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Social embeddedness and agricultural technology diffusion from the perspective of scale differentiation – a case study from China

RESEARCH ARTICLE

Kai Li and Qi Li[①]

Associate Professor, School of Economics, Qufu Normal University, 80 Yantai North Road, Room 720, Rizhao, Shandong, 276800, China P.R.

Abstract

Social embeddedness always plays important role in facilitating agricultural technology diffusion. However, in China, dramatic changes have occurred in the social embeddedness of rural households in the transition from 'acquaintance society' to 'semi-acquaintance society'. Could this be the reason for the debate over the role of social embeddedness? What are the differences in the role of social embeddedness between farmers with different land scales? Based on survey data from 583 rural households from Zhejiang Province, China, we used an endogenous switching regression model to answer these questions. The results indicated there are significant differences in social embeddedness between large- and small-scale households. Although the influence of social embeddedness on technology adoption remains significant, its function is significantly different between small- and large-scale farmers. To avoid technological lock-in for small-scale farmers, the government should strengthen the information push and expand the coverage of environmental-friendly agricultural subsidies for them.

Keywords: social embeddedness, scale differentiation, integrated adoption of chemical fertilizer-reducing technologies, technology diffusion
JEL code: Q120

[①]Corresponding author: liqi@qfnu.edu.cn

1. Introduction

The interpenetration between economic action and its social environment has been a hot topic in sociology and institutional economics. Polanyi (2001) proposed the concept of social embeddedness in direct opposition to the atomistic and rational assumption on human economic decision-making. He argued that the economy was embedded in social, religious, and political institutions, especially in pre-industrial societies. Inheriting Polanyi's notion of embeddedness, however Granovetter (1985) argued in contrast to the over-socialized human hypothesis. Granovetter's formulation 'economic action is embedded in social structure' reactivated and established the current understanding of social embeddedness. Zukin and DiMaggio (1990) extended the concept by classifying it into four types: cognitive, cultural, structural and political. Uzzi (1996) refined the concept of social embeddedness and developed a systematic scheme to characterize its features, functions, and sources. Bögenhold (2013) highlighted the role of social network analysis in understanding social and economic dynamics.

As social embeddedness theory provides unique explanations for the construction of trust and social institutions, collective action, governance of organizational relationships, etc., studies of social embeddedness have proliferated in recent decades. The impact of social embeddedness on economic action is concentrated in the following aspects. First, social embeddedness is considered to be the key factor in the production of trust (Granovetter, 1985; Simpson and McGrimmon, 2008); especially when information is incomplete or asymmetric in a market, trust is the key tool for reducing risk and uncertainty (Granovetter, 2005; Hinrichs, 2000; Mariola, 2012; Uzzi, 1997). Second, social embeddedness affects the flow and quality of information (Brinkley, 2017; Conley and Udry, 2010; Rogers, 2003; Xie *et al.*, 2021); if an individual is in the centre of a social network or in a structural hole, he or she can obtain information more effectively, hence reducing information asymmetry (Burt, 1995; Uzzi, 1997). Outside these situations, weak ties facilitate the fast, low-cost diffusion of novel information (Granovetter, 1973, 2005), and strong ties facilitate the efficient dissemination of tacit knowledge (Nahapiet and Ghoshal, 1998; Uzzi, 1997). Third, social embeddedness affects the acquisition of resources, and strong ties can relax labor and financial constraints of farmers through mutual assistance (Hu, 2016; Krishnan and Patnam, 2014; Zhao *et al.*, 2020). Fourth, social embeddedness is regarded as an important source of reward and punishment, which is an effective governance mechanism against the deviance from internal norms (Chen *et al.*, 2019; Morris and Kirwan, 2011; Sage, 2003).

Rural China has been considered a typical acquaintance society, in which farmers' behaviors are deeply influenced by and thus embedded in social relations (Fei, 1998); thus, the theory of social embeddedness has attracted widespread attention in research on land-use rights transference, entrepreneurship, industrial organizations development and new technology diffusion in China. Zhang and Lv (2017) found that structural, political, cognitive, and cultural embeddedness all have significant impacts on farmers' decision-making regarding farmland transfer-out and transfer-in. A case study of the Haiyuan company proved that mutual trust based on social embeddedness was critical to industrial organization development (Li *et al.*, 2018). Regarding the diffusion of new technology, relational embeddedness or structural embeddedness facilitates farmers' adoption of environment-friendly technology, such as green tillage technology (Cheng *et al.,* 2018; Guo *et al.*, 2020) and ecological farming practices (Qi *et al.*, 2020). However, not all studies agree that social embeddedness facilitate technology diffusion. Empirical studies from different countries have shown that social embeddedness or social networks led to technological 'lock-in', hindering farmers' technology upgrades (Flor *et al.*, 2020; Ma *et al.*, 2018; Wagner *et al.*, 2016).

