although China has achieved some success in deepening the reform of rural finance, the financial difficulties faced by rural areas have not been completely reversed, and the problems of low financial coverage, high financing costs, and low efficiency of capital utilization have not been fundamentally resolved (Motel et al., 2014; Wan et al., 2021; Yiu & Lisa, 2016; Zhong & Dong, 2017). The current number of small and medium-sized financial institutions in rural areas is still insufficient, the level of competition is still relatively low, traditional financial institutions still have substantial control over lending rates and risks, the lending threshold faced by low-income people is still high, and rural low-quality customers still have great difficulties in accessing services provided by formal financial institutions (Fella & Gallipoli, 2014; Letki & MieriA, 2015). Even though the state has targeted policy preferences for this group, the results achieved are far less than expected. Rural finance currently has its inherent vulnerability. Rural areas face an imperfect investment environment, the establishment of rural credit files, and other facilities that constrain the allocation of financial resources to farming areas (Chen et al., 2020; Zoungrana, 2020).

On the other hand, most of the current measures formulated by relevant authorities focus on optimizing and reform rural financial institutions. In contrast, the attention to pastoral, financial needs has been neglected to some extent. Farmers' increasingly urgent demand for diversified financial products has, in turn, caused the relevant measures to fail to effectively and directly address the requirements of need, and supply and demand face a misalignment (Belton, 2012; Weber & Musshoff, 2017). As socioeconomic socioeconomic development continues and the supply-led demand market gradually transforms into a demand-driven demand-following market (Patrick, 1980), it is increasingly important to focus on and reform rural financial needs. At the same time, with the rapid development of digital technology and its wide application and

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regional penetration in various industries, it has become possible to solve the long-standing development bottlenecks faced by rural areas using digital finance (Li et al., 2020; Ren et al., 2018). Relevant research results on the development of the Internet in China show that as of December 2019, the size of rural Internet users in China was 222 million, and the Internet penetration rate in rural areas reached 38.4%. As a deepening of inclusive finance, inclusive digital finance, with the advantageous features of digitalization such as mobile payment and mobile banking, breaks through the relatively narrow coverage limitation faced by traditional financial services has gradually and widely affected the vast rural areas (Duncombe & Heeks, 2002; Whitacre et al., 2014). Digital finance can not only effectively reduce the cost of searching for information and various conversion costs for the users but also effectively connect the poor people; on the other hand, digital finance can also connect a large number of mobile terminals, collect user information to construct and improve the credit collection system of rural financial institutions, promote the flow of financial resources to rural areas, and improve the efficiency of resource allocation, so it can genuinely realize the characteristics of financial inclusion (Jiang et al., 2011). In recent years, the data related to China's digital financial inclusion index published by Peking University also shows digital finance's rapid development. Still, the current development model of digital finance has not reached maturity. The mechanism of digital finance affecting the real economy, such as resident employment, resident consumption, and social innovation, is not yet precise.

As a deepening of financial inclusion, digital finance, with its digital technology advantages, can theoretically effectively improve the challenges that rural financial services have been facing (Arner et al., 2019; Li et al., 2020). Digital finance can break through the geographical limitations of traditional financial coverage areas, reduce the switching and searching costs of economic participants, reach low-income and even poor people, and improve conventional financial service institutions (Berghman et al., 2012; Mamatzakis et al., 2016). Although the above qualitative analysis results show that the development of digital finance can indeed improve the current situation of rural financial development and thus affect the borrowing behavior of farmers, the conclusions mostly remain at the qualitative stage. There are no reliable quantitative conclusions on whether the development of digital finance directly affects farmers' credit demand, especially formal credit demand (Lu, 2018). Since previous indicators to effectively measure the effect of regional digital finance have not reached a standard widely accepted by all scholars, empirical studies related to digital finance are relatively lacking. Such studies have been facilitated by the publication of the Digital Finance Index by the Digital Finance Research Center of Peking University, but most of the current studies that use digital finance as an explanatory variable target mostly the macroeconomic level, the income gap level, the Therefore, this paper hopes to use the China Household Finance Survey (CHFS) micro database and the Digital Finance Index data to quantitatively study the impact of digital finance on the formal credit demand of rural households and fill the gap of empirical research in this area

Rural financial reform has always been one of China's economic reform priorities, and the construction and improvement of the rural financial system have gradually shown a positive trend with the revitalization of the rural economy. However, due to the poor economic infrastructure in rural areas, the relatively low-income level of rural households, the rather strict credit conditions, and the objective market law of banks and other formal financial institutions, the problems faced by rural economic development have not been fundamentally solved, especially the financial accessibility of low-income people, although the state has introduced

many related policies and measures to help the development of rural finance. In particular, the financial accessibility of low- income people has not been significantly improved, and most credit funds have flowed to regions with higher income or development levels, such as cities and towns (Eikemo et al., 2016; Israel & Sabine, 2016; Yazdi-Feyzabadi et al., 2018). And with the complete penetration of Internet technology, rural Internet coverage and the percentage of people using mobile for payments are increasing year by year. Suppose the emergence of digital finance can bring a turnaround in solving the dilemmas faced by rural financial reform. In that case, it will undoubtedly promote agrarian economic reform to a higher level, improve the operation and management of rural finance, and contribute to the rapid and healthy growth of the agricultural economy. Therefore, this paper expects that by conducting a quantitative analysis of the impact of digital finance on rural households' credit demand, we can obtain information on how and to what extent digital finance affects rural households' formal credit demand, and then provide policy references and suggestions for agrarian financial reform and promote further deepening of rural economic reform. This paper makes innovative attempts to select control variables, research perspectives, and robustness tests:

- 1. For the data treatment of the control variable whether to pay attention to financial information, previous studies directly chose the research on whether to pay attention to financial information in the questionnaire. Still, considering that the answers to such questions are more subjective, there may be data bias problems in this paper. However, considering that the answers to these questions are personal and may be biased, this paper adopts the three questions on the interest rate, inflation, and risk perception designed in the questionnaire. It takes the farmers who answer one of the questions as the sample of those concerned about financial information, which can alleviate the bias caused by subjectivity to a certain extent.
- 2. Previous articles mainly focus on shifting demand channels and direction to the group with smartphones in exploring the heterogeneous influence of digital finance on farmers' productive borrowing demand. As a deepening of inclusive finance, digital finance can cover groups that previously could not access formal financial services, especially the poor, and studies have shown that the development of digital finance can achieve inclusive growth, and rural low-income groups benefit more obviously, so this paper increases the sample division for the poor. In exploring the impact of digital finance on rural households' consumer credit demand, previous articles mainly focus on the differences between groups with different education levels. Studies have shown that liquidity constraints can inhibit rural households' consumption to a certain extent, so this paper increases the division of groups with different liquidity constraints based on previous studies.
- 3. Few articles have explored the impact of digital finance on rural households' borrowing behavior, and the robustness tests have primarily focused on the benchmark model. This paper uses the data on the breadth of coverage and depth of use of digital finance to test the robustness of the findings. It uses data from the China Labor Force Dynamics Survey (CLDS) database published by Sun Yat-sen University to test the robustness of the findings to verify the results.

