 ISSN: 2521-9766

DOI Link: https://doi.org/10.61586/FhDW7
Vol.59, Issue.11, Part.1, Nov 2025, PP.2-18

Institutional Drivers and Income Effects of Cooperative Membership: Insights from Chinese Family Farms

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Received Feb 2025 Accepted Oct 2025 Published Nov 2025

Abstract
This paper examines whether cooperative membership improves economic outcomes among Chinese family farms, using the nationally distributed microdata taken from Wu's research study. Shifting the lens from technology to institutions, we estimate the determinants of joining agricultural cooperatives and the income effects of membership. A logit model shows that training exposure, larger farm size, model-farm status, and participation in contract farming significantly increase the probability of joining, whereas never using the internet lowers it. To address selection on observables, propensity score matching (nearest-neighbor and optimal) yields average treatment effects on the treated of 32–37% for total income and 28–33% for per-capita income, with good post-match covariate balance. Interaction and split-sample analyses suggest income scales are strongly interlinked with land area, but the incremental premium from membership is imprecisely estimated for large farms in cross-section. The results support the idea that cooperatives help lower information and transaction costs, ease contract processes, and complement the knowledge-intensive channels described by Wu. Policy recommendations include improving cooperative governance, increasing digitally-supported extension services and targeted training, and professionalizing market intermediation to convert technological improvements into higher and more stable farm incomes.
Keywords: Agricultural cooperatives; Family farms; Farm income; Propensity score matching (PSM); Technology adoption; Transaction costs; Contract farming; Digital extension; China.

Introduction

Family farms in China are the foundation of agricultural output, crucial for food security and acting as centers for promoting modern technologies. Nonetheless, these farms encounter persistent structural issues related to market access, financing, and the efficient adoption of new practices. Agricultural cooperatives have become essential organizations to tackle these problems by decreasing transaction costs, improving access to inputs and credit, and enabling knowledge sharing and collective bargaining. By purchasing inputs in bulk, coordinating marketing efforts, and providing farmer training, cooperatives can increase productivity, stabilize incomes, and reduce risks linked to price fluctuations and liquidity shortages.

The anticipated benefits of joining a cooperative are well supported by theoretical insights. Economically, cooperatives reduce transaction costs and information gaps, helping members secure better profit margins and maintain more stable prices. Socially, membership fosters stronger horizontal and vertical connections among farmers, downstream businesses, and government institutions, which facilitates the sharing of agricultural knowledge and better resource distribution. Additionally, cooperatives act as tools for managing risks and providing financing by offering collective guarantees and facilitating contract farming, enabling members to expand cultivated area and invest in productivity-enhancing technologies.

An expanding body of empirical evidence supports the role of cooperatives. In Ethiopia, Abebaw and Haile (2013) find that participating in cooperatives increases adoption of improved technologies. In rural China, Ma and Abdulai (2016) report welfare and income improvements among apple growers involved in cooperatives, while Wu (2022) demonstrates sizable income gains from knowledge-intensive technologies, like better pest control and fertilizer practices. More recently, He and Chen (2024) show that cooperative enterprise boosts farm revenues and land productivity by improving access to capital, inputs, and modern technology. Evidence from other contexts supports these findings: panel and quasi-experimental studies suggest that membership lowers transaction costs and enhances market access (Kumar et al., 2018; Hanisch et al., 2013), that effective governance increases member benefits (Bijman & Iliopoulos, 2014; Liang et al., 2015), and that membership encourages the adoption of environmentally friendly ('green') technologies (Ma et al., 2023). However, some cautious evidence, like that from Hoken and Su (2018) on a rice cooperative in China, indicates that estimated income effects may lessen after carefully accounting for selection bias and initial conditions. Overall, this literature supports the idea that cooperatives can serve as institutions driving income growth, while highlighting the importance of designs that reliably separate cooperative impacts from other factors.

