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FULL-COST INSURANCE, SOCIAL NETWORK EMBEDDEDNESS, AND GRAIN FARMERS' PERCEIVED VALUE OF INSURANCE: EVIDENCE FROM A SURVEY OF FARMING HOUSEHOLDS IN JIANGSU, SHANDONG, HENAN, AND ANHUI PROVINCES, CHINA

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Abstract
The key to addressing the "High insured amount, low perceived benefit" issue in agricultural insurance for developing countries lies in enhancing farmers' perceived value of agricultural insurance. Drawing on survey data from farmers in in four provinces of China: Jiangsu, Shandong, Henan, and Anhui provinces, this study integrates social networks into a theoretical framework and employs multiple linear regression and Tobit regression to analyze their impact on farmers' perceived value of full cost insurance, elucidating the mechanism through which these networks amplify the perceived value of this full cost insurance. The results demonstrate that social networks enhance farmers' perceived value of full cost insurance through information dissemination, with the rationality of insurance compensation serving as a positive moderating factor. Heterogeneity analysis reveals that the perception-enhancing effect is more pronounced among large-scale farmers. This study provides empirical evidence to refine full cost insurance policies.
Keywords: full cost insurance, social networks, perceived value of insurance, information transmission

1. INTRODUCTION

Agricultural insurance, a cornerstone tool for transferring and mitigating agricultural risks, not only stabilizes farmers' incomes but also sustains agricultural productivity. Consequently, it serves as a critical stabilizer for agricultural development globally. By 2020, developing countries had issued 265 million insurance policies, with insurance markets expanding rapidly (Hazell et al., 2021). However, this proliferation of insurance policies has not translated into expanded coverage, and agricultural insurance has demonstrated limited efficacy in stabilizing farmers' income or consumption (Kramer et al., 2022). Consequently, certain nations aspire to augment the protection afforded by agricultural insurance by enhancing the scope of insurance coverage, a strategy exemplified by China's implementation of full cost insurance. The coverage amount of comprehensive cost insurance is on average 115% higher than that of conventional material cost insurance for wheat, rice, and corn. The increase in the sum insured for full-cost insurance has not led to a significant improvement in risk protection capacity. Taking the wheat pilot areas as an example, since the policy implementation in 2018, the volatility of per capita income among farmers in pilot areas has differed from non-pilot areas by no more than 5%. Similarly, the incentive effect on wheat production has remained virtually unchanged . In other words, compared with conventional material cost insurance, full-cost insurance demonstrates no significant improvement in terms of production incentives and income smoothing. The mechanism by which agricultural insurance stimulates production and stabilizes income operates through stabilizing farmers' income expectations, which subsequently shapes their input allocation decisions and risk management strategies, ultimately enhancing production stability and elevating income levels (Xie et al., 2024; Zou et al., 2022). In most developing countries, two systemic challenges hinder agricultural insurance efficacy: on the one hand, governments' insufficient promotion of insurance literacy, leading to low farmer awareness, and on the other hand insurers' moral hazard behaviors, including non-compliant contractual practices and information asymmetry. These dual deficiencies exacerbate misalignment in farmers' income expectations, eroding trust in the perceived value of full cost insurance. Effectively stabilizing and continuously improving farmers' income expectations is key to enhancing the quality and effectiveness of full-cost insurance. Therefore, while an increase in the insured amount may affect the adoption and outcomes of full-cost insurance, what matters more is farmers' perceived value of full-cost insurance.

Farmers’ income expectations derive from their perceived value of full cost insurance. This perception governs both their adoption of agricultural insurance and their long-term production planning. Farmers’ perceived value of full cost insurance comprises three dimensions: trust in insurers, insurance literacy, and perceived benefits (Mensah et al., 2023). The trust deficit between farmers and insurers arises from information asymmetry, which fosters moral hazard behaviors such as information concealment and contractual non-compliance by insurers. Insurance-related knowledge refers to farmers’ understanding of insurance mechanisms and risk exposure. Mastery of this knowledge reflects their comprehension of insurance functionality and risk perception. Perceived benefits denote farmers’ subjective assessments of post-disaster income loss compensation adequacy, directly indicating the dependability of insurance payouts. It can thus be seen that farmers’ perceived value of full cost insurance is primarily shaped by access to insurance information, policy-related knowledge, and compensation reliability. Consequently, optimizing information dissemination and knowledge-diffusion channels is critical to elevating farmers’ valuation of full cost insurance.

Social networks are the primary means of information transmission among farmers. Farmers in developing countries typically live in natural villages or family units, where they cultivate family land using family labour, which provides the community cohesion necessary for strong social networks. Farmers exhibit significant heterogeneity in terms of individual endowments, and there are substantial differences in information transmission barriers. Among all communication methods, word of mouth remains the most trusted by farmers. Therefore, social networks have become the primary and most trusted channel for farmers in developing countries to access information (Andres et al., 2018).

In summary, how to enhance farmers' awareness of the value of full cost insurance and stabilise their expectations is a core issue that needs to be addressed urgently. Theoretically, developing knowledge-diffusion pathways and enhancing information dissemination can mitigate information asymmetry between farmers and insurers while improving farmers’ understanding of full cost insurance and risk exposure. For farmers, social networks serve as a credible channel for information transmission, exerting the strongest influence on their income expectations. Focusing on China, this study integrates social networks into a theoretical framework, using household survey data from farmers in Jiangsu, Shandong, Henan, and Anhui provinces, to analyze their impact on farmers’ perceived value of full cost insurance and elucidate how social networks amplify full cost insurance’s perceived value. This elucidates the systemic drivers of the full cost insurance industry’s suboptimal development in recent years, improving the full cost insurance policy.

This paper contributes three key innovations: (1) Theoretical: Integrating social networks into a theoretical framework as primary information-transmission channels, we reveal how farmers’ perceived value of full cost insurance forms and strengthens, accounting for endowment heterogeneity across farmers. (2) Methodological: We construct a comprehensive index system for social networks and farmers’ perceived value of full cost insurance, empirically analyzing their relationship to provide an empirical foundation for policy refinement. (3) Policy Design: Investigating the moderating role of insurance compensation rationality, we propose product design optimization measures to enhance full cost insurance efficacy.