LITERATURE REVIEW

The rural finance problem as a global problem has also been the focus of scholars' attention and research, and many relevant theories and explanatory approaches about rural finance have been proposed in different stages and times (Abate et al., 2016; Bateman, 2012; Khosa et al., 2019; Lamberte & Bouman, 1991). The relevant theory was first proposed by (Patrick 1980), who summarized two models of supply and demand in rural financial markets applicable to different levels of agricultural development in developing countries, namely the demand-following and the supply-leading models. The former model suggests that the economic demand of farmers causes the undersupply of relevant financial institutions and financial services and that the order of farmers should precede the supply of finance. The latter is the exact opposite model, which believes that the collection of relevant financial institutions and financial

services is ahead of the monetary demand of farmers. (Henderson & Jason, 2011; Wang et al., 2005) After analyzing the importance of the rural financial need to rural economic development, he summarized the characteristics of farmers' financial condition and accordingly pointed out the shortcomings of the current U.S. rural financial market and proposed three measures for improvement, namely, increasing the loanable funds of community banks, vigorously promoting the construction of rural Heidues et al. (1997) conducted a quantitative and qualitative analysis of the determinants of financial services and product accessibility for pastoral economic agents in Romania, focusing empirically on farm household income, loan use, and factors affecting loans and farm savings, while the qualitative description considered the relationship between the supply side of rural financial services and farm households, as well as farm households' participation in the rural financial market at the (Ray & Floro, 2010). Ray & Floro (2010) found that the lack of supply of traditional loans and institutional weaknesses of microfinance institutions have led to the participation of informal financial institutions in the rural financial capital market. However, their promotion is still hindered in many ways. He argues that such financial institutions should be assisted to improve their management and integration into the overall rural financial capital market and summarizes the idea of formalizing informal finance. Negrusa & Oreffice (2010) concludes that the key to clarifying the relationship between economic agents in developing countries lies in the deepening of the rural financial market and suggests that the main reason for the current lending problems of pastoral economic agents is the lack of formal financial supply. Dermineur, (2014), through the transformation of agricultural credit by commercial banks after 2000, the increase in the rural credit market was primarily derived from indirect financing. Although the scale of direct funding was also increasing, its mainstay was still corporate financing. The proportion of small and marginal farmers did not increase significantly.

Most of the studies on digital financial inclusion have focused on the construction of indicator systems, the influencing factors, and the effect of digital finance on poverty alleviation. The studies specifically on rural areas are not well developed. Dermineur, (2014) constructed eight indicators, including the number of financial institution outlets to evaluate the level of regional financial services. Gr & Ma (2020) found by studying the effect of financial inclusion on the behavior of low- income people and micro and small businesses that if residents have a frequently used financial account, this economic agent may lead to higher consumption, income, and investment. Chakravarty & Pal (2013), for the first time, measured the financial inclusion index in 45 countries using three dimensions: product exposure, usage effects, and geographic penetration, which also provided a reference for subsequent studies and found a significant positive correlation between financial inclusion and the modernization of socioeconomic socioeconomic development. Murphy (2005) found that the development of inclusive digital finance can significantly increase the income level of low-income people through an empirical analysis of data from Ethiopia. Gr & Ma (2020) found a significant poverty alleviation effect of financial inclusion through an empirical study of Asian developing countries after including the urban-rural income gap in the poverty measure. Amaeshi et al. (2016) on the other hand, verified the poverty reduction effect of digital financial inclusion using data from Asia, the Americas, and Latin America.

Many scholars have explored digital finance after its emergence. Still, most of the studies have focused on constructing an evaluation index system for the development degree of inclusive digital finance and the investigation of the factors influencing inclusive digital finance. At the same time, because the evaluation index system of digital finance is not conclusive, the existing

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literature focuses on the study of financial inclusion as an impact factor variable without fully considering the typical digital features of digital finance, and further empirical studies on the impact mechanism of digital financial inclusion based on this are limited (Hunter, 2007; Oliveira et al., 2014; Rubera et al., 2012). Most of the current research on the impact mechanism of traditional inclusive finance focuses on four aspects: macroeconomic level, income gap level, financial regulation level, and Internet+ level, and the micro-level impact is less explored. However, due to the availability of data on digital finance, most of the studies are still focused on the descriptive analysis of the impact. In terms of qualitative research, (Zhang et al., 2020) found that financial innovations that take advantage of digital financial technology can effectively reduce the cost of financial services, promote the coverage of rural financial services to poor and remote areas, and enhance the accessibility of financial services to previously disadvantaged groups, among others. Ryder, (2008) pointed out that digital finance uses its technological advantages to expand the coverage of financial services, reduce the cost of financial services, improve economic efficiency, include what traditional financial institutions consider low-quality customers in financial services, and reduce the exclusion effect on low-quality people. The study by Du Plessis et al. (2015), on the other hand, found the influence of the degree of transportation development on farmers' choice of borrowing channels; the more developed the transportation, the easier it is for farmers to access traditional financial services, so farmers tend to choose conventional financial media, while farmers in less accessible areas turn to use Internet finance for reasons such as the lack of traditional financial coverage.

In terms of quantitative research, Elliehausen & Hannon (2018), starting from the function of consumer finance, found that Internet finance can significantly affect the consumption structure of economic agents and promote the upgrading of consumption structure. Urban residents are more affected considerably than rural residents. He also found the impact of different areas of Internet finance on the consumption structure of urban and rural residents (Feldman, 2014). Feldman (2014) empirically investigates the relationship between digital finance and entrepreneurial behavior and finds that the development of digital finance has a more pronounced effect on entrepreneurship in provinces with lower urbanization rates. After empirically studying the impact of digital finance on residential consumption, (Xiang & Lawley, 2019) found that digital finance significantly increased residential consumption through the influence mechanism of alleviating residential liquidity constraints and improving residential payment convenience during the sample period. The study by Aitken et al. (2010) further found that digital finance can increase rural households' consumption by alleviating the Aitken et al. (2010) further found that digital finance can promote entrepreneurial behavior among rural households by helping the credit constraints faced by rural families and increasing the financial information available to them and that the effect is more pronounced for groups with lower levels of human capital.