Some researchers have sought to explain the heterogeneity of social embeddedness through a structural lens, but their analyses have focused on comparing different types of embeddedness, such as strong and weak ties, structural and relational embeddedness, rather than a certain type of embeddedness in different scenarios (Chen *et al.*, 2020; Hu, 2016; Ma *et al.*, 2018). However, different types of social embeddedness provide different opportunities to receive information and resources, and ultimately cause differences in farmers' decisions or behaviors. Mixed findings on social embeddedness role may indicate differentiation of farmers' social embeddedness. In fact, rural China is undergoing a drastic change from an 'acquaintance society' to a 'semi-acquaintance society' (He, 2000). Since the 1980s, due to differences in household resources endowment and social networks, the occupational choices of farmers varied, rural economic elites separated from agriculture began to emerge, and governance rules and value standards within a village changed, previous strong ties among village members also changed (Tian and Chen, 2013). In recent years, with the transfer of rural land, farmers with a larger social network or in the center of social network, had more opportunities to transfer-in land and become large-scale farmers. Differentiation and competition within farmers emerged (Chen and Liu, 2018; Zhou, 2017). With the continuous reshaping of the social structure, value norms, and allocation of resources within a village, the social embeddedness of farmers with different land operational scales differed a lot (Yang and Yang, 2017). Is the differentiation of farmers' social embeddedness the main reason for the debates over the role of social embeddedness? Given the changes in farmers' social embeddedness, is social embeddedness still important for agricultural technology diffusion? What are the differences in the influencing mechanism of social embeddedness on technology diffusion between farmers of different scales? These questions are poorly understood.

Therefore, from the perspective of the land-scale differentiation of farmers, this article uses samples from Zhejiang Province, China, to identify the differences in social embeddedness between small- and large-scale farmers, and to explain the heterogeneous functions of social embeddedness on their adoption of chemical fertilizer-reducing technologies. The main contribution of this paper is deconstructing the impact of social embeddedness on technology diffusion into direct (namely the traditional influencing mechanism of social embeddedness, such as information exchange and mutual assistance) and indirect impacts (facilitating technology adoption by influencing land operational scale), thus providing a distinctive explanation for the mixed findings on the role of social embeddedness in environmental-friendly technology diffusion.

2. Theoretical analysis

To further illustrate how economic action is socially situated, Granovetter decomposed social embeddedness into two dimensions: structural and relational. Structural embeddedness refers to the structural features of an individual's social network and his or her location within it (Granovetter, 1985, 2005). Relational embeddedness refers to the strength and quality of social relationships (Granovetter, 1973; Nahapiet and Ghoshal, 1998). Zukin and DiMaggio (1990) defined embeddedness more broadly (structural, cognitive, cultural and political), and provide a clearer picture of the interpenetration between economic action and social embeddedness, showing how individual economic action adapts to and simultaneously reshapes the social environment. However, this definition makes verifying the causal relationship between rural household' differentiation and the heterogeneous function of social embeddedness very difficult. Therefore, we adopt Granovetter's classification, focusing on the differences in structural and relational embeddedness.

2.1 Structural embeddedness

Structural embeddedness emphasizes that individuals are influenced by the function and structure of the social network. Differences in structural embeddedness are manifested in the size, centrality and heterogeneity of social networks (Alatas *et al.*, 2016). The larger the social network is, the more information and resources it can provide (Tepic *et al.*, 2012; Wang *et al.*, 2020). Centrality refers to the position of an individual in his or her social network. Individuals at the center of a social network usually take precedence in obtaining resources and information and maintaining cooperative relationships with other members of the network (Choi *et al.*, 2012; Coleman, 2015). The heterogeneity of social relations is also an important feature that refers to the differences in the social and economic characteristics of network members (Hansen, 1999; Thuo *et al.*, 2014). Social networks with high heterogeneity can provide more diverse information and complementary resources. However, high heterogeneity also increases search costs and uncertainty in technology adoption (Rahmandad and Sterman, 2008). In traditional Chinese acquaintance society, farmers can obtain technical information through long-term continuous communications within social networks to reduce technological uncertainty, as well as to obtain necessary resources through mutual assistance (Fei, 1998). With the transfer of rural land, farmers better embedded in local social networks have more opportunities to achieve large-scale land operation. Large- and small-scale farmers are dissimilar in production modes and operating purposes, which induce differences in the demand for agricultural technologies, natural resources, social services and government support (Zhou, 2017).