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Literature Review

Although full cost insurance offers enhanced protection compared to agricultural insurance, its core insurance functions and risk mitigation frameworks align closely with those of conventional agricultural insurance. Consequently, insights derived from research on policy-oriented agricultural insurance remain applicable to optimizing full cost insurance programs. The effectiveness of agricultural insurance’s risk protection function hinges on two mechanisms: pre-disaster risk transfer and post-disaster loss compensation. The pre-disaster effect entails transferring agricultural risks from farmers to insurers upon policy purchase, thereby reducing farmers’ loss probability and severity (Chen & Lin, 2023). The post-disaster effect involves proportional compensation by insurers following risk shocks, as stipulated in policy terms. This compensation either supplements farmers’ immediate income or funds future productive investments (Chen & Lin, 2023; Liu et al., 2022). Both the pre- and post-disaster effects of insurance stabilize farmers’ income expectations, encouraging adoption of new technologies, increased labor input, and expanded production scale (Xie et al., 2024; Zou et al., 2022). The core factor shaping farmers’ participation decisions in agricultural insurance and agricultural development stability hinges on the insurance’s capacity to stabilize income expectations. Farmers’ satisfaction with the risk coverage of insurance products directly shapes their expectations, thereby determining participation decisions (Yazdanpanah et al., 2013). Thus, stabilizing farmers’ income expectations necessitates ensuring their satisfaction with the purchased insurance’s risk coverage. The primary determinant of farmers’ participation decisions in agricultural insurance—and by extension, agricultural development stability—is whether insurance stabilizes farmers’ income expectations. Farmers’ satisfaction with the risk coverage of agricultural insurance products directly shapes these expectations, thereby governing their participation choices (Yazdanpanah et al., 2013). Thus,

stabilizing income expectations requires ensuring farmers' satisfaction with the risk coverage of their chosen insurance.
There are many factors that influence farmers' satisfaction with agricultural insurance and full cost insurance. Existing research demonstrates that farmers' satisfaction with agricultural insurance hinges on three interrelated dimensions: cognitive awareness (e.g., insurance knowledge), institutional trust (e.g., confidence in providers), and risk perception (Azadi et al., 2019). Empirical analyses, such as Liu et al. (2016), utilizing provincial-level dynamic panel data from China, confirm that risk perception and risk management strategies significantly influence insurance adoption. However, agricultural risk perception alone does not fully explain farmers' preferences. Mensah et al. (2023) identify additional determinants, including trust in insurance companies, subjective evaluations of policy-oriented agricultural insurance, and perceived social and behavioral structures tied to insurance benefits. These findings underscore the multidimensional nature of farmers' decision-making, which integrates cognitive, institutional, and socio-behavioral factors. Building on Yazdanpanah's (2013) framework, factors influencing farmers' satisfaction with agricultural insurance can be categorized into two dimensions. The first encompasses direct perceived value, which exerts immediate effects on satisfaction through tangible factors such as perceived insurance premiums, compensation reasonableness, and opportunity costs. The second involves perceived quality of insurance, which indirectly shapes satisfaction by mediating direct perceived value. This category includes accessibility of insurance services (e.g., policy-oriented agricultural insurance), service attitude, and the degree of information transparency. Both types of factors influence farmers' satisfaction with agricultural insurance by affecting their perceived value. Therefore, enhancing farmers' perceived value of agricultural insurance is pivotal to reshaping their expectations and driving high-quality development within the agricultural insurance sector.
Extensive research exists on improving farmers' perceived value of agricultural insurance; however, most studies focus on a single dimension, specifically enhancing insurance awareness and risk perception. Empirical studies underscore the multifaceted drivers of farmers' engagement with agricultural insurance. Patt et al. (2010) employed role-playing simulations with farmers in Ethiopia and Malawi to assess microinsurance programs, concluding that agricultural insurance effectiveness depends on communication strategies that clarify insurance mechanisms. Similarly, Azadi et al. (2019), through a survey of 350 farmers in western Iran, identified climate risk perception as a significant predictor of insurance adoption and adaptive behavior. However, risk perception alone does not fully account for farmers' perceived value of agricultural insurance. Sun et al. (2023) further demonstrated that farmers prioritize insurance adoption only when compensation structures ensure total income surpasses production costs. These findings collectively emphasize the need to integrate transparent communication, risk mitigation, and equitable compensation to enhance the perceived value of policy-oriented agricultural insurance. In summary, farmers' perceived value of agricultural insurance is predominantly shaped by insurance-related knowledge dissemination and compensation adequacy. While both information transmission and knowledge dissemination depend on effective information carriers, scholars have rarely explored strategies to enhance farmers' perceived value of insurance through optimizing these channels.
The dissemination of insurance knowledge, risk perception, and trust in insurance providers are contingent upon information exchange, with social networks grounded in kinship and geographical ties constituting the primary medium for information transmission among farmers. Although relative to formal information transmission methods, social network information transmission is characterized by fragmented, informal, and low-entropy features. Yet, it remains dominant in rural China's information transmission systems amid differential social structures (Cai et al., 2015; Luo et al., 2019). Current research on social networks and insurance predominantly examines commercial insurance, including household property insurance and health insurance. Shi and Du (2024) categorized social networks into internal and external types, demonstrating that internal networks reduce individuals' demand for household property insurance through risk-sharing mechanisms, while external networks stimulate insurance consumption via information dissemination and knowledge spillover. Empirical studies corroborate that social network risk-sharing mechanisms diminish households' reliance on private insurance (Jowett, 2003; De Weerdt & Dercon, 2003). Notably, unlike independent risks such as private health risks or household property risks, agricultural risks are inherently systemic. Systemic risks can compromise the risk-sharing capacity of social networks by affecting entire or partial communities, thereby diminishing their ability to mitigate agricultural risks for farmers. Consequently, social networks cannot mitigate the impact of agricultural risks on farmers through risk-sharing mechanisms. However, scholarly applications of social network theory to examine the impact and promotion mechanisms of agricultural insurance and full cost insurance remain limited.
In summary, while existing research has yielded significant insights into farmers' perceived value of agricultural insurance and the role of social networks, opportunities for deeper exploration remain. Regarding perceived value, Existing studies predominantly examine isolated dimensions such as insurance awareness and risk perception, neglecting to integrate all factors into a unified theoretical framework, identify their commonalities, or apply these insights to

analyze farmers' perceived value of agricultural insurance and strategies to enhance satisfaction with agricultural insurance. Similarly, few studies have systematically examined social networks as primary information dissemination channels to assess their influence on policy-oriented agricultural insurance or full cost insurance adoption.