VARIABLE SELECTION AND MODEL CONSTRUCTION

Data Sources

The data used in this paper are mainly from three databases: firstly, the data on rural households' borrowing and related characteristics are from the "China Household Finance Survey" database, which is currently available for 2011, 2013, 2015, 2017, and 2019, considering that digital finance started to affect rural areas after 2013 as mentioned above. Considering that digital finance started to affect rural areas after 2013, this paper uses 2013, 2015, 2017, and

2019. The samples are selected from the farm households that participated in the survey in all four periods. Secondly, the Digital Inclusive Finance Index data is obtained from the Peking University Digital Inclusive Finance Index database, which is synthesized from the digital financial service data provided by Ant Financial and contains data across provincial, urban, and county areas from 2011 to 2020. Due to data availability, the two databases are combined by year and household code to obtain household panel data for 2013, 2015, 2017, and 2019 and cover the provincial level. Finally, data on the city-level control variables of the sample are obtained from the National Bureau of Statistics of China and the China Urban Statistical Yearbook.

Identification of Farmers' Financial Needs

As mentioned in the literature review section, identifying rural financial needs has been a hot topic of research in this field. Under the premise of the existence of rural financial supply, the fact that farmers do not take out loans does not necessarily mean that farmers do not need financial credit; there are at least two other possible scenarios for the occurrence of this situation: one is that farmers apply for loans but are rejected because the process is troublesome or farmers do not meet the requirements of banks and other financial institutions; the other is that farmers' needs for loan terms, interest rates, etc. cannot be met and they do not take out loans. The other is that the farmer's demand for loan terms and interest rate cannot be met, and the loan is not granted. In previous studies, scholars have divided farmers' credit willingness into more detailed categories, and further classified farmers' credit demand into effective demand, potential demand, and hidden demand, thus including farmers who "consider loans too troublesome, have high costs for other loans, and are not familiar with creditors" into the scope of credit demand. Some scholars have also made a stricter classification of farmers' needs, arguing that farmers who "have not applied for a loan because they are afraid of not being able to repay" should not be included in the range of credit needs.

The question in this paper is whether the development of digital finance can affect farmers' credit demand, so special attention needs to be paid to the problem of sample selection bias in the sample selection. According to the questionnaire design of CHFS, this paper defines farmers with legal credit needs into three categories: those who already have formal credit; those who are willing to take out a loan but have not done so because they "do not know how to apply for a loan, the loan process is troublesome, the repayment period or method does not meet their needs, or they do not know the bank/credit union staff"; and those who have taken out a credit but have only done so. The other category is farmers who have implemented recognition but are rejected only because they "do not know the bank/credit union staff." According to previous studies, this identification can cover all farmers with credit willingness, especially those who have credit willingness but failed to obtain loans due to non-self factors. Therefore, it can effectively alleviate the problem of biased estimation coefficients due to sample selection bias.

Data Processing

Based on the identification method mentioned above, this paper further subdivides the formal credit demand of farmers into productive credit demand and consumer credit demand. Given the availability of data, the credit demand arising from "agricultural production and operation" and "industrial and commercial production and operation" is classified as The credit demand generated by "agricultural production and business" and "industrial and commercial

production and business" is classified as productive credit demand; the credit demand generated by "housing purchase," "automobile purchase," "children's education," "medical treatment" and "credit card" is classified as productive credit demand. The credit demand generated by "housing," "car," "children's education," "medical," and "credit card" is classified as consumer credit demand, and the percentage of farmers with two types of formal credit demand is thus calculated. Since the questions about risk attitude and financial knowledge in the questionnaire are targeted at the respondents, and it is clearly stated in the questionnaire that the respondents are the most knowledgeable about the household financial situation, the respondents are taken as the head of the household in the sample period. The questionnaire surveyed a sample of 16 years old and above, so after eliminating the selection under 16 years old and removing some missing values, this paper finally obtained 21,996 samples and constructed balanced panel data accordingly.

Variable Description

The two explanatory variables in this paper are productive formal credit demand and consumer formal credit demand, which are identified in Section II of this part. The explanatory variables in this paper are the digital financial inclusion index, which includes both the primary digital financial inclusion index and the secondary digital financial inclusion index "depth of digital financial use," "breadth of digital financial coverage," and "depth of digital financial coverage" included in the depth index. Payments", "Funds," "Insurance," "Credit," "Investment," and "Credit." Investment," and "Credit," this paper mainly uses the indexes at the provincial level.

The control variables in this paper are based on the previous literature, and the main variables selected are household characteristics, individual household head characteristics, and area-level variables. The household characteristics variables include household structural characteristics and household economic characteristics such as household size and labor force size, household per capita income, whether the household has a firm-type business, the number of vehicles owned by the family, whether the household owns its own home, household food expenditures, and the total value of durable goods. The individual characteristics of the household head variables take into account the influence of the person who knows the most about the household's financial situation on the economic behavior of the farm household, including age, gender, years of education, marital status, work status, risk preference, whether or not to pay attention to financial information, and whether or not to participate in health insurance. Finally, regional-level variables mainly control regional development status, specifically population density, gross per capita, gross product growth rate, degree of financial development, and urbanization rate. Table 1 below shows the results of descriptive statistics of the main variables.

Table 1 DESCRIPTIVE STATISTICS OF THE MAIN VARIABLES					
Variable Name	Variable Symbols	Average value	Standard deviation	Maximum value	Minimum value
Productive formal credit	pw	0.15	0.36	0.94	0
Consumer formal credit	CW	0.14	0.35	0.82	0
Digital finance index (logarithm)	fi	5.02	0.13	8.16	2.05
Age of household head	age	53.38	11.71	87.22	16.70
Gender of household head (male=1, female=0)	sex	0.9	0.3	1	0

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Years of education of household head	edu	7 1 7	3 39	12.49	0
Marital status of household head (married – 1	marry	0.01	0.28	12.12	0
waital status of nousehold field (filamed $= 1$,	тану	0.91	0.28	1	0
other = 0					
Household head's work status (employed $= 1$,					
other $= 0$)	work	0.85	0.35	1	0
Household head's risk preference (high risk					
preference = 1 , other = 0)	risk	0.09	0.29	1	0
Whether the household head is concerned about					
financial information (concerned = 1, other = 0)	inf or	0.11	0.32	1	0
Whether the head of household participates in					
medical insurance (participation=1, other=0)	me	0.95	0.22	1	0
Household income per capita	income	8977.04	12751.29	18565	565
Number of the household labor force	labor	2.9	1.49	5.5	0.2
Household size	num	4	1.82	11	0
Whether the household conducts company-type					
business (Yes=1, No=0)	company	0.09	0.29	1	0
Number of vehicles in the household	car	0.07	0.31	4	0
Whether the household owns its own home					
(yes=1, no=0)	house	0.97	0.12	1	0
Household expenditure on food (taken as log)	food	8.84	0.96	17.65	0.22
Value of durable household goods (take	durable	7.94	1.34	11.49	0.16
logarithm)					

Benchmark Model

The research question in this paper focuses on the impact of digital financial inclusion on farmers' formal credit demand, further divides the legal credit demand into productive and consumer markets, and constructs the corresponding 0 and 1 dummy variables. Therefore, this paper chooses to use the panel data probit model as the benchmark. The model is set up as follows.

