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Empowering farmers through agricultural supply chains: An ESR and IVQR analysis of income effects in China

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Abstract: Integrating farmers into the modern agricultural industrial system is key to sustaining rural household income growth. Based on field survey data from rural areas in three western Chinese provinces, this study uses an endogenous switching regression (ESR) model to analyse the impact of farmers' participation in agricultural supply chains on their income, and explores the heterogeneous effects of credit constraints and agricultural loans on the incomes of participating and non-participating farmers. The results show that supply chain participation significantly increases farmers' total and operational income, while driving the modernisation of agricultural production methods. Specifically, supply chain participation enables farmers to use agricultural loans efficiently to drive income growth and alleviate income constraints caused by credit restrictions. Furthermore, the positive effect of supply chain participation on operational income is more prominent, especially for low- and middle-income farmers. In contrast, the income-increasing benefits of agricultural loans are more pronounced among middle- and high-income farmers, reflecting differences in loan utilisation capacity across income groups.

Keywords: credit constraints; farmers' participation; income growth; supply chain

Marketisation has increased and diversified demand for agricultural products while intensifying market competition. For developing countries, smallholder farmers are not only the cornerstone of national food security but also a vulnerable group often marginalised in development policies. They grapple with interconnected challenges, including limited access to finance, fragmented market information, outdated production technologies and small-scale farming, all of which hinder the optimal allocation of production factors and slow the transition to agricultural modernisation (Smidt and Jokonya 2022). Integrating smallholders into modern agricultural systems is critical, and agricultural supply chains (ASCs) are widely recognised as a pivotal bridge. By linking farmers to downstream actors, ASCs mitigate the vulnerabilities of small-scale farming and facilitate their participation in high-value markets (de Janvry and Sadoulet 2020; Vos and Cattaneo 2021).

ASCs encompass the entire value chain from production to consumption, involving product circulation, information sharing, value addition, and stakeholder collaboration (Dania et al. 2018; Govindan 2018). Especially in the Agriculture 4.0 era, they contribute significantly to rural development, employment, and poverty reduction (Barrett et al. 2022; Javaid et al. 2022). For example, Behzadi et al. (2018) demonstrated that ASC participation helps organise farmers to cut costs and enhance risk resilience. Zhao et al. (2021) found that ASCs provide technical guidance to improve product quality and boost farmers' income. German et al. (2020) highlighted that ASCs strengthen farmers' market position and stabilise incomes by expanding financial

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access. Despite these proven advantages, many smallholders, especially those in less developed regions, still face barriers to ASC participation, such as insufficient investment capacity, limited awareness of sustainable practices, and inadequate skills to adapt to market demand (Sekaran et al. 2021).

Rural financial exclusion exacerbates these barriers. Traditional rural finance fails to serve smallholders due to a lack of tangible collateral, high transaction costs, and agricultural risks (Khanal and Omobitan 2020). In recent years, agricultural supply chain finance has emerged as a solution (Miller & Jones, 2010). It uses supply chain relationships as collateral substitutes (Yi et al. 2021) and reduces information asymmetry through inter-member ties (Mangla et al. 2021), addressing the dilemmas of traditional finance and optimising resource allocation (Chen et al. 2023). For smallholder-dominated countries like China, ASC-based finance is key to expanding rural financial services and unlocking agricultural productivity (Mehmood et al. 2021; Villalba et al. 2023).

China's 'big country, small farmers' context is unique. Despite policy-driven efforts to promote large-scale, commercialised, and industrialised agriculture, small-scale farming remains dominant, particularly in Western regions (Wang et al. 2020; Rogers et al. 2021). In these areas, fragmented landholdings, limited arable land, and low digital literacy worsen the challenges of accessing ASCs and financial services amid rapid digitalisation. Smallholders' willingness and ability to participate in ASCs are critical for agricultural modernisation, yet two gaps remain: how ASC participation affects smallholders' incomes, and whether it modifies the impact of finance on income.

Although prior studies have yielded valuable insights into understanding ASC-income relationships and rural financial inclusion, three critical gaps persist. Firstly, most research either focuses solely on the income effects of participating in modern agricultural practices (e.g. Ma and Sexton 2021; KC et al. 2023) or examines the role of rural financial factors (e.g. Yang et al. 2018; Zheng and Liu 2025), ignoring the interactions between these two factors. Specifically, it remains unclear whether ASC participation strengthens the income-increasing effect of loans. Secondly, most existing ASC research adopts a macro or organisational-level analytical perspective (e.g. Cordeiro et al. 2022; Feng et al. 2024), paying insufficient attention to micro-level smallholder dynamics and regional specificity. Furthermore, while some studies address ASC heterogeneity (e.g. Hidayati et al. 2023; Liang et al. 2023), few quantify how the benefits of ASC participation and agricultural loans differ across income levels, impeding equitable policy design.

This study fills these gaps using survey data from 887 rural households in Southwest China and an endogenous switching regression (ESR) model. Its key contributions to the literature are threefold. Firstly, the ESR model accounts for both observable and unobservable self-selection biases, yielding more reliable causal inferences. Secondly, this study examines how ASC participation modifies the impact of credit constraints and agricultural loans on income, clarifying whether ASCs enhance loan utilisation efficiency and mitigate the adverse effects of financial constraints. Thirdly, it quantifies the heterogeneous benefits of ASC participation and agricultural loans for low-, middle-, and high-income levels, providing insights into ensuring the equitable distribution of ASC-related benefits.

Against the backdrop of smallholder farmers' vulnerability to market volatility and financial exclusion, agricultural supply chains (ASCs) serve as a coordinated institutional arrangement that integrates farmers into 'shared benefits and risks' interest communities. This integration directly impacts household income by optimising production, mitigating risks, and enhancing financial access, with operational and total income identified as key outcome variables.

Mechanisms of ASC participation on farmer income. ASC participation drives income growth primarily through three interrelated mechanisms: income security via risk reduction, cost efficiency via scale effects, and value addition via quality improvement.

Firstly, smallholder farmers face severe market price volatility due to weak bargaining power and limited price forecasting capabilities. ASCs address this by formalising contracts between farmers and downstream stakeholders. Pre-signed sales contracts secure a fixed or minimum guaranteed price for farmers, locking in revenue before production (Candemir et al. 2021). ASC intermediaries, such as cooperatives or leading enterprises, implement price support to further stabilise farmers' income expectations (Wang et al. 2022). This stability not only prevents income erosion during market downturns but also incentivises long-term productivity-enhancing investment, laying the foundation for sustained income growth.

