Asian Journal of Agriculture and Rural Development
Volume 15, Issue 2 (2025): 166-173

Impact of agricultural extension training on economic performance of rice farms: An investigation in Vietnam's Mekong river delta

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Article History
Received: 6 March 2025
Revised: 21 April 2025
Accepted: 9 May 2025
Published: 13 June 2025

Keywords
Economic performance
Extension
Impact
Matching approach
Rice farm
Training.

ABSTRACT
Agricultural training has been seen as an effective method to improve farmers' knowledge of agricultural techniques and farming management skills, which may enhance farm performance. This study aimed to estimate the impact of training provided by public agricultural extension agencies on trainees' rice farming outcomes, such as productivity, gross margin, and profitability. The household survey was conducted in the Vietnamese Mekong River Delta's Hau Giang province. A sample size of 230 rice farmers, including 120 participants and 110 non-participants of the training, was interviewed to gather primary data with a structured questionnaire. The propensity score matching method was employed to estimate the impact of the training on the farm outcomes of trainees by controlling for biased selection. Results reveal that training in agriculture significantly increases farmers' rice productivity, gross margin, and profitability. This may conclude that participation in agricultural extension training may help farmers adopt more knowledge of technology and farm management skills, which leads them to use inputs, manage farms more efficiently, and have better marketing strategies. The policy implication of the study is that agricultural extension agencies should expand agricultural training programs to all farmers who have not engaged in any training course regarding agricultural production and management.

Contribution/Originality: This study employs propensity score matching for controlling selection bias and first estimates the impact of agricultural extension training on farms' economic performance in Vietnam. The findings reveal the significant effect of agricultural training on rice farmers' productivity, gross margin, and profitability. The policy implication of the study is that agricultural extension agencies should expand to deliver agricultural training to all farmers.

DOI: 10.55493/5005.v15i2.5403
ISSN(P): 2304-1455/ ISSN(E): 2224-4433

How to cite: Nhan, T. Q., & Nay, N. V. (2025). Impact of agricultural extension training on economic performance of rice farms: An investigation in Vietnam's Mekong river delta. *Asian Journal of Agriculture and Rural Development*, *15*(2), 166–173.

1. INTRODUCTION

Vietnam, a net rice importer before 1989, has recently become known as one of the globe's three largest rice exporters. This great achievement may be explained by the impactful results of the renovation policy since 1986 (Pingali & Xuan, 1992). Indeed, Vietnam's rice production increased more than threefold during three decades, from

1985 to 2015 (Song et al., 2020). The reform policy has shifted the country's economy from a centrally planned system to a market-oriented one.

From the shifting point, many important and strategic policies on agriculture and rural development have been promulgated by the central government of Vietnam. In this regard, the policy on agricultural extension was one of the most crucial policies to help improve agricultural production remarkably in Vietnam. In 1993, the government of Vietnam issued Decree No. 13/1993/ND-CP on agricultural extension, and under this Decree, the public extension system of Vietnam was officially formed in March 1993. Accordingly, Vietnam's public agricultural extension system is organized into five levels from the central to the grassroots levels, including central, provincial, district, commune, and village, and its main activities place emphasis on such following areas:

First, it builds demonstration models showcasing advanced farming techniques to transfer to farmers. The models often focus on applying new varieties, effective methods, and technology as well. Second, it provides training to farmers. Training is considered an effective method to diffuse or transfer new agricultural techniques or innovations to farmers since the models cannot demonstrate all new farming techniques in the pilot sites. Third, it holds science and technology forums and exhibitions that serve as platforms for farmers to directly exchange knowledge, experience, and practices with specialists, managers, and successful farmers who effectively apply new techniques. Besides technical transfer, it also disseminates new regulations and policies related to agriculture, farmers, and rural development, and provides market information to farmers.