Production / Consumption financial demand_{it} $\neg 0 \neg 1$ lnfinancialindex_{it} \neg 2head of household controls_{it} household controls_{it} city controls_{it}

The panel data are constructed by selecting farm households surveyed in 2013, 2015, 2017, and 2019, with i being each farm household and t being the year. In the model, production/consumption financial demand is the formal production credit demand and consumption credit demand of farm households, respectively, and is a 0,1 dummy variable, production/consumption economic demand equal to 1 means farm households have formal credit demand, and similar to 0 means they do not have legal credit demand. The Infinancialindex is the logarithm of the digital financial inclusion index at the provincial level; head of household controls is the control variable at the household level; household controls is the control variable at the household level; household controls are the control variable at the province and city of the farming household, and the random error of the model is the unexpected error of the model. Finally, the Γ_{ii} is the arbitrary error term of the model.

Model Endogeneity

In studying the macro impact class of digital finance, the problem of model endogeneity is inevitable. This paper analyzes the three possible factors causing endogeneity based on the problem under study and the model set.

The first type of reverse causality problem, the development of digital finance, can enhance or reduce farmers' demand for formal credit. At the same time, farmers' markets for traditional credit may also promote farmers' use of digital finance, so there is a potential reverse causality problem in this paper. Still, from the data source, farmers' credit data comes from farmers' micro databases. In contrast, the data of the digital financial inclusion index comes from provincial digital finance. Therefore, the two are from different databases. Thus, the reverse causality can be considered to be significantly reduced.

The second type of measurement error problem, firstly, the data source from the perspective of China Household Finance Survey and Research Center adopts a stratified, threestage sampling design method proportional to the scale measure (PPS) to ensure the accuracy and reliability of the sample, the construction of the digital finance index also combines subjective and objective assignment to determine the weight data, and the database data has robustness; secondly, from the perspective of the identification of the explanatory variables. As mentioned above, this paper includes farmers who are willing to borrow but fail to implement the loan behavior due to various factors in the sample, which can effectively alleviate the measurement error problem. From the above two aspects, it can be concluded that measurement error is almost non-existent in this model.

The third type of omitted variable problem, even if we introduce different control variables, there may still be variables related to digital finance in the residual term, causing bias in the estimated coefficients. This paper uses the instrumental variables approach to solve this problem. By referring to the previous research literature, two instrumental variables are used in this paper: for productive formal credit, the geographical distance from the capital city of each province to the city of Hangzhou is used as an instrumental variable by referring to (Borowiecki, 2013), while for formal consumer credit, a reference is made to (Michael & Stelios, 2018) to construct a "Bartik instrument," using the product of the first-order difference in time between the lagged PFC index and the PFC index as the instrumental variable. The reasons are as follows: for the distance instrumental variable, because the data of the digital finance index comes from Ant Financial, whose headquarters is located in Hangzhou, and scholars have found the spatial effect of the digital finance index through research, the farther the distance from Hangzhou, the more difficult it is to promote digital finance, so the distance is directly related to the digital finance development of the city, but the distance-like variable does not change with economic growth, which is consistent with the instrumental characteristics of the variables. For consumer formal credit demand, using distance as an instrumental variable does not pass the endogeneity test, i.e., the instrumental variable regression does not outperform the model without the introduction of instrumental variables, and the regression coefficients appear to have opposite signs, so the paper re-finds the instrumental variable of lag term and product for consumer credit demand.

RESULTS AND DISCUSSION

Productive Formal Credit

Table 2 below presents the regression results of digital finance on farmers' productive formal credit demand, where regression (1) is the result of the panel probit model regression and regression (2) is the result of the IV-Probit model that takes into account the introduction of instrumental variables endogenous to digital finance.

TABLE 2 REGRESSION RESULTS FOR PRODUCTIVE FORMAL CREDIT DEMAND Explained variable: demand for an abundant traditional credit			
	-1.288***	-4.602***	
Digital Financial Inclusion Index	(-10.01)	(-12.65)	
	-0.021***	-0.008***	
Age of household head	(-9.02)	(-4.47)	
	0.215**	0.134**	
Gender of household head	(2.48)	(2.49)	
	0.007	0.001	
Y ears of education	(0.98)	(0.24)	
	-0.051	-0.041	
Marital status	(-0.55)	(-0.70)	
	0.043**	0.07***	
Medical insurance or not	(0.44)	(1.06)	
Whether to conduct company-type	0.551***	0.373***	
business	(8.26)	(7.99)	
	0.341***	0.250***	
Whether owning a house or not	(2.28)	(2.57)	
	0.420***	0.180***	
City GDP per capita	(0.11)	(6.25)	
Degree of financial development of	-0.130	0.187	
the city	(-1.59)	(3.23)	
	5.674***	20.979***	
Constant	(8.16)	(12.38)	
Observed value	21996	21996	

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The regression results show that the digital inclusion index has a significant negative effect on farmers' demand for productive formal credit, which indicates that farmers in areas with the high development of digital inclusion have a lower probability of having sizeable legal credit demand. The control variables at the household head level also show that the risk attitude of the household head and the level of financial and economic literacy of the household head also significantly affect the formal credit demand of the household and the fact that the higher the risk appetite of the household head and the higher the level of financial literacy of the household head, the higher the probability of productive credit demand of the household, which is also consistent with economic intuition. In addition, the younger the head of household, the higher the household's need for productive formal credit, and the higher the probability of significant credit

demand for male heads of household compared to females. This is consistent with the fact that farmers who own their own homes have a higher probability of successfully obtaining a loan; the urban-level control variables show that the growth rate of regional GDP, i.e., the faster the level of regional economic development, is associated with a higher probability of productive credit demand.