Secondly, smallholder farming is characterised by high transaction costs, including the search for information, contract negotiations, input procurement, and inefficient production practices. ASCs internalise these costs through collective action. By aggregating farmers' demands, ASC intermediaries negotiate bulk discounts with input suppliers, reducing per-unit costs of seeds, fertilisers, and pesticides (Krishnan et al. 2021). Moreover, intermediaries facilitate information sharing and provide

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free technical training, helping farmers adopt efficient management practices to reduce resource waste and production costs (Candemir et al. 2021). These cost-saving effects directly increase net operational income by channelling resources from non-productive to core production activities.

Thirdly, amid diverse consumer demand for high-quality, traceable agricultural products, smallholder farmers often fail to meet quality standards due to limited technical knowledge and limited access to certification. ASC intermediaries provide standardised guidelines for planting, harvesting, and processing, ensuring products meet market quality benchmarks to access premium markets (Creppy et al. 2024). In addition, ASCs integrate simple processing and packaging services to transform raw agricultural products into high-value commodities (Cramer et al. 2022). By combining risk mitigation, cost reduction, and value enhancement, ASC participation directly boosts both operational incomes derived from agricultural production and total incomes comprising operational incomes plus non-agricultural incomes indirectly supported by ASC-driven efficiency gains. Based on this, we propose:

H_{1a}: Participation in agricultural supply chains significantly increases farmers' total household incomes.

H_{1b}: Participation in agricultural supply chains significantly increases farmers' operational incomes.

ASC participation and financial constraints. Traditional rural finance faces a 'triple dilemma' in serving smallholder farmers: a lack of tangible collateral, high transaction costs from scattered households, and elevated default risks due to agricultural uncertainty (Khan et al. 2024). This dilemma causes severe financial constraints, whereby farmers either fail to obtain loans or avoid applying for loans to prevent rejection. Such constraints restrict productive investment and technology adoption, further suppressing income growth. ASCs mitigate these financial bottlenecks by enhancing smallholder creditworthiness through three interrelated mechanisms.

First, ASC participation expands farmers' access to endogenous and exogenous financing channels. Within ASC networks, upstream and downstream members provide production-cycle-tailored in-kind or cash advances. For instance, leading enterprises supply seeds and fertilisers on credit at the planting stage, with repayment deducted from harvest proceeds; affiliated cooperatives offer interest-free prepayments based on verified expected output (Karaman and Yigit 2022). Financial institutions also prioritise loans backed by the contractual stability of ASCs (Villalba et al. 2023). Second, ASCs replace physical collateral with relational collateral, such as ASC contracts and future output commitments. Farmers can use purchase contracts with processing enterprises as collateral, as these ensure stable repayment streams (Zhang 2025). Upstream suppliers may also accept procured inputs (e.g. machinery, fertilisers) as collateral, lowering credit access thresholds (Yi et al. 2021). Third, ASC intermediaries act as 'information brokers', providing financial institutions with detailed data on farmers' production capacity, historical output, and contract performance, which banks cannot acquire independently and efficiently. This reduces risk assessment costs and improves credit rating accuracy (Darby et al. 2022). Collectively, these mechanisms enable previously credit-excluded farmers to access production funds and alleviate the constraints faced by moderately constrained groups. Based on this, we propose:

H_2: Participation in agricultural supply chains alleviates the negative impact of financial constraints on farmers' income.

ASC participation and agricultural loan efficiency. Even when farmers obtain agricultural loans, traditional lending models suffer from low fund utilisation efficiency. Loan diversion to non-productive uses or low-return investments limits income-generating potential (Khanal and Omobitan 2020). ASCs address this by enhancing loan-to-income conversion efficiency through targeted guidance, resource reallocation, and monitoring. First, ASC intermediaries provide tailored loan allocation guidance. Leveraging market insights, leading enterprises recommend that farmers invest in high-yield crops or precision machinery aligned with current and projected demand (Chen et al. 2022), channelling funds to proven income-enhancing activities and avoiding blind investment by independent farmers. Second, ASC-driven production efficiency gains free up labour and funds for non-agricultural income activities. Farmers may also use loans for non-agricultural skill training to enhance their capacity to engage in high-value non-farm work (Sagbo and Kusunose 2021). Third, ASCs incorporate loan utilisation monitoring clauses in contracts, ensuring that funds are directed to high-priority income-generating uses. This oversight reduces waste and ensures exclusive allocation to income-enhancing activities, improving loan-to-income conversion efficiency. Accordingly, we propose:

H_3: Participation in agricultural supply chains can improve the efficiency of converting agricultural loans into incomes for farmers.

The mechanisms through which ASC participation affects farmers' income are illustrated in Figure 1.

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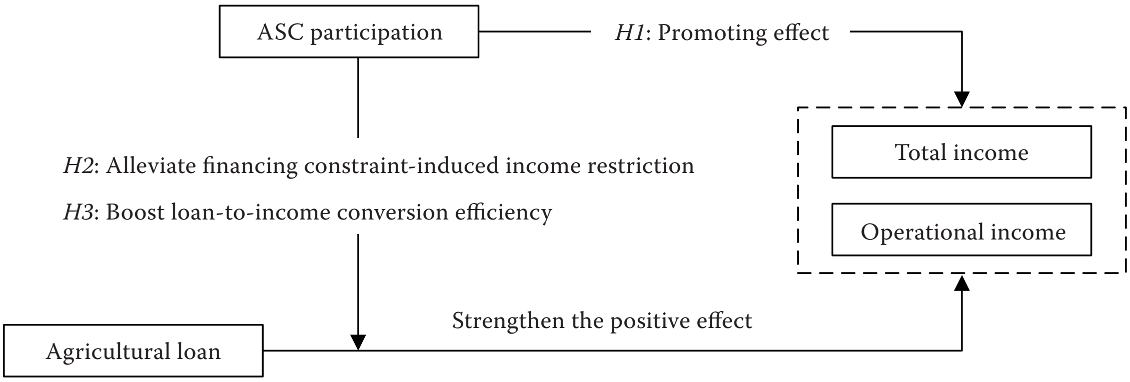

Figure 1. Mechanism diagram

ASC – agricultural supply chain
Source: Authors' own processing

MATERIAL AND METHODS

Data sources

This study utilises primary data from a household survey conducted by the research team in July–August 2023, covering three Western Chinese regions: Sichuan Province, Chongqing Municipality, and Guizhou Province. The questionnaire captures core information on household demographics, agricultural production and operational status, ASC participation, and access to formal agricultural loans. To guarantee the scientific rigor and representativeness of the sample, a multi-stage stratified random sampling method was adopted. In each region, 3–5 counties (districts) with relatively mature ASC development were selected based on local agricultural industry reports and government statistics. Within selected counties (districts), 2–4 towns with heterogeneous agricultural industrialisation levels were chosen to capture differences in ASC maturity. Two villages were randomly selected from each sampled town, and 10–15 rural households were further randomly sampled per village to minimise selection bias. A total of 1 000 questionnaires were distributed through face-to-face interviews. After data cleaning, we excluded samples with missing key information, logical inconsistencies, or outliers, and 973 valid questionnaires were retrieved. Given the study's focus on smallholder farmers engaged in agricultural production, non-agricultural-oriented samples were further excluded, resulting in a final sample size of 887 for the empirical analysis.