2.2 Relational embeddedness

Uzzi (1996) argued that relational embeddedness is an alternative exchange system outside the market, which results in trust, high-quality information sharing, and joint problem-solving arrangements. Relational embeddedness can be measured by emotional intensity, intimacy, and reciprocal services (Granovetter, 1973). In traditional Chinese acquaintance society, although there is a pattern of difference sequence, the ties within a village are strong. People in rural areas tend to trust relationships based on kinship, geography or karma (Fei, 1998). With the disappearance of urban-rural mobility restrictions, farmers who were better embedded in local social networks had more occupational choices, and many of them gradually became the rural elites (including rural political elites, economic elites and social elites) (Xie *et al.*, 2017). With social division, the cooperation in agricultural production disappeared. Moreover, the competition for economic resources and political influence gradually disintegrated the mutual trust between smallholders and elites (Han, 2019; Qian *et al*, 2015).

In summary, in the transition from an 'acquaintance society' to a 'semi-acquaintance society', farmers with different social embeddedness made radically different occupational and land operational choices. Their choices reshaped the social structure, value norms and allocation of resources within a village, which in turn converted the structural and functional differences of social embeddedness between individuals into social stratum differences. Therefore, to fully understand the role of social embeddedness in technology diffusion, the social stratum of a farmer (large or small scale) is a situational factor that cannot be ignored. This means that we need to analyze the direct impact of social embeddedness on farmers' technology adoption, as well as its indirect impact through influencing farmers' land operational choices. According to the above theoretical analysis, we build a systematic analysis framework (as shown in Figure 1) to explain the differences in the function of social embeddedness on technology adoption between farmers with different land scales.

3. Data and methods

3.1 Data

This paper takes rice chemical fertilizer reducing technology as an example, to explain the heterogeneous function of social embeddedness on agricultural technology adoption between large- and small-scale farmers. Rice is the main food crop with the largest planting area in China, and the excessive use of chemical fertilizers and pesticides in rice production will not only be adverse to safe consumption and endanger human health, but also cause irreversible damage to cultivated land (Yan *et al*, 2017; Zhou and Zhang, 2013; Zhu *et al.*, 2014). Considering farmers usually show preferences in technology that match their endowments (Dorfman,

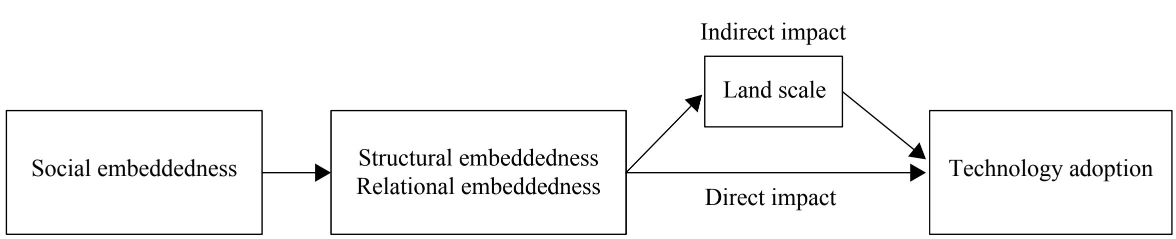

Figure 1. Influencing mechanism of social embeddedness on technology adoption.

1996; Zheng *et al.*, 2018), if we choose a certain chemical fertilizer-reducing technology as the previous studies, we may overestimate or underestimate the impact of social embeddedness on farmers' technology adoption. Therefore, this paper chose the integrated adoption of chemical fertilizer reducing technologies (IACFRTs) as the dependent variable. The chemical fertilizer-reducing technologies in this study are taken from the integrated agricultural production model developed by the Chinese Academy of Agricultural Sciences (Miao *et al.*, 2017). Of the 11 core rice cultivation technologies, we selected five chemical fertilizer-reducing technologies: (1) soil testing and formula fertilizer; (2) organic fertilizer; (3) straw returning; (4) slow-release fertilizer; and (5) deep fertilizing. These technologies constitute a divisible technology package. All the technologies involve different production steps and have different functions in reducing the use of chemical fertilizer, and each can be adopted independently. Additionally, their functions are complementary, integrated adoption of these technologies can improve technical efficiency. Integrated adoption of all the five technologies has higher requirements for farmers' resources and technical information acquisition, which facilitates the accurate assessment of the impact of social embeddedness.