Regression, after adding instrumental variables to control for endogeneity, similarly shows that digital financial inclusion has a significant dampening effect on farmers' productive formal credit demand.

Since the economic significance of the coefficients obtained from the probit model regression is relatively weak, the average marginal effects of the above two reversals are calculated in this paper after relapse, and the results are shown in Table 3 below.

Table 3 MARGINAL EFFECTS OF DEMAND FOR PRODUCTIVE FORMAL CREDIT				
Explained variable:	Explained variable: demand for an abundant traditional credit			
Explanatory Variables	Explanatory VariablesRegression (1)Regression (2)			
	-0.171***	-0.983***		
Digital Inclusive Finance Index	(-10.31)	(-9.01)		
Observations	21996	21996		

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The average marginal effect of digital finance on demand for productive formal credit changes significantly after controlling for endogeneity using instrumental variables. For example, the regression results (2) show that controlling for endogeneity reduces the probability of sizeable formal credit demand by an average of 0.98% for every 1% increase in the digital financial inclusion index. In comparison, the probit model results without controlling for endogeneity show a reduction of 0.17%.

Consumer Credit Demand

Similar to the treatment of productive formal credit demand, we do panel probit regressions, and instrumental variable IV-probit regressions for the effect of digital finance on farmers' consumer legal credit demand, respectively, and the results are shown in Table 4 below.

Table 4 REGRESSION RESULTS FOR CONSUMER FORMAL CREDIT DEMAND			
Explained varia	ble: consumer legal credit d	emand	
Explanatory Variables Regression (1) Regression (2			
	0.229***	0.429***	
Digital Inclusive Finance Index	(2.95)	(4.30)	
	0.058***	0.095***	
Marginal effects	(2.62)	(3.52)	
Age of household head	-0.011***	-0.010***	
-	(-6.14)	(-6.60)	
Gender of household head	0.018	0.018	
	(0.28)	(0.35)	
Whether high-risk appetite	0.07	0.069	
	(1.26)	(1.37)	
Number of the household labor force	0.112***	0.106***	

	(5.77)	(6.45)
Household size	-0.037**	-0.037***
	(-2.40)	(-2.86)
Whether owning a home or not	0.449*****	0.404***
	(3.61)	(3.69)
Degree of urban financial development	0.319***	0.269***
	(6.14)	(6.29)
Urbanization rate	-3.508***	-3.042***
	(-6.58)	(-6.89)
Observed value	21996	21996

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

From the regression results, we can see that both regression (1) and regression (2) show that digital finance has a significant boosting effect on farmers' demand for formal consumer credit, and the marginal effect shows that for every 1% increase in the index of digital financial inclusion after controlling for endogeneity using the instrumental variable, the probability of farmers' demand for consumer formal credit increases by 0.095%, while the regression results without the instrumental variable show that the probability increases by 0.058%. The regressions without the instrumental variables show an increase of 0.058%, which is not as large as the change in the probability of productive formal credit. Still, since previous studies have shown that the introduction of instrumental variables may have a magnifying effect on the regression coefficients, the focus of attention in this paper should be on the direction of sign and significance of the coefficients. The control variables at the household head level show that the age of the household head has a significant adverse effect on the consumer credit demand of farm households. The younger the household head is, the higher the demand for formal credit for household consumption, which is consistent with the current consumer perceptions and habits of the younger group; the gender of the household head, unlike productive credit, does not have a significant effect on the consumer credit demand of farm households, reflecting that there is no significant difference between male and female consumers in terms of consumer credit. In addition, the risk preference of the household head does not significantly affect the consumer credit of farmers, probably because consumer credit tends to satisfy current consumption and is relatively less speculative than lending for productive purposes; the attention of farmers to financial information also significantly affects consumer credit of farmers, which is consistent with economic intuition and economic facts. The household-level control variables, on the other hand, show that farmers are more likely to have a demand for formal consumer credit the higher the number of the household labor force, the household owns its own home, the higher the number of vehicles owned, the higher the household expenditure on food, and the greater the value of durable goods held; household size, on the other hand, shows a significant dampening effect on farmers' consumer credit, somewhat at variance with previous studies that found that the higher the number of household members, the higher the demand for borrowing. However, the extent of the effect is not statistically significant and may be influenced by the sample. The urban level control variables show that the degree of regional financial development significantly contributes to the demand for formal consumer credit among rural households. In contrast, the regional urbanization rate has a significant inhibitory effect on consumer credit among rural households, i.e., the less urbanized the region is, the greater the demand for formal consumer credit among rural households, which may be due to the urban-rural income gap, where the relatively insufficient income level in rural areas leads to a higher demand for consumer credit.

Demand is higher.

FURTHER DISCUSSION: HETEROGENEITY ANALYSIS AND ROBUSTNESS TESTING

Heterogeneity Analysis of Productive Formal Credit Demand

There are two possible ways in which the demand for productive credit from farmers can be reduced; one is that there is a channel shift in the market for great credit from farmers and the overall level of demand does not decrease, and the other is that some factor causes a reduction in the level of demand for productive formal credit from farmers.

First, according to the design of the CHFS questionnaire, we define farmers' borrowing from informal financial institutions such as friends and relatives and private financial organizations as casual credit demand and describe lending for agriculture, industrial and commercial production as productive everyday credit demand, and lending for housing, cars, children's education, and medical care as consumer informal credit demand according to the purpose of borrowing. The descriptive statistics show that the proportion of farm households with productive casual credit demand decreases from 22.40% to 13.71% from 2013 to 2019, showing the same overall decreasing trend as the sizeable formal credit demand. Further regression analysis of the model indicates that the digital finance index also has a statistically significant adverse effect on the market for productive informal credit, and the specific results of the model regression are given in Table 5 below.

Table 5 REGRESSION RESULTS OF THE DEMAND FOR PRODUCTIVE INFORMAL CREDIT			
Explained variable: demand for abundant everyday credit			
Explanatory Variables	Explanatory VariablesRegression (1)Regression (2)		
	-1.02***	-2.74***	
Digital Inclusive Finance Index	(-8.67)	(-4.04)	
Observations	14062	49062	

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Combining the above results, this paper argues that the decrease in farmers' productive formal credit demand is not due to a shift to informal channels and that the development of inclusive digital finance hurts both formal and casual abundant credit demand, i.e., the development of digital finance reduces the overall level of farmers' great credit demand.