In addition to income-focused evidence, recent studies document broader behavioral and efficiency channels. Duan and Luo (2024, using logit, ordered probit, and propensity score matching on a large multi-province survey of grain family farms in China, show that cooperative participation significantly increases farmers' engagement in land-quality protection practices, underscoring sustainability externalities that extend beyond short-run income. Kinikli & Yercan (2025) combine Data Envelopment Analysis with Tobit regression in Türkiye's

ISSN: 2521-9766

dairy sector and find that, while non-members are more efficient on average and larger farms are generally more efficient, most fully efficient small farms are cooperative members, implying that cooperatives disproportionately help smallholders close efficiency gaps. Complementing this, Gaillard & Derville (2021), in six Indian villages, report that cooperative membership is associated with higher incomes particularly among land-constrained farmers, reinforcing the view that well-governed cooperatives can be both inclusive and pro-poor.

Despite progress, two key gaps still exist. First, most research centers on smallholders, leaving less known about family farms operating at larger scale with distinct organizational and market constraints; and second, many studies evaluate technology adoption in isolation, without examining the border institutional influence of cooperatives on income. These gaps lead to two research questions: (RQ1) What factors influence cooperative membership among Chinese family farms, and (RQ2) Does membership improve total and per-capita household income after controlling for observable selection?. We hypothesize that cooperative membership is positively associated with household income, conditional on observables, and that capability/connectivity proxies (training, internet use, contracting, model-farm status) increase the probability of joining.

This study addresses these questions using cross-sectional microdata from 847 family farms in Wu (2022), shifting focus from technology to institutional organization. We first estimate a logit membership model to identify individual, farm-level, and institutional predictors of participation. We then assess the income association with OLS under rich controls and use propensity score matching (PSM) to mitigate bias from observable differences. By comparing our results with Wu's (2022) technology-related effects, we evaluate whether cooperatives primarily facilitate adoption, generate independent market-organization rents, or both. This analysis aims to inform scalable, institution-based policies for modernizing Chinese agriculture.

Materials and Methods

This study employs a quantitative approach to examine the determinants of cooperative membership among family farms in China and to estimate its economic impact on household income. The analysis is based on secondary micro-level data originally collected and used in Wu (2022), who investigated the adoption and income effects of new agricultural technologies. The dataset consists of cross-sectional information on 847 family farms across several provinces in China, covering the years 2017–2019. It includes detailed socio-demographic, institutional, and economic characteristics, as well as farm-level indicators such as total income, per capita income, farm size, access to credit, and cooperative membership. By repurposing this dataset, the present study shifts the analytical focus from technology adoption to the role of cooperative membership in influencing economic outcomes. While Wu (2022) evaluated income effects of technology adoption via endogenous switching, our design shifts the lens to the institutional channel of cooperative membership, following an extensive literature on cooperatives and rural welfare (for example, Abebaw & Haile, 2013; Ma & Abdulai, 2016; He & Chen, 2024).

Model Specification

The empirical analysis is conducted in two stages. First, the determinants of cooperative membership are estimated using a binary logistic regression model:

$$P(Cooperative_i = 1) = \frac{exp^{Z_i\gamma}}{1+exp^{Z_i\gamma}} \quad (1)$$

Where *Cooperative*$_i$ equals one if household i is a member of a cooperative and zero otherwise, the vector includes individual characteristics (age, education, years of farming experience, training), farm characteristics (farm size, family labor, loans, internet use), and institutional factors (contract farming participation, model farm status, and access to government extension services). This specification allows identification of the most relevant socio-economic and institutional drivers of cooperative membership. Logistic regression is commonly used for participation decisions and offers well-understood diagnostics and effect summaries (Hosmer et al., 2013; Wooldridge, 2010).

Second, to assess the economic effect of cooperative membership on farm income, both Ordinary Least Squares (OLS) and Propensity Score Matching (PSM) are used to mitigate potential self-selection bias. The primary income equation is outlined as:

$$Y_i = \alpha + \beta Cooperative_i + \delta' X_i + \epsilon_i \quad (2)$$

Where Y_i represents either the log of total farm income or the log of per capita income ($Y_i \in$ {*ln(total income)*, *ln(per-capita income)*}), *Cooperative*$_i$ is the treatment. Inference uses heteroskedasticity-consistent covariance estimators with small-sample refinement HC3 (MacKinnon & White, 1985), and X_i is a vector of control variables identical to those in the first-stage model.