Variable section

Dependent variable. The dependent variables include farmers' total household income and operational income. Total household income '*rev*') includes multiple income categories, including operational income, wage income, property income, and transfer income. Given that total household income is influenced by household size, this study employs *per capita* rural household income as the measure of total household income. Operational income ('*rev_oper*') focuses on agricultural-related gains to exclude non-agricultural components. Both variables are log-transformed to mitigate heteroscedasticity and skewed income distributions.

Treatment variable. The core treatment variable is ASC participation ('*pisc*'), a binary variable coded 1 if a household participates in ASCs and 0 otherwise. Consistent with the definition of ASCs as core organisation-driven systems integrating supply, production, transportation, processing, and sales (Han et al. 2020), this study defines ASC participation as the establishment of interest linkages via market transactions, contractual cooperation, labour participation, or equity cooperation with ASC core entities, including cooperatives, leading agricultural enterprises, or rural e-commerce platforms. Sample descriptive statistics show that cooperative linkages dominate participation (44%), while direct enterprise participation is relatively rare (6%). Notably, this variable may introduce reverse causality. Farmers with higher incomes may have greater access to information and stronger understanding of agricultural industrialisation, enhancing their capacity and willingness to participate in ASCs. This potential endogeneity is addressed in subsequent analyses.

Independent variable. The first key explanatory variable is 'financing constraints (*cons*)', which covers both supply-side and demand-side credit constraints. Specifically, a household is defined as 'credit-constrained'

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(assigned 1) if it has unmet credit demand, including non-application, rejected application, or partial loan approval. The second key explanatory variable is 'agricultural loans (*loan*)', measured as formal loans for agricultural production, including planting, breeding, and agricultural infrastructure construction, divided by the number of household members. Survey-year loans are excluded to account for production cycle lags.

Instrumental variable. To address endogeneity arising from reverse causality between ASC participation and farmers' income, this study introduces 'farmers' awareness of agricultural supply chains' as the first instrumental variable. The core identification assumption for adopting this instrumental variable is that farmers' understanding of agricultural supply chains may affect their decision to participate in such chains; however, this awareness does not directly determine their income level. Additionally, considering that transport and logistics conditions significantly impact farmers' willingness and ability to participate in the agricultural supply chains, and this factor is not directly correlated with farmers' income, this study selects 'transportation and logistics conditions' as the second instrumental variable.

Control variable. Three-dimensional control variables are included to isolate core effects: individual, household, and regional characteristics. These control variables include the respondent's gender, age, marital status, educational level, health status, the proportion of the labour force in the household, whether any family member holds a village cadre position, the household's part-time employment status, the area of contracted farmland, the status of farmland transfer, participation in agricultural skills training, internet signal coverage, and road conditions. Considering the rapid progress of China's agricultural industry in the context of digital transformation, farmers' digital literacy and skills significantly impact their income (Hou et al. 2019). Therefore, this study further includes 'computer proficiency', 'e-commerce proficiency', and 'digital financial management' to measure farmers' digital capabilities. The definitions and assignment methods for these variables are detailed in Table 1.

Descriptive statistics

Descriptive statistics for all variables are presented in Table 2, and inter-group difference analysis is shown in Table 3. As can be seen from Table 2, the average *per capita* total income of the surveyed households is USD 4 077, far exceeding the 2022 national rural *per capita* disposable income (around USD 2 820.54, China Statistical Yearbook 2023.). The average *per capita* agricultural operational income reaches USD 1 983, accounting for 48.6% of total income, underscoring the dominant role of agricultural operations in household income composition. Notably, the income distribution demonstrates high heterogeneity. *Per capita* total income ranges from USD 21.97 to 86 020.17, with a median of 2 342, indicating half of the surveyed households have income below this threshold. The large standard deviation further confirms the substantial income disparity among the sample households. In terms of credit-related variables, approximately 14% of the sample households are subject to credit constraints. The average *per capita* agricultural loan is 1 446.9, with a large standard deviation. This pattern reflects a dual structure in loan demand: most households only apply for small-scale loans to meet daily agricultural production needs, while a small subset of households obtain large-sum loans for scaled agricultural operations. In terms of ASC participation, sample households exhibit relatively low ASC awareness, with merely 19% of them participating in ASCs. This phenomenon indicates insufficient grassroots dissemination of ASC-related knowledge and low farmer participation willingness, suggesting considerable potential for ASC integration and development in southwestern China. From the perspective of individual characteristics, the sample farming population shows ageing, low educational attainment and weak digital literacy. Male household heads account for 88%, with an average age of 56.78 years; most of them have an educational background below junior high school. Digital skill penetration is low, only 27% master basic computer operations, and 12% use digital financial products, highlighting the urgent need to improve farmers' ability to apply information technology. In terms of household characteristics, part-time farming is relatively rare, with only 9% of households engaging in it, indicating that most sample households still rely on traditional full-time agricultural production. The average contracted farmland area is 5.47 mu (1 mu ≈ 0.066 7 hectares); 48% of households have transferred in farmland, and 23% have transferred out farmland, reflecting active farmland circulation under China's rural 'Three Rights Separation' reform. For regional characteristics and instrumental variables, the average score of local transportation and logistics conditions is 3.76, indicating generally favourable infrastructure conditions for ASC participation. The average score of ASC awareness is 1.57, and the average score of internet development level is 3.40.

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Table 1. Variable selection

	Variable	Variable assignment
Dependent variables	total income	*per capita* sum of operating, wage, transfer, and property incomes
	operating income	*per capita* net income from agriculture, forestry, animal husbandry, and fishery
Core explanatory variables	credit constraint	1 = unmet credit demand (no application/rejection/ partial approval); 0 = otherwise
	agricultural loan	*per capita* formal agricultural loans
Treatment variable	agricultural supply chain participation	1 = participated; 0 = otherwise
Individual characteristics	gender	gender of the household head
	age	age of the household head (years)
	marital status	1 = married; 0 = unmarried/widowed/divorced
	education	6 levels (1 = no schooling; 2 = primary school or below; 3 = junior high school; 4 = high school; 5 = junior college; 6 = bachelor's degree or above)
	health status	5 levels (1 = very unhealthy; 2 = unhealthy; 3 = average; 4 = mostly healthy; 5 = very healthy)
	computer proficiency	1 = can use basic functions; 0 = otherwise
	e-commerce proficiency	1 = can buy/sell agricultural goods online; 0 = otherwise
	digital finance	1 = can use digital financial products; 0 = otherwise
Household characteristics	labour force	proportion of household members aged 16–64
	village cadre	1 = has household member as cadre; 0=otherwise
	part-time employment	1 = engages in part-time work; 0=otherwise
	contracted land	area (mu)
	land transfer-in	1 = transferred in land; 0 = otherwise
	land transfer-out	1 = transferred out land; 0 = otherwise
	training	1 = participated in agricultural training; 0 = otherwise
Regional characteristics	internet	4 levels from low to high: 1 = E network; 2 = 3G; 3 = 4G; 4 = 5G
	road	4 levels from low to high: 1 = dirt road; 2 = gravel road; 3 = cement road; 4 = asphalt road
Instrumental variables	awareness of agricultural supply chain	5 levels from low to high: 1 = completely unaware; 2 = heard of it; 3 = generally aware; 4 = fairly aware; 5 = very aware
	transportation and logistics conditions	5 levels from low to high: 1 = very poor; 2 = poor; 3 = average; 4 = good; 5 = very good