In summary, the main responsibilities of extension workers are to transfer technical advances, provide information related to market and farming techniques, spread knowledge, and deliver training to farmers to improve their capacity and efficiency in agricultural production (Nguyen & Nguyen, 2016). Over the past three decades of formation and operation, Vietnam's public agricultural extension system has played a significant role in the development of the agricultural industry through its activities of providing training, advice, and transferring new and advanced technologies to farmers (Dang, Li, & Bruwer, 2012; Ministry of Agricultural and Rural Development, 2019).

However, few studies on agricultural extension areas in Vietnam have been found. A study by Truong (2022) assessed the farmers' satisfaction with the quality of agricultural extension services in the central region of Vietnam's province of Quang Binh. The author indicated that three crucial factors, including assurance, reliability, and sympathy, had a positive impact on the farmers' satisfaction with the quality of extension services. Trinh, Hoang, and Drysdale (2023) investigated extension workers' perception of using information and communication technology tools such as cellphones, computers, internet, TVs, radio, and newspapers for agricultural extension services in the South Coastal Central region of Vietnam.

As mentioned earlier, providing new technological knowledge to farmers is one of the main functions of extension agencies in Vietnam. Therefore, this study aims to provide empirical evidence on the impact of agricultural training on trained farmers' farm economic outcomes, such as yield, gross margin, and profitability. The study collected data from 120 trained and 110 non-trained rice farmers in the Mekong River Delta's Hau Giang province and used the propensity score matching method for data analysis. The results of this study fill a major gap in the literature on the impact of extension training on the economic outcomes of farmers in Vietnam.

There is currently no research available on the effects of agricultural training provided by public extension agencies on farm performance in Vietnam. This study aims to provide empirical evidence on the impact of agricultural training on trained farmers' outcomes, such as yield, gross margin, and profitability. Data was collected from 120 trained rice farmers and 110 non-trained farmers in Hau Giang province of the Mekong River Delta, and the propensity score matching method was used for data analysis. The results of this study address a significant gap in the literature regarding the impact of extension training on the economic outcomes of farmers in Vietnam.

2. LITERATURE REVIEW

Previous studies on the impact of agricultural training programs have primarily focused on two areas: the effect of training on trainees' technical knowledge and adoption of new technologies, and the impact of agricultural training on trainees' farm performance.

Training is seen as a potential way to improve farmers' knowledge of agricultural techniques and farming skills, as well as to encourage the adoption of new technologies. Agricultural extension training is often referred to as a form of formal and informal educational activities designed to help individual farmers or a group of farmers achieve specific goals (Gwivaha, 2015; Oduwole, Sennuga, Willberforce, & Ebhohon, 2022). Agricultural training has been recognized as an effective way to enhance farmers' awareness of agricultural technology (Asayehegn, Weldegebrial, & Kaske, 2012; Challa & Tilahun, 2014; Kinyangi, 2014). The training content is often designed to transfer knowledge or skills on agricultural topics that aim to benefit farmers (Oduwole et al., 2022; Stewart et al., 2015). Extension agents often deliver new agricultural technology and innovation, new farming techniques, market information, policies related to agriculture and rural development, which may have a positive impact on farmers' technological knowledge, such as using high-yielding varieties, proper application of herbicides and pesticides, and implementing new methods of irrigation (Rasanjali, Wimalachandra, Sivashankar, & Malkanthi, 2021). Training has been illustrated to be an important factor in influencing farmers' adoption of new and advanced agricultural technology (Seelan, Laguette, Casady, & Seielstad, 2003). Nakano, Tsusaka, Aida, and Pede (2018) stated that agricultural training can spread new knowledge on agricultural technologies to farmers, which enhances agricultural productivity and reduces the poverty situation in rural areas.