Propensity Score Matching (PSM)

Because membership is not randomly assigned, we complement OLS with PSM (Rosenbaum & Rubin, 1983; Stuart, 2010; Caliendo & Kopeinig, 2008). PSM comes from the logit model in equation (1). We implement nearest-neighbor (1:1) and optimal matching as nonparametric preprocessing for causal estimation (Ho et al, 2011). The Average Treatment Effect on the Treated (ATT) is calculated as:

$$ATT = E[\,Y(1) - Y(0) \mid Cooperative = 1\,] \quad (3)$$

Where *Y(1)* is the observed income of cooperative members and *Y(0)* is the counterfactual income of the same group had they not participated. Covariate balance is judged with standardized mean differences and visual diagnostics ("love plots"), targeting a Standardized Mean Difference $|SMD| \leq 0.1$ as a practical benchmark (Austin, 2009; Stuart, 2010). As a sensitivity check for hidden bias, Rosenbaum bounds can be applied to the matched estimates (Rosenbaum, 2002).
This two-step method, combining binary logistic regression with Propensity Score Matching (PSM), is widely recognized in cooperative impact evaluation literature. PSM is used to reduce self-selection bias caused by non-random cooperative participation, as first suggested by Rosenbaum and Rubin (1983).

Robustness and Diagnostic Tests
For the logit model in equation (1), we assess multicollinearity using variance inflation factors (VIF), while noting limitations of rigid VIF rules of thumb (O'Brien, 2007). In the OLS analysis, we test for heteroskedasticity with Breusch–Pagan tests and report HC3-robust standard errors regardless (Breusch & Pagan, 1979; MacKinnon & White, 1985). We examine residual behavior, including linearity and normality of errors, through standard plots and tests; the model specification adheres to cross-sectional econometric standards (Wooldridge, 2010).
To explore heterogeneity by scale, we interact membership with a large-farm indicator and estimate split-sample models, reflecting evidence that cooperative and adoption benefits may increase with operated area (Wu, 2022; Ma & Abdulai, 2016). Additionally, we run models with province and year fixed effects to control for location and time confounders.

Ethical Considerations
This study utilizes secondary data from Wu (2022). The original dataset anonymized all identifiers, and this analysis maintains the same ethical standards, ensuring confidentiality and proper acknowledgment of the data source (Table 1).

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Table 1: Variables Definition

	Variable	Description	Type	Expected Effect
Dependent Variables	Total Income	Total operating income of the household farm (ten-thousand-yuan, log-transformed for analysis).	Continuous	Higher for cooperative members
	Per Capita Income	Total income divided by household size (ten thousand Chinese yuan CNY per capita, log-transformed).	Continuous	Higher for cooperative members
Key Independent Variable	Cooperative Membership	1 if the household is a member of an agricultural cooperative, 0 otherwise.	Binary	Positive impact on income
Control Variables	Age	Age of the household head (years).	Continuous	Mixed effect: older people may resist membership, but experience can be positive
	Education	Education level of the household head (ordinal scale).	Ordinal	Higher education increases the likelihood of joining cooperatives
	Family Labors	Number of family members engaged in farming.	Continuous	A larger labor supply may facilitate membership and higher income
	Years of Farming	Farming experience of household head (years).	Continuous	More experienced farmers may be more likely to join
	Training Experience	1 if the household received agricultural training, 0 otherwise.	Binary	Expected to increase the probability of cooperative membership
	Farm Size	Total cultivated land area (mu).	Continuous	Larger farms are more likely to benefit from cooperative services
	Loans	1 if the household received agricultural loans, 0 otherwise.	Binary	Positive association with membership and income
	Model Family Farm	1 if officially recognized as a model farm, 0 otherwise.	Binary	Likely increases the probability of cooperative membership
	Contract Farming	1 if the household engaged in contract farming with enterprises, 0 otherwise.	Binary	Positively related to cooperative membership
	Internet Use	1 if the household uses the internet for agricultural information, 0 otherwise.	Binary	Enhances information access and membership likelihood
	Past Career	The previous occupation of the household head before farming.	Categorical	May influence the decision to join cooperatives
	Government Extensions	1 if the household received government extension services, 0 otherwise.	Binary	Expected to influence membership and income positively
	Province	Province of residence (categorical).	Categorical	Controls for regional heterogeneity
	Year	Survey year (2017–2019).	Categorical	Controls for time effects