mu – conventional Chinese land area unit, with 1 mu equal to 1/15 hectare (roughly 0.0667 ha).
Source: Authors' own elaboration

As shown in Table 3, statistically significant differences are observed between ASC participants and non-participants. Specifically, ASC participants have substantially higher *per capita* total income and *per capita* operational income, with both differences being significant at the 1% level. This indicates the positive contribution of ASC participation to household economic returns. Compared with non-participating households, participants face fewer credit constraints and obtain larger agricultural loans. From the perspective of individual characteristics, ASC participants are younger and demonstrate superior human

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Table 2. Descriptive statistics

		Variable	Mean	SD
Dependent variables		total income	4 077.33	7 367.53
		operating income	1 983.13	6 883.52
		wage income	1 688.29	2 107.52
Core explanatory variables		credit constraint	0.14	0.35
		agricultural loan	1 446.92	7 126.05
Treatment variable		agricultural supply chain participation	0.19	0.39
Control variables	individual characteristics	gender	0.88	0.33
		age	56.78	11.38
		marital status	0.96	0.19
		education	2.78	0.96
		health status	3.95	1.06
		computer proficiency	0.27	0.44
		e-commerce proficiency	0.54	0.50
		digital finance	0.12	0.33
	household characteristics	labour force	0.64	0.26
		village cadre	0.18	0.38
		part-time employment	0.09	0.29
		contracted land	5.47	9.90
		land transfer-in	0.48	0.50
		land transfer-out	0.23	0.42
		training	0.45	0.50
	regional characteristics	internet	3.40	0.53
		road	2.91	0.50
Instrumental variables		awareness of agricultural supply chain	1.57	0.92
		transportation and logistics conditions	3.76	0.95

Source: Authors' own elaboration

capital endowments. They have higher educational attainment, better health status, and stronger digital skills. No statistically significant differences are found in gender, marital status, or digital finance adoption between the two groups. In terms of household characteristics, participating households possess more favourable production and resource conditions. They have a larger labour force, a higher proportion of village cadre members, more part-time employment opportunities, and a larger contracted farmland area. Additionally, participants are significantly more likely to engage in farmland transfer-in and agricultural skills training while being less prone to farmland transfer-out. In addition, consistent with the instrumental variable relevance assumption, ASC participants show significantly higher awareness of the agricultural supply chain and better local transportation and logistics conditions.

Econometric model

Based on the theoretical analysis above, this paper constructs the following benchmark regression model:

$$rev_i = \beta_0 + \beta_1 pisc_i + \beta_2 cons_i + \beta_3 loan_i + \beta_4 control_i + \varepsilon_i \quad (1)$$

where: rev_i – the *per capita* income of household *i*; *pisc* – a treatment variable that measures whether farmers participate in the supply chain; *cons* – the credit constraints faced by farmers; *loan* – the amount of agricultural loans obtained; *control* – the control variables that may affect farmers' income; ε – the error term; β – the coefficients to be estimated.

Estimation using the ordinary least squares (OLS) method may suffer from self-selection bias, leading to endogeneity. Besides self-selection, omitted variable bias is another concern. Since numerous factors influence household income, it is difficult to include all rel-

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Table 3. Inter-group difference analysis

		Variable	Non-participation mean value	Participation mean value	Difference mean value	t value
Dependent variables		total income	20 314.56	66 998.64	–46 684.08***	–11.02
		operating income	6 073.48	49 000.67	–42 927.19***	–10.82
Core explanatory variables		credit constraint	0.17	0.04	0.13***	4.47
		agricultural loan	4 444.47	35 694.92	–31 250.45***	–7.36
Control variables	individual characteristics	gender	0.87	0.91	–0.04	–1.36
		age	57.47	53.82	3.65***	3.76
		marital status	0.96	0.97	–0.01	–0.55
		education	2.71	3.10	–0.39***	–4.84
		health status	3.91	4.14	–0.23**	–2.57
		computer proficiency	0.23	0.40	–0.17***	–4.43
		e-commerce proficiency	0.50	0.72	–0.22***	–5.26
		digital finance	0.11	0.15	–0.04	–1.28
	household characteristics	labour force	0.63	0.68	–0.05**	–2.12
		village cadre	0.16	0.25	–0.09***	–2.76
		part-time employment	0.08	0.14	–0.06**	–2.48
		contracted land	4.68	8.88	–4.21***	–5.01
		land transfer–in	0.42	0.77	–0.36***	–8.62
		land transfer–out	0.26	0.12	0.14***	3.91
		training	0.38	0.74	–0.36***	–8.71
	regional characteristics	internet	3.40	3.44	–0.04	–0.91
		road	2.90	2.94	–0.04	–0.94
Instrumental variables		awareness of agricultural supply chain	1.42	2.22	–0.80***	–10.73
		transportation and logistics conditions	3.81	3.99	–0.18**	–2.40
n			720	167		

*** and ** denote statistical significance at the 1% and 5% levels, respectively.
Source: Authors' own elaboration

evant explanatory variables in the model completely. Additionally, the model may involve unobservable factors (e.g. farmers' risk attitudes, regional market environment, and long-term production habits), which can cause both biases. In the absence of randomised controlled trials (RCTs), propensity score matching (PSM) is commonly used to address endogeneity caused by observable variables such as age and gender. However, it cannot fully control for the impact of unobservable characteristics between participating and non-participating households, potentially resulting in 'hidden bias' (Ding and Abdulai 2020). Effective methods to address unobservable factors include the Heckman selection model and the endogenous switching regression (ESR) model proposed by Lokshin and Sajaia (2004). However, the Heckman model only analyses the income effects of participants and does not cover non-participating households. Therefore, this study employs the ESR model. The advantages of the ESR model are that it minimises estimation errors due to omitted variables, addresses self-selection bias caused by unobservable factors, and allows simultaneous examination of both groups.

