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IMPACT OF OUTGROWER SCHEME ON YIELD, OUTPUT PRICE, AND INCOME: A RICE-FARM-LEVEL STUDY IN THE MEKONG DELTA, VIETNAM

Tran Quoc Nhan

College of Rural Development, Can Tho University
Can Tho 270000, Vietnam
tqnhan@ctu.edu.vn

Raulston Gillette

Faculty of Agriculture, Kagoshima University
Kagoshima 890-0065, Japan
raulstongillette61@gmail.com

Tomoyuki Yutaka

Faculty of Agriculture, Kagoshima University
Kagoshima 890-0065, Japan
yutaka@agri.kagoshima-u.ac.jp

Nguyen Duy Can

College of Rural Development, Can Tho University
Can Tho 270000, Vietnam
ndcan@ctu.edu.vn

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Abstract

In this study, we attempt to examine the effects of participation in a rice out grower scheme on several outcomes, such as rice income and output price, in Vietnam's Mekong Delta by using the propensity score matching approach and employing cross-sectional data gathered from 248 rice growers. The results reveal that participation in the outgrower scheme has a significantly positive impact on farmers' rice income and output selling price. A possible implication of the results of this study is that the outgrower scheme may help increase rice households' income in the Mekong Delta.

Keywords: impact, outgrower scheme, outcome, Mekong Delta, rice
JEL Classification Codes: L1, L2, Q1

I. *Introduction*

Rice production in the Mekong Delta plays an important role in the economic sector, including not only farming households but also the national economy, by generating around 50%–60% of farming households' income and supplying over 90% of Vietnam's rice export volume annually (GSO, 2017), while the Delta represents only 12% of the country's land area. The Delta annually produces approximately 56% of Vietnam's rice volume (GSO, 2016). Remarkably, the country, which was previously known as a net importer of rice prior to 1989, has recently become the world's third largest rice exporter, providing approximately 18% of the global market for rice. However, Vietnam's export price is fairly low compared with the export price for rice from several other countries (FAO, 2016), possibly because the rice exported from the country is not of high quality.

Although rice-farming households located in the Mekong Delta play a crucial role in the Vietnamese rice sector chain, the majority of the rice-farming households in this area remains poorly, with an income per capita per day of less than 2 USD (Coxhead et al., 2012). Two reasons may explain this situation. First, rice farms are often scattered and small scale; for example, rice land holdings per rice-based farming household are, on average, 1.4 ha (GSO, 2012). Second, the benefits of increased exports and prices are not likely to be distributed to rice households who actually operate rice-farming due to the presence of several intermediate actors involved in the rice sector chain (Ngoc & Anh, 2014). Loc and Son (2011) reported that around seven marketing actors are engaged in the rice value chain in the Mekong Delta, and nearly all paddies of various qualities produced in the Delta (93%) are collected from a multitude of individual households by numerous assemblers who resell the paddy collected to millers and rice export enterprises. This procurement process may result in the mixing of numerous rice varieties with different qualities and lead to difficulties in managing rice quality through the marketing process (Nhan & Yutaka, 2017).

To improve rice-farming household incomes and upgrade the rice sector chain, in 2013 the Vietnamese government officially promulgated a policy for linking small rice farmers to enterprises through contract schemes under Decision No.62/2013/QD-TTg, which was amended by Decree No.98/2018/ND-CP (2018). Here, the government of Vietnam aimed to establish a legal or regulatory framework that will encourage farmers and enterprises to use contract schemes in the production and distribution of agricultural commodities in general and of rice products in particular. Through contract farming or outgrower schemes, a firm can fully control the entire process of rice production and output delivery from farmers' rice fields, which may help improve the quality of rice. Indeed, the firm directly provides major farming input and technical supervision and collects farmers' paddy. More importantly, the policy on contract schemes can help restructure Vietnam's rice sector and transform it into a credible supplier of quality rice from a quantity-focused producer (Demont & Rutsaert, 2017).

In response to this policy, several contract schemes have been implemented by enterprises and farmers in the Mekong Delta. Over the last few years, the number of enterprises and rice farmers operating contract farming schemes has grown remarkably in this region. Paddy cultivation areas established through a contract scheme account for approximately 10% of the Delta's paddy planted area (GSO, 2017). Rice farmers who engage in contract schemes expect to obtain higher selling prices and crop incomes compared with independent farmers. Therefore, evaluating the influence of contract schemes in rice crops on participants' outcomes, such as yield, output price and return, is crucial to understand how the government policy on contract schemes interacts with farmers' crop outcomes in this region.