Results

This section synthesizes the quantitative evidence on (i) who joins cooperatives and (ii) how cooperative membership relates to income among Chinese family farms, while situating the findings against Wu (2022), who documented sizable income gains from adopting new agricultural technologies. Throughout, log-income coefficients are interpreted as semi-elasticities; percentage effects are reported as $100[\exp^{\beta}-1]$.

1. Descriptive patterns

Table 2 summarizes statistics of cooperative membership. In the working sample (N = 842), 38% of farms are cooperative members. Unadjusted comparisons reveal substantial income gaps: members' average total income is 141.09 (10k CNY units) versus 75.25 for non-members (Welch p=0.0001), and per-capita income is 66.85 vs. 45.73 (Welch p=0.046). In proportional terms, these are roughly 88% (total) and 46% (per-capita) relative to non-members' means. These raw gaps motivate causal analysis that conditions on covariate imbalances.

Table 2. Summary statistics & Welch t-tests by cooperative membership

Statistic	All (N=842)	Non-member (n=522)	Member (n=320)	Diff (Mem–Non)	p-value
Total income (10k CNY)	100.0	75.25	141.09	65.84	0.000112
Per-capita income (10k CNY)	53.8	45.73	66.85	21.12	0.04627
Farm size (mu)	313.0	—	—	—	—
Cooperative share	0.380	—	—	—	—

Notes: Income measured in 10,000 CNY. Farm size is measured in Chinese acres, mu, which is roughly equivalent to 667 square meters; logs are used in regressions.

2. Determinants of cooperative membership

A binary logit of membership on household, farm, and institutional covariates indicates that training, farm size, model-farm status, and contract farming are positively associated with joining, while "internet = never" is negatively associated (Table 3). Average marginal effects (AMEs) are reported in percentage points (pp).

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Table 3. Logit for cooperative membership (N=842)

Variable	Logit β (SE)	p	Odds ratio (e^{β}) [95% CI]	AME (pp) [95% CI]
Training	0.858 (0.187)	<0.001	2.36 [1.63, 3.41]	17.5 [10.3, 24.6]
ln(Farm size)	0.318 (0.073)	<0.001	1.37 [1.19, 1.59]	6.5 [3.7, 9.3]
Model farm	0.492 (0.166)	0.003	1.64 [1.18, 2.26]	10.0 [3.6, 16.5]
Contract farming	0.437 (0.194)	0.024	1.55 [1.06, 2.26]	8.9 [1.3, 16.5]
Internet = never	−0.598 (0.225)	0.008	0.55 [0.35, 0.85]	−12.1 [−20.7, −3.4]
Internet = sometimes	−0.208 (0.179)	0.245	0.81 [0.57, 1.15]	−4.4 [−11.7, 3.0]
Age	0.011 (0.012)	0.349	1.01 [0.99, 1.03]	0.23 [−0.25, 0.70]
Education	−0.009 (0.085)	0.916	0.99 [0.84, 1.17]	−0.18 [−3.59, 3.22]
Year of farming	−0.001 (0.008)	0.859	1.00 [0.98, 1.01]	−0.03 [−0.34, 0.28]
Family labor	0.038 (0.080)	0.632	1.04 [0.89, 1.22]	0.78 [−2.41, 3.97]
Loans	0.085 (0.162)	0.601	1.09 [0.79, 1.50]	1.73 [−4.74, 8.19]
Gov. extension	−0.419 (0.317)	0.186	0.66 [0.35, 1.22]	−8.5 [−21.1, 4.1]
Constant	−3.103 (0.785)	<0.001	—	—

Notes: Baseline for internet is “often.” AMEs are average marginal effects on Pr(membership). Odds-ratio CIs use ±1.96·SE on β—report pseudo-R^2 and, if computed, AUC in the table notes. Model fit: AIC=1022.6.