The endogenous switching regression model is divided into two stages. The first stage is the selection equation, analysing factors influencing farmers' decision to participate in ASCs. The second stage is the outcome equation, evaluating ASC participation's impact on farmers' income. By comparing the heterogeneous effects of explanatory variables across the two groups, this model reveals the specific contribution of agricul-

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tural supply chain participation to improving farmers' economic well-being. The empirical equations of the ESR model are specified as follows:

In the first stage, the selection equation for farmers' participation in the agricultural supply chain is:

$$P_i = \gamma_1 Z_i + \gamma_2 I_i + \mu_i \tag{2}$$

where: P_i – a binary choice variable, P_i = 1 if household i participates in the agricultural supply chain, and P_i = 0 if otherwise; Z_i – a set of explanatory variables influencing the participation decision, including individual, household, and socio-economic characteristics; I_i – the instrumental variable; μ_i – the random error term.

In the second stage, the outcome equations for participating and non-participating households are specified separately:

$$Y_{Ti} = \beta_T X_{Ti} + \sigma_{T\mu}\lambda_{Ti} + \varepsilon_{Ti} \quad \text{if} \quad P_i = 1 \tag{3}$$

$$Y_{Ui} = \beta_U X_{Ui} + \sigma_{U\mu}\lambda_{Ui} + \varepsilon_{Ui} \quad \text{if} \quad P_i = 0 \tag{4}$$

where: Y_{Ti} and Y_{Ui} – the *per capita* income of participating and non-participating households, respectively; X_{Ti} and X_{Ui} – the core explanatory variables affecting household income, including farmer's credit constraint $cons_i$ and agricultural loan amounts $loans_i$; ε_{Ti} and ε_{Ui} – the random error terms for the outcome equations.

When the decision variable P_i and income Y are both influenced by unobservable factors, the error terms of the selection and outcome equations are correlated (corr(μ,ε) ≠ 0), indicating the existence of selection bias. To correct this selection bias, the ESR model incorporates the inverse Mills ratios λ_{Ti} and λ_{Ui} in the outcome equations, as well as the covariances of the error terms $\sigma_{T\mu} = \text{cov}(\varepsilon_{Ti}, \mu_i)$ and $\sigma_{U\mu} = \text{cov}(\varepsilon_{Ui}, \mu_i)$. The parameters of this simultaneous equations model are estimated using the full information maximum likelihood (FIML) method, ensuring consistent and efficient estimation results.

The ESR model results reveal the heterogeneous impacts of explanatory variables on the income of participating and non-participating households. To further quantify the net effect of agricultural supply chain participation on farmers' income, this study calculates the average treatment effect, reflecting the average income impact of ASC participation. This calculation is based on comparing the actual income scenario and the counterfactual income scenario, considering participants' expected income if they did not participate, and *vice versa*. The average treatment effect on the treated group (*ATT*) and the average treatment effect on the untreated group (*ATU*) are calculated in Equations (5) and (6).

RESULTS AND DISCUSSION

Instrumental variable validity test. To verify the validity of the selected instrumental variables 'Agricultural Supply Chain Awareness' and 'Transportation and Logistics Conditions', this study first conducts baseline regression using the two-stage least squares (2SLS) method, with results reported in Table 4. The validity test covers four core dimensions: endogeneity test, underidentification test, weak instrument test, and overidentification test. In particular, the Hausman test yields a statistic of 1.583, with a P-value of 0.057, which rejects the null hypothesis of 'no endogeneity'. This confirms that the core explanatory variable 'Agricultural Supply Chain Participation' is indeed endogenous in the baseline regression model, thereby justifying the use of instrumental variables to address endogeneity issues. The underidentification test examines whether the instrumental variables are sufficiently correlated with the endogenous variable to identify the model. As shown in Table 4, the Kleibergen–Paap rk LM statistic is 33.475, with a P-value of 0.000, strongly rejecting the null hypothesis of 'instrumental variables underidentification'. This indicates that the two selected instrumental variables can effectively explain the variation of the endogenous variable, confirming the model's identifiability. The Cragg-Donald Wald F statistic is 27.150, which is significantly higher than the Stock-Yogo weak instrument critical value of 19.93 at the 10% significance level. This result indicates that the instrumental variables are not weak, and the 2SLS estimation results are free from weak instrument bias. Since this study uses two instrumental variables to explain one endogenous variable, the Hansen J test is adopted to verify the exogeneity of instrumental variables. As shown in Table 4, the Hansen J test statistic is 1.583, with a P-value of 0.208. This fails to reject the

$$ATT = E(Y_{Ti} \mid P_i = 1) - (Y_{Ui} \mid P_i = 1) = (\beta_T - \beta_U) X_{Ti} + (\sigma_{T\mu} - \sigma_{U\mu})\lambda_{Ti} \tag{5}$$

$$ATU = E(Y_{Ti} \mid P_i = 0) - E(Y_{Ui} \mid P_i = 0) = (\beta_T - \beta_U) X_{Ui} + (\sigma_{T\mu} - \sigma_{U\mu})\lambda_{Ui} \tag{6}$$

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Table 4. Baseline regression

Variable	Total income of farmers	Participation in agricultural supply chain
	second stage	first stage
Participation in agricultural supply chain	0.930** (0.442)	
Awareness of agricultural supply chain		0.0863*** (0.019)
Transportation and logistics conditions		0.0420*** (0.012)
Control variables	yes	yes
Constant	7.515*** (0.487)	–0.480*** (0.171)
Endogeneity	Hausman test	1.583* [0.057]
Underidentification	K–Paap rk LM statistic	33.475*** [0.000]
Weak instrument	Cragg–Donald statistic	27.150 {19.93}
Overidentification	Hansen test	1.583 [0.208]

*, ** and ***significance levels at 10%, 5% and 1%, respectively; *P*-values are in square brackets, Stock-Yogo weak ID test critical values at the 10% significance level are in braces, and robust standard errors are in brackets

Source: Authors' own elaboration

null hypothesis of 'no overidentification issues', confirming that the selected instrumental variables have no direct correlation with the error term of the outcome equation and meet the exogeneity requirement.

Additionally, the first-stage regression results in Table 4 show that both instrumental variables have significant positive effects on the endogenous variable, which is consistent with theoretical expectations. Specifically, higher awareness of agricultural supply chains and better transportation and logistics conditions can significantly promote farmers' participation in agricultural supply chains, further verifying the rationality of instrumental variables' selection.

