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THE ECONOMIC COST OF LEAVING FARMER-RELATED SOCIAL NETWORKS IN RURAL VIETNAM: A QUASI-EXPERIMENTAL APPROACH

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Abstract

Addressing rural marginalization stands as a pivotal economic and political imperative in Vietnam, where rural areas currently sustain approximately 62% of Vietnam's population. Politically, the agrarian class has been revered as the primary catalyst within the Vietnamese revolutionary framework, epitomizing an intrinsic of the proletariat, and recognized as the "root of revolution" within the ideological framework of the Vietnamese Communist Party since 1930. This paper explored the role of social networks in rural Vietnam by estimating the economic cost of leaving such networks in terms of the reduction in household income. We used the propensity score matching method as a quasi-experimental design together with a primary survey in rural North Vietnam. Our empirical results show that leaving the farmer-related social networks costs the household 22.3-24.6% of household income. Our results suggest that farmer-related social networks are very important in rural Vietnam and it would be an endogenous potential that helps the country overcome the rural marginalization and enhance prosperity.

Keywords: Propensity Score Matching, Kernel Matching Algorithm, Social Capital, Social Networks

INTRODUCTION

Addressing rural marginalization stands as a pivotal economic and political imperative in Vietnam where rural areas currently sustain approximately 62% of Vietnam's population. Moreover, rural locales have historically served as the foundational base for Vietnam's political evolution, spanning from decolonization to national unification. Throughout nearly a century of struggle for independence and unity, rural regions have occupied a distinctive position in the nation's endeavors toward sovereignty establishment, development, and defense. Politically, the agrarian class has been revered as the primary catalyst within the revolutionary framework, epitomizing a steadfast and intrinsic of the proletariat, and recognized as the "root of revolution" within the ideological framework of the Vietnamese Communist Party since 1930. Officially, the Vietnamese government has consistently underscored the enhancement of rural economic conditions as a steadfast policy focus within development strategies.

Leveraging intrinsic aspects of rural society as intangible assets is fundamental to enhancing the effective utilization of resources within the existing framework of rural production. As articulated by Moyes et al. (2012), the focal point of rural development has shifted from merely attracting enterprises from external sources to harnessing local resources for sustainable transformation. Wiessinger (2007) underscores that while unfavorable conditions and resource deficits contribute to rural marginalization, they do not fully account for it, particularly in regions with sparse populations and limited policy interventions. Interestingly, such regions sometimes demonstrate greater viability than more affluent areas, suggesting the presence of intangible assets intertwined with the dynamics of marginalization. He posits that these intangible assets are rooted in the social structure of local communities, encompassing what he refers to as "intrinsic aspects."

Recent insights recognize that the utilization of resources is not primarily tied to geographical proximity, as traditionally emphasized by the "agglomeration effect" within the framework of new economic geography. Effective resource utilization is increasingly associated with socioeconomic and political connections (social connectivity or relational remoteness), rather than geographical location. These notions embody various facets of social capital, delineated as a "missing link" for development. As Grootaert (1998) articulates, while natural, physical, and produced capital only partially shape economic growth by overlooking the dynamics of how economic actors interact and organize themselves to foster growth and development, the pivotal component lies in social capital.

This paper explores the important role of social capital in the form of massive social organizations in rural Vietnam. Particularly, we empirically examine whether, and to what extent, leaving farmer-related social networks has a causal economic impact on household income. We limit the scope of the study to two massive social organizations that are significantly famer-related, namely the Famer's Association and the Vietnamese Communist Party.

LITERATURE REVIEW

Social networks are fundamentally about creating, maintaining, and utilizing relationships that give individuals and groups access to valuable resources and support (Zinke-Wehlmann, 2021). These networks are structured as nodes – representing individuals, organizations, or entities – connected by various interdependencies such as friendship, kinship, common interests, financial exchanges, or even competitive relations. According to Putnam (1993), social networks are integral components of social capital. He asserts that collective social capital, embodied in networks, norms, and trust, constitutes a composite asset of a community, representing its capacity for cooperation and collective action.

According to Bourdieu (1986), social capital manifests as an uneven distribution of a specific "social power," reflecting an individual's access to networks. This social capital empowers individuals to accrue advantages through opportunistic actions contingent upon social obligations and available networks. Nevertheless, numerous studies indicate that social capital also plays a pivotal role in facilitating the dissemination of knowledge and diminishing transaction costs by fostering trust and minimizing opportunistic behaviors (Bowles & Gintis, 2002). Collier (2002) points out the economic effect of social capital stemming from its inherent nature of social interaction. Firstly, social interaction enhances the capacity to make allocative decisions through two primary mechanisms: imitation, which diminishes transaction costs, and aggregation, which consolidates diverse knowledge. Secondly, social interaction contributes to increased output by fostering trust and establishing reputations regarding the reliability of other agents. Thirdly, social interaction engenders coordinated action through various means, including spontaneous coordination driven by societal norms or deliberate coordination resulting from conscious decisions.