We employed a random sample of 583 households from a survey on the IACFRTs in Zhejiang Province in 2018. Zhejiang Province, a demonstration area for eco-friendly development in China, has taken the lead in the extension of fertilizer-reducing technologies. More importantly, it is one of the first regions in the economic reform and opening up, leading the way in urbanization. Thus, farmers in Zhejiang Province have higher degree of differentiation in occupation and land size. Benefiting from the development of the non-state-operated economy, farmers in Zhejiang Province have more employment opportunities. In 2020, the wage income of rural residents in Zhejiang Province reached 19,510 yuan (61.1% of disposable income), while the national average wage income only 6,974 yuan (38.4% of disposable income). As to land size, data from the third national agricultural census reveal that the proportion of large-scale households in Zhejiang Province is 10.12%, while the nationwide proportion is only 1.73%.

Households were randomly selected based on a multistage cluster approach. First, 2-3 counties were randomly selected from 11 major grain-producing counties in the Hangjiahu Plain (including 2 counties in Hangzhou, 7 in Jiaxing, and 2 in Huzhou). The Hangjiahu Plain, a typical cultivation region for single and double crop rice in Central China, is located to the south of Taihu Lake and is a well-known rice producing area in China. Then, in each selected county, we randomly selected 1-2 villages from the list of main rice-growing villages provided by the county agriculture bureau, and randomly selected approximately 15-20 households from a list of small- and large-scale households provided by village cadre (to compare the structural and functional differences in social embeddedness between small-scale households and large-scale households, the ratio of small-scale households to large-scale households is approximately 2:1[1]). The survey collected information on four aspects: personal information about the head of household and basic information about the household, cost-benefit details of rice production, information about the IACFRTs, and information about socialized services and government support. The survey was conducted one-on-one, and 655 questionnaires were completed, of which 583 were valid, for a response rate of 89.01%.

3.2 Variable selection

A precise definition of large- and small-scale households is a prerequisite for this research. According to the national production subsidy classification standard and related research (Luo *et al.*, 2017), this article regards farmers with more than 3.33 ha of operational land as large-scale households, and other farmers as small-scale households.

The dependent variable is the farmers' IACFRTs. If the interviewed farmer adopted all five technologies, he or she was considered as 'integrated adoption of chemical fertilizer-reducing technologies' (IACFRTs received a value of 1). If he or she didn't adopt any technology or adopted only certain technologies, he or

[1] This is the main reason why the proportion of large-scales farmers in our sample is much higher than the regional and nationwide proportion.

she was not considered to have 'integrated adoption of chemical fertilizer-reducing technologies' (IACFRTs received a value of 0).

The core variables are the two types of social embeddedness. The first is structural embeddedness. Differences in structural embeddedness are reflected in the scale, centrality, and heterogeneity of social networks. In this study, three factors are used to measure structural embeddedness. First, the number of villagers with whom the interviewed farmer keeps in frequent contact is used to measure the size of social networks. Social networks are usually based on geographic relations and kinship, so face-to-face interactions within these networks are still the main way for farmers to obtain information (Zhang and Cao, 2017). Second, whether the interviewed farmers have management roles in their villages is used to measure their centrality in social networks. This approach is based on the fact that village managers currently play an elite role in rural China – they are both agents of the state's interests and representatives of the interests of local communities (Sun, 2009). As such, they are located at the most important nodes in the social networks of villages. This centrality can introduce comparative advantages into the ability to obtain information and resources. Third, the proportion of non-farm and farm households that have different operational scales among the total number of acquaintances of the interviewed farmers is used to measure the heterogeneity of their social networks. Currently, farmer differentiation is mainly driven by productivity differentiation; therefore, non-farm households and farmers with different operational land scales may provide heterogeneous information regarding production and technology to the farmers studied. The second type is relational embeddedness, which is closely linked to trust (Uzzi, 1996; Wilson and Kennedy, 1999); therefore, farmers' main chemical fertilizer-reducing technologies information acquisition channel is used to measure farmers' trust in individuals with close or distant relationships (Gloy *et al.*, 2000; Rogers, 2003; Ward and Pede, 2015). If a farmer's main information acquisition channel is relatives or friends, then this farmer trusts only strong ties such as kinship, geographic relationships, which limit the amount and quality of information he can obtain. On the opposite, if a farmer can trust weak ties (such as agricultural technicians and mass media), he or she will obtain more heterogeneous information.

The identification variable is the number of registered residents in a household. Since there is a certain level of endogeneity between farmers' land operational scale and the IACFRTs, an endogenous switching regression (ESR) is adopted to address potential endogeneity issues. According to the ESR model, we must find an identification variable for whether a farmer can reach a large operational scale that does not directly affect the use of IACFRTs. This study uses the number of registered residents in a farm household as the identification variable. The allocation of land among households in rural China is based on the number of the registered population in each household. Generally, the more people live in a household, the larger the acreage that household can obtain. In Zhejiang Province, however, as the per capita arable land is only 0.037 ha, almost no household can directly reach the threshold of large-scale operation (3.33 ha). Additionally, a large number of registered residents within a household does not mean that more farming workers are available in the household. Therefore, such households do not necessarily prefer labor-intensive fertilizer-reducing technologies or show differences in their IACFRTs.

