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Digital credit and insurance: Improving economic well-being for rural households

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ABSTRACT

The integration of digital technologies in credit and insurance services has important implications for the economic well-being of rural households. This paper utilizes cross-sectional data from a 2022 survey conducted with 476 rural households in China to explore the influence of digitally coordinated credit and insurance (DCCI) on economic well-being. Results indicate that DCCI significantly enhances both net incomes and farm incomes of rural households. Particularly, younger households, those engaged with digital technologies, and those facing high natural risks see greater benefits. Additionally, we find that reducing credit rationing and enhancing risk resilience are key mechanisms through which DCCI improves economic outcomes. The robustness of these results is confirmed through various analytical methods and measures. This study highlights the important role of digital transformation in the credit and insurance sectors for fostering economic growth in the rural sectors of emerging markets.

1. Introduction

The disparity in economic well-being between rural and urban households has been a focal point for agricultural policymakers since the 1930s. While there has been a noticeable improvement in the economic well-being of rural households relative to their urban counterparts, significant inequalities persist. Agricultural policies have traditionally sought to bolster financial support for agricultural production, enhance farm income and overall well-being, and establish safety nets for farmers. A key policy initiative has been to facilitate the entry of young and emerging farmers into the industry by improving access to credit and conservation opportunities (Katchova, 2008). Nevertheless, the absence of robust insurance markets introduces 'risk rationing,' where potential borrowers, wary of losing collateral, opt out of loans despite the availability (Giné & Yang, 2009; Naranjo et al., 2019). The coordination of credit and insurance (CCI) is increasingly recognized as a crucial financial strategy to mitigate such risk rationing that stifles agricultural investment and income opportunities for farmers in developing regions (Hill & Viceisza, 2012; Wu & Li, 2023). This coordinated approach is essential not only for enhancing agricultural productivity but also for narrowing the economic well-being among rural households in developing countries. The economic well-being is measured by various indicators, including income, earnings, wealth, consumption expenditures, employment opportunities, and living standards (Mishra et al., 2002; Rodriguez et al., 2002; Sala-i-Martin,

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2006; Wolff & Zacharias, 2009; Lu and Horlu, 2017). Income is one of the most frequently used measure in the agricultural sector (El-Osta, 2002; Mishra et al., 2002; Katchova, 2008). Following the existing research, we use rural households' net income to measure their economic well-being. Previous studies have examined either the effect of digital credit or digital insurance on the well-being of households (Chen et al., 2024; Wang et al., 2024). This study provides a more comprehensive analysis of the effect of digitally co-ordinated credit and insurance (DCCI) on rural households' economic well-being, based on a survey of rural households' involvement in the DCCI, and their life-cycle stages.

The integration of credit and insurance is increasingly common in emerging economies to improve the economic-welling including India, Ghana, Costa Rica, Malawi, and Kenya (Cecchi et al., 2024). Research by Naranjo et al. (2019) indicates that farmers are more likely to accept loans that include insurance, especially under conditions of certain liability and when facing uncertainty about their financial obligations. Similarly, Ndegwa et al. (2020) find that loans with embedded insurance are more popular than traditional loans, highlighting the critical role of coordinated credit and insurance in improving rural households' economic outcomes. Furthermore, Carter et al. (2016) observe that in environments with low collateral, standalone insurance contracts cannot effectively encourage small farmers to adopt new technologies. However, combining insurance with credit has proven more effective in fostering technological adoption and enhancing economic well-being among rural households. Overall, access to coordinated credit and insurance (CCI) is closely linked to the economic prosperity of rural communities.

However, some scholars point out the challenges associated with the coordination of credit and insurance, particularly its dependence on government support and the inefficiencies of cooperatives (Jensen, 2000; Petrick, 2004). Annan (2022) also raises concerns that purchasing insurance with credit might encourage riskier behavior due to moral hazard, potentially exacerbating the costs in this market. Karlan et al. (2014) suggest that while mitigating risk can lead to higher investments, the bundling of insurance with credit should leverage the existing infrastructure and possibly the trust that communities hold in microfinance institutions or banks to effectively market and distribute insurance. Consequently, the combined use of credit and insurance does not necessarily guarantee an increase in agricultural investment and income.

The delivery of agricultural credit and insurance services through digital technology is increasingly prevalent in emerging economies. For example, mobile phones are being used to access agricultural insurance and credit services (Xu et al., 2002), and remote sensing technology is being integrated into index insurance schemes in developing countries (Carter et al., 2016; Miranda & Gonzalez-Vega, 2011). This has given rise to a new form known as digitally coordinated credit and insurance (DCCI). China, with its robust fintech sector and extensive user base, is leading the expansion of DCCI services (Hua & Huang, 2021). As a result, China has emerged as a key example in understanding the operational dynamics and socioeconomic impacts of the widespread adoption of DCCI. The experiences and lessons from DCCI in China could offer valuable insights for other emerging economies.

Utilizing cross-sectional data from 476 rural households across 137 digital villages in China in 2022, we examine the impacts and mechanisms of DCCI on the economic well-being of rural households. Our findings highlight that DCCI significantly enhances their economic well-being, with notably greater benefits observed among younger rural households, as well as those adopting digital technologies, and those facing high systematic natural risks. These insights are crucial for shaping farm policies that should particularly support these vulnerable groups (Lusardi & Mitchell, 2014). Additionally, easing credit rationing and boosting risk resilience capacity are identified as significant mediating factors in the effectiveness of DCCI.