Lynn and Mandarano (2009) develop social network concepts as platforms where linked individuals engage in repeated interactions. These interactions can influence behaviors and foster collaboration, potentially leading to the establishment of collaborative equilibria - where the actions of one participant influence the outcomes for others, particularly in networks characterized by dense connections or structural hubs.

Social networks also act as a channel for the flow of social capital, which is crucial for societal functionality and productive outcomes. Hellerstein and Neumark (2020) assume that social networks enhance economic well-being by improving labor market efficiencies through the effective transfer of information. The facilitation of information flow can significantly impact employment outcomes and economic opportunities. The collective aspect of social capital, as highlighted by Putnam, emphasizes that trust, civic engagement norms, and social networks are pivotal in improving society's efficiency by enabling coordinated actions. Individuals use information from social networks to infer social relationships. Tabassum et al. (2018) demonstrate that individuals make judgments based on statistical inferences and the proportionality of shared connections from this platform. This process underscores the importance of network density and the breadth of mutual connections in shaping social perceptions and interactions. Networks rich in social capital typically exhibit strong norms of reciprocity and high levels of trust, facilitating more straightforward collaborations and contributing to higher and more stable economic returns.

While valuable insights regarding the economic impacts of social networks have been gleaned from field studies, the reliance on such methods presents limitations, particularly the lack of extensive household surveys. This scarcity of comprehensive data hinders efforts to thoroughly examine and understand how social network influences economic outcomes, especially within rural contexts. In his seminal work, Putnam (1993) presented compelling evidence showcasing the influential role of social networks, in contributing significantly to economic prosperity in Northern Italy. Building upon this, the Food and Agriculture Organization (FAO) (2014) highlights that robust producers' organizations play a pivotal role in enhancing economic success by offering a myriad of services to producers. These services include broadening access to natural resources, and input and output markets, as well as facilitating the dissemination of information and knowledge, ultimately enabling producers to participate more effectively in policymaking processes. In rural America, Hoyman et al. (2016) find that heterogeneous membership in social organizations positively influences per capita income. Similarly, Narayan and Pritchett (1997) demonstrate in their study of rural Tanzania that official networks correlate with increased household income. In the context of rural Indonesia, Jumirah and Wahyuni (2018) reveal that social participation levels and cooperativeness indices positively impact household expenditure.

Social connectivity can entail costs associated with participation and maintenance. The upkeep of close-knit groups, for instance, may impose constraints on resource mobility, reflecting a form of social obligation that necessitates sacrificing resource optimization. In cases where the benefits derived from such social networks do not outweigh these costs, it becomes detrimental, ultimately diminishing household economic well-being.

Levien (2015) provides evidence from rural India indicating that social connectivity can be deleterious, particularly when better-connected individuals exploit their position as brokers, monopolizing profits to the detriment of other community members. Similarly, Sabatini (2008) observes that strong family ties and tight social networks can negatively impact both per capita income and life expectancy.

In Vietnam, studies on the economic impacts of social capital in Vietnam encounter limitations in scope. Van Ha et al. (2004) do a survey in a paper-recycling craft village to assess the influence of various forms of social capital on household income and expenditure but the study points out that association membership does not significantly affect household income. In contrast, using the Viet Nam Access to Resource Household Survey 2014, Do and Minamoto (2021) present that Vietnamese Communist Party membership yields a 22% increase in the total income of households in rural Vietnam.

EMPIRICAL STRATEGY AND DATA

Empirical Strategy

This paper employs a quasi-experimental design to estimate the causal impact. The propensity Score Matching (PSM) method is widely used in causality analysis, especially after the emergence of the "credibility revolution", in which economic analysis needs to work on the causality instead of a correlation. For example, Tiatité (2023) uses the PSM method to estimate the effect on farmer household agricultural productivity by matching the household in a cooperative or agricultural organization with those who do not. Also, Bhattacharjee (2022) exploits the impact of social networks on out-of-pocket healthcare expenditure in India through this approach.