3. Income effects with rich controls (OLS)

Controlling for human capital, production structure, and institutional covariates, cooperative membership is positively related to income. For total income, the coefficient on membership is β=0.145 (HC3 SE=0.080; p=0.071) implying an effect of 15.6% $[e^{0.145} - 1]$. For Per-capita income, β=0.138 (HC3 SE=0.081; p=0.087) implies 14.8% (Table 4).

The OLS premium (15%) is notably smaller than the raw gaps, as expected once we net out selection on observables and, importantly, potential mediating channels (size, contracting, model status) that may themselves be enhanced by cooperatives. Conditioning on such variables yields a conservative estimate of the membership premium, closer to a controlled direct effect than a total effect.

Wu’s endogenous switching regressions isolate gains from technology adoption per se, with more potent effects on non-adopters and larger farms. Our OLS shows that after accounting for farm size and market organization (contracts), the residual membership premium persists, which is consistent with cooperatives providing non-technological advantages (lower transaction costs, collective bargaining, market access) in addition to fostering adoption.

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Table 4. OLS on log income (HC3 robust SE, N=842)

Variable	ln(Total) β (SE)	p	ln(Per-capita) β (SE)	p
Cooperative member	0.145 (0.080)	0.071 *	0.138 (0.081)	0.087 *
ln(Farm size)	0.412 (0.036)	<0.001 ***	0.423 (0.036)	<0.001 ***
Contract farming	0.481 (0.094)	<0.001 ***	0.472 (0.094)	<0.001 ***
Model farm	0.357 (0.091)	<0.001 ***	0.342 (0.091)	<0.001 ***
Internet = *never*	−0.313 (0.103)	0.002 ***	−0.319 (0.103)	0.002 ***
Age (years)	−0.017 (0.006)	0.006 ***	−0.017 (0.006)	0.006 ***
Education	0.092 (0.040)	0.022 **	0.095 (0.040)	0.018 **
Family labor	0.077 (0.043)	0.076 *	−0.336 (0.045)	<0.001 ***
Years farming	0.004 (0.004)	0.307	0.003 (0.004)	0.431
Training	−0.052 (0.089)	0.559	−0.060 (0.090)	0.507
Loans	0.058 (0.081)	0.473	0.062 (0.081)	0.446
Internet = *sometimes*	−0.062 (0.086)	0.476	−0.054 (0.087)	0.535
Gov. extension	0.163 (0.172)	0.342	0.154 (0.171)	0.369
Constant	1.528 (0.410)	<0.001 ***	1.711 (0.408)	<0.001 ***

Note: *significant at 10%level, ** significant at 5% level, *** significant at 1% level.

4. Causal estimates via propensity score matching (PSM)

PSMs are estimated with the same covariates as in the membership logit. Nearest-neighbor (1:1, without replacement) and optimal matching achieve good post-match balance (standardized mean differences generally ≤0.15); matched sample sizes are 320 treated and 320 controls (Table 5).

Average Treatment Effects on the Treated (ATT) from outcome regressions on matched samples (HC3 SE) are shown in Table 4. Relative to OLS, the PSM magnitudes are larger, as expected if OLS controlled away some pathways through which membership raises income (for example, size expansion, contract facilitation). Within the usual ignorability assumption, these ATT figures provide credible causal benchmarks for the total income effect of membership.

Wu's main takeaway is that adoption raises income, especially for larger landholders and for specific technologies (pest control, fertilizer). Our PSM results show that joining the cooperative yields income gains on the same order of

ISSN: 2521-9766

magnitude as those adoption effects, suggesting cooperatives may be a policy-salient institutional lever that accelerates or complements the adoption process identified by Wu.