Based on previous research (Gao *et al.*, 2019; Senyolo *et al.*, 2021), the following are used as control variables: education, age of the head of household, proportion of non-farm income in total household income, and distance to demonstration areas.

The descriptive statistics (Tables 1 and 2) indicate that the farmers who adopted all five technologies accounted for only 38.42% of the sample. Furthermore, 25.71% of the small-scale farmers adopted all the technologies, while 58.08% of the large-scale households have adopted all the technologies. The difference between the two groups of households was significant (Table 2). Additionally, the results indicate that the farmers generally had a low educational level; they were older; and non-farm income was an important income source for most of the sample households.

Table 1. Variable selection and descriptive statistics.

Variable name		Definition	Mean	SD[1]
Dependent variable	IACFRTs[1]	Whether adopted all five fertilizer reducing technologies: 0 = No; 1 = Yes	0.38	0.49
Scale variable	Land scale	Whether large-scale farm households: 0 = No; 1 = Yes	0.39	0.49
Structural embeddedness	Size	Number of villagers with whom the interviewed farm households keep frequent contact	8.98	5.64
	Centrality	Whether the interviewed farm households have management roles in their villages: 0 = No; 1 = Yes	0.10	0.30
	Heterogeneity	Proportion of non-farm households and farm households that have different operational scales among the total number of acquaintances (%)	35.49	26.71
Relational embeddedness	Main information acquisition channel	1 = Relatives or friends; 2 = Specialized households or village cadres; 3 = Agricultural inputs vendors; 4 = Government agricultural technicians; 5 = Mass media	2.16	1.11
Control variable	Education	1 = Primary school; 2 = Middle school; 3 = High school; 4 = Beyond high school	2.04	0.78
	Age	Age of head of household	53.40	11.05
	Proportion of non-farm income	Proportion of non-farm income to total income (%)	43.78	29.22
	Access to IACFRTs	Distance between farmers and the nearest technology demonstration area (meters)	2,022.45	3,670.66
Identification variable	Number of residents registered	Number of residents registered in a household	4.95	4.42

[1] IACFRTs = integrated adoption of chemical fertilizer-reducing technologies; SD = standard deviation.

3.3 Methods

This study adopts the ESR model to rectify the self-selection bias between the operational land scale of the households and their IACFRTs. Compared with the other two mainstream approaches dealing with self-selection bias, Heckman correction and propensity score matching (PSM), the ESR model can redress the self-selection bias caused by the observable and unobservable variables (Hill *et al.*, 2021). Furthermore, the validity of PSM and regression adjustment (RA) depends on the conditional independence assumption (CIA), which means that once observable variables are controlled, the land operational scale is random and uncorrelated with the technology adoption. When the CIA condition is less checked, the ESR model is more helpful (Abdulai and Huffman, 2014; Lokshin and Sajaia, 2004; Ma and Abdulai, 2016).

The ESR model consists of a selection and an outcome equation. The selection equation is used to examine the impact of social embeddedness on the operational land scale of the farmers, which demonstrates the indirect impact of social embeddedness on the IACFRTs. The outcome equation is applied to examine the direct impact of social embeddedness on the IACFRTs. Specifically, the equations are as follows:

$$L_i^*=a+\gamma_1 S_i+\beta_1 X_i+u_i \quad L_i=1 \text{ if } L_i^*>0,\ L_i=0 \text{ otherwise} \tag{1}$$

$$T_i^*=b+\gamma_2 S_i+\varphi L_i^*+\beta_2 Y_i+v_i \quad T_i=1 \text{ if } T_i^*>0,\ T_i=0 \text{ otherwise} \tag{2}$$

Where L_i^* denotes the land scale of household i; φ is the estimation coefficient of land scale in the outcome equation; L=1 denotes a large-scale household; L=0 denotes a small-scale household; T_i^* is the observed value of the adoption; T=1 denotes the IACFRTs; T=0 denotes no adoption; S_i denotes the social embeddedness of household i; γ_1 and γ_2 denote the estimation coefficients of social embeddedness in the selection equation and outcome equation, respectively; X_i and Y_i denote the control variables that influence the production scale of and technology adoption of household i, respectively; a and b are constants in the selection equation and outcome equation, respectively; and u_i and v_i are the residual terms in the selection equation and outcome equation, respectively.