2.2 Theoretical Framework and Research Hypotheses

This section integrates the transmission mechanisms of the Susceptible-Infected-Susceptible (SIS) epidemiological model into the causal analysis framework of social networks. By leveraging dynamic transmission mechanisms, we analysis the diffusion pathways of insurance knowledge within farmers' relational networks and reveal the reinforcement mechanisms governing information transmission efficiency.

2.2.1 Characteristics of social network information transmission

Epidemic models originated to describe disease transmission dynamics by mathematically constructing ordinary differential equations to analyze population-level immunity equilibria (Hethcote, 1976). Key characteristics of these models include: (1) stratification of susceptible and immunized populations, (2) infection and recovery rates, and (3) equilibrium dynamics. Information transmission and knowledge diffusion in social networks share analogous structural properties, prompting their adaptation to study technology adoption (e.g., Aral & Walker, 2012; Axsen & Kurani, 2011) and policy evaluation (Wolf et al., 2015). The diffusion mechanism of insurance knowledge within rural social networks is analogous to the transmission dynamics of infectious diseases in a population. This study adapts epidemiological transmission models to characterize the dissemination dynamics of full cost insurance knowledge through social networks. Assuming a social network comprising N farmers, we define $i(t)$ as the proportion possessing comprehensive full cost insurance knowledge (including policy-oriented agricultural insurance and property insurance products), and $s(t)$ as the proportion lacking such knowledge. When farmers with *high insurance awareness* interact with farmers with *low insurance awareness*, insurance-related knowledge is transmitted probabilistically; as a result, some farmers with *low insurance awareness* gradually acquire more full cost insurance knowledge. Based on this, the dynamic evolution of the ratio of farmers with *high insurance awareness* to farmers with *low insurance awareness* in the social network is described as follows:

$$\begin{cases} i(t_0)=i_0 \\ s(t)+i(t)=1 \\ \frac{di(t)}{dt}=\delta(t)i(t)(1-i(t))-\mu(t)i(t) \end{cases} \tag{1}$$

In Equation (6.1), i_0 denotes the initial number of farmers with *high insurance awareness*, $\delta(t)$ represents the information transmission ratio and $\delta(t)>0$, $\mu(t)$ signifies the proportion of farmers transitioning from *high* to *low insurance awareness* (termed the exit rate). Setting the derivative $\frac{di(t)}{dt}=0$ in Equation (6.1) to zero yields the equilibrium point:

$$i^*=\begin{cases} 0 \\ 1-\frac{\mu(t)}{\delta(t)} \end{cases} \tag{2}$$

Equation (6.2) demonstrates that the equilibrium point i^* is determined by the exit rate $\mu(t)$ and the information transmission ratio $\delta(t)$. While the exit rate $\mu(t)$ is theoretically linked to the knowledge forgetting rate, the behavioral dynamics differ fundamentally from epidemiological recovery processes. Specifically, the probability of *high insurance awareness* farmers reverting to *low insurance awareness* status due to knowledge attrition is negligible ($\lim_{t\to\infty}\mu(t)=0$). Consequently, the growth of *high insurance awareness* farmers within the social network is predominantly driven by the information transmission ratio $\delta(t)$.

2.2.2 Social Network SIS Model

To examine the impact of $\delta(t)$ on shifts in farmers' perceived value of full cost insurance within social networks, this study incorporates structural characteristics of social networks. By analyzing node interactions through the Susceptible-Infected-Susceptible (SIS) model framework, we elucidate the mechanisms driving the enhancement of farmers' perceived value of full cost insurance. Assume the social network topology is modeled as a graph G(N, L), where N and L represent the sets of nodes (farmers) and edges (social interactions between farmers), respectively. The graph G(N, L) is encoded by an adjacency matrix $(l_{ij})_{N\times N}$, where $l_{ij}=1$ if nodes i and j share a social connection, and $l_{ij}=0$ otherwise. Let k denote the degree of node i, defined as $k=\sum_j l_{ij}$. Using this framework, Equation (6.1) is reformulated to incorporate network topology:

$$\delta_k(t)=v+f(k,a_t,r(t)) \tag{3}$$

In Equation (3), v denotes the dependency propagation speed, capturing the dependency effect of insurance adoption on farmers with latent low insurance awareness. The propagation function $f(k,a_t,r(t)$ models the influence of social network interactions on individual behavior. a_t represent the proportion of high-insurance-awareness neighbors at time t, where $a_t\in[0,k]$. Finally, r quantifies the influence degree through a non-linear function.

As farmers possessing high insurance awareness disseminate information to their *low insurance awareness* counterparts, the efficacy of this influence attenuates over time. Building on Luo et al. (2020), this study incorporates an information decay function to characterize the propagation of social network influence toward individuals, formalized as:

$$r(t)=\theta e^{c-\eta t} \quad (4)$$

In Equation (4), c encapsulates time-invariant parameters governing influence propagation, such as social network structure and individual characteristics, while b corresponds to the information decay coefficient. The dynamic propagation of social network influence is thus formalized through the following differential equation:

$$g(a_t,r(t))=\frac{a_t}{k-a_t}r(t)=\frac{a_t}{k-a_t}\theta e^{c-\eta t} \quad (5)$$

Combining equations (6.5) and (6.3), we obtain:

$$\delta_k(t)=v+\frac{a_t}{k-a_t}\theta e^{c-\eta t}q \quad (6)$$

In Equation (6), q represents the probability that an individual with a social network degree k encounters another individual possessing *high insurance awareness* within their network. Consequently, $\frac{a_t}{k-a_t}q$ serves as a quantitative measure of the influence strength exerted by farmers' social networks.