Concerns on contract farming schemes have steadily risen in Vietnam. A study by Oanh, Nga and Lebailly (2016) focused on the efficiency of tea production through contract farming. Wang et al. (2014) estimated the economic impact of contract schemes on safe vegetable marketing. Trifkovíc (2014) measured the welfare effects of vertical integration and contracts in the catfish sector on participants' welfare in Vietnam. Similarly, the number of studies on contract schemes in the rice sector in the Mekong Delta has increased. A study by Nhan and Yutaka (2018) examined factors affecting rice growers' participation in a contract scheme. Another study by Nhan and Yutaka (2017) evaluated the effects of contract arrangements on rice contract enforcement. A study by Dung and Nam (2015) used descriptive statistics to compare the production costs and gross margins of rice cultivation with and without a contract scheme. Vinh and Dinh (2014) assessed the performance of rice production-distribution under a contract scheme and proposed solutions to its development. To the best of our knowledge, however, none of these studies estimate the effects of a rice outgrower scheme on participants' outcomes, such as rice income and output price, in Vietnam, particularly in the Mekong Delta.

Herein, the present study aims to assess whether adoption of an outgrower scheme by rice farmers has great impacts on rice crop outcomes. Specifically, this study estimates the effects of outgrower scheme adoption on yield, output price, and return for rice cultivation by using a dataset gathered from participants and non-participants of a rice outgrower scheme in the Delta, and using the propensity score matching (PSM) approach. The current study fills an important gap in the literature by providing concrete evidence that furthers the understanding of how much of an impact outgrower schemes have on farmers' crop outcomes in the Delta. In the following section, we describe the outgrower scheme. In Section III, we present data and descriptive statistics. Section IV presents the methodological approach used for this study. We then present and discuss the main results before providing key conclusions and possible policy implications in Section VI.

II. *Description of the Outgrower Scheme*

1. Overview on Outgrower Schemes

Contract farming is often referred to as the production of an agricultural commodity conducted with a pre-plant agreement between a farmer and a buyer in which the farmer commits to producing a certain product in a certain manner and the buyer commits to purchasing this product (Minot & Sawyer, 2016). Under the contract terms, the buyer usually provides major farming inputs (e.g., seed, fertilizer, and pesticide), credit, and/or technical assistance to contract farmers (Eaton & Shepherd, 2001). Thus, contract farming is often seen as an intermediate institutional arrangement that may allow enterprises to participate in, and control, the process of production without owning or operating the farms (Key & Runsten, 1999). In reality, the specific terms and design of contracts may dramatically vary (Bellemare & Bloem, 2018). The literature reveals that the terms "contract farming" and "outgrower scheme" are often used interchangeably (Wendimu, Henningsen, & Gibbon, 2016), although a major difference between the two schemes is that the former usually refers to private-led schemes, while the latter refers to scheme arrangements involving public enterprises, parastatals, government agencies, or non-governmental organizations (Glover, 1990; Glover & Kusterer, 1990). In the present case, we focus solely on outgrower schemes led by a public firm in Vietnam's Mekong Delta.

Interestingly, assessments of the effects of contract farming on participants in developing countries have long been debated (Glover, 1990; Minot, 1986; Minot & Sawyer, 2016). Findings from numerous previous studies showed that contract farming exerts positive and significant effects on crop outcomes or household welfare (Bellemare, 2012; Birthal, Jha, Tiongco, & Narrod, 2008; Bolwig, Gibbon, & Jones, 2009; Cahyadi & Waibel, 2013; Hu, 2013; Jones & Gibbon, 2011; Maertens & Swinnen, 2009; Maertens & Velde, 2017; Miyata, Minot, & Hu, 2009; Naryananan, 2014; Wainaina, Okello, & Nzuma, 2014; Warning & Key, 2002). However, these studies mostly examined high-value products, including industrial and horticultural crops, and the poultry and dairy sectors while rarely studying staple foods, which may create a considerable gap in the impacts of contract schemes in staple crops on farmers' crop outcomes (Maertens & Velde, 2017).