Table 5. ATT of cooperative membership on log income (PSM)

Matching method	Outcome	ATT β (SE, HC3)	p	ATT % =100(exp$^{\beta}$−1)
Nearest-neighbor (1:1)	ln(Total)	0.279 (0.102)	0.006 **	32.24%
Optimal	ln(Total)	0.313 (0.103)	0.002 **	36.81%
Nearest-neighbor (1:1)	ln(Per-capita)	0.244 (0.104)	0.020 *	27.60%
Optimal	ln(Per-capita)	0.284 (0.105)	0.007 **	32.83%

Note: *, **: significant at the 5 and 1% levels, respectively.

5. Heterogeneity by farm size

A large farm is defined as an indicator equal to 1 for holdings at or above the sample median land area (mu). In the interaction model for log total income, the coefficient on cooperative membership is $\beta_{coop} = 0.044$ (SE = 0.104, p = 0.675) and the interaction term is $\beta_{\mathrm{coop}\times\mathrm{large}} = 0.197$ (SE = 0.149, p = 0.188). The implied membership effect is therefore 4.5% for small farms ($100[exp^{0.044} - 1]$) and 27.2% for large farms ($100\left[exp^{(0.044+0.197)} - 1\right]$). Split sample OLS yields β coop = 0.117 β coop =0.117 (SE = 0.108, p = 0.281 p=0.281) among small farms and $\beta_{coop} = 0.156$ (SE = 0.115, p = 0.176) among large farms (Table 6). These estimates are optimistic but imprecise at conventional levels.

Table 6. Heterogeneity (interaction & split-sample on ln(Total))

Specification	Coef. on Coop	p	Large farm	p	Coop×Large	p
Interaction model	0.044 (0.104)	0.675	0.306 (0.134)	0.023 *	0.197 (0.149)	0.188
Split sample	Coef. on Coop	p				
Small farms	0.117 (0.108)	0.281				
Large farms	0.156 (0.115)	0.176				

* Significant at the 5% level.

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6. Robustness: province–year fixed effects

Adding province and year fixed effects leaves the membership coefficient near 0.14 (~15%) in both income equations. HC3 variances are numerically unstable in dense FE settings; using HC2 or province-clustered SE is advisable. The sign and magnitude of the membership effect are stable relative to baseline OLS and directionally consistent with PSM.

7. Mechanisms and policy relevance

Taken together with Wu (2022), the pattern of coefficients in our data points to three complementary channels through which cooperatives can raise incomes. First, information and learning: the strong gradients for training participation and the penalty for never using the internet in the membership model are consistent with cooperatives acting as information hubs that lower fixed costs of adopting knowledge-intensive practices (including pest control and fertilizer protocols emphasized by Wu). Second, market organization: the sizable associations of contract farming and model-farm status with both membership and income indicate reduced transaction costs and improved market access, channels that are orthogonal to technology per se yet complementary to it. Third, scale: the positive role of farm size in predicting both membership and income suggests that cooperatives help unlock scale-related efficiencies, a precondition under which Wu also documented larger adoption gains. While these mechanisms are not identified causally in this cross-section, their alignment with the coefficients provides a coherent narrative in which cooperatives both enable technology adoption and confer organizational advantages.

For policy calibration, the propensity-score estimates imply income gains on the order of 28–37% for members (ATT on log income). In contrast, OLS estimates that condition on size, contracting, and model-farm status yield a tighter lower bound of roughly 15%. Because the OLS specification likely partials out pathways through which membership operates (for example, expansion of cultivated area or facilitated contracting), we regard the PSM range as the more appropriate benchmark for total effects under the usual ignorability assumption, with OLS read as a conservative bound. Policies that strengthen cooperative governance, expand digital extension and training, and professionalize contract intermediation are therefore expected to produce joint gains by raising adoption margins highlighted in Wu (2022) and by improving organizational efficiency documented here.

8. Limitations and avenues for strengthening identification

The analysis is based on cross-sectional data; despite rich controls and matching, unobserved selection may remain. Two design features merit particular caution. First, several covariates (contract farming, model-farm status, and even farm size) may be downstream of cooperative participation; conditioning on them in OLS likely yields conservative estimates of the total effect. Second, PSM addresses selection on observables but is sensitive to hidden bias; formal sensitivity analyses

ISSN: 2521-9766

(for example, Rosenbaum bounds) and balance diagnostics should be reported alongside ATT estimates.