Agricultural training helps improve trainees' farm outcome performances. Agricultural training tremendously enhanced the production of agriculture, livestock, and poultry in the Northern region of Pakistan (Khurshid, Saboor, Khurshid, & Akhtar, 2013). Luther, Mariyono, Purnagunawan, Satriatna, and Siyaranamual (2018) used the difference in difference method to measure the impact of farmer field schools on the vegetable productivity of farmers in Bali and East Java of Indonesia. By using PSM method, Khode et al. (2020) proved that training had a positive impact on dairy farmers' milk productivity and annual net income in India. Wonde, Tsehay, and Lemma (2022) used PSM to reveal that participating in the training helped trainees increase yields of maize and wheat by 10.10% and 26.66%, respectively, and raised wheat farm income by 19.64% in Ethiopia. Using both PSM and inverse probability weighting methods, Schreinemachers, Wu, Uddin, Ahmad, and Hanson (2016) revealed that training may increase land productivity by 47%, profitability by 50%, and net income by 48% for smallholder farmers. Murshed - E - Jahan, Beveridge, and Brooks (2008) indicated that fish farmers who participated in training gained 23% higher productivity and 52% higher return. Kijima, Ito, and Otsuka (2012) reported that the training program increased the adoption of improved rice-farming practices and the profit of rice cultivation in Uganda, using PSM approach and weighted regression model. Similarly, Wordofa and Sassi (2017) demonstrated that participation in training programs significantly improved household farm income in eastern Ethiopia. Todo and Takahashi (2013) showed that participation in training programs enhanced farmers' real income due to the adoption of new agricultural practices.

3. MATERIALS AND METHODS

3.1. Model used for Impact Estimation

To accurately assess the impact of agricultural extension training on trainees' farm outcomes, it is important to compare the outcomes of trainees and non-trainees. However, simply comparing the mean value of outcomes between the two groups may not be a reliable method, as there may be other factors that contribute to the differences in outcomes besides the training itself. For example, the characteristics of the households and farms, such as age, education, experience, and farm size, may differ between the two groups and could potentially affect the outcomes (Caliendo & Kopeinig, 2008).

To address this limitation, we utilized the propensity score matching (PSM) approach developed by Rosenbaum and Rubin (1985) to assess the impact of agricultural extension training on farm outcomes. Specifically, we calculated the average treatment effect on the treared (ATT), which measures the difference in expected outcome for farmers who participated in the training compared to those who did not (Caliendo & Kopeinig, 2008). This can be expressed as follows.

$$ATT = E[Y_{1i} - Y_{0i}|P_i = 1] = E[Y_{1i}|P_i = 1] - E[Y_{0i}|P_i = 1] \quad (1)$$

Where Y_{1i} is the outcomes (such as productivity, gross margin and profitability) of the farmer who has participated in the training, while Y_{0i} is the outcomes of the same farmer when not participating in the training. P_i takes 1 if the farmer has joined the training, otherwise 0.

However, we are unable to accurately estimate the ATT in Equation 1 due to the missing value of $E[Y_{0i}|P_i = 1]$. Indeed, both outcomes created by the same farmer with and without the training cannot be observed simultaneously. Thus, we must replace $E[Y_{0i}|P_i = 1]$ with a proper substitute. As earlier discussed, using the average outcome of actual non-trainees as a substitute is not strongly recommended. In this investigation, farmers' decisions to participate in the training may be based on their characteristics rather than randomly assigned. This implies that variables influencing participation in the training may also affect the outcome of the subject, generating biased estimated results.

To address this issue, the PSM technique can be used to treat farmers who have participated in the training as a treated group, while farmers who did not receive the training but have similar characteristics or propensity scores as those in the treated group as a control group. This allows us to use the expected outcomes of the control group to replace $E[Y_{0i}|P_i = 1]$ in Equation 1. By doing so, we can estimate ATT through two steps.

First, we use the probit regression model to generate the propensity score, which is defined as the probability of each farmer's participation in agricultural extension training.

$$p(X_i) = Pr(P_i = 1|X_i) = \alpha + \rho_i X_i + \varepsilon \quad (2)$$

Where $p(X_i)$ is denoted as the probability of each farmer joining the training; X_i is a vector of covariates affecting farmers' decision to join the training; α is an intercept; ε is an error term.