The effects of contract farming on participants' outcomes are likely to differ across commodities even within a similar context and may be inconsistent across a variety of settings (Bellemare & Bloem, 2018). Several empirical studies discuss contract farming carried out in several cases with negative impacts on participants. Little and Watts (1994) showed conflicts between farmers and contract firms, the imbalance of power between the two contracting parties, intra-household tensions over labor division and allocation of new revenues, and increasing rural inequality. Singh (2002) concluded that contract schemes may cause an increase in social inequality in a community and create conflicts between contract participants and non-participants. Eaton and Shepherd (2001) demonstrated that contract farming schemes may create a negative impact on the incomes of participants due to the monopsonic and opportunistic behavior of the contract firm, poor quality control, and no transparency of pricing.

Otsuka, Takahashi and Nakano (2016) critically concluded in their review of the literature on the impact of contract farming in developed and developing countries that the practice strongly contributes to enhancing the production efficiency and income from contracted crop due to improvements in production and marketing methods.

2. Description of the Outgrower Scheme in the Surveyed Area

In this study, we focus on the rice outgrower scheme operated by LT firm. The contract scheme led by LT firm is often referred to as one of the most successful contract farming schemes in the Mekong Delta in terms of number of participants (Nhan & Yutaka, 2018). Thus, this rice outgrower scheme was specifically chosen to examine its impacts on participants' crop outcomes in the present work.

LT firm was founded in 1993 under the name AG Plant Protection Joint-stock Company. As an investor, the provincial government holds approximately 24% of the shares of this company. The company changed its name in 2015 and continues to be a publicly held establishment, but it has allowed several foreign investors to become major shareholders. At the beginning of its operation, the firm was a distributor and manufacturer of rice, corn seeds, and agrochemicals. Since 2010, however, LT firm has expanded into rice processing and trading by establishing five rice millers located in four Mekong provinces. The firm has established a network including 25,000 integrated rice farmers and provides major inputs and technical assistance to these farmers; it also purchases rice growers' output. Approximately 600 field staff directly monitor and supervise over those farmers during rice-farming. Thus, the firm manages the whole process of rice cultivation by farmers, which may help trace the origin of outputs, which is strongly required by both foreign importers and high-income domestic consumers. The firm ultimately trades in the export market, to which 80% of its output is allotted; only 20% of LT form's rice output is allocated to high-income class buyers in the domestic market. Consequently, LT firm has become one of the largest rice exporters in Vietnam.

When establishing a contract, LT firm first approaches the local authority, and expresses its intent to operate a contract scheme in the area. After indenting areas in which it can contract rice farmers, with assistance from the local authorities, the firm holds a meeting with rice farmers who reside in the identified contracting area and are able to participate in its contract scheme. At this point, the farmers may decide whether to participate in the outgrower scheme. Finally, the firm and participating individual farmers sign a written contract prior to planting rice; this contract specifies the variety, the paddy growing area, anticipated paddy output, and other quality specifications (e.g., purity, immature grains, and moisture content). The contract also describes the responsibilities and obligations of the contracting parties.

On the one hand, the firm directly provides contracted farmers with major inputs (e.g., seed, pesticides, and fertilizers), and deducts these original costs from paddy sales after harvest (without interest). It also offers technical instruction through field staff who regularly visit the farmers. Hence, the firm controls most of the process of paddy cultivation to ensure output quality. Thus, the firm often offers contract farmers with a paddy price at least 5% higher compared with regular market prices (it offers market price plus premium), and commits to buying the entire output of contract farms that meet its standards. The firm also provides free transportation of paddy crop from farms to its factory.

On the other hand, contract farmers must use the contract firm's seeds and pesticides but may not use its fertilizer (70% contract farmers do not use the fertilizer provided by the firm). Moreover, contract farmers must comply with the field staff's instructions throughout the growing season. If contract farmers sell their paddy to the firm, they will not pay any extra costs to it (e.g., technical guidance and interest incurred on the cost of inputs). However, if farmers do not sell their output to the firm, they must pay a fee for the technical instruction provided, as well as some interest incurred on the cost of inputs. This fee is considered as a form of punishment if farmers violate the contract.