By combining the selection and the outcome equations, we can obtain the total impact of social embeddedness on the IACFRTs (including both the direct and indirect impacts), as shown in the following equation:

$$T^*=h+(\gamma_2+\gamma_1\varphi)S+\beta_3 I+\beta_4 D+\varepsilon \qquad (3)$$

Where γ_2 denotes the direct impact of social embeddedness on the IACFRTs, $\gamma_1\varphi$ denotes the indirect impact; and $(\gamma_2+\gamma_1\varphi)$ is the overall impact. I is the control variable, D is the identification variable, β_3 and β_4 are the estimation coefficients, respectively; h is a constant; and ε is the random disturbance.

4. Social embeddedness differences between large- and small-scale households

The social embeddedness of the large-scale households differed significantly from that of the small-scale households (Table 2). In terms of structural embeddedness, the number of villagers who maintained contact with large-scale households was approximately twice as large as that for small-scale farmers. The social networks of large-scale households were also more heterogeneous (the proportion of non-agricultural farmers or unequal-scale farmers among the acquaintances in their social network was as high as 60%). While the social networks of small-scale farmers were smaller and more homogeneous, showing the typical characteristics of strong ties. In terms of relational embeddedness, both the large- and small-scale households chose to trust geographical and business-based relationships (the means were 2.89 and 2.24, respectively, and the two groups exhibited no significant difference). This is consistent with the characteristics of a semi acquaintance society; whether large-scale or small-scale, farmers' trust in weak ties is still insufficient.

Table 2. IACFRTs[1] and social embeddedness for large- and small-scale households.

	Variable	**Large-scale households**		**Small-scale households**		***t*-test**
		Mean	**SD[1]**	**Mean**	**SD**	**Sig[2]**
Dependent variable	IACFRTs	0.58	0.50	0.26	0.44	0.000***
Structural embeddedness	Size	12.35	6.37	6.80	3.75	0.000***
	Centrality	0.12	0.32	0.09	0.28	0.018**
	Heterogeneity	60.95	19.70	19.02	15.29	0.002***
Relational embeddedness	Main information acquisition channel	2.89	1.19	2.24	1.66	0.2400*

[1] IACFRTs = integrated adoption of chemical fertilizer-reducing technologies; SD = standard deviation.

[2] *, **, *** are significant levels at 10, 5 and 1%, respectively.

5. Functional differences of social embeddedness between large-scale and small-scale households

5.1 Land scale endogeneity test

To assess the validity of the ESR model, it is necessary to first test whether the land scale is an endogenous variable in the outcome equation firstly. Based on shared random effects, we establish the relationship of residual terms between u_i and v_i:

$$\begin{cases} u_i = \omega\theta_i + \zeta_i \\ v_i = \theta_i + \xi_i \end{cases} \tag{4}$$

In Equation (4), θ_i, ζ_i, and ξ_i are hypothesized to be independent and identically distributed with a mean of 0 and a variance of 1; θ_i denotes the shared random effect; ω is the estimated coefficient; and ζ_i, and ξ_i are the error terms. The covariance matrix between residual terms u_i and v_i is derived as follows:

$$\mathrm{Cov}(u_i, v_i) = \Sigma = \begin{pmatrix} \omega^2+1 & \omega \\ \omega & 2 \end{pmatrix} \tag{5}$$

Furthermore, the relationship of residual terms between u_i and v_i can be expressed as follows:

$$\rho = \frac{\omega}{\sqrt{2(\omega^2+1)}} \tag{6}$$

Where ρ is the correlation coefficient of residual terms u_i and v_i. If ρ=0, then the land scale of the farm household is an exogenous variable; the selection and outcome equations are estimated separately, and the unbiased estimator of the coefficient is then derived. Otherwise, the land scale is an endogenous variable, and the ESR model is suitable for estimating the coefficient.

The results (Table 3) show that $\rho \neq 0$ (significant at the 10% level), indicates that the land scale is endogenous. As such, the selection and outcome equations cannot be estimated separately, and the ESR model is suitable.

5.2 Identification variable validity test

The registered number of residents in a household had a significant (at the 5% level) negative impact on the operational scale of farm households. As discussed above, the per capita operational land in Zhejiang Province is 0.037 ha. A household with 10 registered family members would have only 0.37 ha of land, which is far less than 3.33 ha, the threshold for a farm to be considered large-scale. Additionally, Zhejiang is among the leading regions in development of non-state-operated economy. Thus, households with a larger number of registered residents face higher survival pressure. Accordingly, these households are more likely to take on other non-farming jobs and leave the agricultural sector.