This paper contributes to the field in several key ways. Firstly, it expands upon existing research which primarily focuses on the impact of digital finance alone (Chen et al., 2024; Wang et al., 2024). We explore the combined effect of DCCI on the economic well-being of rural households, addressing the significant role of risk as an obstacle to investment and growth as highlighted by Karlan et al. (2014). This study fills the gap by examining the joint effect of credit and insurance in a digital context. Secondly, we analyze the causal relationship between DCCI and the economic well-being of rural households. While current research often explores how digital finance influences households' investment performance, portfolio construction, risk-taking and consumption inequality through avenues like investment diversification, non-agricultural employment or entrepreneurship (Goodell et al., 2021; Hu et al., 2024; Chen et al., 2024), there is scant focus on the specific impact of digitally coordinated credit and insurance on the economic well-being of rural households. Thirdly, we propose theoretical transmission mechanisms that address the issue of risk rationing in agricultural investment by rural households (Boucher et al., 2008; Xu et al., 2002). Meanwhile, our mechanism analysis indicates that digitally combining credit with insurance can mitigate rural households' risk rationing. These results provide a theoretical foundation for practical policy recommendations aimed at enhancing the risk resilience of rural households.

The rest of the paper is structured as follows. Section 2 offers theoretical analysis and hypothesis development. Section 3 presents the data and model design. Section 4 explains the empirical models used to investigate the impact of DCCI, while Section 5 presents the results of further analysis. Section 6 concludes.

2. Theoretical analysis and hypothesis development

2.1. The impact of DCCI on rural households' economic well-being

Traditional CCI has lots of limitations on time and space. Firstly, there is information asymmetry between commercial banks and insurance companies. Thereby the coordination cost of credit and insurance is high. Secondly, the claim process of agricultural insurance is often characterized by multiple approval steps and prolonged processing periods, thereby diminishing its effectiveness as collateral for credit financing. Finally, the effectiveness of CCI is influenced by the underlying risk structure and the property rights environment (Carter et al., 2016). As financial technologies (fintech) and insurance technologies (insurtech) increasingly integrate with the financial services industry, ranging from satellite remote sensing in index insurance to smartphone imaging, DCCI has become

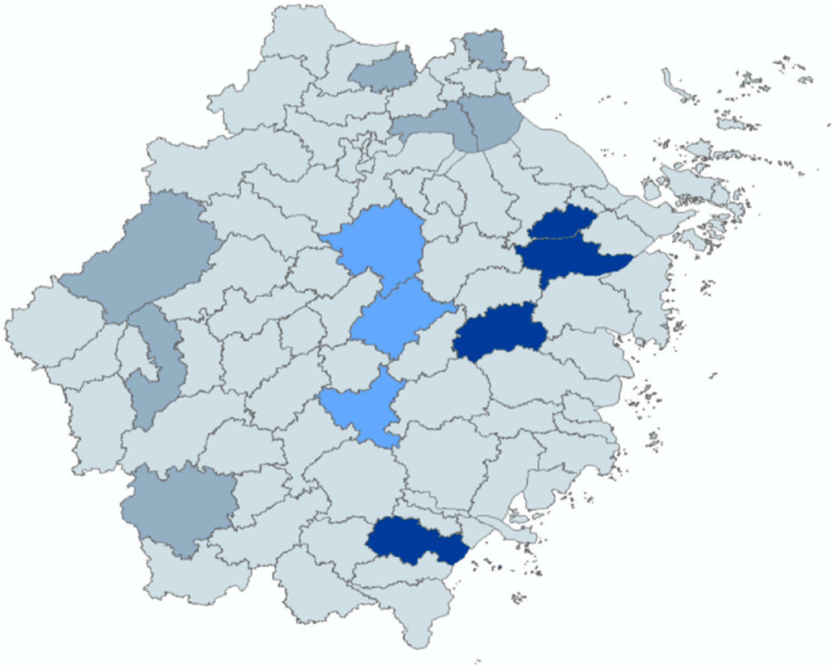

Fig. 1. Sample counties from east, middle and west of Zhejiang province, China

Fig. 1 shows the sample counties (districts) we choose from east, middle and west of Zhejiang province, China. We select Longquan county, Chun'an county, Qujiang district, Nanxun district, Jiashan district, Haiyan county, Haining city from west of Zhejiang province. We select Zhuji city, Dongyang city, Jinyun city from middle of Zhejiang province. We select Rui'an city, Tiantai county, Haishu district, and Fenghua district from east of Zhejiang province.

a notable innovation. Leveraging e-commerce platforms like Taobao and JD, and digital platforms of commercial banks (Yang & Masron, 2024), DCCI can access rural household assets, and credit information more efficiently (Chen et al., 2024). Besides, DCCI use data mining and machine learning to improves data quality, accuracy, customer identification, overcoming information asymmetry and transaction costs in traditional CCI (Malladi et al., 2021), which will foster the interlink between agricultural banks and insurance companies.