III. *Methodological Approach*

1. Impact Estimation Model

Regression and matching methods are usually used to examine the outcome effects of treatment and adjust the selection bias that may be caused by the decisions and outputs of stakeholders (Jalan & Ravallion, 2003; Maertens & Swinnen, 2009). Using the average outcome of non-participants as an approximation is not recommended because participants and non-participants may differ systematically even in the absence of treatment and contribute to the socalled selection bias (Caliendo & Kopeinig, 2008). The potential selection bias owing to associations between observable covariates and household participation may be solved by either including those covariates in the regression model (Aakvik, 2001) or employing a matching technique.

$$Y_i=\varphi_i+\alpha C_i+\beta X_i+u_i \quad (1)$$

Where Y_i represents an outcome variable (e.g., rice income, output price), C_i is a dummy variable representing whether a household enters into the rice outgrower scheme, and X_i is a vector of farm and household characteristics. The effect of participation in the outgrower scheme on crop outcomes can be measured via the coefficient α of the variable for contract scheme participation when all other factors are held constant (Imbens, 2004; Madadala, 1983; Wooldridge, 2002). However, rice farmers are more likely to self-select into the rice outgrower scheme than not, and this estimated effect may, thus, be biased by the fact that some factors affecting participation in the outgrower scheme may simultaneously influence crop outcome variables. Therefore, if such factors are not included in the regression model, they may be correlated with the error term (u_i) leading to biased estimate of α. In this case, counterfactual factors would be observed, and causal effects may be inferred if participation is randomly assigned (Rao et al., 2016). Unfortunately, participation in the outgrower scheme in our sample does not appear to be randomized. To solve this problem, we used the PSM approach to estimate the impacts of participation in the outgrower scheme on participants' crop outcomes, such as yield, output price, and return, in our case.

Indeed, matching methods are usually applied to non-experimental data to facilitate comparison between treated and similarly observable non-treated subjects (Rao et al., 2016). The PSM technique is a matching method that has been widely used in previous studies estimating the impacts of treatment participation (e.g., contract farming, agricultural technology adoption) on crop outcomes or household welfare (Hu, 2013; Maertens & Swinnen, 2009; Maertens & Velde, 2017; Wainaina et al., 2014; Wendimu et al., 2016).

With regard to quantitative impact evaluation in our case or binary treatment, we assume that D_i denotes a binary treatment equal to 1 if a household i participates in the outgrower scheme and 0 otherwise. Note that D is the same dummy treatment C in equation (1). The potential outcomes are defined as Y_i (Di) for each household i, where $i=1, 2..., N$, and N is the total population. Thus, the individual treatment effect (ITE) for a household i can be measured as

$$\text{ITE}_i=Y_i\,(1)-Y_i\,(0) \quad (2)$$

However, ITE_i cannot be measured because only one of the two potential outcomes can be observed for each household i at the same time, as indicated by Caliendo and Kopeinig (2008). To address this problem, we use the PSM approach proposed by Rosenbaum and Rubin (1983) and estimate the average treatment effect on the treated (ATT) because it can be considered the main parameter. Therefore, ATT can be defined as the difference between the expected outcome variables (e.g., yield, output price, return) with and without participation in the rice-outgrower scheme for those who actually participated in the outgrower scheme (Caliendo and Kopeinig, 2008). Hence, ATT can be written as follows:

$$\text{ATT}=E[Y(1)-Y(0)|D=1]=E[Y(1)|D=1]-E[Y(0)|D=1] \quad (3)$$

Estimation of ATT in equation (3) is impossible since the counterfactual outcome - $E[Y(0)|D=1]$ - is not observed. Thus, we must choose a proper substitute for it to estimate the ATT. Yet simply using the mean outcome of non-participants - $E[Y(0)|D=0]$ - to replace with $E[Y(0)|D=1]$ in equation (3) would not be a proper choice, particularly in non-experimental studies (non-randomized assignments) because components which affect the participation decision may also affect the expected outcome variable (Caliendo & Kopeinig, 2008). Thus, simply comparing between the participants and non-participants will have the problem of selection bias as earlier mentioned. To overcome this problem a conditional independence assumption (CIA) was imposed and the propensity score theorem follows this approach.

The PSM technique reduces the risk of participation selection bias because it treats households that actually participate in the outgrower scheme as a treated group and other households that had not participated in the outgrower scheme but have similarly observed variables X with households in the treated group as a control group (Caliendo & Kopeinig, 2008). Therefore, we can replace the counterfactual outcome - $E[Y(0)|D=1]$ - in equation (3) with the expected outcome of the control group. Thus, ATT can be displayed as:

$$ATT=E_{X|D=1}[E\{Y(1)|D=1, X\}-E\{Y(0)|D=0, X\}] \quad (4)$$

Where X is a vector of observed attributes of households that may influence the decision making to engaging in the outgrower scheme and/or expected outcomes of those households. This is used as explanatory variables.