5.3 Direct impact of social embeddedness on the IACFRTs

The results of the outcome equation (Table 3) indicate that the social network scale had significant (at the 5% level) direct impacts on the IACFRTs. The impact of the social network scale was positive; the larger the scale, the higher the probability of adoption. This conclusion is consistent with previous studies, such as Li and Xu (2017), Lv *et al.* (2021), and Zhang *et al.* (2022). Compared with traditional technology, IACFRTs are more costly. Larger social networks not only provide more information regarding production technologies, thereby reducing uncertainty of the technology (Gessesse *et al.*, 2018; Wang *et al.*, 2020), but also result in more abundant resources, thereby promoting technology adoption (Wossen *et al.*, 2013). The centrality and heterogeneity of social networks did not have a significant impact, which is consistent with many empirical research from China (such as Guo *et al.*, 2020; Sun and Bian, 2011), but different from those in other countries (such as Thuo *et al.*, 2014). The reason for the former may be that village managers work 'full time' in their positions and are separated from agriculture; as such, their identities as village managers do not bring enough resources for farming and agricultural technology adoption. The latter occurs because although social network heterogeneity leads to more abundant information, it also increases information redundancy, which requires more costs to identify useful information. In this situation, technology diffusion is referred to as 'complex contagion', smallholder farmers need more data to verify the net benefits of the technology (Beaman *et al.*, 2021). Furthermore, the IACFRTs is more knowledge intensive, and network externalities and increasing informational returns are both important self-reinforcement mechanisms for its diffusion (Kallis and Norgaard, 2010). However, higher heterogeneity means more communication and coordination costs. If farmers fail to cooperate, negative feedback in social networks will hinder the new technology diffusion, leading to technological 'lock-in' (Flor *et al.*, 2020; Wagner *et al.*, 2016). As a result, if farmers lack enough discriminatory ability, or lack coordination, the heterogeneity may weaken the positive impact of the social network, and even make farmers delay technology adoption strategically. What's more, as we discussed, rural areas are semi acquaintance societies, and farmers' level of trust in weak ties is still low.

Relational embeddedness did not have significant impacts on the IACFRTs, a conclusion that is consistent with Cheng *et al.* (2018). Because both large- and small-scale households obtained technical information from specialized households or agricultural input vendors, the information sources differed little. Additionally, Zhejiang is leading the transition to green development in China. In 2014, the province implemented an initiative to 'treat polluted water, prevent floods, address waterlogging, secure water supply, and conserve water'. In 2015, it implemented the 'plan for reduction of chemical fertilizers and pesticides'. Farmers already received much information about chemical fertilizer-reducing technologies. Thus, differences in evaluation and adoption of the new technology mainly depend mainly on their personalities or family resources.

5.4 Indirect impact of social embeddedness on the IACFRTs

Since social embeddedness can indirectly reinforce IACFRTs by promoting larger-scale land operations, the difference in the impact of social embeddedness between large-scale and small-scale households is embodied mainly by the indirect impact of social embeddedness on the IACFRTs (the results of the selection equation in Table 3).

As shown in Table 3, the results indicate that both structural embeddedness (scale and heterogeneity of social networks) and relational embeddedness had a significant positive impact on land operational scale, thereby indirectly reinforcing the IACFRTs and creating the difference in the function of social embeddedness between large- and small-scale households.

The social network scale had significant direct impacts (Table 4). Currently, rural land transfer usually occurs between people who know each other. The larger a social network is, the more opportunities there are to achieve a large operational land scale through land transfer.

Heterogeneity also had significant direct impacts (Table 4). A higher degree of social network heterogeneity means that in a social network, more farmers work in non-farming jobs; thus, they have more opportunities to expand their land operational scale. Additionally, households have more opportunities to obtain heterogeneous information and resources, further helping farmers improve their farming capacity. However, heterogeneity has a significant indirect impact and insignificant direct impact, indicating that heterogeneity has certain 'threshold effects' (Magnan *et al.,* 2015; Munshi, 2004; Rahmandad and Sterman, 2008; Valente, 1996). Heterogeneity has a positive effect only when farmers can distinguish useful information from other information or when the benefits of coordination in social networks outweigh the costs. Otherwise, heterogeneity reduces the

Table 3. Endogenous switching regression model estimation results.[1,2]