Moreover, DCCI facilitates the information sharing between commercial banks and insurance companies (Marcelin et al., 2022), agricultural insurance companies can benefit from commercial banks' marketing channels. Finally, leveraging cutting-edge technologies like block chain and the internet of things (IoT), DCCI allows financial institutions to collect more household's information and reduces their default risk effectively (Yang & Masron, 2024). Based on this analysis, we propose our first hypothesis:

H1. DCCI has a higher impact on rural households' economic well-being than traditional CCI

2.2. The transmission mechanism of DCCI and rural households' economic well-being

Utilizing a variety of digital platforms, such as e-commerce sites, commercial banks' digital financial platforms, and government-supported 'San nong' service platforms, digitally coordinated credit and insurance (DCCI) can effectively gather and analyze farmers' credit records from their everyday online transactions (Xu et al., 2002; Chen et al., 2024; Chishti et al., 2025). This data is processed into sophisticated risk assessments and loan review information (Riley, 2018). Consequently, DCCI has the potential to extend financial services to previously underserved groups, reducing credit rationing and enhancing access to finance for those who have traditionally been excluded from conventional financial systems (Benami & Carter, 2021; Xu et al., 2002). This innovative approach not only democratizes financial access but also improves the inclusivity and efficiency of financial services in rural areas (Chen et al., 2024). Based on those analysis, we can develop the following hypothesis:

H2. DCCI improves rural households' economic well-being by mitigating their credit rationing

Leveraging advanced technologies such as remote sensing and integrated data analytics, DCCI offers farmers index-based insurance, which provides payouts based on objective weather and environmental data that individual farmers do not influence (Carter et al., 2016; Ehlers et al., 2021). This method simplifies claims and ensures impartiality in payouts. In addition, DCCI facilitates access to other forms of online insurance tailored to mitigate risks associated with volatile farm investments, such as in high-risk fertilizers and enterprises (Cai, 2016; Karlan et al., 2014). These higher-risk investments typically offer the potential for higher returns.

Beyond boosting incomes, DCCI also plays a crucial role in reducing income volatility (De Nicola, 2015). This financial stability

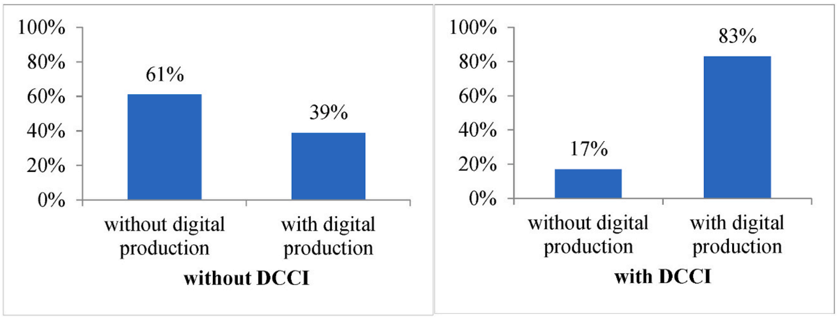

Fig. 2. Difference in digital production for rural households with DCCI and without DCCI
Fig. 2 shows the difference in digital production for rural households with DCCI and without DCCI. Our histogram results indicate that rural households with DCCI have higher propensity to engage in digital production.

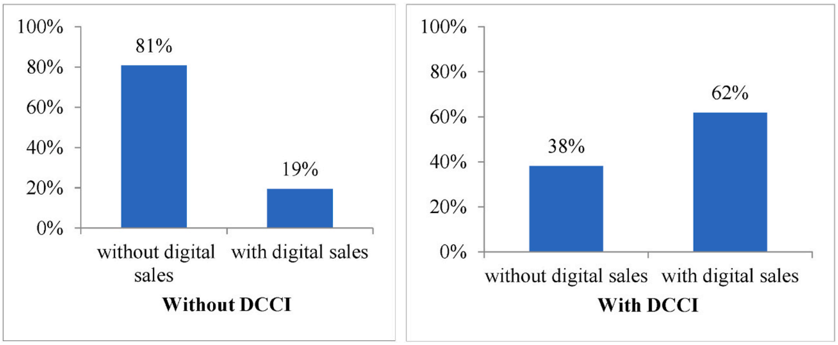

Fig. 3. Difference in digital sales for rural households with and without DCCI
Fig. 3 shows the difference in digital sales for rural households with DCCI and without DCCI. Our histogram results indicate that rural households with DCCI have higher propensity to engage in digital sales.

prevents farmers from being forced to sell productive assets in tough times, which in turn decreases the incidence of food insecurity and enhances child health and overall well-being (Jensen et al., 2018; Karlan et al., 2014; Tafere et al., 2019). Overall, DCCI not only enhances agricultural productivity and profitability but also contributes significantly to improving the quality of life for rural communities. Based on the above analysis, we develop our following hypothesis:

H3. DCCI improves rural households' economic well-being by improving risk resilience capacity

3. Data description and model setting

3.1. Data description

This study utilizes a survey of rural households in east, middle and west of digital villages from Zhejiang Province of China. We randomly select 498 rural households to conduct our survey, each of whom operates at least 1.65 acres. Among them, 164 were from the west, 150 from the middle, and 184 from the East (Fig. 1).

We choose our sample rural households from digital villages of China as the regions where digitalization develops the fastest are also the regions where rural households have higher access to DCCI to increase food production and maintain economic gains (Li et al., 2023). The development of DCCI in China provides a reference for other emerging economies as digital elements have become the new engine of economic development. In 2022, the digital village construction level in Zhejiang of China reached 68.3%, ranking first for 4 years in succession in China. A total of 378 provincial-level digital villages have been constructed till July 2022.

We employ a multistage sampling procedure to select our observation units. First, we divide the 378 provincial-level digital villages into three groups based on their geographical location: middle, east and west location. Second, we randomly select 80 rural households who have obtained DCCI among three groups, and 240 rural households in total. Finally, we match those 240 rural households with others who have adopted traditional CCI, DC (digital credit), or DI (digital insurance) and have planted the same crops as those who have adopted the DCCI. We excluded any invalid questionnaires, leaving a remainder of 476 samples. Overall, 133 rural households have adopted DCCI, 152 rural households have adopted CCI, 226 rural households have adopted DC, and 156 rural households have adopted DI.