The empirical procedure of the PSM technique often proceeds via two steps (Kassie, Shiferaw, & Muricho, 2011). In the first step, we estimate propensity scores, $P(X)$ or the probability of each household's participation in the outgrower scheme. We then construct a control group by matching participants with non-participants with propensity scores. In the second step, we calculate the ATTs for outcome variables (e.g., yield, output price, return) by using matched households in the treated and control groups. In general, a PSM estimator for the ATT can be written as:

$$ATT_{(PSM)}=E_{P(X)|D=1}[E\{Y(1)|D=1, P(X)\}-E\{Y(0)|D=0, P(X)\}] \quad (5)$$

Remarkably, in using PSM to estimate ATTs two major assumptions are made. First, all covariates influencing the assignment of treatment and potential outcomes must be observed (Caliendo & Kopeinig, 2008), which is referred to as CIA. Second, an overlap condition or common support, which helps ensure that control subjects with the same observable variables are available for each treated subject (Nannicini, 2007), exists.

2. Selection of Variables to Generate Propensity Scores

Observable covariates influencing the selection of participation and outcome variable but not influenced by participation in the contract scheme should be chosen for the probit or logit regression model to estimate propensity scores (Austin, 2011; Caliendo & Kopeinig, 2008; Maertens & Swinnen, 2009; Smith & Todd, 2005). The major goal of the propensity score estimation process is to make good matches or balance covariates (Girma & Gardebroek, 2015; Kassie, Shiferaw, & Muricho, 2011).

Based on previous studies (e.g., Awotide, Fashogbon, & Awoyemi, 2015; Maertens &

Table 1. Definition of Independent Variables Used in Probit Model

Covariate	Description
Age of household head	Continuous variable (years)
Rice-farming experience of head	Continuous variable (years)
Education of household head	Continuous variable (years of schooling)
Family size	Continuous variable (persons)
Rice land area	Continuous variable (ha)
Boat owning	Dummy variable (1 if own, 0 otherwise)
Storage owning	Dummy variable (1 if own, 0 otherwise)
Tractor owning	Dummy variable (1 if own, 0 otherwise)
Membership in farmer's organization	Dummy variable (1 if participate, 0 otherwise)

Swinnen, 2009; Maertens & Velde, 2017) and evidence from our investigation, nine covariates were selected, and used in the probit model to estimate propensity scores in this study. These covariates were selected because they could influence both outgrower scheme participation and crop output variables. The descriptions of these covariates are presented in Table 1.

3. Use of Matching Techniques

Several matching techniques, such as kernel-based matching (KBM), nearest neighbor matching (NNM), stratified radius matching, and Mahalanobis matching (Caliendo & Kopeinig, 2008) have been developed. In this study, we used the KBM and NNM methods to match participants, and non-participants in terms of propensity scores because these matching techniques are the most common ones (Becerril & Abdulai, 2010). KBM uses the weighted averages of all individual households in the control group to construct counterfactual outcomes and, thus, yields low variance because it uses all of the information from the controls (Caliendo & Kopeinig, 2008). The weights can be referred to as inverse proportions of the distance between the propensity scores of treated and control groups (Becerril & Abdulai, 2010). Meanwhile, NNM uses individual households in the control group to match a treated individual household with the closest propensity score, thereby reducing bias. Consequently, the two matching methods are highly likely to be complementary.

The covariates used to generate the propensity scores were carefully considered before and after matching with three indicators, including the equality of means for treated and control groups, a standardized bias reduction, and the pseudeo-R^2 values of the probit model, to ensure the quality of the matching process. Accordingly, no significant differences should remain among covariates between the treated and untreated groups after matching on propensity scores (Caliendo & Kopeinig, 2008). Stuart and Rubin (2007) reported that the mean absolute standardized bias in matched samples should be less than 25% and recommended this value as an indicator that the matching process is satisfactory. Pseudo-R^2 values, which show how well the regressors explain the likelihood of contract participation from the propensity score estimation before and after matching, should be relatively low after matching because no systematic differences should exist in the distribution of covariates between groups (Maertens & Velde, 2017).