PSM stems from the quasi-experimental design that attempts to mimic randomization by constructing a comparison group (Gertler et al., 2016, p. 143). In our PSM framework, a group of households **with no membership** in the farmer-related massive social networks is used as the **treatment group**. We develop a counterfactual of the treatment group, namely a statistical **comparison group** (control group) using propensity score. Comparing the outcome of the treatment group and control group provides us with the causal impact of solely leaving the social networks. In other words, we estimate how the average income of the household in farmer-related social networks would change solely due to leaving the social networks.

According to Rosenbaum and Rubin (1983), to examine the change in household income denoted $Y_t^{t=1}$ for households participating in the treatment group, and $Y_t^{t=0}$ for the comparison group. The difference in household income is calculated as follows:

$$\Delta \mathrm{Y}=\mathrm{Y}_{\mathrm{i}}^{\mathrm{t}=1}-\mathrm{Y}_{\mathrm{i}}^{\mathrm{t}=0} \quad (1)$$

Therefore, the average treatment effect on the treated (ATT) will be:

$$\tau=\mathrm{E}(\Delta \mathrm{Y}|\mathrm{T}=1)=\mathrm{E}\left(\mathrm{Y}_{\mathrm{i}}^{\mathrm{t}=1}|\mathrm{T}=1\right)-\mathrm{E}\left(\mathrm{Y}_{\mathrm{i}}^{\mathrm{t}=0}|\mathrm{T}=0\right) \quad (2)$$

The idea of "matching" is to compare the outcome of interest between households in the treatment group and those not in the comparison group, while ensuring that they have similar characteristics. By doing so, we aim to create a counterfactual like what would be observed in a randomized experiment. However, the more characteristics of the groups we use to match, the more difficult we can match (the curse of dimensionality). Rosenbaum and Rubin (1983) proved that matching based on the propensity score of participating in the intervention was as good as exact matching based on characteristics if two following assumptions are satisfied:

1) Conditional Independence Assumption: The potential outcome for households without participation is independent of characteristics X. If this assumption holds, where the vector of observed covariates remains unchanged, the household income has the same distribution that the participating household would have experienced had they not participated in the intervention:

$$Y^{t=0},Y^{t=1} \perp T|X,\forall X \quad (3)$$

$$\tau=E(\Delta Y|T=1)=E\left(Y_i^{t=1}|T=1,X\right) - E\left(Y_i^{t=0}|T=0,X\right) \quad (4)$$

If potential household income is independent of the participation decision conditional on covariates X, it is also independent of the participation decision conditional on the propensity score (Rosenbaum and Rubin, 1983). That is, the propensity score is one possible balancing score, defined as the possibility of a household member participating in the treatment on covariates X.

2) The Common Support Assumption:

$$P_i(X) = Prob(T = 1|X) \quad (5)$$

$$0<P(T=1|X)<1 \quad (6)$$

This assumption assures that households with the same X values have a positive probability of having both membership and non-membership status. Therefore, the average treatment effect is only estimated in the region of this common support. The common support assumption enhances matching results by excluding households at the extreme ends of the propensity score distribution. It guarantees that characteristics observed in the treatment group are also present in the comparison group.

If the two above assumptions hold, the PSM estimator for ATT can be expressed:

$$\tau=E[\Delta Y|T=1, P(X)] =E_{P(X)|T=1}\{E[Y_1^{T=1}|T=1, P(X)]\}-E[Y_1^{T=1}|T=1, P(X)]\} \quad (7)$$

Equation (7) indicates that the PSM estimator corresponds to the average difference in household income between the two groups within the common support region.

Let P_i denote the propensity score for the participant i, conditional on the covariates X_i: $P_i \equiv E(T_i|X_i)$; let I_1 and I_0 respectively denote the sets of all households in treatment and control groups; S_P denotes the common support region; N_1 and N_0 respectively denote the number of all households in $S_1=I_1\cap S_P$ and $S_0=I_0\cap S_P$. Denote $C(P_i)$ as the set of neighbors to the participant $i \in S_1$, in which if $j \in S_0$ and $P_j\in C(P_i)$, then the "neighbor" j is matched to the participant. The treatment effect τ is transformed to simply the mean difference in outcomes over the common support region, weighted by the distribution of propensity score of participants:

$$\begin{aligned}\tau &= E(Y_{1i}-Y_{0i}|T_i=1) = E(Y_{1i}|T_i=1) - E(Y_{0i}|T_i=1)\\ &= E(Y_{1i}|T_i=1) - E_{P_i|\,T_i=1}[E(Y_{0i}|T_i=1,P_i)]\\ &= E(Y_{1i}|T_i=1,P_i) - E_{P_i|\,T_i=1}[E(Y_{0i}|T_i=1,P_i)]\\ &= \frac{1}{N_1}\Sigma_{i\in S_1}Y_{1i} - \frac{1}{N_1}\Sigma_{i\in S_1}\hat{E}(Y_{01}|T_i=1,P_i) = \frac{1}{N_1}\Sigma_{i\in S_1}[Y_{1i} - \hat{E}\,(Y_{01}|T_i=1,P_i)]\\ &= \frac{1}{N_1}\Sigma_{i\in S_1}[Y_{1i} - \Sigma_{j\in S_0}Y_{0j}.\omega(i,j)]\end{aligned}$$