Second, ATT is estimated by matching the treated group and the control group based on similar propensity scores. Thus, ATT can be re-written as follows:

$$ATT_{PSM} = E[E\{Y_{1i}|p(X_i)\} - E\{Y_{0i}|p(X_i)\}|P_i = 1] \quad (3)$$

Where ATT_{PSM} is referred to as the mean difference of outcomes between the treated group (trainees) and the control group (non-trainees) properly matched by the propensity score - $p(X_i)$.

In this study, the nearest neighbor matching method was employed to match trainees and non-trainees with similar propensity scores. This matching technique uses each farmer in the control group to match a treated farmer who has the most similar propensity score, which may help reduce bias.

3.2. Definitions of Variables used in Empirical Model

Due to using the PSM method for assessing the impact of agricultural training programs, three kinds of variables are in this study (Table 1).

First, the treatment variable, which is referred to as the dependent variable, displays whether farmers engage in the training.

Second, explanatory variables or covariates were used to construct propensity scores. Regarding covariates selected for probit model, covariates that affect both selection into farmers' participation in training and outcomes of the subject and are not influenced by the participation should be included in the probit model to estimate propensity scores (Austin, 2011; Caliendo & Kopeinig, 2008; Maertens & Swinnen, 2009; Smith & Todd, 2005). Based on earlier empirical evidences from Wonde et al. (2022); Khode et al. (2020); Wordofa and Sassi (2017); Schreinemachers et al. (2016) and Kijima et al. (2012) background of study area, nine covariates were used in the probit model.

Third, outcome variables or impact indicators, such as productivity, gross margin, and profitability, were used to examine the impact of training in agriculture. The productivity was measured in tons per hectare. Gross margin was the difference between total revenue and variable cost estimated in millions of Vietnamese Dong (VND) per hectare. Profitability was defined as the ratio of gross margin and variable cost.

Table 1. Definitions of selected variables used in the empirical model.

Items	Description
Treatment variable	
Participation in training	1 if the farmer participates in agricultural extension training
Covariate	
Age of head	Age of household head in years
Education of head	Schooling of household head in years
Farming experience	Year of rice-farming experience
Family labor	Number of family labor for rice cultivation (Person)
Rice land area	Farm land area for rice cultivation (ha)
Internet use	1 if the household uses the internet, and 0 otherwise
Cooperative membership	1 if the household is a member of cooperative, and 0 otherwise
Farms visited by extension worker	1 if the household has been visited by extension worker, and 0 otherwise
Distance to commune people's committee	The distance from household to commune people's committee (km), this measure the accessibility to extension agency
Outcome variable	
Yield	Yield of rice (Ton/ha)
Gross margin	Difference between total revenue and variable cost (Million VND/ha)
Profitability	Ratio of gross margin and variable cost

3.3. Study Site and Data Collection

The primary data used for this study were collected through a household survey conducted in March 2023 in four communes of Hau Giang province's Long My district. Hau Giang is located in the south-western region of Vietnam and is considered the central province of the Mekong River Delta. The majority of farmers in the province rely on rice farming for their income. The Mekong River Delta, also known as the "rice bowl" of Vietnam, contributes around 55% of the country's paddy production and 95% of its total rice exports annually (GSO, 2021). Hau Giang province was chosen as the location for this study due to its comprehensive agricultural extension system. It officially has four levels of administrative structure, including a provincial extension center, district extension stations, commune extension staff, and village extension collaborators. In comparison, other provinces typically only have extension agents at the commune level who also work as extension collaborators.

A random sampling method was employed to select respondents who are both participants and non-participants in agricultural extension trainings. The participants were chosen from lists provided by the district station of agricultural extension, while the non-participants were selected from lists provided by village leaders. It was important for both groups of respondents to cultivate their rice in the same villages to ensure the similarity of natural conditions, infrastructure, and social context. A total of 230 rice farmers were interviewed, with 120 respondents having participated in agricultural extension training at least once in the past two years and the remaining 110 having never engaged in the training. Each chosen commune had around 58 rice farmers, with 30 participants and 28 non-participants in the trainings.