When farmers frequently interact with individuals characterized by *high insurance awareness* (e.g., large-scale grain farmers or grassroots village officials), the social network strength $\frac{a_t}{k-a_t}q$ intensifies. Given the $a_t\in[0,k]$, it follows that $\frac{a_t}{k-a_t}>0$, and $\delta_k(t)$ consequently rises. As shown in Equation (2), , $\frac{di^*}{d\delta(t)}=\frac{\mu(t)}{\delta(t)^2}>0$, this increase in $\delta_k(t)$ elevates the non-zero equilibrium point i^*. These dynamics underpin the formulation of hypotheses 1 and hypotheses 2.

Hypothesis 1: The strength of social networks can increase farmers' perceived value of full cost insurance.

Hypothesis 2: The strength of social networks can increase farmers' perceived value of full cost insurance through information transfer.

Equation (6.6) defines the base influence strength parameter θ, which serves as a key factor shaping farmers' perceived value of full cost insurance during information dissemination, particularly regarding the reasonableness of insurance payouts. A higher degree of payout reasonableness corresponds to an increase in $\frac{a_t}{k-a_t}\theta$, where θ exerts a positive moderating effect on this relationship. This mechanism serves as the foundation for Hypothesis 3.

Hypothesis 3: The reasonableness of insurance compensation can play a regulatory role in enhancing the perceived value of full cost insurance for social network strength.

Additionally, we compute the partial derivative of equation (6) with respect to c to obtain $\frac{d\delta_k(t)}{d\frac{a_t}{k-a_t}}=\theta e^{c-\eta t}$. As demonstrated by $\frac{d\delta_k(t)}{d\frac{a_t}{k-a_t}}>0$—a relationship already established in hypothesis 1—the magnitude of $\frac{d\delta_k(t)}{d\frac{a_t}{k-a_t}}$ exhibits dependency on c. Here, c encompasses constant factors affecting information propagation, such as social network structure, individual characteristics (e.g., risk tolerance), and disaster experience. This observation underscores that the capacity of social network strength to amplify the perceived value of full cost insurance significantly depending on individual attributes. Building on this heterogeneity, Hypothesis 4 is formulated.

Hypothesis 4: The perceived value of full cost insurance in terms of social network strength varies depending on individual characteristics.

3 METHODOLOGY AND DATA SOURCE

3.1 Variable selection

3.1.1 Dependent variable

Dependent variable: Perceived value of full cost insurance (perce). This variable captures farmers' perceived value of agricultural insurance. After full cost insurance is sold to farmers, insurers must assess damages incurred by policyholders prior to disbursing payments. During this process, the perceived value of insurance is shaped by three factors: first, the insurance premium (Yu et al., 2018); second, the efficiency and transparency of the claim settlement process (Mensah et al., 2023); and third, the adequacy of compensation relative to risk-induced losses. Building on this foundation, the study adapts the methodology of Chen and Zhang (2024) to construct a risk perception indicator system across three dimensions: first, claims processing efficiency; second, premium affordability; and third, coverage adequacy. The entropy weight method is applied to assign objective weights to these criteria, deriving a composite perceived value index for full cost insurance. The full indicator framework is presented in Table 1.

Table 1 Construction of Perception Indicators for Full cost Insurance

Variable	Item	Variable meaning
Claims process	Do you think the full cost insurance claims process is straightforward?	1 (very complicated) ~ 5 (very straightforward)
Agricultural insurance price	What do you think of the price of full cost insurance?	1 (very unreasonable) ~ 5 (very reasonable)
Agricultural insurance coverage	How would you rate the level of coverage provided by full cost insurance?	1 (very low) ~ 5 (very high)
	Do you think full cost insurance meets your needs?	1 (Not at all) ~ 5 (Completely sufficient)

3.1.2 Core explanatory variable

Core explanatory variable: social network strength (social). Social network strength characterizes the density and quality of interpersonal ties within a social network (Zhang et al., 2020). Following Li et al. (2015), farmers' social networks are categorized into kinship networks (informal networks) and official networks. Kinship networks, defined by frequent interactions with relatives by blood or marriage and close acquaintances (Wang Zhigang and Hu Ningning, 2024; Luo and Liu, 2022), reflect informal social bonds. Official networks encompass regular engagement between farmers and village-level officials, such as village party secretaries, village committee members, and administrative personnel. Furthermore, within agricultural production systems, large-scale grain farmers serve as opinion leaders in rural social networks, exerting greater influence compared to smallholder farmers. Guided by this framework, the study develops a tripartite indicator system encompassing kinship ties and peer networks, grassroots village cadres, and large-scale grain farmers. The social network strength index is derived through application of the entropy weight method, with full indicator specifications detailed in Table 2.

Table 2 Construction of social network strength indicators

Variable	Item	Variable meaning
Family and friends network	Do you often communicate with your family, friends, and neighbours?	1 (almost never) ~ 5 (frequently)
Cadre network	Do you often communicate with village cadres?	1 (almost never) ~ 5 (frequently)
Large-scale grain farmers	Do you often communicate with large-scale grain farmers?	1 (almost never) ~ 5 (frequently)

3.1.3 Mediator Variable

Information transmission intensity (infor). The study operationalized farmers' information acquisition by posing the question: *'Can you obtain useful information from people around you?'* Responses were quantified using a five-point Likert scale (1 = *almost no valuable information*; 5 = *frequent acquisition of actionable insights*), where higher scores reflect greater capacity to extract socially embedded knowledge.

3.1.4 Moderator Variable

Claim reasonableness (lndevia * social**)**. This study employs unit compensation deviation as a proxy measure for compensation rationality, where higher deviation corresponds to diminished compensation rationality. $compensation\ rationality = -unit\ payment\ deviation = -\frac{|Total\ actual\ payments - Total\ amount\ payable|}{insured\ area}$ (Ju & Gu, 2023). Total compensation is calculated as: Total Compensation = Unit Insured Amount × Damaged Area × Compensation Ratio × Loss Rate. The unit insured amount under full cost insurance exhibits regional heterogeneity. Drawing on local government policy documents, Table 3 synthesizes location-specific unit insured amounts across Jiangsu, Shandong, Henan, and Anhui.