We also collect rural households' total input spending according to their purchasing of each agricultural input, including pesticides,

Table 1
Definition of the variables and summary statistics.

	Variable	Description	observations	Mean	Std. Dev.
Dependent variable	NI	Annual net-income (Yuan)	476	39,551.99	17080.13
Independent variable	DCCI	1 if rural households obtain digitally combined credit and insurance	476	0.279	0.449
	DC	1 if rural households obtain digital credit	476	0.475	0.500
	DI	1 if rural households obtain digital insurance	476	0.328	0.470
	CCI	1 if rural households obtain combined credit and insurance	476	0.319	0.467
Mediating variables	RR	risk resilience of rural households	476	0	1.572
	CR	ratio of credit rationing	476	0.532	0.241
Moderating variables	Digital sales	percentage of agricultural products sold on e-commerce platform in total output	476	0.121	0.177
	Digital production	1 if digital technology used in production	476	0.271	0.445
Control variables	Capin	Log (Rural households' capital input annually) (yuan)	476	10.275	1.283
	Labin	number of labors in agriculture	476	3.120	4.986
	Land	cultivated land area of rural households	476	6.678	2.195
	COOP	1 if rural households are cooperative members	476	0.326	0.469
	Gen	1 if head is male	476	0.752	0.432
	Edu	head's education (years)	476	11.935	3.178
	Age	Head's age (years)	476	45.863	16.371

Table 1 shows the definition of the variables and summary statistics. DCCI = digital coordination of credit and insurance; DI = digital insurance; DC = digital credit; CCI = coordinated credit and insurance.

and seeds. We also collect rural households' total amount of planted farmland. We collect rural households' agricultural output value in accordance with their production and sales of respective crops. Finally, we obtain rural households' net agricultural income from their farm output and input information.

Other information related to digital sales, such as whether selling agricultural output online and digital technology adoption, such as whether adopting digital remote sensing technology, are also collected (see Figs. 2 and 3). We also collect famers' financial information regarding DC, DI, CCI and DCCI.

Figs. 2 and 3 highlight the difference in rural households' adoption on digital production and digital sales. Rural households with DCCI have a higher probability to adopt digital production and digital sales, accounting for 83% and 62%, respectively, compared to those without at 39% and 19%. Our results suggest that DCCI lowers the access threshold for digital users, especially for rural households who adopt digital production and digital sales. We expect that digital technology adoption in terms of production or sales reinforces the effect of DCCI on rural households' income.

3.2. The settings of the model

3.2.1. Basic model

To investigate how DCCI affects rural households' economic well-being, we follow Katchova (2008) and measure farmers' economic well-being in terms of household income. We adopt a linear regression approach, as given below:

$$Y_i = a_0 + a_1 DCCI_i + a_k^{'} X_i + \varepsilon_i \tag{1}$$

$$Y_i = \gamma_0 + \gamma_1 CCI_i + \gamma_2^{'} X_i + \varepsilon_i \tag{2}$$

$$Y_i = \beta_0 + \beta_1 DC_i(DI_i) + \beta_2^{'} X_i + \varepsilon_i \tag{3}$$

In the above models, i denotes the individual rural household; Y_i denotes our dependent variable, referring to rural households' income; $DCCI_i$ denotes our key independent variable, denoting whether rural households had adopted DCCI; X_i represents a set of control variables, including gen, edu, age, capin, laborin, and coop. respectively, and a_k (k = 1, 2, …,6) denotes coefficients concerning estimation. To compare the joint effect of DCCI, the traditional coordinated effects of CCI, and the effects of each separately, we also run a regression analysis of CCI, DC, or DI on rural households' income (Models (2) and (3)).

3.2.2. Two-stage least square regression

To address endogeneity for model (1), we establish the following model:

$$DCCI_i = b_0 + b_1 \mathrm{IV}_i + b_2^{'} X_i + \varepsilon_i \tag{4}$$

$$Y_i = c_0 + c_1 DCCI_i^{'} + c_2^{'} X_i + \varepsilon_i \tag{5}$$

where IV_i represents Eq. (4)'s instrument variable and $DCCI_i^{'}$ is the exogenous component after the endogenous bias is eliminated. We use the geographical distance between Hangzhou and each village in our sample as the instrumental variable concerning DCCI.

Table 2
Factor analysis results of farmers' risk resilience capacity.

Dimension	Description	Factor loading
Robustness	After something challenging has happened, it is easy for my farm to bounce back to its current profitability	0.9683
	Personally, I find it easy to get back to normal after a setback.	0.4636
Adaptability	If needed, my farm can adopt new activities, varieties, or technologies in response to challenging situations.	0.4466
	As a farmer, I can easily adapt myself to challenging situations.	0.4550
Transformability	For me, it is easy to make decisions that result in a transformation.	0.5238
	After facing a challenging period on my farm, I still have the ability to radically reorganize my farm.	0.6521

Following Meuwissen et al. (2019), we cover all three resilience capacities (robustness, adaptability, and transformability) (see Table 2). We construct a risk-resilience capacity index that conforms to the behavior characteristics of farmers. The principal component analysis method is used for factor analysis, with two common factors extracted according to the principle that the eigenvalue was greater than 1. The KMO test value was 0.798, and the cumulative variance contribution rate reached 80.

Table 3
Benchmark regression results.