A structured questionnaire was designed to collect primary data from rice farmers, focusing on household demographics, farm characteristics, social networks, production costs, rice sales, and rice yield. The questionnaire was tested for relevance with the field situation before being officially administered to rice farmers.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Characteristics of Trained and Non-Trained Farmers

The results showed significant differences in socio-economic characteristics between trained and non-trained farmers (Table 2). Regarding human capital, the trained farmers were generally older and tended to have a higher level of education compared to the non-trained farmers. However, the difference in years of schooling was not statistically significant. Both groups had similar levels of experience in rice farming and the number of family labor members.

In terms of farm size, the rice land area of trainees was significantly larger than that of non-trainees. The survey results also showed that a higher percentage of households in the trainee group used the internet compared to the non-trainee group. Additionally, it was found that farmers in the trainee group were more likely to participate in agricultural cooperatives than those in the non-trainee group. The study also revealed that trained farmers lived closer to the commune people's committee compared to non-trained farmers. This suggests that trained farmers, who have a more favorable location, may receive more visits from extension workers than non-trained farmers.

In summary, there were significant differences in farm and household characteristics between the trainee and non-trainee groups, which suggests that the distribution of the sample across the two groups was not random. This could potentially lead to various outcomes among trained and non-trained farmers

Table 2. Characteristics between trainees and non-trainees (t-test results).

Variable	Trainees	Non-trainees	p-value
Age of head (Year)	53.52	51.14	0.076
Education of head (Year of schooling)	7.94	7.3	0.123
Farming experience (Year)	27.92	26.24	0.257
Family labor (Number)	2.45	2.63	0.239
Rice land area (ha)	1.89	1.54	0.061
Internet use (Dummy)	0.68	0.55	0.044
Cooperative membership (Dummy)	0.66	0.26	0.000
Farms visited by extension worker (Dummy)	0.95	0.51	0.000
Distance to commune people's committee (km)	1.65	2.47	0.000

4.2. Probit Model Results

. The primary objective of utilizing the probit model was to generate propensity scores, which were then used to match trainees and non-trainees with similar scores. This allowed for the creation of treated and control groups.

The results of the probit model showed factors influencing the farmers' decision to participate in the training course. Specifically, five covariates were found to have a significant association with farmers' decisions to join the agricultural training courses (p-values < 0.05). These covariates included the age of the household head, internet usage, cooperative membership, visits from extension workers, and distance from the farm to the commune people's committee (Table 3). These results were supported by several previous studies. Wordofa and Sassi (2017); Schreinemachers et al. (2016), and Kijima et al. (2012) reported that the age of the household head, experience in rice cultivation, membership in local organizations, and distance to town had a significant association with participation in trainings. On the contrary, Kosim, Aji, and Hapsari (2021) stated that the age of farmers had no impact on engaging in the training. Todo and Takahashi (2013) indicated that years of schooling of the household head had a significant and positive impact on participation in training.

It was found that other factors, such as the education and farming experience of the household head, family labor, and rice land size, had no remarkable association with participating in the agricultural extension training

To sum up, the results revealed that some selection biases remained among farmers. This suggests that farmers' participation in the training courses was not randomly assigned and influenced by their farm and household characteristics, which may lead to biased results of assessing the training impact on farm performance if the biases are not eliminated.

Table 3. Probit results analysis for generating propensity scores.

Covariate	Coefficient	Std. err.	*z*-value
Age of head	0.0317**	0.0161	1.97
Education of head	0.0202	0.0328	0.62
Farming experience	-0.0184	0.0142	-1.29
Family labor	-0.0168	0.0879	-0.19
Rice land area	0.0208	0.0682	0.31
Internet use	0.4231**	0.2141	1.98
Cooperative membership	0.7107***	0.2095	3.39
Farms visited by extension worker	1.4032***	0.2871	4.89
Distance from farm to commune people's committee	-0.1504**	0.0608	-2.47
Constant	-2.6763***	0.7515	-3.56
LR Chi2 (9)	91.82		
Prob > Chi2	0.0000		
Pseudo R2	0.2884		
Log likelihood	-113.29		

Note: ** and *** display significance levels at 0.05 and 0.01, respectively.