Table 3 Full cost insurance coverage in various regions

Region	Coverage Amount (Yuan)	Data Source
Anhui Province (Chizhou City, Anqing City)	860	Anhui Provincial Department of Finance
Henan Province	1000	Henan Provincial Department of Finance, Henan Provincial Department

Region	Coverage Amount (Yuan)	Data Source
		of Agriculture and Rural Affairs, Henan Banking and Insurance Regulatory Bureau
Jiangsu Province (Xuzhou City)	1000	Jiangsu Provincial Department of Finance
Shandong Province	950	Shandong Provincial Department of Finance

3.1.5 Control variables

Adapted from Zhang et al. (2020), control variables are stratified into three categories: First, individual characteristics: wheat planting duration (plant), level of education (educa), and village official's household (offica); Second, household characteristics: household size (popul), agricultural income share (income), and operational scale (scale); Third, production conditions: cooperative membership (coope), land fragmentation (plots), and disaster exposure (disas).

3.1.6 Instrumental Variable

Frequency of participation in collective activities (activi). To address potential endogeneity, this study employs an ordinal instrumental variable measuring farmers' frequency of engagement in village collective activities. Participants were asked, *'Do you frequently participate in collective activities?'* Responses were quantified using a five-point Likert scale (1 = *almost never*; 5 = *frequently*), where higher values reflect greater social engagement.

3.2 Data sources and descriptive analysis

Research targeting full cost insurance and agricultural risk management necessitates a study population with foundational awareness of agricultural insurance mechanisms and heterogeneity in risk exposure. Jiangsu, Shandong, Henan, and Anhui—China's primary grain-producing provinces—are disproportionately vulnerable to meteorological disasters, aligning with these criteria. In 2018, China initiated a pilot program for full cost insurance across 24 counties in six provinces, including Shandong, Henan, and Anhui. By 2021, policy coverage was expanded to major grain-producing counties in 13 provinces nationwide, with Jiangsu Province incorporated into the extended rollout. Field research for this study targeted the following locations: (1) Yanggu County (Shandong); (2) Ruzhou City (county-level administrative unit) and Puyang County (Henan); (3) Dongzhi County and Guixi District (Anhui); (4) Weining County and Jiangyan District (Jiangsu). The survey location is shown in Figure 1.

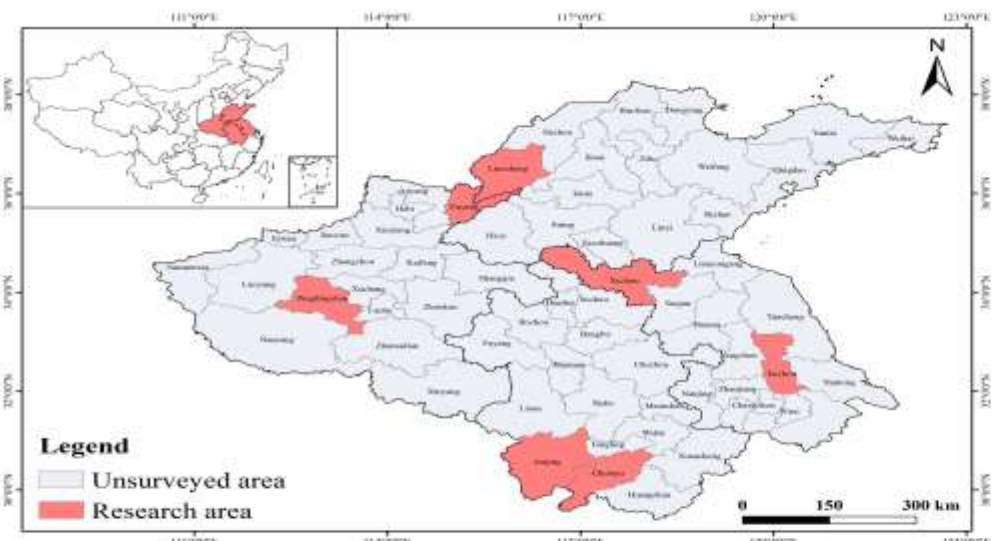

Figure 1 Research Area Schematic Map
(Source: http://bzdt.ch.mnr.gov.cn/)

These regions encompass disaster-impacted and non-impacted zones, areas with continuous full cost insurance pilot implementation (early adopters), and regions incorporated during mid-policy expansion (late adopters). Farmers in these areas demonstrate a foundational grasp of agricultural insurance and risk dynamics, yet exhibit considerable heterogeneity in risk perception, socioeconomic status, and policy engagement—attributes critical for analyzing differential impacts of insurance mechanisms. Therefore, the data in this study are derived from field surveys in the aforementioned regions, and the descriptive statistics of each variable are presented in Table 4.

Table 4 Descriptive analysis of variables

	N	SD	Min	Max
Dependent variable				
Perceived value of full cost insurance (perce)	804	0.258	.111	1
Explanatory variable				
social network strength (social)	804	0.232	0	1
Control variables				
cooperative membership (coope)	804	0.477	1	2
village official's household (office)	803	0.170	1	2
household size (popul)	803	1.053	1	8
level of education (educa)	803	0.449	1	4
agricultural income share (income)	804	30.661	4	100
wheat planting duration (plant)	804	8.997	5	44
operational scale (scale)	804	43.138	1	199.895
number of plots（plots）	804	3.595	1	25
disaster exposure（disas）	804	13.819	0	60
Mediator Variable				
Information transmission intensity（infor）	804	0.984	1	5
Moderator Variable				
claim reasonableness（lndevia * social）	686	1.220	0	6.271
Instrumental variable				
frequency of participation in collective activities（activi）	804	0.773	1	5

3.3 Baseline Model

In the baseline regression analysis, the independent and dependent variables are continuous, while the control variables are ordinal. Consequently, this study employs a multiple linear regression model to assess how social networks enhance the perceived value of full cost insurance.

$$perce_i=\alpha_0+\alpha_1 social_i+\sum controls_i+\varepsilon_i \qquad (7)$$

In Equation (7), $perce_i$ represents the perceived value of full cost insurance by farmer i; $social_i$ represents the strength of the social network of farmer i; $controls_i$ is a set of control variables; ε_i represents random disturbance terms; α_0 is a constant term; and α_1 is the coefficient to be estimated.