	(1)	(2)	(3)	(4)
DCCI	0.023***			
	(0.006)			
DC		0.019***		
		(0.006)		
DI			0.018***	
			(0.005)	
CCI				0.017***
				(0.006)
Gen	0.016*	0.015*	0.014*	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)
Age	0.0004*	0.0004**	0.0005**	0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Edu	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Capin	0.01***	0.009***	0.01***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Labin	0.001*	0.001	0.001	0.0005
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Land	0.004***	0.004***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)
Coop	0.016**	0.015**	0.017***	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	476	476	476	476
R^2	0.204	0.199	0.198	0.194

Table 3 shows the baseline regression results. Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets. DCCI = digital coordination of credit and insurance; DI = digital insurance; DC = digital credit, CCI = coordinated credit and insurance.

3.2.3. Mediation effect model

We introduce the following model to further verify the mechanism and influencing paths of DCCI on rural households' income.

$$Med_i = e_0 + e_1 DCCI_i + e_2^{'} X_i + \varepsilon_i \tag{6}$$

where Med_i denotes mediators, which involve the ratio of credit rationing (RCR_i) and the risk resilience capacity (RR_i). Eq. (6) is in line with the fundamental model, and its meaning in terms of variables is kept the same as Eq. (1).

3.3. Variable selection and descriptive statistics

Table 1 displays the definitions and descriptive statistics of the variables. The dependent variable is rural households' annual net income. The key independent variable is a dummy variable. If the rural households acquire DCCI, then the dummy variable is assigned a value of 1; otherwise, it is assigned a value of 0. This key independent variable is determined through the responses of surveyed farmers to the following questions: (1)"Did you obtain a bank loan last year?" and "Did you purchase agricultural insurance last year?" (2) If the response to both questions is "yes," further inquiry is made regarding whether the bank loan was secured using an insurance as collateral. (3) "Was the entire process, from the farmer's application to the disbursement of the loan, conducted online?" (4) "Was the process of purchasing agricultural insurance, from underwriting to claims settlement, completed online?"

Based on the responses to these four questions, we can decide whether rural household have accessed DCCI. If yes, the variable is coded as 1; otherwise, it is coded as 0.

Table 4
Two-stage least square regression results.

	(1)	(2)	(3)	(4)
DCCI	0.068**			
	(0.028)			
DC		0.06**		
		(0.025)		
DI			0.062**	
			(0.027)	
CCI				0.059**
				(0.025)
Gen	0.015*	0.014	0.008	0.014*
	(0.008)	(0.008)	(0.009)	(0.008)
Age	0.0003	0.0004*	0.001***	0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Edu	0.002**	0.002*	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Capin	0.009***	0.007*	0.008**	0.006*
	(0.003)	(0.004)	(0.003)	(0.004)
Labin	0.001**	0.001	0.001*	0.001
	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Land	0.004***	0.004**	0.003**	0.003**
	(0.001)	(0.001)	(0.002)	(0.002)
Coop	0.016**	0.012*	0.02***	0.01
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	476	476	476	476
R^2	0.109	0.12	0.091	0.112

Table 4 shows the IV regression results. Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets. DCCI = digital coordination of credit and insurance; DI = digital insurance; DC = digital credit. CCI = coordinated credit and insurance.

Following existing research of Petrick (2004), Miranda and Gonzalez-Vega (2011) and Carter et al. (2016), the control variables used in the study are gender (gen_i), education (edu_i), age (age_i), capital input ($capin_i$), labor input ($laborin_i$), land input (land_i), and cooperative membership ($coop_i$). The capital inputs include fertilizer, pesticide, irrigation, and so on. CCI represents the traditional coordinated credit and insurance, DC and DI denote whether rural households acquire digital credit or digital insurance, respectively. As shown in Table 1, 27.9% of rural households in the sample acquired DCCI, 32.8% of rural households adopted digital credit, 47.5% of rural households adopted digital insurance, and 31.9% of rural households adopted CCI.

4. Empirical results

4.1. Baseline regression results

Table 3 presents the baseline regression results, including the joint effect of DCCI on rural households' net income, and the separate effects of DC and DI. Table 2 also reports the traditional combined effect of CCI. DCCI, CCI, DC, and DI exhibit a positive and significant effect on rural households' net income, but the effect of DCCI is greater. The average marginal effect of DCCI on rural households' income is 2.3% (909.69 Yuan, standard error = 0.006), compared to 1.9%, 1.8% and 1.7% for digital credit or digital insurance alone, or traditional CCI, respectively. Our results are consistent with several previous studies that digitally combined credit with insurance generates a higher demand for and supply of credit in agricultural investment, thus generating higher income (Carter et al., 2016; Karlan et al., 2014; Miranda & Gonzalez-Vega, 2011; Naranjo et al., 2019). We further confirm that digital technology, including big data, cloud computing, and artificial intelligence, plays a distinct role in generating and obtaining information to address issues of asymmetric information and moral hazard in the rural finance market; thus, the coordinated income effect of DCCI has been empowered (Cornelli et al., 2023). Our results also indicate that DCCI can reshape the rural finance market by alleviating the triple challenges of isolation, small-scale transactions, and risk in rural microfinance (Benami & Carter, 2021). However, as DCCI extends their services into rural corners, significant consumer protection challenges must be addressed. These include the issue of unobservable contract quality in index insurance, predatory lending in digital credit markets, and exacerbating underlying inequalities in access to financial services (Kono & Takahashi, 2010; Benami & Carter, 2021).