4.3. Impact Results of Agricultural Extension Training

As previously discussed, propensity scores generated from the probit model were used to match trained farmers with non-trained ones who have similar propensity scores. Before interpreting the estimated results, it is crucial to assess the quality of the matching process to ensure its reliability. The first step involved examining the common support region, which includes only the households used in the matching process. Figure 1 illustrates the distribution of propensity scores and the common support area. The data presented in Figure 1 indicate a substantial overlap in the propensity scores between the treated and untreated groups. This suggests that the common support assumption was likely met, confirming the effectiveness of the matching process.

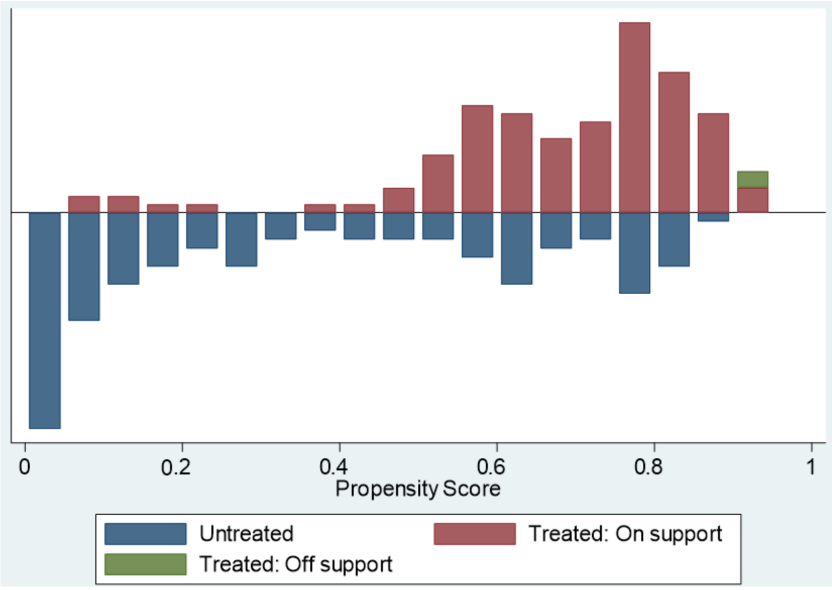

Figure 1. Propensity score distributions and common support area.

Secondly, it is important to check the reduction of mean standardized bias before and after matching. The results in Table 4 indicated that the mean standardized bias was reduced by approximately 5.8 and 5.6 after using the kernel and nearest neighbor matching methods. The pseudo R2 values were 0.012 and 0.013, and the test of the likelihood ratio for the joint regressors was not statistically significant. These findings suggest that although there was initially bias in the covariates between the trainee and non-trainee groups, this bias was effectively eliminated through the use of matching methods. Therefore, the ATT can be accurately calculated (Rosenbaum & Rubin, 1985).

Table 4. PSM quality indicators before and after matching.

Indicator	Before matching	After matching by kernel	After matching by neighbor
Pseudo R^2	0.2884	0.012	0.013
p > Chi^2	0.0000	0.926	0.898
Mean standardized bias	42.0	5.8	5.6