In this study, the mediating variables are ordinal variables. Therefore, we adopt the Oprobit model for ordinal multi-category variables to analyse the mediating role of information transmission in social networks.

$$infor_i=\beta_0+\beta_1 social_i+\sum controls_i+\mu_i \qquad (8)$$

In the equation: $infor_i$ represents the information transmission intensity of farmer i; $social_i$ represents the social network intensity of farmer i; $controls_i$ is a set of control variables; μ_i represents the random disturbance term; β_0 is a constant term; β_1 is the coefficient to be estimated.

4 RESULTS AND ANALYSIS

4.1 Baseline Model Estimates

To assess multicollinearity risks and ensure model robustness, variance inflation factor (VIF) tests were conducted across all variables. Results indicated a maximum VIF of 2.03 and a mean VIF of 1.45, both well below the threshold of 5, confirming no significant multicollinearity. A multiple linear regression model was employed to analyze the relationship between social network strength and farmers' perceived value of full cost insurance. The regression estimates, detailed in Table 5. As evidenced in Table 5, social network strength exerts a statistically significant positive effect on farmers' perceived value of full cost insurance, even in the baseline model without control variables (Column 1). Columns 2–4 progressively incorporate controls for individual characteristics (e.g., literacy level), household attributes (e.g., income share), and production conditions (e.g., disaster exposure). Across all specifications, the coefficient for social network strength remains robustly positive at the 1% significance level, demonstrating its independent explanatory power over perceived value. This consistency confirms that the relationship is neither confounded by nor mediated through individual, household, or production-related factors. Consequently, Hypothesis 1 is empirically validated.

Table 5 Benchmark regression results

	(1)	(2)	(3)	(4)
	perce	perce	perce	perce
social	0.919***	0.964***	0.909***	0.872***
	(0.024)	(0.025)	(0.028)	(0.035)
plant		0.004***	0.001*	0.002***
		(0.001)	(0.001)	(0.001)
educa		-0.010	-0.031**	-0.012
		(0.014)	(0.014)	(0.014)
offic		0.082*	0.043	0.040
		(0.043)	(0.040)	(0.039)
popul			0.019***	0.016***
			(0.005)	(0.005)
income			0.002***	0.002***
			(0.000)	(0.000)
scale			-0.000	0.000
			(0.000)	(0.000)
coope				-0.086***
				(0.014)
plots				0.011***
				(0.002)
disas				0.000
				(0.000)
Constant	0.143***	-0.126	-0.065	-0.015
	(0.013)	(0.089)	(0.086)	(0.090)
N	804	803	803	803
R-squared	0.686	0.707	0.750	0.774

4.2 Endogeneity and Robustness Tests

4.2.1 Endogeneity Test

Social networks improve farmers' understanding of insurance terms and compensation mechanisms through information dissemination, thereby elevating their perceived value of agricultural insurance. However, this relationship is bidirectional: farmers with higher perceived value may expand their social networks via mutual assistance among villagers and insurance-related outreach, suggesting reverse causality. Beyond reverse causality, while the baseline regression controlled for individual characteristics, household attributes, and production conditions, unobserved variables (e.g., individual capabilities or local official rapport) may remain omitted. To address endogeneity arising from bidirectional causality and omitted variables, this study conducted instrumental variable (IV) analysis.

Existing studies demonstrate that farmers' social network strength serves as a critical proxy for social capital endowment. Consequently, social expenditures—widely adopted as instrumental variables (IVs) in social network research (Wang and Zhang, 2022; Zhang et al., 2020)—were initially considered. Social expenditures theoretically correlate with social networks, as they reflect efforts to maintain relationships. Furthermore, exogeneity is plausible since expenditures themselves do not directly influence perceived value of full cost insurance. However, during data collection, farmers exhibited recall bias regarding social expenditures, with some intentionally misreporting due to privacy concerns, introducing measurement error. To address this, the ordinal variable "whether frequently participating in village collective activities" was selected as an alternative IV. Participation in collective activities strengthens social ties (relevance condition) while lacking a direct pathway to influence insurance perceptions (exogeneity condition), satisfying IV assumptions. This study employs two-stage least squares (2SLS) regression to mitigate endogeneity.

Table 6 presents the instrumental variable (IV) regression results. The Cragg-Donald Wald F-statistic (351.71) substantially exceeds the Stock-Yogo critical value of 16.38 at the 10% maximal IV size threshold, confirming the strength of the instrumental variable. The Kleibergen-Paap Lagrange Multiplier (LM) statistic rejects the underidentification null hypothesis at the 1% significance level, confirming instrument relevance. After addressing endogeneity, the regression coefficients for farm household social network strength remain statistically significant at the 1% level, demonstrating empirical robustness of the model.

Table 6 Endogeneity Test

	(1)	(2)
	social	perce
activi	0.147***	
	(0.009)	
social		1.155***
		(0.067)
Control variables	Control	Control
Cragg-Donald Wald F	351.71	
	(16.38)	
Kleibergen-Paap rk LM	95.761	
	(0.000)	
Constant	0.405***	-0.399***
	(0.097)	(0.125)
N	803	803
R-squared	0.6084	0.738

4.2.2 Robustness Checks

(a) Replacing the explained variable

This study examines the determinants of farmers' perceived value of full cost insurance by constructing a multidimensional indicator system encompassing claims settlement efficiency, price reasonableness, and coverage adequacy. Item weights were calculated using the entropy weight method. To mitigate subjective bias in indicator selection and model specification bias, multiple linear regression analyses were performed with each component of the indicator system as a dependent variable. As shown in Table 7, regression coefficients for social network strength exhibited statistically significant positive effects (1% significance level) across all indicators. Social networks were found to enhance farmers' perceptions of claims settlement efficiency, price reasonableness, and coverage adequacy. These results confirm the validity of the selected explanatory variables and underscore the empirical robustness of the baseline regression analysis.