Estimation results. This study uses Stata 17.0 (StataCorp LLC., USA) to estimate the selection equation and outcome equations of the endogenous switching regression (ESR) model, with detailed results reported in Table 5. Both the log-likelihood (Log-L) values and Wald test statistics indicate good model fit. For the total income equation, the residual correlation coefficient for participating households (ρ_T) is 0.457, indicating a positive correlation between unobservable factors affecting supply chain participation and unobservable factors affecting the income of participating households. In contrast, the residual correlation coefficient for non-participating households (ρ_U) is –0.265, reflecting a negative correlation between these unobservable factors for non-participants. For the operational income equation, ρ_T = 0.286 and ρ_U = –0.232, presenting a consistent correlation pattern. These results confirm that farmers' supply chain participation decisions are not random but are significantly influenced by unobservable characteristics that also affect their income, verifying the existence of self-selection bias. The LR test statistic for the total income equation is 13.32, and for the operational income equation is 4.84, both rejecting the null hypothesis of 'independence between the selection equation and outcome equations' at the 10% significance level. This further confirms the presence of selection bias, ignoring such bias would lead to biased estimation results. Thus, the use of the ESR model in this study is methodologically justified.

Selection equations show that a higher level of education, e-commerce proficiency and digital financial literacy significantly increase farmers' likelihood of participating in agricultural supply chains. This is because better-educated farmers with stronger digital skills

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Table 5. Estimation results of decision and income equations

Variable	Total income (*rev*)			Operating income (*rev_oper*)		
	selection equation	outcome equation		selection equation	outcome equation	
	ASC participation	participation	non-participation	ASC participation	participation	non-participation
Credit constraint		–0.14 (0.378)	–0.942*** (0.124)		–0.194 (0.501)	–0.632*** (0.134)
Agricultural loan		0.066*** (0.014)	0.037** (0.015)		0.058*** (0.020)	0.043** (0.022)
Gender	0.066 (0.181)	0.192 (0.225)	0.177 (0.143)	0.050 (0.180)	0.477 (0.295)	0.107 (0.179)
Age	0.002 (0.007)	0.005 (0.009)	0.009* (0.005)	0.002 (0.007)	0.003 (0.011)	0.002 (0.006)
Marital status	0.143 (0.368)	–0.584 (0.622)	0.077 (0.245)	0.142 (0.356)	–0.300 (0.506)	0.116 (0.300)
Education	0.193*** (0.074)	–0.049 (0.094)	–0.027 (0.061)	0.183** (0.076)	0.050 (0.152)	0.106 (0.070)
Health	0.006 (0.062)	0.061 (0.077)	0.058 (0.046)	0.006 (0.063)	0.083 (0.112)	0.032 (0.052)
Computer proficiency	–0.073 (0.160)	0.315* (0.177)	0.027 (0.133)	–0.077 (0.160)	0.433* (0.250)	–0.223 (0.171)
E-commerce proficiency	0.278* (0.142)	0.331** (0.159)	0.272** (0.106)	0.280* (0.144)	0.418* (0.222)	0.046 (0.136)
Digital finance	0.297** (0.143)	–0.202 (0.171)	–0.080 (0.151)	0.279* (0.144)	–0.246 (0.237)	0.186 (0.179)
Labour force	0.087 (0.241)	0.129 (0.298)	0.364** (0.175)	0.107 (0.242)	0.285 (0.404)	0.393* (0.214)
Village cadre	–0.193 (0.185)	–0.230 (0.181)	0.122 (0.141)	–0.170 (0.182)	–0.429 (0.306)	0.386** (0.166)
Part-time employment	0.438** (0.189)	–0.057 (0.196)	0.289** (0.122)	0.436** (0.191)	–0.066 (0.228)	–0.288 (0.186)
Contracted land	0.020* (0.011)	–0.006 (0.005)	–0.001 (0.006)	0.020* (0.012)	0.002 (0.006)	0.025*** (0.009)
Land transfer-In	0.719*** (0.130)	0.265 (0.234)	0.058 (0.097)	0.722*** (0.135)	0.623** (0.279)	0.813*** (0.139)
Land transfer-out	–0.268* (0.155)	0.484** (0.228)	0.111 (0.101)	–0.255* (0.152)	0.497 (0.326)	–0.609*** (0.128)
Training	0.322** (0.126)	0.280 (0.170)	–0.032 (0.099)	0.318** (0.126)	0.608*** (0.211)	0.272** (0.121)
Internet	0.022 (0.112)	–0.109 (0.158)	0.009 (0.084)	0.017 (0.111)	0.404* (0.211)	0.314*** (0.097)
Road	0.102 (0.116)	0.504*** (0.159)	0.052 (0.085)	0.099 (0.118)	0.522*** (0.173)	0.052 (0.099)
Awareness of agricultural supply chain	0.319*** (0.063)			0.322*** (0.063)		

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Table 5 To be continued

Variable	Total income (*rev*)			Operating income (*rev_oper*)		
	selection equation	outcome equation		selection equation	outcome equation	
	ASC participation	participation	non-participation	ASC participation	participation	non-participation
Transportation and logistics conditions	0.211*** (0.065)			0.217*** (0.066)		
ρ_T		0.457*** (0.133)			0.286** (0.119)	
ρ_U			–0.265*** (0.084)			–0.232* (0.123)
LR test	13.32*** [0.001]			4.84* [0.089]		
Wald	104.74*** [0.000]			192.42*** [0.000]		
Log-L	–1 639.38			–1 839.48		
n	887	887	887	887	887	887

*, ** and ***significance levels at 10%, 5% and 1%, respectively; *P*-values are in square brackets, robust standard errors are in brackets

ASC – agricultural supply chain; LR – likelihood-ratio

Source: Author's own elaboration

have greater access to market information, adaptability to modern ASC operations, and ability to use digital transaction platforms. Part-time employment, larger contracted farmland, and agricultural training also promote ASC participation. Specifically, part-time households have diversified risk-bearing capacity, while larger land scales and training improve production efficiency, making them more attractive to ASCs entities. Farmland transfer-in significantly boosts ASC participation, expanding production increases ASCs' support demand, whereas transfer-out reduces participation, reflecting weaker agricultural engagement. Instrumental variables both exert strong positive effects on participation, consistent with theoretical expectations: enhanced ASC awareness mitigates information asymmetry, while improved logistics lowers transaction costs for ASC collaboration.

Outcome equations reveal heterogeneous income effects across participants and non-participants. For non-participants, credit constraints significantly reduce total incomes and operational incomes, restricting investment in high-quality inputs or technology, as they rely solely on formal financial institutions for traditional financing. For participants, this negative effect weakens and becomes statistically insignificant, confirming H_2.

Agricultural loans benefit both groups but to a greater extent for participants. In particular, the coefficient of agricultural loans for participating households' total income is 0.066, which is 78.5% higher than that coefficient for non-participants. The coefficient for participating households' operating income is 0.058, 33% higher than that for non-participants. This heterogeneous effect supports H_3. ASC-standardised, market-oriented operations guide participants to allocate loans to high-value links, avoiding inefficient investment, aligning with Fowowe (2020) and Nakano and Magezi (2020), who highlight that institutional support (vs. loan amount) mitigates information asymmetry and ensures income-enhancing fund use.