Future work can sharpen causal interpretation and unpack mechanisms along three directions: panel designs with farmer fixed effects around cooperative entry (or staggered rollouts), instrumented designs that exploit plausibly exogenous variation (such as historical cooperative density, timing of county-level extension or e-commerce programs, or distance-based instruments), and mediation frameworks that decompose the membership effect into technology-adoption and market-organization components. Additional priorities include heterogeneity by province and crop, distributional effects via quantile regressions, and intensity-of-participation (dose) models to capture returns to deeper engagement within cooperatives.

Discussion

We examined the factors influencing cooperative membership and its relationship with family-farm income in China using the same microdata environment as Wu (2022), but with a focus on institutional mechanisms rather than technology alone. Three patterns stand out:

First, selection into cooperatives is strongly related to capability and connectivity: training exposure, larger operating area, contract farming, and model-farm status are positively associated with membership, whereas never using the internet is negatively associated. These covariates align with channels commonly attributed to cooperatives, reduced search and bargaining costs, improved input quality and marketing opportunities, and denser information flows, and mirror the knowledge-intensive pathways emphasized by Wu (2022). Evidence that cooperatives facilitate adoption and learning in related contexts (for example, Ma, Zheng, & Nnaji, 2023) is consistent with this interpretation. Because the analysis is cross-sectional, we cannot isolate whether cooperatives attract better-resourced farms or help members acquire these attributes, but the associations are economically significant.

Second, after conditioning on extensive observables, cooperative membership remains positively related to income. OLS estimates imply gains of roughly 15% for both total and per-capita income (borderline statistical significance with robust HC3 SEs). In comparison, PSM on the same covariates yields average treatment effects on the treated in the 28–37% range for total income and 28–33% for per-capita income, with conventional significance. Under selection-on-observables and satisfactory post-match balance (Austin, 2009; Stuart, 2010; Ho *et al*., 2011), these ATT magnitudes provide credible benchmarks for the total effect among matched members. The larger PSM estimates relative to OLS are consistent with OLS conditioning away pathways plausibly affected by membership (for example, area expansion, contract intermediation), which moves OLS toward a conservative controlled-direct effect. The overall magnitudes cohere with Chinese evidence showing income improvements from cooperative participation and development (Ma & Abdulai, 2016; He & Chen, 2024) and with findings from Brazil that gains

ISSN: 2521-9766

operate through expanding production value and market access (Neves et al., 2021). At the same time, cases of limited or null effects exist (Hoken & Su, 2018), underscoring contextual dependence.

Third, heterogeneity by scale is suggestive but not definitive. Interaction terms between membership and large-farm status are positive yet imprecise, and split-sample estimates are larger for the large-farm subsample but not statistically distinct. This pattern is consistent with Wu's (2022) finding that adoption returns scale with operated area, while also reflecting limited power and multicollinearity with size-related controls in a cross-section.

Several null findings sharpen the interpretation. After controlling for other factors, loans and government extension are not robustly related to membership or income; "sometimes" using the internet does not differ from "often" in income regressions; and training has no direct association with income conditional on other covariates. Together with the strong roles of contracts and model-farm status, these patterns suggest that bundled organizational services within cooperatives, rather than single programmatic inputs, may be critical for income gains, a view that resonates with governance-performance links in the cooperative literature (Bijman & Iliopoulos, 2014; 2023) and with ethnographic evidence on grassroots leadership (Wang, He, & Wilmsen, 2023). Hogeland (2006) also highlights key concepts about the evolution of celebrity economic culture between the Nourse and Sapiro models, highlighting the tension between economic and democratic members.

Robustness checks support the central conclusions while cautioning inference. Adding province and year fixed effects leaves the membership coefficient near 0.14 log points; however, HC3 variances are numerically unstable with dense FE due to high leverage. Alternative variance estimators (HC2 or province-clustered SEs) and sensitivity analyses to hidden bias (Rosenbaum bounds) are advisable when emphasizing FE or matching results.