Variable	Selection equation (land scale)			Outcome equation (IACFRTs)		
	Coefficient	SD	Z-value	Coefficient	SD	Z-value
Land scale				1.0551***	0.3373	3.13
Size	0.1387***	0.0205	6.74	0.0253*	0.0138	1.84
Centrality	-0.3676	0.3191	-1.15	0.0901	0.1970	0.46
Heterogeneity	0.0692***	0.0061	11.41	-0.0001	0.0046	-0.01
Main information acquisition channel	0.1910**	0.0781	2.44	0.0579	0.0524	1.11
Age	-0.034***	0.0096	-3.53	0.0105*	0.0056	1.88
Education	0.4330***	0.1323	3.27	0.2699***	0.0818	3.30
Proportion of non-farm income	-0.0134***	0.0035	-3.79	0.0016	0.0020	0.79
Access to ICFRTs	0.0002***	0.0001	2.70	-0.0004***	0.0001	-8.22
Number of residents registered	-0.1486*	0.0711	-2.09			
Constant	-4.3580	0.9733	-4.48	-2.4124	0.4223	-5.71
ρ				-0.4026**	0.2245	-1.79

[1] *, **, *** are significant levels at 10, 5 and 1%, respectively.

[2] IACFRTs = integrated adoption of chemical fertilizer-reducing technologies; SD = standard deviation.

Table 4. Decomposition of the social embeddedness impact on the IACFRTs.[1]

Variable		Impact	Results
Structural embeddedness	Size	Direct impact	0.0253
		Indirect impact	0.1463
		Total impact	0.1716
	Heterogeneity	Direct impact	-0.0001
		Indirect impact	0.0730
		Total impact	0.0729
Relational embeddedness	Main information acquisition channel	Direct impact	0.0579
		Indirect impact	0.2015
		Total impact	0.2594

[1] IACFRTs = integrated adoption of chemical fertilizer-reducing technologies.

efficiency of households in utilizing information and hampers the adoption of new technologies. Compared with small-scale farmers, large-scale farmers undoubtedly have stronger land management capabilities and greater ability to distinguish useful information from other information.

Relational embeddedness also significantly promotes large-scale operations. In addition to providing information on chemical fertilizer-reducing technologies, relational embeddedness can provide other information and resources, such as information on sales or policy support. Information and resources can effectively reduce the operating costs of households, and increase their operating efficiency, thereby motivating farmers to increase their operational scale to maximize their interests.

When land area of households approaches the 'large scale' threshold, farmers have a stronger demand for IACFRTs that have a scale effect, such as irrigation and fertilizer application; this situation promotes the IACFRTs.

Concerning the impact of the control variables on the IACFRTs, the selection equation (Table 3) indicates that the education, age, proportion of non-farm income, and distance between farmers and nearest technology demonstration area have significant impacts on the operational scale of households. Farmers who are younger, have a higher education level, and spend less time on non-farming work are more likely to have large-scale farms, because they have enough ability or opportunities to operate them. The outcome equation indicates that the age and education of the head of household, as well as distance between farmers and nearest technology demonstration area had significant positive impacts on the IACFRTs, because older or better-educated farmers had a better understanding of the economic and environmental costs of fertilizer overuse. As such, they have a stronger motivation to adopt IACFRTs, i.e. to 'save costs and improve efficiency' and to achieve sustainable farming. The distance to demonstration areas had a negative impact, indicating that demonstration areas have a positive effect on IACFRTs.

6. Discussion and conclusions

This paper analyzed the differences of social embeddedness and its heterogeneous function between small- and large-scale farmers. Based on survey data of 583 rice farmers from Zhejiang Province, China, this study first compared the differences in social embeddedness between 354 small-scale and 229 large-scale farmers. The *t*-test results showed that large-scale (vs small-scale) households had a larger social network scale with stronger heterogeneity. Then, we employed the ESR model to analyze the direct and indirect impacts of social embeddedness on the IACFRTs, and summarized the functional differences of social embeddedness between large- and small-scale farmers. The results of our empirical analysis showed that although social embeddedness remains important to the diffusion of chemical fertilizer-reducing technologies, its function differs significantly depending on the adoption of technology between small and large-scale farmers. In particular, if we focus only on the direct impact of social embeddedness on farmers' adoption, the function of the heterogeneity of social networks, i.e. relational embeddedness on promoting large-scale operations, will be underestimated or even ignored. This may be an important reason why previous studies found that the influence of relational embeddedness on technology adoption was not significant.

Large-scale households have been well embedded in the development of modern agriculture, and the role of social embeddedness is more prominent. Therefore, the government should pay more attention to the technological 'lock-in' problem caused by overly heterogeneous structural embeddedness in small farmers. On the one hand, the government should disseminate information about environmental-friendly technologies for small-scale farmers, and provide accessible technical guidance and demonstrations. On the other hand, policymakers should expand the coverage of environmental-friendly agriculture subsidies, particularly in terms of providing more subsidies for environmental-friendly inputs and socialized services, to lower the threshold of technology adoption for small farmers, instead of roughly pursuing scale-scale production in the early stages.

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Conflict of interest

The authors declare that there is no conflict of interest.

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