PSM can only control for the selection bias caused by observable covariates; thus, systematic differences between participants and non-participants may still remain after matching if a particular portion of the selection procedure relies on unobserved covariates (Smith &

Todd, 2005). The robustness of estimates obtained under the CIA holding was tested using a simulation-based sensitivity analysis proposed by Nannicini (2007) and applied in earlier empirical studies (Maertens & Swinnen, 2009; Maertens & Velde, 2017). This method assumes that the CIA holds given the observed covariate and unobserved binary covariate U. Hence, once U is not observed, the outcome of the controls cannot be used to estimate the counterfactual outcome of the treated group (Nannicini, 2007). In the present study, a dummy confounder was simulated to mimic possible unobserved factors influencing both outcome and selection, and the PSM estimates were compared with baseline results (no simulated confounder).

IV. *Data and Descriptive Statistics*

A household survey was conducted between August and September 2016 to gather primary data and measure the impact of the outgrower scheme on several outcome variables (e.g., yield, output price, return). The process of data collection included three stages. First, we identified the outgrower scheme conducted by LT firm located in Chau Thanh District, An Giang Province, Mekong Delta; the firm has operated an outgrower scheme in this area since 2012. Two villages, namely, Vinh Binh and Vinh Hanh, were purposely chosen to collect household-level data because these villages are considered the earliest operators of LT firm's outgrower scheme and, thus, include a larger number of participants compared with other areas. Next, a questionnaire was pretested on a sample population to adjust relevant questions prior to conducting household interviews. The questions mainly focused on demographic characteristics, land holdings, farm and household assets, and values of the latest rice crop (e.g., yield, volume of crop, labor, input cost, miscellaneous cost, selling price); these data will allow us to calculate production costs, revenues, and rice returns. We also gathered information on the scheme arrangements of outgrowers. Finally, after modifying the questionnaire, oral interviews were conducted with a total of 248 rice-farming households. All interviewees were randomly selected. In particular, 118 non-outgrower households were selected from lists provided by hamlet heads, and 130 outgrower households were selected from a list provided by LT. Both groups of households reside and conduct rice-farming in the same area, which helps ensure that the natural conditions, traffic infrastructure, and culture status are homogenous between groups.

Table 2 shows the results of Student's *t*-tests on the equality of mean values of a variety of socioeconomic characteristics relevant to participants and non-participants in the outgrower scheme. Heads of outgrower households tended to be slightly younger and have fewer years of rice-farming experience compared with heads of non-outgrower households. The education level of the heads of outgrower and non-outgrower households, as well as their family size, appeared similar. Overall, the human capital in both groups revealed little difference. In terms of natural capital, the average rice-land area per household of the sample population was 1.88 ha, and the area of rice land between participants and non-participants in the scheme was similar.

Our investigation also showed differences in some major physical assets between the two groups. In detail, the proportion of outgrower households owning a boat (with a small loading capacity in the range of 1-2 tons) was larger than that of non-outgrower households. This boat is usually used to transport farming inputs since farms are often inaccessible by truck. Similarly, the proportion of outgrowers owning a tractor was remarkably larger than that of

Table 2. Household and Farm Characteristics for Outgrowers and Non-outgrowers

Variable	Contract farmers	Non-contract farmers	All sample	p-value
Age of head (years)	44.72	47.90	46.42	0.065*
Rice-farming experience of head (years)	21.14	25.16	23.30	0.015**
Education of head (years of schooling)	5.83	6.45	6.16	0.269
Family size (persons)	4.77	4.53	4.65	0.312
Rice land area (ha)	1.92	1.85	1.88	0.889
Boat owning (dummy)	0.48	0.27	0.37	0.016**
Storage owning (dummy)	0.03	0.07	0.05	0.334
Tractor owning (dummy)	0.17	0.03	0.10	0.007***
Membership in farmer's organization (dummy)	0.24	0.13	0.18	0.125

Note: *, ** and ***denote significances at 0.1, 0.05 and 0.01 levels, respectively.
Source: Own calculation

Table 3. Outcome Values of Rice Production with and without the Outgrower Scheme

Outcome variable[1)]	Outgrowers	Non-outgrowers	Mean difference	p-value
Variable costs ('000 VND ha^{-1})	19,144	19,098	47	0.914
Yield (kg ha^{-1})	7,544	7,622	77	0.613
Selling price (VND kg^{-1})	5,649	5,118	531	0.000***
Return ('000 VND ha^{-1})	23,298	19,898	3,399	0.001***

Note: [1)] 1 USD is taken here as 22,500 VND at the time of the survey.
*** denotes significance at 0.01 level.
Source: Own calculation

non-outgrowers. The proportion of households owning a storage facility was similar between the two groups. These findings suggest that the physical capital of outgrower households is slightly better than that for non-participants. In terms of social capital, the proportion of outgrower households with a member participating in farmer-based organizations (e.g., agricultural cooperative, cooperative group, farmer club) was larger than that of non-outgrower households, but the difference observed between these groups was not significant.