Table 7 Robustness test: replacing explanatory variables

	(1)	(2)	(3)	(4)
	prote	deman	claim	price
social	12.243***	12.143***	5.278***	8.678***
	(0.954)	(0.885)	(0.562)	(0.728)
Control variables	Control	Control	Control	Control
N	803	803	803	803
R-squared	0.4245	0.3991	0.2940	0.3262

(b) Replacing explanatory variables

This study operationalizes the explanatory variable social network strength through three dimensions: kinship-friendship networks, official networks (e.g., cadres), and large-scale grain farmer networks. An indicator system was developed, with item weights assigned via the entropy weight method. Consistent with prior methodology, variables constructed through similar indicator systems were analyzed by employing their constituent indicators as explanatory variables in multiple linear regressions. Table 8 reports regression outcomes, revealing statistically significant positive coefficients (1% significance level) for kinship-friendship networks, official networks (cadres), and large-scale grain farmer networks on farmers' perceived value of full cost insurance. These findings indicate that all three social network dimensions enhance farmers' evaluations of policy-oriented agricultural insurance. Results in Table 8 validate the explanatory variable's construct validity and reinforce the robustness of the baseline regression analysis.

Table 8 Robustness test: replacement of explanatory variables

	(1)	(2)	(3)
	perce	perce	perce
neigh	0.181***		
	(0.012)		
cadre		0.166***	
		(0.009)	
grower			0.156***
			(0.007)
Control variables	Control	Control	Control
Constant	0.128	-0.048	0.220**
	(0.105)	(0.122)	(0.103)
N	803	803	803
R-squared	0.599	0.658	0.721

(c) Winsorise method

The micro-level data analyzed in this study originate from field surveys conducted in rural households. Given substantial heterogeneity in individual and household endowments among respondents, self-reported variables—such as social network relationships and perceived value of agricultural insurance—are susceptible to subjective biases, which may introduce outliers. To address this, a 5% Winsorization was applied to continuous variables derived from subjective evaluations, trimming extreme values at both tails of the distribution. Table 9 presents the regression results for social network strength's impact on farmers' perceived value of agricultural insurance after Winsorization. Columns (1)–(4) demonstrate that the regression coefficient for social network strength remains statistically significant at the 1% level, even with the progressive inclusion of control variables. These findings confirm the robustness of the baseline regression results.

Table 9 Robustness test: Winsorize method

	(1)	(2)	(3)	(4)
	perce	perce	perce	perce
social	0.999***	1.042***	0.946***	0.977***
	(0.020)	(0.027)	(0.031)	(0.031)
coope		0.025*	-0.038***	-0.062***
		(0.013)	(0.012)	(0.013)
offic		0.088**	0.036	0.033
		(0.041)	(0.037)	(0.036)
popul			0.017***	0.018***
			(0.005)	(0.005)
educa			-0.022*	-0.006
			(0.013)	(0.013)
income			0.002***	0.002***
			(0.000)	(0.000)
plant			0.002***	0.002***
			(0.001)	(0.001)
scale			-0.000	0.000
			(0.000)	(0.000)
plots				0.012***
				(0.002)
disas				0.000
				(0.000)
Constant	0.102***	-0.137*	-0.037	-0.108
	(0.011)	(0.081)	(0.083)	(0.083)
N	804	803	803	803
R-squared	0.723	0.727	0.780	0.799

4.3 Heterogeneity Tests

4.3.1 The share of agricultural income

Households heavily reliant on agricultural income exhibit heightened risk perception due to their economic dependence on crop yields. This study stratifies households into terciles based on agricultural income share: high (top 30%), low (bottom 30%), and medium (middle 40%) agricultural income cohorts. Regression results (Table 10) reveal a declining gradient in the coefficient magnitude of social network strength's impact on perceived insurance value across high- to low-income groups (Columns 1–3). This gradient likely reflects differential vulnerability to risk shocks across income strata. Agricultural income hinges on crop yields, market prices, and input costs. During yield declines caused by agricultural risks, input costs become sunk investments, exacerbating income loss for affected households. High agricultural dependence households, with diminished economic resilience, struggle to buffer such shocks independently, amplifying their demand for risk mitigation information and insurance products. Social networks facilitate the diffusion of risk-related information and insurance literacy, disproportionately benefiting high agricultural dependence households.

Table10 Proportion of agricultural income

	(1)	(2)	(3)
	perce	perce	perce
	High proportion of agricultural income	Medium proportion of agricultural income	Low proportion of agricultural income
social	1.045***	0.926***	0.642***
	(0.056)	(0.035)	(0.043)
Control variables	Control	Control	Control
Constant	0.158	-0.161*	0.212**
	(0.230)	(0.093)	(0.093)
N	260	803	370
R-squared	0.821	0.731	0.733

4.3.2 The scale of agricultural planting

Land concentration concentrates risks, heightening agricultural risk perception and insurance demand among large-scale farmers relative to smallholders. Existing research on operational scale heterogeneity employs divergent household categorization criteria. For instance, Ma et al. (2020) operationalized household differentiation via agricultural income share, while Jiang and Wang (2020) classified households by labor and land endowments. In practice, Chinese jurisdictions classify large-scale farming households based on cultivated land area, though jurisdictional thresholds diverge. This analysis avoids heterogeneity grouping based on household classification, instead stratifying samples into high-value (operational scale >70%) and low-value (operational scale <30%) cohorts. Table 11 summarizes baseline regression results stratified by agricultural operational scale. Coefficients for the low-value group are smaller than those for the high-value group, though significance levels remain consistent. This disparity aligns with the risk aggregation effect: scale-expanding farmers intensify land use via transfers, adopting machinery and specialized production to raise productivity. However, land concentration amplifies risk exposure. High-value households face elevated capital/labor inputs, rendering them more vulnerable to cost shocks and thus more reliant on full cost insurance. Consequently, high-value households exhibit greater insurance literacy and dependence on social networks for risk mitigation knowledge, providing empirical support for Hypothesis 4.