Data

Data acquisition

The data acquisition process was implemented in two steps:

Step 1: Conduct a preliminary survey, gather general information, provide answer guidelines, and finalize the survey form, confirming with households their readiness to respond: From September 2022, the survey team did a field trip to communes that participated in the Vietnamese government's new rural model program in Ha Nam, Hai Phong and Quang Ninh province. In each commune, the survey team worked with households introduced by the local police office to collect general information for the survey, discuss the survey's purpose, requirements, and survey topics, explain the meanings of terms and difficult questions, and discuss potential issues that might require additional information or corrections to finalize the official questionnaire. The survey team also confirmed with household representatives their readiness to answer the survey once the questionnaire was finalized and scheduled to be delivered to the households by the end of December 2022 or the beginning of January 2023.

Step 2: Send and collect the questionnaire to household representatives: Based on the results of the preliminary survey, the questionnaire was finalized according to the feedback from the households anticipated in Step 1. After official approval, from the end of December 2022 to early January 2023, the official questionnaire was sent to each household that had been previously engaged and agreed to respond to the survey in Step 1. In February 2023, the questionnaires were collected for analysis and statistical processing.

In this survey, we collected data from household heads related to (i) general information about the household and its location; (ii) characteristics of the household, including settlement issues, household size, education level, total monthly household income, living area, and owned assets; and (iii) information about participation in the social networks.

Table 1 presents the descriptive statistics and balance test (t-test) results. Membership households who participate in these social networks, either the Vietnamese Farmer's Association or farmer-related social networks, enjoy statistically higher economic well-being than non-participating households. However, this does not imply that the observed differences solely arise from the massive official social organizations. It might happen in a different way: The rich households might prefer to participate in social networks. Therefore, we employ the PSM method to mimic randomization and examine the impact of solely those networks on household income.

Table 1: Summary of characteristics

	Farmer's Association Only			Farmer-Related Social Networks		
	Membership	Non-membership	Difference	Membership	Non-membership	Difference
Household's income	2.299	2.039	0. 26*	2.458	2.04	0.418***
Household's size	4.034	3.604	0.429*	4.000	3.604	0.396*
Education level	1.756	1.868	-0.113	2.686	1.868	0.819***

Living land area	4.915	4.915	0.332***	5.246	4.915	0.331***
Income assets	2.426	2.554	-0.129	2.736	2.554	0.181
Number of observations	90	53		169	53	

Note: *** p < 0.01, ** p < 0.05, * p < 0.10
Source: Authors'

EMPIRICAL RESULTS AND DISCUSSION

4.1. Model diagnostics and selection

Table 2 presents the estimation from the logistic and probit regression models for the propensity score of having connections with the Farmer's Association. We extend social networks to Farmer's related social networks by including also Communist Party of Vietnamese, an important massive organization working for the benefit of Vietnamese farmers in Table 3. In the logistic regression model, we report both odd ratios and coefficients.

	Famer's Association (Logit, Odds)	Famer's Association (Logit, β)	Famer's Association (Probit, β)
Household's size	1.250*	0.223*	0.124
	(0.168)	(0.134)	(0.078)
Education level	0.950	-0.052	-0.028
	(0.116)	(0.122)	(0.075)
Living land area	2.013**	0.700**	0.426**
	(0.609)	(0.302)	(0.181)
Income assets	0.934	-0.069	-0.039
	(0.095)	(0.102)	(0.062)
Constant	0.027**	-3.628**	-2.174**
	(0.043)	(1.617)	(0.958)
Number of observations	143	143	143
Log-likelihood	-88.939441	-88.939441	-89.050601
LR Chi^2	10.678**	10.678**	10.456**
Pseudo R^2	0.057	0.057	0.055

AIC	187.879	187.879	188.101
BIC	202.693	202.693	202.915

Table 2: Estimating Propensity Score of having connections in Farmer's Association

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
Source: Authors'

For a balanced sample, we use several variables of household characteristics for the logit/probit model, i.e., household size (labor), educational level of household head (human capital), living land area (land), and assets that can generate income source (capital). The coefficient of the educational level of household head and living land area is positive and statistically significant. The high-living land area is associated with a higher probability of having membership in the social networks. The coefficient of income assets is negative but not statistically significant. The propensity score is computed for all households, and then each household in the treatment group can (no membership in either Farmer's Association or Vietnamese Communist Party) be matched with households with the most closed propensity score.