4.2. Two-stage least square regression

There is a possibility that DCCI may be inversely related to rural households' income. Rural households who earn more money are more likely to engage in DCCI. To address such potential endogeneity, a two-stage least-squares regression was run using the instrumental variable method. Following Lee et al. (2023), the geographical distance between Hangzhou and each village in our sample was selected as the instrumental variable concerning DCCI. As the birthplace of Alipay and the most significant service supply hub for digital finance in China, Hangzhou was selected as the digital center in China. Table 4 shows the results. The joint effect of DCCI is still large and significant, compared to the single effect of DI or DI alone, and the traditional CCI. The average marginal effect in the

Table 5
Mechanism analysis.

	(1)	(2)
	CR	RR
DCCI	−0.148***	0.322**
	(0.028)	(0.155)
Gen	0.024	0.362**
	(0.025)	(0.163)
Age	0.0005	0.0003
	(0.001)	(0.005)
Edu	0.01***	0.018
	(0.003)	(0.022)
Capin	−0.005	−0.045
	(0.009)	(0.055)
Labin	−0.0002	−0.014
	(0.001)	(0.015)
Land	−0.001	0.069**
	(0.002)	(0.033)
Coop	0.07***	0.566***
	(0.024)	(0.167)
Observations	476	476
R-squared	0.097	0.065

Table 5 shows the mediating effect of DCCI on rural households' income. Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets. RR = risk resilience, CR = ratio of credit rationing.

two stage least square regression was 0.068, greater than 0.023 in the baseline model, indicating that the effect of DCCI on rural households' income in the benchmark regression was underestimated. Our study reaffirms that DCCI may avoid the moral hazard inefficiencies in the traditional CCI illustrated by Annan (2022), as DCCI operates on a "trigger and claim" basis, and eliminates the need for post-disaster surveys and loss determinations by integrating meteorological big data, agricultural big data, and credit information big data. Thus, enhancing the coordinated effect on famers' agricultural output and income effectively. We also run robust test with the Entropy Balancing-OLS method. Instead of net income, we use farm income to run the regression, our results are robust across different methods and different measures (see Appendix A1).

5. Further analysis

5.1. Mechanism analysis

5.1.1. The mediating effect of credit rationing

We report the mediating effect of credit rationing on rural households' income in the first column of Table 5. Our results show that DCCI has a significantly negative effect on credit rationing (CR), indicating that DCCI affects rural households' income through mediating their credit rationing. Our results indicate that DCCI can effectively obtain and process information in the credit market at a lower cost (Xu et al., 2002), which can reduce moral hazard among rural households and credit rationing among commercial banks (Wu & Li, 2023). Our findings further confirm that DCCI effectively reduce expenses associated with screening, monitoring, and risk-hedging, and improving market imperfections in rural settings with the growing presence of smartphones and e-commerce platforms (Xu et al., 2002).

5.1.2. Mediating effect of risk resilience

According to the regression results presented in the second column of Table 5, DCCI has a positive and significant effect on improving rural households' risk resilience. Our results indicate that DCCI affects rural households' income through improving their risk resilience. Our results further confirm that DCCI can overcome rural households' risk aversion in agricultural investment effectively (Wong et al., 2020; Wu & Li, 2023). Such strategy plays a crucial role in promoting the uptake of improved agricultural technologies and increasing crop productivity (Carter et al., 2016; Sitko et al., 2018). Meanwhile, DCCI has the potential to overcome the limitations of traditional CCI, such as high transaction costs and moral hazard issues.

5.2. Heterogeneity analysis

5.2.1. Natural risk heterogeneity analysis

Our chosen sample province has a complicated natural geography and geomorphology, with mountains comprising over 70% of the total area. Mountainous areas are usually risk-prone regions where natural disasters, such as flash floods, are high. Farmer households in mountainous areas usually have low collateral assets, as real estate in mountainous areas typically have low market value). Consequently, people of these regions confront high credit rationing and risk rationing.

Based on the above analysis, we test whether the income effect of DCCI differs between high-regional risk areas and low-regional

Table 6
Natural risk heterogeneity analysis results.

	(1)	(2)
	High natural risk areas	Low natural risk areas
DCCI	0.065***	0.049**
	(0.015)	(0.024)
Gen	−0.03	0.041**
	(0.025)	(0.018)
Age	0.0001	0.002***
	(0.001)	(0.001)
Edu	−0.003	0.009***
	(0.002)	(0.003)
Capin	−0.009	0.030***
	(0.006)	(0.006)
Labin	−0.0001	0.001
	(0.001)	(0.001)
Land	0.002	0.049**
	(0.002)	(0.024)
Coop	0.021	0.004
	(0.015)	(0.019)
Observations	110	388
R-squared	0.244	0.229

Table 6 shows rural households' regional heterogeneity regression results. Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets.

Table 7
Digital technology uptake heterogeneity analysis results.

	(1)	(2)	(3)	(4)
DCCI	0.046**	0.024	0.047**	0.030
	(0.019)	(0.021)	(0.018)	(0.02)
DP	0.036**	0.029*		
	(0.016)	(0.016)		
DCCI*DP		0.087**		
		(0.037)		
DS			0.123***	0.113***
			(0.042)	(0.042)
DCCI*DS				0.20**
				(0.099)
Gen	0.034**	0.036**	0.038**	0.041***
	(0.016)	(0.016)	(0.015)	(0.016)
Age	0.002***	0.002***	0.002***	0.002***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Edu	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Capin	0.025***	0.025***	0.025***	0.025***
	(0.005)	(0.005)	(0.005)	(0.005)
Labin	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Land	0.005***	0.005***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Coop	0.009	0.011	−0.004	−0.002
	(0.015)	(0.015)	(0.015)	(0.015)
Observations	476	476	476	476
R-squared	0.238	0.246	0.244	0.250

Table 7 shows rural households' digital technology adoption heterogeneity regression results. Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets. DCCI = Digitally coordinated credit and insurance, DP = Digital production, DS = digital sales.

risk areas (mountainous and non-mountainous areas) (Table 6). DCCI has a positive and significant effect on rural households in both high-regional risk areas and low-regional-risk areas. However, the effect is greater in high-regional risk areas. Our results further confirm the findings of Carter et al. (2016) that DCCI is more effective in low-collateral environments or risk-prone regions.