There are many potential influencing factors and complex channels that exist for digital finance to reduce the probability of productive formal credit demand of farm households. Combining the previous literature review on digital finance and the availability of data, this paper tries to observe whether low-income families within the sample period are more affected by digital finance. The reasons are as follows: on the one hand, as mentioned in the literature review, inclusive digital finance is a continuous deepening of the development of inclusive finance, and using the inherent advantages of digital technology can break the problems of narrow financial coverage such as the inadequate setting of bank business outlets, and can effectively alleviate the conflicts of cost and interest faced by farmers in financial credit, increase the rationing of financial resources to low- quality customers, and effectively alleviate the slowing down of. On the other hand, scholars have studied poor farmers in 15 provinces and cities across China and found that the majority of poor farmers are willing to take out credit, but

very few of them take out loans due to various subjective and objective factors, and at the same time, as mentioned in the theoretical foundation section, scholars have found that the formal credit demand of poor farmers is mainly productive. The regression results of this sample segmentation explore whether digital finance effectively increases the accessibility of financial services for the poor. Since the 2013 CHFS questionnaire did not involve a survey on whether farmers are lacking, this paper selects data from 2015, 2017, and 2019 to classify the sample and then conducts cross-sectional data regressions. The regression results are shown in Table 6 below.

Table 6 PRODUCTIVE FORMAL CREDIT DEMAND OF POOR AND NON-POOR FARMERS			
Ex	plained variable: consumer leg	al credit demand	
	Explanatory Variables	Regression (1)	Regression (2)
		-2.77	-26.45***
Poor Households	Digital Inclusive Finance Index	(-1.53)	(-9.96)
	Marginal effects	-0.43	-6.01***
	Observed value	8998	8998
	Explanatory variables	Regression (1)	Regression (2)
		-1.54*	-8.39*
	Digital Inclusive Finance Index	(-1.78)	(-4.62)
Non-poor households	Marginal effect	-0.19*	-1.16***
	Observed value	11272	11272

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The above regression results show that regression (1) shows that the inhibitory effect of digital financial inclusion is statistically more significant for the non-poor group, while regression (2) shows that the productive credit demand of the poor group is more deeply reduced by digital financial inclusion than that of the non-poor group, and the marginal effect is more significant, with each 1% increase in digital finance leading to a 6.01% reduction in the probability of productive formal credit demand for the poor group. The reduction in the probability of productive formal credit demand for the poor is more significant than the 1.16% reduction in the probability for the non-poor. This paper considers the results of regression (2) after the introduction of instrumental variables plus stable and reliable, because the instrumental variables in this paper address the problem of omitted variables, including various potential factors affecting the development of digital finance such as the degree of economic growth, so the results of regression are not reliable to some extent.

There are many channels of influence behind, it may be that the development of digital finance provides financial services to poor farmers, so that poor farmers have access to the convenient payment and investment functions provided by digital finance and obtain certain returns greater than production or the efficiency of capital turnover is improved to a certain extent and thus reduce the frequency of loans, or digital finance to a certain extent gives priority to alleviating the poor households, a low-quality The current data does not allow this paper to identify the channels of influence, but digital finance has inevitably touched the poor farmers. The media of efficiency improvement brought by digital technology has made the farmers, after controlling for other variables. Productive formal demand is reduced.

Heterogeneity Analysis of Consumer Formal Credit Demand

As mentioned in the literature review, digital financial inclusion as a deepening of digital

finance can break through the geographical limitations of traditional financial institutions and expand the coverage of the financial system, making more residents have access to more financial products and services, while the essential feature of digital finance is to provide more financial access possibilities for low-quality farmers such as those who are constrained by liquidity, thus releasing their previously suppressed demand. The most important feature of digital finance is that it can provide low-quality farmers, such as those with liquidity constraints, with greater access to finance, thereby releasing their repressed demand. Therefore, digital finance can increase consumption and demand for consumer credit by expanding the scope and target audience of financial services and alleviating the liquidity constraints faced by farmers. In this paper, we use the cash currently held by farmers as their liquid assets based on the CHFS questionnaire and classify different groups according to the level of liquid assets.

Table 7 CONSUMER FORMAL CREDIT DEMAND FOR DIFFERENT LIQUIDITY CONSTRAINED GROUPS			
	Explained variable: consumer leg	al credit demand	
	Explanatory Variables	Regression (1)	Regression (2)
		0.40**	0.55**
	Digital Inclusive Finance Index	(1.69)	(2.43)
Highly liquid assets	Marginal effects	0.09*	0.14**
	Observed value	8210	8210
	Explanatory variables	Regression (1)	Regression (2)
		0.28**	0.41**
	Digital Inclusive Finance Index	(2.46)	(3.65)
Low liquidity assets	Marginal effect	0.05**	0.09***
	Observed value	12329	12329

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

As can be seen from the results in Table 7 above, the results of regression (1) show that digital inclusion has a significant positive boost for both groups with different levels of liquid assets, and the positive effect on low liquid asset farmers is statistically more significant; the results of regression (2) are similar, and the demand for formal consumer credit among farmers with high liquid assets shows a more significant The results of regression (2) are similar, and the demand for formal consumer credit among farmers with high liquid assets shows a more significant increase with the development of digital finance, with each 1% increase in inclusive digital finance increasing the probability of demand for formal consumer credit among farmers with high liquid assets by 0.144%. This shows that although inclusive digital finance has released the consumption of farmers with high liquidity constraints to a certain extent, it has not exceeded the degree of release for farmers with significant liquid assets. Thus, it is evident that although inclusive digital finance has generally promoted the consumption of residents and alleviated the liquidity constraints faced by some farmers, the degree of alleviation is still relatively light, and there is still room for deepening and improving the development of digital finance.

Robustness Test

In this paper, we first replace the digital finance index with digital finance coverage breadth and usage depth data from the perspective of variables to test the robustness of the above results.

In addition, this paper uses data from the China Labor Force Dynamics Survey (CLDS) database published by Sun Yat-sen University to validate the findings. However, the questionnaire on formal credit demand is not as detailed as that of the CHFS. Moreover, it is more concerned with whether the borrowing behavior of farmers has occurred rather than the more precise definition of whether they are willing to borrow without having done so. Therefore, it is not the ideal data for the research questions in this paper, but we can still use it to verify the findings.

The CLDS questionnaire contains a survey of respondents' loan usage from formal financial institutions such as banks and credit unions. Following the division mentioned above between productive and consumer credit demand, this paper defines loans used for production purposes as great credit demand and loans used for house construction, housing, consumer durables, education, and medical treatment as consumer credit demand. This paper considers that the regression results are more stable and reliable after controlling for the endogeneity of the model, so only the regressions with the introduction of instrumental variables are performed in the robustness test (2). The regression results are shown in Tables 8 and 9 below, including the corresponding household, head of household, and city-level control variables.