The outcome equations further reveal heterogeneous impacts of control variables. Digital skills, including computer and e-commerce proficiency, only boost participants' income; they have no significant effect on non-participants. Participating households integrate into modern ASC systems, where digital skills reduce information asymmetry, expand sales channels, and improve transaction efficiency. Non-participants that mainly engaged in traditional self-sufficient farming or local small-scale sales lack application scenarios for digital skills, so these skills do not translate into income growth. Traditional factors that dominate

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Table 6. Average treatment effect of participation on total income

Group	Decision stage		Treatment effect
	participate in supply chain	not participate in supply chain	
Participation group	10.532 (0.042)	9.588 (0.033)	ATT = 0.944*** (0.000)
Non-participation group	9.489 (0.020)	9.281 (0.018)	ATU = 0.208*** (0.000)
Heterogeneity effect	H_1 = 1.043	H_0 = 0.307	△ = 0.736
Entire sample	9.681 (0.021)	9.344 (0.017)	ATE = 0.337*** (0.000)

***significance level at 1%; robust standard errors are in parentheses

ATE – average treatment effect; ATT – average treatment effect on the treated group; ATU – average treatment effect on the untreated group

Source: Authors' own elaboration

income in traditional agriculture lose their statistical significance in ASCs. In particular, labour force and contracted farmland only benefit non-participants' operating income, as ASCs rely on standardisation and mechanisation, reduce labour dependence and prioritise high-value crops over land scale.

Farmland transfer behaviour exerts asymmetric impacts on operational income, with stronger effects on non-participants. Farmland inflow positively affects both groups but more markedly for participants, who expand scale to meet supply chain orders, than non-participants, who use it for traditional cash crop scale expansion. Farmland outflow significantly reduces non-participants' operational income but has no significant effect on participants, who can offset losses via agricultural supply chain (ASC) collaboration. Agricultural training and road infrastructure only boost participants' operating income. ASCs provide training application platforms, and frequent product circulation benefits from efficient roads, while non-participants face training-market mismatches and local sales.

The average treatment effect is of significant importance. It helps identify and correct estimation biases caused by observable and unobservable variables. By constructing counterfactual scenarios, we can measure the income difference between the treatment group (participants) and control group (non-participants). The results for total income and operational income are presented in Tables 6 and 7, respectively.

Table 6 shows significant heterogeneity in the total income effect of ASC participation between participants and non-participants. Specifically, the ATT and ATU are 0.944 and 0.208, respectively. This represents participants' potential income loss if they withdraw and non-participants' potential gain if they join. The ATE for the entire sample is 0.337, which is statistically significant at the 1% level, representing the average positive income impact of supply chain participation

Table 7. Average treatment effect of participation on operational income

Group	Decision stage		Treatment effect
	participate in supply chain	not participate in supply chain	
Participation group	9.801 (0.053)	8.550 (0.074)	ATT = 1.251*** (0.000)
Non-participation group	8.566 (0.025)	7.288 (0.033)	ATU = 1.278*** (0.000)
Heterogeneity effect	H_1 = 1.235	H_0 = 1.262	△ = –0.027
Entire sample	8.799 (0.026)	7.526 (0.035)	ATE = 1.273*** (0.000)

***significance level at 1%; robust standard errors are in parentheses

ATE – average treatment effect; ATT – average treatment effect on the treated group; ATU – average treatment effect on the untreated group

Source: Authors' own elaboration

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across all households. The significant gap between *ATT* and *ATU* reflects transitional heterogeneity, indicating the income effect of ASC participation varies by participation status. This heterogeneity suggests that participating households likely had pre-existing advantages, such as superior resource access, stronger management capabilities, and higher production efficiency, prior to joining the supply chain. Notably, this advantage persists even after addressing the endogeneity arising from reverse causality. This phenomenon reveals an 'elite capture' characteristic in agricultural supply chains of South-western China. Advantaged farmers face lower entry barriers and gain more, while traditional smallholders encounter higher barriers and fewer benefits. This phenomenon is observed in both agricultural cooperative economic organisations and agricultural loans (Gelo et al. 2020; Liu et al. 2021).

Table 7 shows distinct operational income effects with no significant 'elite capture'. Unlike total income, the *ATU* for operational income is slightly higher than the *ATT*, with a heterogeneity gap of –0.027. This indicates no significant transitional heterogeneity. Non-participants who are integrated into ASCs can achieve operational income growth comparable to existing participants, validating H_1 and suggesting more equitable operational income promotion via ASCs. The reason may be that operational income depends directly on agricultural production efficiency and sales, as supply chains provide standardised production guidance and stable sales channels to all participants, regardless of their pre-existing advantages, thereby reducing 'elite capture'.

Intra-group heterogeneity. While prior analysis finds no significant operational income effect difference between ASC participants and non-participants, this section explores how ASC participation, agricultural loans, and credit constraints impact farmers across operational income levels using the instrumental variable quantile regression (IVQR) model, addressing endogeneity while capturing heterogeneous effects across income quantiles. Consistent with the ESR model, 'ASC awareness' and 'transportation and logistics conditions' are used as instrumental variables to mitigate endogeneity of the core variables. Five representative quantiles are selected to cover the full income spectrum: 10% (low-income), 25% (lower-middle-income), 50% (middle-income), 75% (upper-middle-income), and 90% (high-income). The regression results are reported in Table 8.

As shown in Table 8, the income-increasing effect of agricultural loans varies significantly by income level, showing a 'threshold effect' and 'strengthening trend'. Coefficients for low- and lower-middle-income farmers are –0.003 and 0.024, respectively, both statistically insignificant.

The negative coefficient for low-income farmers reflects ineffective utilisation. Small farming scales limit economies of scale, and limited access to technology or management prevents high-return investments. For middle-income and above farmers, effects turn significant and strengthen with income, driven by stronger resource-matching capabilities, such as solid finances, market access and advanced technology, enabling scale

Table 8. Quantile regression of different operational income levels

Variable	Quantiles of household operational income level				
	Low income (10%)	Lower-middle income (25%)	Middle income (50%)	Upper-middle income (75%)	High income (90%)
Agricultural loans	–0.003 (0.039)	0.024 (0.031)	0.054** (0.024)	0.080*** (0.020)	0.102*** (0.023)
Credit constraints	–0.387 (0.305)	–0.468* (0.242)	–0.555*** (0.190)	–0.632*** (0.168)	–0.698*** (0.176)
Participation in ASC	2.355* (1.326)	1.920** (0.926)	1.453** (0.737)	1.040* (0.547)	0.688 (0.496)
Control	yes	yes	yes	yes	yes
Constant	4.039*** (1.511)	4.634*** (1.115)	5.272*** (0.773)	5.837*** (0.659)	6.317*** (0.774)
n			887		

*, ** and ***significance levels at 10%, 5% and 1% levels, respectively; robust standard errors are in parentheses

ASC – agricultural supply chain

Source: Authors' own elaboration

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expansion, precision machinery purchase, or high-value crop adoption to maximise loan returns.