Table 11 Heterogeneity of agricultural operating scale

	(1)	(2)
	perce	perce
	High-value group planting scale	Low-value group with small planting scale
social	1.035***	0.898***
	(0.048)	(0.067)
Control variables	Control	Control
_cons	-0.760***	-0.169
	(0.112)	(0.165)
N	236	240
R-squared	0.915	0.825

4.4 Mechanism discussion

The theoretical framework posits dual mechanisms through which social network strength enhances farmers' perceived value of full cost insurance: (1) mediation via information transmission and (2) moderation via compensation rationality. Given the ordered nature of the mediator (information transmission) and the continuous property of the moderator (compensation rationality), this study employs an ordered Logit model and multiple linear regression to test these pathways independently. Results, detailed in Table 6, reveal that social network strength exerts a statistically significant positive effect on information transmission intensity, confirming that robust social networks amplify the diffusion of insurance-related knowledge among networked individuals. Existing research demonstrates that information dissemination intensity directly influences farmers' perceived value of agricultural insurance and subsequent adoption willingness (Mensah et al., 2023). This occurs as enhanced information transmission mitigates information asymmetry between farmers and insurers while improving comprehension of policy terms. For instance, Kirchner and Musshoff (2024) empirically validated this mechanism in a study of 479 Malian smallholders, where interpersonal communication and direct engagement with insurance agents strengthened perceptions of coverage reliability. Their follow-up discrete choice experiment further revealed that digital innovations in information delivery elevate farmers' preference for insurance by addressing informational gaps in risk management decisions, thereby amplifying perceived comprehensiveness of protection (Kirchner & Musshoff, 2024). These findings collectively underscore that effective information transmission refines farmers' insurance cognition, reduces misconceptions about coverage limitations, and resolves asymmetric information in agricultural decision-making. Additionally, localized networks (e.g., cooperatives or social networks) heighten the situational relevance and trustworthiness of disseminated information compared to traditional or digital media (Wale & Mkuna, 2022). Consequently, socially embedded information channels foster greater farmer acceptance and trust, significantly bolstering perceived insurance efficacy. These insights corroborate Hypothesis 2.

Table 12, Column (2) reports the moderation analysis of compensation rationality. The interaction term between social network strength and compensation rationality exhibits a statistically significant positive coefficient at the 1% level, indicating that higher compensation rationality amplifies the positive relationship between social network strength and farmers' perceived value of full cost insurance. This suggests that equitable claims settlement practices—such as transparent payouts aligned with farmers' expectations—enhance the role of social networks in fostering trust and perceived insurance efficacy. Conversely, insurers' refusal to pay or underpayment (Bulte & Lensink, 2023) erodes trust by exacerbating information asymmetry and misunderstandings about policy terms, particularly among farmers with limited insurance literacy. When farmers possess adequate insurance knowledge and symmetrical information, inequitable compensation directly undermines trust, reversing perceived value. Thus, social networks primarily enhance perceived value by improving insurance awareness and mitigating information asymmetry during dissemination. These findings validate Hypothesis 3.

Table 12 Mechanism analysis

	(1)	(2)
	infor	perce
	Order-logit	Mreg
social	9.469***	1.127***
	(0.546)	(0.055)
lndevia_social		0.068***
		(0.011)
Control variables	Control	Control
_cons		0.080
		(0.093)
N	803	686
R-squared		0.754

5 CONCLUSIONS AND POLICY RECOMMENDATIONS

This study integrates the SIS epidemic dynamics model into causal inference analysis of social networks, developing a theoretical framework for social network information reinforcement. It empirically analyzes the impact of social network strength on farmers' perceived value of full cost insurance using survey data from Jiangsu, Shandong, Henan, and Anhui, coupled with multiple linear regression. Baseline regression results indicate that social network strength significantly enhances farmers' perceived value of full cost insurance. Mechanism analysis reveals that social networks amplify perceived value through information transmission, with compensation rationality acting as a moderating factor. Robustness is confirmed via three robustness checks—explanatory variable substitution, explained variable substitution, and Winsorization—supplemented by instrumental variable (IV) analysis with frequency of participation in group activities to address endogeneity concerns. Heterogeneity analysis demonstrates that farmers with high agricultural income dependence and large-scale operations exhibit greater reliance on social networks' information transmission. Consequently, social network strength exerts a stronger influence on perceived value within these subgroups. Based on the above research conclusions, this paper draws the following policy recommendations:

First, prioritize the cultivation of key nodes within social networks, such as grassroots village officials, large-scale grain farmers, and cooperative leaders, which serve as critical bridges for disseminating agricultural insurance information and knowledge. Governments should institutionalize training programs to enhance these nodes' capacity to actively propagate information, leveraging specialized workshops and policy briefings. Furthermore, regional agricultural insurance information platforms should be established to consolidate governmental policies, claims settlement precedents, and technical resources. Such platforms would integrate online and offline channels, optimizing information transmission efficiency through centralized, accessible data hubs.

Second, enhance the compensation mechanism design of full cost insurance. Governments should enhance regulatory oversight to ensure procedural fairness in claims adjudication and guarantee transparency throughout the claims process. Institutionalize accountability frameworks to hold village cadres liable for ineffective claims administration and regulatory noncompliance. Additionally, intensify capacity-building programs for claims adjusters, enforcing accountability protocols to ensure strict adherence to claims assessment guidelines—including mandatory on-site inspections—to validate incident authenticity.

Third, adopt tailored strategies for distinct farmer cohorts. Governments should capitalize on social networks' information diffusion to advance commercial insurance adoption and deliver comprehensive agricultural risk diversification strategies for large-scale farmers. Concurrently, facilitate access to agricultural machinery and technology services to bolster productivity. For high-agricultural-dependency households, prioritize income stabilization through expanded social service subsidies, safeguarding agricultural production against volatility.

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