5.2.2. Digital technology adoption heterogeneity analysis

Rural households that adopt digital technology in agricultural production face both higher yields and higher risk versus households that do not uptake digital technology. Thus, it is uncertain whether households adopting digital technology have a new benefit from their agricultural technology investment. To determine whether the income effect of DCCI is heterogeneous for two kinds of rural households, we use the interaction term to measure the heterogeneous effect. We use digital sales or digital production to measure

Table 8
Rural households' age heterogeneity analysis results.

	(1) Young group	(2) Middle-age group	(3) Old-age group
DCCI	0.029**	0.021***	0.001
	(0.012)	(0.007)	(0.005)
Gen	0.018	0.015*	−0.008
	(0.014)	(0.008)	(0.008)
Age	−0.001	−0.0004	0.006***
	(0.001)	(0.001)	(0.002)
Edu	0.003	0.002**	0.001
	(0.002)	(0.001)	(0.001)
Capin	0.014**	0.009**	0.0003
	(0.006)	(0.004)	(0.002)
Labin	0.008	0.0004	−0.0002
	(0.005)	(0.0003)	(0.0003)
Land	0.007**	0.003*	0.001
	(0.003)	(0.002)	(0.001)
Coop	0.042**	0.007	0.008
	(0.018)	(0.005)	(0.007)
Observations	175	277	24
R^2	0.256	0.148	0.407

Table 8 shows rural households' age heterogeneity regression results. Based on the age of the household head, the data were divided into the youth group (35 years old and below), the middle age group (35 years old and 60 years old below) and the elderly group (60 years old and above). Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets. DP = Digital production, DS = digital sales.

rural households' digital technology adoption.

Results are reported in Table 7. We find that DCCI significantly improves the incomes of rural households who adopt digital sales or digital production technology. Our results indicate that DCCI can effectively hedge the production risk for rural households and loan default risk for banks. Our results are consistent with the findings that DCCI is more effective for rural households with risk preference on agricultural technology (Wu & Li, 2023).

5.2.3. Age heterogeneity analysis

The economic well-being of rural households also differs with life-cycle stages. Young farm households may have significantly lower economic well-being or more unequally distributed income compared to older farm peers (Katchova, 2008). So we examine the income effect of DCCI among different age groups. Columns 1–3 of Table 8 show that DCCI has positive and significant effect on the income of young and middle-aged groups. The income effect of DCCI is positive but not significant among old-age rural households.

The fact that the income effect of DCCI is greater among young and middle-age groups is possibly attributable to these groups being more adept at using smartphones when applying DCCI. The well-being of young and beginning farmers is of interest to Chinese policymakers. Examining these trends has important implications for Chinese farm policy, which currently provides special assistance for young farmers.

6. Conclusions

Drawing on survey data from 476 rural households in China in 2022, we demonstrate that digitally coordinated credit and insurance (DCCI) has a significant and positive impact on rural households' net incomes, yielding a 2.3% increase (equivalent to 909.69 Yuan, standard error = 0.006) for every 1% rise in DCCI participation. This positive effect is notably stronger among rural households that engage with digital technologies or platforms, as well as those facing high natural risks, such as those in mountainous regions. Additionally, younger rural households exhibit a more pronounced benefit from DCCI.

These findings underscore the importance of targeting DCCI initiatives toward younger rural populations and those in high-risk areas to maximize economic benefits. Moreover, our results highlight that DCCI contributes to income growth by alleviating credit rationing and enhancing risk resilience among rural communities. This evidence strongly advocates for the expansion of DCCI services as a strategic tool to bolster economic stability and growth in vulnerable rural sectors.

Our findings have important implications. First, our study underscores the substantial benefits of digitally coordinated credit and insurance (DCCI) in improving the economic well-being of rural households. Primarily, DCCI effectively mitigates risk and credit rationing, suggesting that governments could boost agricultural investments in rural areas by fostering the integration of digital credit and insurance services. Secondly, DCCI is not a one-size-fits-all solution. The efficacy of DCCI varies: it is particularly advantageous for younger households, households adopting digital technology and those in regions prone to natural disasters, such as mountainous areas. This indicates a need for local governments to prioritize investments in digital infrastructure in these high-risk zones to maximize the impact of DCCI. In conclusion, as digital technologies continue to reshape the rural financial landscape, the integration of digital credit and digital insurance in serving rural households presents both opportunities and risks. Institutional innovations, such as fail-safe audit mechanisms, robust regulatory frameworks, and comprehensive consumer protection initiatives, are critical to ensuring the reliability and equity of these services. The combined use of digital credit and insurance must address challenges such as credit overextension, moral hazard, and the unobservable quality of index insurance contracts. A well-structured approach to development programming and policy formulation should carefully consider these inherent risks.

While our findings are promising, they come with limitations due to the scope of our data collection. Our sample was drawn exclusively from rural households in a Chinese province where digital village initiatives were first piloted. While this provided a unique opportunity to observe DCCI in action, future research could further enrich our understanding by exploring its impact in a variety of rural settings across different regions. This would help confirm and extend the applicability of our results globally.