Credit constraints' negative effect on operational income 'gradually intensifies' with income. For low-income farmers, the coefficient is insignificant. Small scales reduce external credit demand, and internal funds meet limited investment needs. For lower-middle-income farmers, negative effects emerge; for middle- to high-income farmers, effects strengthen and remain highly significant. Higher income drives expanded production and high-return investments, increasing credit demand. Credit constraints here directly restrict the seizing of market opportunities, causing greater losses.

In addition, ASC participation exerts the strongest income effect on low- and lower-middle-income farmers, showing 'diminishing marginal returns'. The supply chain coefficient for low-income farmers is 2.355 and statistically significant, which is the largest across all quantiles. From lower-middle- to high-income farmers, both the magnitude and significance of the coefficient decline. This reflects ASC's 'compensatory role' for disadvantaged groups. Low- and lower-middle-income farmers overcome inherent barriers such as limited market access, information asymmetry, financing constraints through ASC-provided stable sales, technical guidance, and resources, releasing suppressed income potential. High-income farmers, with mature channels, advanced conditions, and sufficient funds, only gain incremental benefits.

Discussion. This study confirms that ASC participation significantly increases farmers' total and operational income (supporting H_{1a} and H_{1b}), consistent with existing consensus (Candemir et al. 2021; Krishnan et al. 2021; Wang et al. 2022). A key extension lies in quantifying heterogeneous treatment effects. While operational income gains are equitable across participants, total income exhibits 'elite capture'. Advantaged farmers benefit more due to non-agricultural income disparities tied to initial endowments. This resolves inconsistencies in prior studies on benefit. IVQR results further validate ASCs' 'pro-poor' potential (Barrett et al. 2022) with quantile-level evidence that the income effect is strongest for low-income farmers and diminishes gradually, becoming insignificant for high-income groups. This 'compensatory effect' highlights ASCs' social value in narrowing income gaps by addressing disadvantaged farmers' key pain points.

This study advances rural finance-ASC interaction research in three ways. First, regarding financial constraint mitigation (H_2), existing studies (Karaman and Yigit 2022; Villalba et al. 2023) focus on credit accessibility, but we demonstrate ASCs neutralise the income-damaging effects of constraints, credit constraint coefficients become statistically insignificant for participants. This moves beyond formal constraint alleviation to substantive impact evaluation. Second, for loan conversion efficiency (H_3), while prior work (Fowowe 2020; Nakano and Magezi 2020) notes institutional support matters for loan effectiveness, we explicitly identify ASCs as a key enabler and quantify efficiency gains. Mechanisms explain why ASCs act as 'efficiency amplifiers', addressing rural finance's long-standing puzzle of heterogeneous loan returns. Third, a major innovation is integrating research on ASC governance and rural financial inclusion, which was previously siloed. Traditional rural finance studies focus on institutional models (Khan et al. 2024), while ASC research emphasises production coordination. We uncover a synergistic cycle: ASCs resolve rural finance's 'triple dilemma' (no collateral, high costs, high risk) via relational guarantees, information intermediation, and collective action, expanding financial access. In turn, improved finance enhances farmers' ASC participation capacity. This perspective corrects the narrow view of ASCs as merely production/sales coordinators and identifies ASC intermediaries as critical to financial inclusion. Confirming Darby et al. (2022), ASCs reduce information asymmetry as 'local brokers', offering financial institutions a viable pathway to serve smallholders.

Despite the insightful findings, this study still has some limitations that point to future research directions. First, the study focuses solely on three provinces in western China, where agricultural production is dominated by smallholder farming and economic development lags behind that in eastern regions, this may limit the generalisability of the findings to other regions or countries with different socio-economic conditions and agricultural systems. Second, this study only discusses the variable coefficients related to the role of agricultural loans in agricultural supply chains. Future research could further explore the mediating role of agricultural loans to deepen mechanism understanding. Third, although this study examines the impact of agricultural supply chain participation on farmers' income, it does not address other potential outcomes, such as productivity, environmental sustainability or social welfare. Future research could specifically investigate these dimensions to provide a more holistic assessment of supply chain impacts.

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CONCLUSION

Using field survey data from rural China, this study employs the ESR and IVQR models to analyse three core issues: the income effect of ASC participation, the heterogeneous impacts of credit constraints and agricultural loans between participants and non-participants, and intra-group income effect differences across income quantiles. Key findings are summarised as follows. First, ASC participation drives income growth and production modernisation. It significantly increases rural households' total income and operational income, shifts production factor dependence from traditional inputs such as labour and farmland to modern factors such as human capital, technological innovation, infrastructure, and aligns with agricultural modernisation trends. Second, ASCs alleviate credit constraints and enhance loan efficiency. Credit constraints exert a significant negative impact on non-participants' operational income, and agricultural loans have a stronger income-increasing effect on participants, confirming that ASCs improve loan utilisation by reducing information asymmetry and providing production guidance. Third, income effects vary across income levels. ASC participation has the strongest 'compensatory' effect on low- to lower-middle-income farmers; agricultural loans only benefit households above the median income; and the negative effect of credit constraints intensifies with income.

Based on the above conclusions, this study proposes targeted policy recommendations to promote inclusive supply chain participation and sustainable rural income growth.

First, optimise rural financial services to alleviate credit constraints. The government should use structural monetary policy tools to guide financial institutions to increase rural credit supply and establish a multi-party risk compensation system involving governments, banks, and supply chain leading enterprises to reduce agricultural loan risk premium. Prioritise financial support for low- and middle-income farmers, such as providing interest subsidies for small agricultural loans and simplifying loan application procedures for supply chain participants. The government should also explore 'supply chain + credit' models to lower financing thresholds for smallholders.

Second, strengthen supply chain coordination to ensure inclusive participation. The government should regulate the surplus distribution between supply chain entities by formulating industry standards for profit sharing or minimum purchase prices, preventing 'elite capture' and safeguarding smallholders' interests. It should also launch targeted ASC operation programmes to enhance farmers' awareness and capabilities, and provide one-off financial subsidies for farmers joining supply chains to offset initial adaptation costs.

Third, accelerate the digital transformation of agricultural production and distribution to support modern supply chains. Invest in rural digital infrastructure such as 5G networks and IoT sensors to meet the data and connectivity needs of supply chains. Promote big data application in agricultural product traceability and market demand forecasting to improve supply chain efficiency. Specifically, collaborate with digital platform enterprises to offer hierarchical training and workshops, helping farmers master digital tools for production management and sales.

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