Table 8 IV-PROBIT MODEL FOR ROBUSTNESS TESTING			
Productive credit needs Consumer credit deman			
Explained variables	Regression (1)	Regression (2)	
The breadth of digital inclusive	-4.151***	0.301***	
financial coverage index	(-18.85)	(4.19)	
Digital Inclusive Financial Usage	-1.981***	2.762***	
Depth Index	(-7.77)	(4.27)	
Control variables	Control	Control	
Observed value	21996	21996	

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1, p<0.1.

Table 9 IV-PROBIT MODEL FOR CONCLUSION-AIDED VALIDATION			
Productive credit needs Consumer credit demand			
Explanatory Variables	Regression (1)	Regression (2)	
	-8.401***	1.724**	
Digital Inclusive Finance Index	(-18.18)	(2.36)	
Control variables	Control	Control	
Observed value	8167	8167	

Note: Z-values of regression results are shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

The regression results show that after replacing the variables, the breadth of digital finance coverage and depth of use still have a significant decreasing effect on farmers' productive formal credit demand and a significant promoting impact on the possibility of farmers' consumer legal credit demand. The findings of the empirical analysis are consistent with the above findings even after replacing the database. Therefore, the regression results and conclusions related to the impact of digital finance on farmers' formal credit demand obtained above are robust. The development of inclusive digital finance has a directional opposite effect on farm households' productivity and the consumer credit market.

CONCLUSIONS AND RECOMMENDATIONS

This paper constructs panel data using the China Household Finance Survey (CHFS) database published by Southwest University of Finance and Economics and the China Household Inclusive Finance database, focusing on the impact of digital finance development on the product and consumer formal credit demand farmers. Using panel probit models and IV-probit models, empirical analyses are conducted for the above two types of legal credit demand, followed by heterogeneity exploration and robustness tests. The final findings of the study are as follows.

The development of inclusive digital finance has a significant inhibitory effect on farmers' productive formal credit demand but a significant facilitative effect on farmers' consumer legal credit demand. Digital finance has a heterogeneous impact on the two types of formal credit demand, and the development of digital finance profoundly affects the structure of farmers' formal credit demand. The reduction in the probability of farmers' productive legal credit demand caused by digital finance is not because the emergence of digital finance shifted farmers' credit channels from formal to informal credit demand, but the development of digital finance on farmers' productive formal credlegaland differs between poor and non-poor households. The inhibitory effect of digital inclusive finance on poor farmers is more pronounced, behind which it can be reflected that digital inclusive finance can reach poor farmers and make. Still, the productive formal credit demand decrease as the efficiency of financial services is improved.

Based on the above research findings, this paper proposes the following policy recommendations. With the development of digital finance, the inclusive digital services are expanding, and farmers are enjoying the convenience of digital inclusive digital own credit structure is profoundly affected by the transformation. However, most of the rural financial reform policies introduced by the state before have focused on the supply side of financial credit, focusing on improving the efficiency of financial institutions' services while formulating relevant policies to cover farmers who cannot access appropriate services. Therefore, this paper suggests that when promoting rural economic reform, relevant departments should pay attention to the transformation of the structure of farmers' formal credit demand in the context of digital finance development, promote rural financial reform to focus on the combination of financial supply and demand, and establish a corresponding regulatory system to promote the healthy and sound development of rural finance. At present, digital finance has made full development, improving the efficiency of financial services and reaching farmers who used to have difficulty in accessing formal financial services, but there is still room for improvement. In the future, with the further development of digital finance, the further popularization of the Internet in rural areas, the penetration of Internet financial products and net lending in rural areas, the efficiency of rural financial services will be even more The government should seize the opportunity of digital finance development, improve the corresponding supervision and regulation mechanism, promote the healthy and steady development of digital finance and formulate relevant policies to promote digital finance to better serve rural finance, and then promote the deepening reform of rural finance into a new stage.

REFERENCES

- Abate, G.T., Rashid, S., Borzaga, C., & Getnet, K. (2016). Rural finance and agricultural technology adoption in Ethiopia: does the institutional design of lending organizations matter?. *World Development*, *84*, 235-253.
- Aitken, C.K., McMahon, T.A., Wearing, A.J., & Finlayson, B.L. (1994). Residential Water Use: Predicting and Reducing Consumption 1. *Journal of Applied Social Psychology*, 24(2), 136-158.
- Amaeshi, K., Adegbite, E., Ogbechie, C., Idemudia, U., Kan, K.A.S., Issa, M., & Anakwue, O.I. (2016). Corporate social responsibility in SMEs: a shift from philanthropy to institutional works?. *Journal of business* 17 1528-2635-26-4-190

Ethics, 138(2), 385-400.