CRediT author statement

Jinhua Zhang: Conceptualization, Formal analysis, Funding acquisition, Writing – original draft Shuangyu Chen: Data curation, Formal analysis, Methodology, Writing – original draft John W Goodell: Writing – original draft, Writing – review & editing Anna Min Du: Conceptualization, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Further robustness testing

For further testing, we adopt the reweighting method of entropy balancing to produce balanced samples (Hainmueller, 2011). Table A1 displays the means, variances, and skewness of covariates for the treatment and control groups before and after entropy balancing. Results are that there are significant differences in the first three moments of the covariates before entropy balancing. However, after applying optimal weights for matching, the first three moments of the covariates between the control and treatment groups are closely similar.

Table A1
Balance testing

Variable	Treatment group			Before matching			After matching		
				Control group			Control group		
	mean	variance	skewness	mean	variance	skewness	mean	variance	skewness
Gen	0.802	0.161	−1.518	0.741	0.192	−1.100	0.800	0.160	−1.500
Age	43.81	170.60	−0.970	40.21	297.70	−0.846	43.760	170.400	−0.959
Edu	11.770	12.420	−0.163	11.970	9.611	−0.081	11.750	12.400	−0.152
Capin	10.520	1.569	0.370	10.220	1.651	−0.427	10.510	1.567	0.398
Labin	2.872	14.020	3.551	3.174	27.28	3.715	2.869	14.000	3.556
Land	7.295	3.864	0.581	6.542	4.935	1.998	7.287	3.869	−0.683
Coop	0.361	0.233	−0.695	0.318	0.217	0.782	0.363	0.232	0.571

Table A1 shows the balance test before entropy balance matching.

Table A2 presents the estimation results. Column (1) shows that CDCI has positive and significant effect on rural households' agricultural net income. The coordinated effect is higher than digital credit or digital insurance alone, and also higher than traditional. Our results are consistent across different model setting.

Table A2
Entropy balancing

	(1)	(2)	(3)	(4)
	EB-OLS	EB-OLS	EB-OLS	EB-OLS
DCCI	0.046**			
	(0.019)			
DC		0.035**		
		(0.014)		
DI			0.034*	
			(0.02)	

(continued on next page)

Table A2 (*continued*)

	(1)	(2)	(3)	(4)
	EB-OLS	EB-OLS	EB-OLS	EB-OLS
CCI				0.031**
				(0.013)
Gen	0.001	0.016	0.058**	0.016
	(0.03)	(0.024)	(0.029)	(0.024)
Age	0.001	0.001	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Edu	0.008**	0.007***	0.006**	0.007***
	(0.003)	(0.002)	(0.003)	(0.002)
Capin	0.032***	0.028***	0.029***	0.027***
	(0.012)	(0.01)	(0.01)	(0.01)
Labin	0.001	0.001	0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Land	0.018***	0.014***	0.005	0.013***
	(0.006)	(0.005)	(0.007)	(0.005)
Coop	0.023	0.014	0.032	0.016
	(0.021)	(0.014)	(0.02)	(0.014)
Observations	476	476	476	476
R-squared	0.178	0.152	0.185	0.144

Table A2 shows the robustness test of DCCI on rural households' agricultural income. Levels of significance: ***1%, **5%, *10%, The values in brackets are robust standard errors. DCCI = digital coordination of credit and insurance; DI = digital insurance; DC = digital credit; CCI = coordinated credit and insurance.

Table A3
Benchmark regression results of farm income on DCCI

	(1)	(2)	(3)	(4)
DCCI	0.046***			
	(0.014)			
DC		0.039***		
		(0.014)		
DI			0.038***	
			(0.013)	
CCI				0.033**
				(0.014)
Gen	0.043**	0.042**	0.039**	0.043**
	(0.02)	(0.02)	(0.019)	(0.02)
Age	0.001**	0.001**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Edu	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Capin	0.025***	0.023***	0.024***	0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
Labin	0.002**	0.001*	0.002**	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Land	0.03**	0.027*	0.033**	0.026*
	(0.015)	(0.015)	(0.015)	(0.015)
Coop	0.011***	0.011***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	476	476	476	476
R^2	0.207	0.203	0.204	0.199

Table A3 shows the baseline regression results. Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets. DCCI = digital coordination of credit and insurance; DI = digital insurance; DC = digital credit, CCI = coordinated credit and insurance.

Table A4
Two-stage least square regression results of farm income on DCCI

	(1)	(2)	(3)	(4)
DCCI	0.145**			
	(0.069)			
DC		0.127**		
		(0.06)		
DI			0.132**	
			(0.066)	
CCI				0.124**
				(0.062)
Gen	0.042**	0.039*	0.027	0.04**

(*continued on next page*)

Table A4 (*continued*)

	(1)	(2)	(3)	(4)
	(0.02)	(0.02)	(0.021)	(0.02)
Age	0.001*	0.001**	0.002***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Edu	0.006***	0.005**	0.006***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Capin	0.023***	0.018**	0.02***	0.017**
	(0.007)	(0.008)	(0.008)	(0.008)
Labin	0.002**	0.002*	0.002**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Land	0.029*	0.022	0.039**	0.017
	(0.016)	(0.015)	(0.017)	(0.016)
Coop	0.011***	0.01***	0.009**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	476	476	476	476
R^2	0.129	0.138	0.121	0.133

Table A4 shows the IV regression results. Levels of significance: ***1%, **5%, *10%. The robust standard errors are reported in brackets. DCCI = digital coordination of credit and insurance; DI = digital insurance; DC = digital credit. CCI = coordinated credit and insurance.

Data availability

Data will be made available on request.

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