	Farmer-related Social Organization (Logit, Odds)	Farmer-related Social Organization (Logit, β)	Farmer-related Social Organization (Probit, β)
Household's size	1.164 (0.139)	0.152 (0.119)	0.086 (0.069)
Education level	1.317*** (0.135)	0.275*** (0.102)	0.284*** (0.057)
Living land area	1.619** (0.336)	0.482** (0.208)	0.284** (0.118)
Income assets	0.972 (0.093)	-0.028 (0.095)	-0.014 (0.055)
Constant	0.089** (0.101)	-2.417** (1.133)	-1.390** (0.638)
Number of observations	222	222	222

Log-likelihood	-113.56679	-113.56679	-113.48768
LR Chi^2	16.898***	16.898***	17.06***
Pseudo R^2	0.069	0.069	0.070
AIC	237.134	237.134	236.975
BIC	254.147	254.147	253.989

Table 3: Estimating Propensity Score of having connections in either the Farmer's Association or Communist Party of Vietnam

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
Source: Authors'

Between the two models, the logit model is preferred in both two cases due to the higher McFadden R^2, the lower AIC, and the lower BIC.

4.2. Causal impact

The causal impact is empirically estimated using kernel matching algorithms on propensity score. In kernel matching algorithms, each participant in the treatment group is matched to all non-participants with higher weight is given to a more proximal (in propensity score) non-participant: The weight function ω(i,j) depending on the distance between P_i and P_j. The traditional empirical weight function ω(i,j) has the form:

$$\omega(\mathrm{i},\mathrm{j}) = \frac{\mathrm{G}(\frac{P_j - P_i}{h})}{\sum_{k \in S_0} \mathrm{G}(\frac{P_k - P_i}{h})}$$

where h is a smoothing parameter or a bandwidth, G(●) is a kernel function with various forms: Epanechnikov, Rectangle, Uniform,Triangle, Biweight, Triweight, Cosine, Parzen.

Table 4: Treatment effect of social networks on household income

	Famer's Association Only		Farmer-related Social Networks	
	τ	SD	τ	SD
Kernel matching				
Epanechnikov	-0.097	0.165	-0.266**	0.144
Rectangle	-0.115	0.160	-0.283**	0.141
Uniform	-0.115	0.152	-0.283**	0.125
Triangle	-0.091	0.148	-0.260*	0.142
Biweight	-0.091	0.163	-0.259*	0.147
Triweight	-0.090	0.160	-0.255*	0.143

Cosine	-0.090	0.158	-0.257**	0.139
Parzen	-0.090	0.171	-0.252*	0.154
Treatment group's observation	53		53	
Control group's observations	90		169	
Number of observations	143		222	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The bootstrapped standard error for kernel matching (200 times); Optimal bandwidth is automatically calculated using user-written *kmatch* command in Stata.

Source: Authors'

Table 4 presents the impact of the farmer-related massive social networks. We found that when a household has farmer-related social network membership, exit from such social network would lead to an economic cost equivalent to 0.252 to 0.283 in reduction of natural logarithm form of income. This economic cost means a significant reduction of 22.3% - 25.4% in household income.

Interestingly, when we restrict our data to Farmer's Association only, instead of farmer-related massive social networks, kernel matching algorithms report an insignificant change in terms of household income. Our results are still consistent and robust when the matching algorithm is changed from kernel matching to radius matching. In other words, if a household connects with the farmer-related massive social network solely through the membership of the Farmer's Association, leaving such association costs insignificant reduction in household income. Our results imply a dynamic and integrated role of farmer-related social networks in rural Vietnam. The result of Farmer's Association membership is consistent with Do (2020) who argues that "being a member of an organization [Farmer's Association] has its own utility cost". He empirically showed that the impact of such an organization in the Vietnam Access to Resources Household Survey 2012 – 2014 was ambiguous because the group effect might crowd out the effect of collectively embedded resources within the group. As a result, in the 2012 sample, 52% of the households had membership in the farmer association, but 16.1% will leave the Farmer Association in 2014.

CONCLUSION

Our findings highlight the significant and integrated role of farmer-related social networks in rural Vietnam. The presence of substantial organizational memberships, such as the Farmer's Association or the Communist Party of Vietnam, underscores the importance of these social capital forms in enhancing economic activities for households. Membership in farmer-related social networks offers economic advantages, and exiting these networks can incur substantial economic costs. Farmers with extensive resources, represented by their membership in large organizations like the Farmer's Association and the Communist Party of Vietnam, benefit significantly from social capital, including social networks, high social trust, and strong political connections to leaders.