Policy implications follow strengthening cooperative governance and managerial capacity (Bijman & Iliopoulos, 2014; 2023), scaling digital extension and data-driven advisory services that lower information frictions (Wu, 2022; Ma et al., 2023), and professionalizing contract intermediation to reduce transaction costs and stabilize marketing channels (Neves et al., 2021). Because selection tilts toward larger or better-connected farms, inclusion safeguards, targeted training, and digital access for smaller operations are warranted (Kumar et al., 2018; Wang et al., 2023).

Conclusion and Recommendations

The study analyzed the microdata setting presented by Wu (2022), but with an institutional lens. We find that cooperative membership is more prevalent among farms with training exposure, larger operating area, model-farm status, and contract farming, and less prevalent among those that never use the internet. After conditioning on extensive observables, membership is associated with an income premium of roughly 15% in OLS with HC3 standard errors, a conservative estimate given that some controls (such as farm size, contracts, model status) may be

ISSN: 2521-9766

partially endogenous to membership. Under the selection-on-observables assumption, propensity-score matching indicates larger total effects, about 28–37% for total income and 28–33% for per-capita income, consistent with cooperatives reducing information and transaction costs and helping monetize technology adoption through improved market organization. The interaction between membership and large-farm status is positive but imprecise, though income levels themselves scale with size, echoing the scale-sensitive gains emphasized by Wu. Taken together, these results imply that cooperatives act through three mutually reinforcing channels, information (training and digital connectivity), organization (contracts and market access), and scale (land operated), and that the observed premium reflects the joint operation of these channels rather than a single programmatic input.

Policy should prioritize strengthening cooperative governance and accountability, scaling digitally enabled extension and targeted training to lower information frictions, and professionalizing contract intermediation so that quality inputs and marketing advantages are reliably passed through to members. Complementary finance should be bundled with advisory and market services to relax liquidity constraints in ways that raise productivity, with inclusion safeguards to onboard and retain smaller farms. In implementation, priority actions include (i) minimum governance standards with periodic performance audits; (ii) interoperable digital advisory platforms linked to input suppliers and buyers; (iii) standardized contract templates with transparent pricing and quality clauses; and (iv) results-based subsidies tied to onboarding smallholders and documented income gains. Cost-effectiveness can be enhanced by targeting high-potential value chains and regions with existing aggregation points. Given the cross-sectional design, future work should deploy panel or quasi-experimental strategies and formal mediation analysis to quantify how much of the membership effect operates through technology adoption versus market access, thereby sharpening both mechanism and external validity. Robustness can be further strengthened by province-clustered or randomization-inference SEs, alternative matching estimators (for example, full matching), and placebo tests on pre-determined covariates. External validity should be probed by replicating the design in provinces with different market depth and digital coverage, and by collecting cooperative-level governance metrics to explain between-cooperative variation in impacts.

Relevance to Saudi Arabia is significant due to the country's agro-ecological and market conditions, which differ notably in terms of aridity, water constraints, and the prominence of date palm and greenhouse value chains. The mechanisms identified here (information, organization, and scale) are directly portable to Saudi agriculture. Member-oriented cooperatives that bundle digital extension, input procurement, and contract intermediation could lower search and bargaining costs for date growers, greenhouse vegetable producers, and small-ruminant farms; accelerate uptake of water-efficient fertigation and integrated pest management; and help farms meet quality/traceability standards for modern retail and export.

Shared assets (for example, grading/packing, cold chain, and group certification) would unlock scale economies and stabilize margins, aligning with Vision 2030 goals on food-system upgrading and resilience. A practical roadmap would begin with pilot cooperatives in dates and protected horticulture, embed rigorous evaluation (phased rollouts or matched DiD), and codify successful governance and digital-advisory templates for national scale-up.

Acknowledgment:
This work was supported by Ongoing Research Funding program (ORF-2025-932), King Saud University, Riyadh, Saudi Arabia.

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