- Arner, D.W., Zetzsche, D.A., Buckley, R.P., & Barberis, J.N. (2019). The identity challenge in finance: from analogue identity to digitized identification to digital KYC utilities. *European business organization law review*, 20(1), 55-80.
- Bateman, M. (2012). The Role of Microfinance in Contemporary Rural Development Finance Policy and Practice: Imposing Neoliberalism as "Best Practice." *Journal of Agrarian Change*, 12(4).
- Belton, B. (2012). Culture, social relations, and private sector development in the Thai and Vietnamese fish hatchery sectors. *Asia Pacific Viewpoint*, 53(2), 133–146.
- Berghman, L., Matthyssens, P., & Vandenbempt, K. (2012). Value innovation, deliberate learning mechanisms, and information from supply chain partners. *Industrial Marketing Management*, 41(1), 27–39.
- Borowiecki, K.J. (2013). Geographic Clustering and Productivity: An Instrumental Variable Approach for Classical Composers. *Journal of Urban Economics*, 73(1), 94–110.
- Chakravarty, S.R., & Pal, R. (2013). Financial inclusion in India: An axiomatic approach. *Journal of Policy Modeling*, 35(5), 813–837.
- Chen, J., Rong, S., & Song, M. (2021). Poverty vulnerability and poverty causes in rural China. *Social Indicators Research*, 153(1), 65-91.
- Dermineur, E.M. (2014). Single Women and the Rural Credit Market in Eighteenth-Century France. Journal of Social History, 1, 175–199.
- Du Plessis, S., Jansen, A., & Von Fintel, D. (2015). Slave prices and productivity at the Cape of Good Hope from 1700 to 1725: Did everyone win from the trade? *Cliometric*, 9(3), 289–330.
- Duncombe, R., & Heeks, R. (2002). Enterprise across the digital divide: information systems and rural microenterprise in Botswana. *Journal of International Development*, 14(1), 61–74.
- Eikemo, T.A., Clare, B., Tim, H., & Rory, F. (2016). The First Pan-European Sociological Health Inequalities Survey of the General Population: The European Social Survey Rotating Module on the Social Determinants of Health. *European Sociological Review*, 33(1), jcw019.
- Elliehausen, G., & Hannon, S.M. (2018). The Credit Card Act and Consumer Finance Company Lending. *Journal of Financial Intermediation*, *34*, 109–119.
- Feldman, M.P. (2014). The character of innovative places: entrepreneurial strategy, economic development, and prosperity. *Small Business Economics*, 43(1), 9-20.
- Fella, G., & Gallipoli, G. (2014). Education and Crime over the Life Cycle. *Computing in Economics & Finance*, 81(15–07), págs. 1484-1517.
- Hall, J.N., Ahn, J., & Greene, J. C. (2012). Values Engagement in Evaluation: Ideas, Illustrations, and Implications. *American Journal of Evaluation*, 33(2), 195–207.
- Heidues, _F_, Davis, J.R., & Schrieder, G. (1997). Agricultural Transformation and Implications for Designing Rural Financial Policies in Romania. *CERT Discussion Papers*, 25(3), 351–372.
- Henderson, & Jason. (2011). Crisis in U.S. Financial Markets—Spillover and Recovery Prospects in Rural America: Discussion. *American Journal of Agricultural Economics*, 91(5), 1209–1210.
- Hunter, _D_. (2007). Pricing of Spread Options on stochastically correlated underlyings. *Journal of Computational Finance*, *12*(12), 31–61.
- Israel, & Sabine. (2016). How social policies can improve financial accessibility of healthcare: a multi-level analysis of unmet medical need in European countries. *International Journal for Equity in Health, 15*(1), 41.
- Jiang, Y., Shi, X., Zhang, S., & Ji, J. (2011). The threshold effect of high-level human capital investment on China's urban-rural income gap. *China Agricultural Economic Review*, *3*(3), 297–320.
- Khosa, A., Burch, S., Ozdil, E., & Wilkin, C. (2020). Current issues in PhD supervision of accounting and finance students: Evidence from Australia and New Zealand. *The British Accounting Review*, 52(5), 100874.
- Lamberte, M.B., & Bouman, F. (1991). Small, Short and Unsecured: Informal Rural Finance in India. *American Journal of Agricultural Economics*, 73(3).

- Letki, N., & Mieri?A, I. (2015). Getting support in polarized societies: income, social networks, and socioeconomic context. Social Science Research, 49, 217–233.
- Li, J., Wu, Y., & Xiao, J. J. (2020). The impact of digital finance on household consumption: Evidence from China. *Economic Modelling*, 86, 317–326.
- Mamatzakis, E., Matousek, R., & Vu, A.N. (2016). What is the impact of bankrupt and restructured loans on Japanese bank efficiency? *Journal of Banking & Finance*, 72(NOV.SUPPL.), S187–S202.
- Michael, C., & Stelios, R. (2020). The effect of military spending on income inequality: evidence from NATO countries. *Empirical Economics*, 58(3), 1305-1337.
- Motel, P.C., Choumert, J., Minea, A., & Sterner, T. (2014). Explorations in the Environment– Development Dilemma. *Environmental & Resource Economics*, 57(4), 479–485.
- Murphy, & J. (2005). Unpacking the Foundations of ISLLC Standards and Addressing Concerns in the Academic Community. *Educational Administration Quarterly*, 41(1), 154–191.
- Negrusa, B., & Oreffice, R. (2010). QUALITY OF AVAILABLE MATES, EDUCATION, AND HOUSEHOLD LABOR SUPPLY. *Economic Inquiry*, 48(3), 558–574.
- Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management*, 51(5), 497–510.
- Patrick, H.T. (1980). Financial Development and Economic Growth in Underdeveloped. *Countries. Money and Monetary Policy in Less Developed Countries*, 37-54.
- Ray, D., & Floro, M. S. (2010). Vertical Links Between Formal and Informal Financial Institutions. *Review of Development Economics*, 1(1), 34–56.
- Rubera, G., Griffith, D.A., & Yalcinkaya, G. (2012). Technological and Design Innovation Effects in Regional New Product Rollouts: A European Illustration. *Journal of Product Innovation Management*, 29(6), 1047–1060.
- Ryder, N. (2008). THE FINANCIAL SERVICES AUTHORITY AND MONEY LAUNDERING. *Cambridge Law Journal*, 67(3), 635–653.
- Wang, S., Findlay, C., Watson, A., Cheng, E., & Gang, Z. (2005). Rural Financial Markets in China. *China Journal*, 93(53), 159.
- Weber, R., & Musshoff, O. (2017). Can flexible agricultural microfinance loans limit the repayment risk of low diversified farmers? *Agricultural Economics*, 48(5).
- Whitacre, B., Gallardo, R., & Strover, S. (2014). Does rural broadband impact jobs and income? Evidence from spatial and first-differenced regressions. *The Annals of Regional Science*, 53(3), 649–670.
- Xiang, D., & Lawley, C. (2019). The impact of British Columbia's carbon tax on residential natural gas consumption. *Energy Economics*, 80(MAY), 206–218.
- Yazdi-Feyzabadi, V., Bahrampour, M., Rashidian, A., Haghdoost, A.A., Javar, M.A., & Mehrolhassani, M.H. (2018). Prevalence and intensity of catastrophic health care expenditures in Iran from 2008 to 2015: a study on Iranian household income and expenditure survey. *International Journal for Equity in Health*, 17(1), 44.
- Yiu, & Lisa. (2016). The Dilemma of Care: A Theory and Praxis of Citizenship-Based Care for China's Rural Migrant Youth. *Harvard Educational Review*, 86(2), 261–288.
- Zhang, X., Tan, Y., Hu, Z., Wang, C., & Wan, G. (2020). The Trickle-down Effect of Fintech Development: From the Perspective of Urbanization. *China & World Economy*, 28(1), 23–40.
- Zhong, C., & Dong, N. (2018). The Research On The Dilemma Of The Local Government Finance In Less-Developed Areas: Xingguo County Survey. *The Singapore Economic Review*, 63(04), 885-897.
- Zoungrana, T.D. (2021). The effect of wealth on the choice of household drinking water sources in West Africa. *International Journal of Finance & Economics*, 26(2), 2241-2250.