Table 3 reports the outcome values, including yield, output price, and return, for both groups of rice households in the study area. We mainly used variable costs, such as those related to the acquisition of seeds, fertilizers, pesticides, hired and family labor, machinery, and fuel, to calculate the return for one hectare of rice cultivation. We also calculated the output price per kilogram, and yield by kilogram per hectare. We estimated the return or the gross margin of rice production per hectare, which is referred to as the difference between revenue and variable costs. The results in Table 3 show that outgrower households tend to obtain dramatically higher selling prices and gross margins as compared with non-outgrower ones. We also found that rice yields per hectare and variable costs are relatively similar between the two groups of farmers.

Table 4. Propensity Score Estimated for Contract Farmers Using Probit Model

Variable	Coefficient	Std. Err.	z	*p*-Value
Age of household head	-0.0044	0.0211	-0.21	0.834
Rice-farming experience	-0.0336	0.0218	-1.54	0.123
Education of head	-0.0844	0.0418	-2.02	0.037**
Family size	0.1262	0.0986	1.28	0.201
Rice land area	-0.0459	0.0569	-0.81	0.419
Boat owning	0.8062	0.2609	3.09	0.002***
Storage owning	-0.2827	0.5868	-0.48	0.630
Tractor owning	1.5103	0.5423	2.78	0.005***
Membership in farmer's organization	0.6645	0.3188	2.08	0.037**
Constant	0.4114	0.9229	0.45	0.656
Log likelihood	-70.2308			
LR chi2(9)	32.18			
Prob > chi2	0.0002			
Pseudo-R^2	0.1864			
Number of observation	248			

Note: ** and *** denote significance at 0.05 and 0.01 levels, respectively.
Source: Own calculation

V. *Results and Discussion*

1. Estimation of Propensity Scores

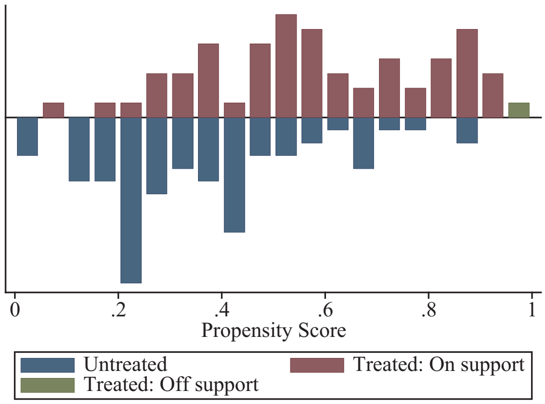
Table 4 presents the results of the binary probit model for estimating propensity scores or probability of participation in the outgrower scheme. Four factors were significantly associated with outgrower scheme participation. Specifically, education of the household head was negatively associated with adoption of the outgrower scheme, while tractor ownership, boat ownership, and membership in farmers' organizations were positively associated with participation in the scheme. The results of the probit regression model showed that other covariates, including age and farming experience of the household head, family size, rice land size, and storage ownership, are not highly associated with outgrower scheme participation.

Overall, the above results reveal that some self-selection influences the decision to become an outgrower. In other words, participation in the outgrower scheme is more likely biased toward household heads with less education, households with a boat and tractor, and households with a member participating in farmers' organizations than toward household heads with advanced age and experience, family size, rice land area, and storage holding.

2. Examination of Matching Quality

Prior to discussing the estimated effect of the outgrower scheme on outcome variables (e.g., output price, rice income), we carefully checked the quality of the matching procedure. The propensity scores generated from the probit model were used to match outgrower households with non-outgrower ones. Figure 1 displays the propensity score distributions and the areas of common support; the bias in the distribution of propensity scores between the

FIGURE 1. PROPENSITY SCORE DISTRIBUTION AND COMMON SUPPORT PROPENSITY SCORE ESTIMATION



Note: "Treated: On support" and "Treated: Off support" showing the observations in the treated group display consistent comparison and inconsistent comparison, respectively.
Source: Own calculation

treated and untreated groups is also illustrated in this figure. The results reveal a considerable overlap in the propensity scores of the treated and untreated groups, thus suggesting that the assumption of a common support, which can help avoid poor matches, is satisfactory.