This study provides evidence that the diversification of farmer-related social network memberships contributes to the economic well-being of rural households in Vietnam. This finding suggests an endogenous potential for government initiatives to promote rural development strategies, helping to combat rural marginalization and enhance prosperity.
However, the quantitative methods employed in this study cannot fully elucidate the underlying mechanisms. Further research should incorporate qualitative approaches, such as case studies or ethnographic methods, to gain a deeper understanding of the impact of farmer-related social network memberships on the economic conditions of the agrarian class in rural Vietnam. Combining qualitative methods with propensity score matching in impact evaluations with quasi-experimental interventions will be instrumental in testing the theoretical conditions and assumptions underlying the quantitative analysis.

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APPENDICES

Appendix 1: Balancing test

Appendix 1.1. Balancing table of the means covariates (Epanechnikov, optimal bandwidth)

Means	Raw			Matched (ATE)		
	Treated	Untreated	Std. Diff.	Treated	Untreated	Std. Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: The Farmer-related Massive Social Organization						
Household's size	4	3.604	0.280	3.784	4.002	-0.154
Education level of household head	2.686	1.868	0.477	2.374	2.342	0.019
Living land area	5.246	4.915	0.408	5.177	5.158	0.023
Income assets	2.736	2.554	0.098	2.706	2.512	0.104
Panel 2: The Farmer's Association						
Household's size	4.033	3.604	0.302	3.802	3.829	-0.019
Education level of household head	1.756	1.868	-0.074	1.780	1.701	0.052
Living land area	5.247	4.915	0.445	5.186	5.191	-0.007
Income assets	2.426	2.554	-0.069	2.397	2.619	-0.120

Appendix 1.2. Balancing table of the means covariates (Epanechnikov, optimal bandwidth)

Variances	Raw			Matched (ATE)		
	Treated	Untreated	Ratio	Treated	Untreated	Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: The Farmer-related Massive Social Network						
Household's size	1.905	2.090	0.911	1.901	2.013	0.944
Education level of household head	3.359	2.540	1.323	3.120	3.349	0.932

Living land area	0.535	0.784	0.683	0.311	0.202	1.539
Income assets	2.724	4.141	0.658	2.628	3.547	0.741
Panel 2: The Farmer's Association						
Household's size	1.965	2.090	0.940	2.116	1.788	1.183
Education level of household head	2.052	2.540	0.808	2.100	2.110	0.995
Living land area	0.329	0.784	0.420	0.266	0.159	1.671
Income assets	2.705	4.141	0.653	3.119	3.888	0.802

Appendix 2: Common support diagnostic

Appendix 2.1. Common support diagnostic of the mean covariates: Means

Means	Common support			Standardized difference		
	Matched	Unmatched	Total	(1) – (3)	(2) – (3)	(1) – (2)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: The Farmer-related Massive Social Network						
Household's size	3.845	4.688	3.905	-0.043	0.557	-0.601
Education level of household head	2.413	3.5	2.491	-0.043	0.558	-0.601
Living land area	5.198	4.776	5.167	0.039	-0.501	0.540
Income assets	2.651	3.222	2.692	-0.024	0.303	-0.327
Panel 2: The Farmer's Association						
Household's size	3.822	4.750	3.874	-0.036	0.613	-0.650
Education level of household head	1.8	1.750	1.797	0.002	-0.032	0.034
Living land area	5.190	4.011	5.124	0.092	-1.544	1.636
Income assets	2.486	2.262	2.473	0.007	-0.118	0.125