With regard to estimating the impact of agricultural extension training, results showed that participation in the training had a remarkable impact on increasing yield or productivity, gross margin, and profitability of rice farms. The mean difference value of rice productivity between the treatment and control groups was 138 and 147 kg/ha, matched by nearest neighbor and kernel methods, respectively (Table 5). This result was in line with the studies of Kosim et al. (2021); Mgendi, Mao, and Qiao (2021); Oduwole et al. (2022) and Cheruiyot (2022). Tambi (2019) reported that agricultural training might increase approximately 3% of crop production. Wonde et al. (2022) revealed that the training also helps farmers in Ethiopia increase yields of maize and wheat by 10% and 27%, respectively. Singh, Bharati, Chandra, and Dwivedi (2020) reported that after participating in scientific training, farmers in India increased 14.4%, 14%, and 13.5% of rice yield, wheat yield, and mustard yield, respectively. The explanation for higher productivity may be that farmers receiving the training have better knowledge of farming techniques and better management skills. Training had a positive and significant association with the application of modern technology (Tambi, 2019). Rasanjali et al. (2021) stated that farmers might remarkably gain technological knowledge through participating in agricultural extension training.

Evidence from Table 5 showed that trained farmers obtained 7.2% higher gross margin of rice production as compared to non-trained ones. This result is consistent with earlier studies of Todo and Takahashi (2013) and Kijima et al. (2012). Wordofa and Sassi (2017) revealed that annual farm income generated by trainees was significantly higher than that of non-trainees in Eastern Ethiopia. Schreinemachers et al. (2016) The trainings might increase the net household income of smallholder vegetable farmers in Bangladesh by about 48%. Davis et al. (2012) reported that farmer field school trainings help enhance the crop income of smallholder farmers in East Africa. Wonde et al. (2022) proved that wheat farmers who join agricultural training might increase approximately 20% of their income. Trainees often generate higher farm income since they obtain better technical knowledge, farming skills, and adoption of advanced practices (Khode et al., 2020).

As a consequence, trained farmers achieve significantly higher profitability as compared to non-trained ones (Table 5). In summary, the implication of these results may suggest that participation in agricultural extension training has a positive and significant impact on farm economic performances, such as productivity, gross margin, and profitability for rice growers in the Mekong Delta.

Table 5. The impact of cooperative channel use (PSM results).

Outcome	Algorithms	Treated	Control	ATT	*t*-value
Productivity	Unmatched	8.17	8.06	0.108*	1.71
	Neighbor	8.17	8.03	0.138**	2.01
	Kernel	8.17	8.02	0.147**	2.12
Gross margin	Unmatched	33.53	31.06	2.46***	3.41
	Neighbor	33.53	31.27	2.26**	2.03
	Kernel	33.49	31.24	2.25**	2.16
Profitability	Unmatched	1.75	1.57	0.18***	3.41
	Neighbor	1.75	1.62	0.14**	2.03
	Kernel	1.75	1.61	0.15**	2.00

Note: *, ** and *** display significance levels at 0.1, 0.05 and 0.01, respectively.

5. CONCLUSION

This study aimed to assess the effects of agricultural extension training on rice farmers' productivity, gross margin, and profitability in Hau Giang province located in Vietnam's Mekong River Delta. A case study involving 230 rice farmers was conducted, utilizing propensity score matching to address selection bias in the training program. The analysis indicated a selection bias between trainees and non-trainees, influenced by several factors such as the household head's age, internet usage, cooperative membership, visits from extension workers, and the farm's distance from the commune people's committee.

By applying the propensity score matching method, the study effectively eliminated selection bias, ensuring more accurate impact estimates. The findings demonstrated that agricultural training programs provided by extension agencies had a significant positive effect on rice farm performance, enhancing productivity, gross margin, and profitability. This improvement can be attributed to farmers acquiring advanced technical knowledge and better farm management skills, enabling them to adopt more effective farming techniques. Consequently, trained farmers were able to implement improved agricultural practices, leading to better overall farm outcomes.

The findings of this study suggest that agricultural extension agencies should broaden agricultural training programs to include all farmers who have not previously participated in any training courses related to agricultural production and management.

Funding: This study received no specific financial support.
Institutional Review Board Statement: The Ethical Committee of the Can Tho University Research Ethics Committee for Social Sciences and Humanities, Vietnam, has granted approval for this study on 12 September 2024 (Ref. No. CTU-RECSH24009).
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

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