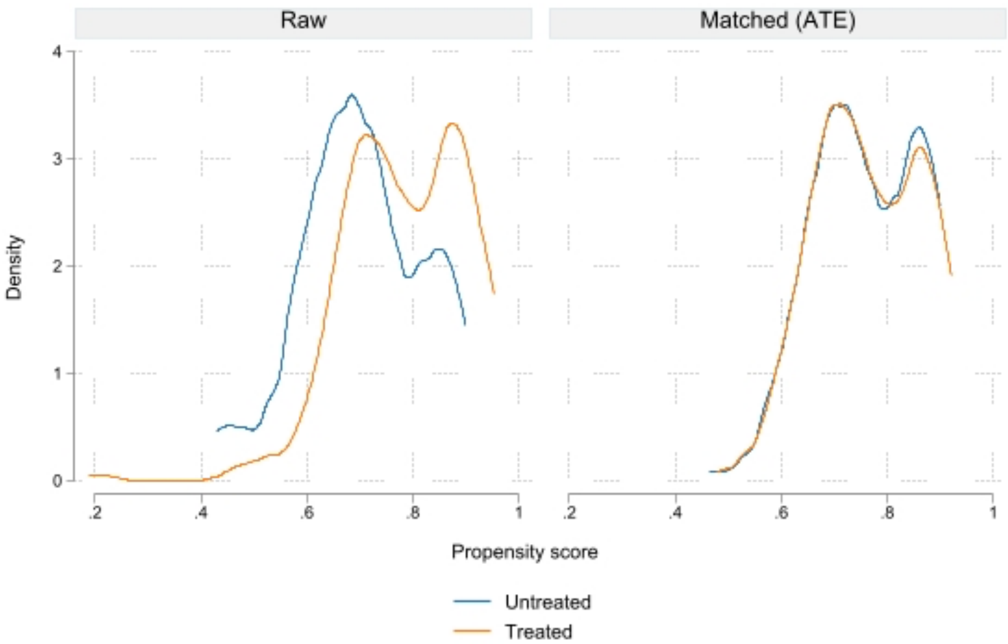
Appendix 2.2. Common support diagnostic: Variances

Variances	Common support			Standardized difference		
	Matched	Unmatched	Total	(1) / (3)	(2) / (3)	(1) / (2)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: The Farmer-related Massive Social Organization						
Household's size	1.888	2.496	1.968	0.959	1.268	0.756
Education level of household head	3.200	3.333	3.274	0.977	1.018	0.960
Living land area	0.300	4.730	0.611	0.491	7.738	0.063
Income assets	2.971	4.028	3.051	0.974	1.320	0.738
Panel 2: The Communist Party						

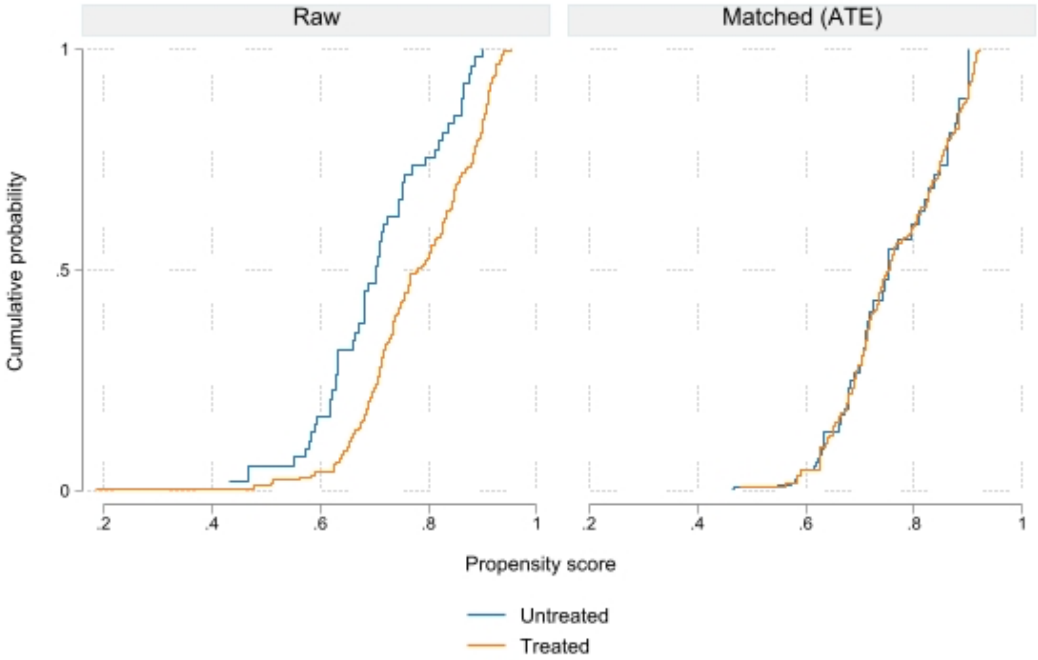
Household's size	1.868	3.2	1.924	0.971	1.663	0.584
Education level of household head	3.494	4.7	3.537	0.988	1.329	0.743
Living land area	1.003	0.290	0.962	1.043	0.301	3.462
Income assets	3.594	2.622	3.586	1.002	0.731	1.371
Panel 3: The Farmer's Association						
Household's size	1.849	5.071	2.040	0.906	2.486	0.365
Education level of household head	2.251	1.929	2.219	1.014	0.869	1.167
Living land area	0.238	4.487	0.519	0.458	8.640	0.053
Income assets	3.232	3.312	3.216	1.005	1.030	0.976

Appendix 3: Kernel density and cumulative distribution plots

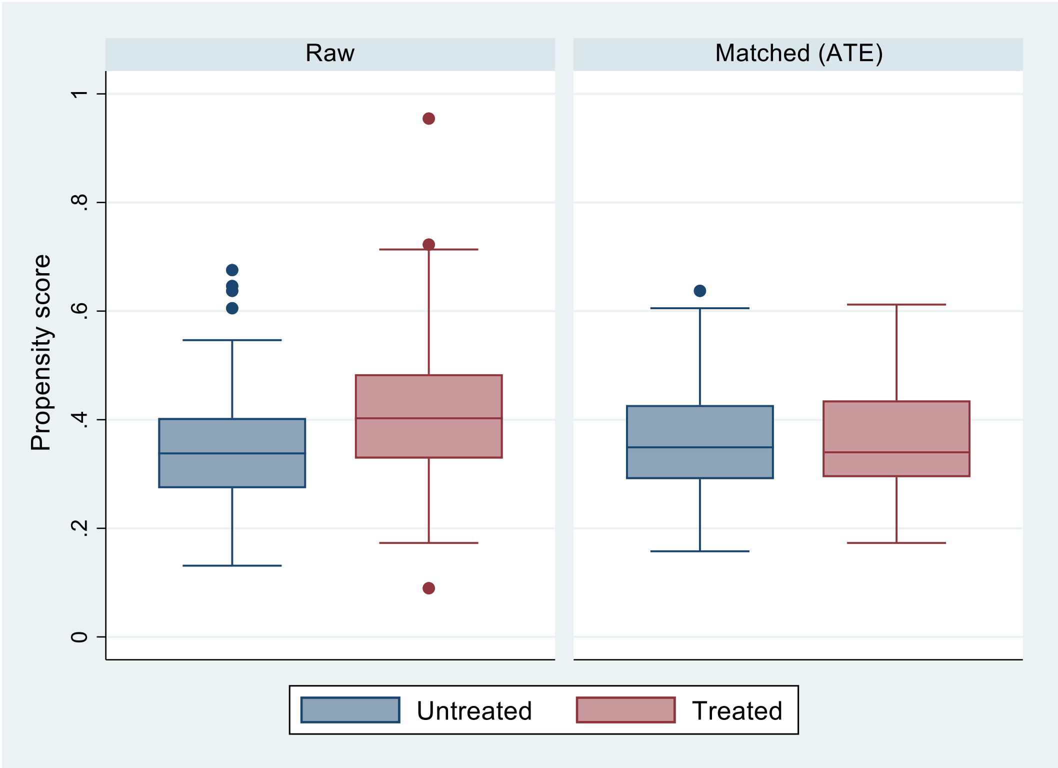
Appendix 3.1. Kernel density of raw and matched data



Appendix 3.2. Cumulative distribution of raw and matched data



Appendix 4: Box plots for the raw and the matched data



Appendix 5: Baseline regressions

Variable	OLS Baseline			MWFE estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Farmer-related Social Network	0.224*			0.192		
	(0.126)			(0.122)		

Famer's Association		0.242*			0.207	
		(0.138)			(0.145)	
Household's size	0.090**	0.066	0.096	0.154***	0.151**	0.140*
	(0.041)	(0.048)	(0.088)	(0.037)	(0.048)	(0.076)
Education level of household head	0.106***	0.066	0.047	0.066**	0.012	0.026
	(0.026)	(0.041)	(0.047)	(0.031)	(0.046)	(0.026)
Living land area	0.119**	0.069	0.117	0.076	-0.007	0.066
	(0.052)	(0.068)	(0.075)	(0.064)	(0.090)	(0.102)
Income assets	0.183***	0.227***	0.194***	0.144***	0.165***	0.175***
	(0.029)	(0.035)	(0.043)	(0.029)	(0.03)	(0.055)
Constant	0.689**	0.795**	0.531	0.855**	1.089	0.775
	(0.295)	(0.394)	(0.500)	(0.355)	(0.494)	(0.555)
Cluster by household	Yes	Yes	Yes	No	No	No
Province, Commune, and District FE	No	No	No	Yes	Yes	Yes
Observations	222	143	84	221	142	84
R^2	0.302	0.276	0.297	0.4254	0.4315	0.3705

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The table shows OLS (columns 1 – 3) and Multiple-way Fixed-effect estimates (4 – 6). Clustered standard errors are shown in parentheses.

Source: Authors'