Balancing properties, as a component of quality matching, were examined through the equality of mean values for variables between the treated and untreated groups before, and after matching. The results of balancing tests for the NNM and KBM methods shown in Table 5 suggest the presence of significant differences in the mean values of four covariates before matching between the treated and control groups; after matching, however, these differences are substantially eliminated (e.g., the smallest *p*-value is 0.285 after matching). This finding implies that the distribution of variables is similar between the treated and control groups after matching.

Balancing power was also measured by the reduction in the mean absolute standardized bias between matched and unmatched samples. Table 6 indicates that the standardized mean difference for all confounding covariates used in the propensity scores is reduced to 5% and 8% after matching for KBM and NNM, respectively. These results may lead to large reductions in total bias in the range of 75%–80%. Table 6 reports that the pseudo-R^2 values decrease from approximately 19% before matching to between 1.4% and 1.9% after matching for KBM and NNM, respectively. The likelihood-ratio tests of the joint regressors are insignificant or rejected after matching but consistently significant before matching. The implication of these results is bias exists in the covariates, but this bias can be eliminated using the prescribed matching methods.

In summary, the two methods used for PSM are relatively successful in terms of balancing covariate distributions between households participating and not participating in the outgrower scheme. Thus, they may be used to estimate ATT (Rosenbaum & Rubin, 1985).

Table 5. Covariates Balancing Test and Bias Reduction

Variable		Treated	Control	% bias	% bias reduction	p-value
Age of household head	Unmatched	44.72	47.90	-33.4		0.065*
	KB. Matched	45.07	45.57	-5.3	84.3	0.777
	NN. matched	44.72	44.52	2.1	93.7	0.908
Rice-farming experience	Unmatched	21.14	25.16	-44.4		0.015**
	KB. Matched	21.42	20.64	8.6	80.7	0.619
	NN. matched	21.14	20.85	3.2	92.7	0.847
Education of head	Unmatched	5.83	6.45	-20.0		0.269
	KB. Matched	5.79	5.65	4.6	77.0	0.802
	NN. matched	5.83	5.77	1.8	90.7	0.917
Family size	Unmatched	4.77	4.53	18.2		0.312
	KB. Matched	4.79	4.82	-2.2	87.9	0.917
	NN. matched	4.77	4.80	-9.2	49.4	0.652
Rice land area	Unmatched	2.92	2.85	2.5		0.889
	KB. Matched	2.91	2.70	8.3	-228.4	0.615
	NN. matched	2.92	2.86	2.5	2.2	0.881
Boat owning	Unmatched	0.48	0.27	43.5		0.008***
	KB. Matched	0.47	0.49	-3.9	92.0	0.847
	NN. matched	0.48	0.54	-12.2	74.9	0.540
Storage owning	Unmatched	0.03	0.07	-17.6		0.334
	KB. Matched	0.04	0.02	6.9	61.0	0.612
	NN. matched	0.03	0.02	7.6	57.1	0.563
Tractor owning	Unmatched	0.17	0.03	48.3		0.007***
	KB. Matched	0.16	0.10	20.4	57.7	0.339
	NN. matched	0.17	0.10	23.3	51.6	0.285
Membership in farmer's organization	Unmatched	0.24	0.13	27.4		0.125
	KB. Matched	0.25	0.26	-2.8	89.8	0.894
	NN. matched	0.24	0.20	11.8	57.1	0.553

Note: * , ** and *** denote significance at 0.1, 0.05 and 0.0l levels, respectively.
Source: Own calculation

Table 6. PSM Quality Indicators before and after Matching and Sensitivity Analysis

Matching methods	Pseudo R^2 before matching	Pseudo R^2 after matching	p>Chi2 before matching	p>Chi2 after matching	Mean standardized bias before matching	Mean standardized bias after matching	%|bias| reduction
KM	0.186	0.014	0.000	0.989	27.4	5.3	79.8
NNM	0.186	0.019	0.000	0.964	27.4	7.6	74.9

Source: Own calculation

3. Effect Estimation of the Rice Outgrower Scheme

The estimated effects of participation in the outgrower scheme on outcome variables using the NNM and KBM methods are displayed in Table 7. The results in Table 7 show that participation in the outgrower scheme has no impact on the rice yield of the sampled

Table 7. Estimated Effect of LT Outgrower Scheme on Rice Income and Output Price

Outcome[1)]	Matching methods	Mean of outcome variables		ATT	t-Value
		Participant	Non-participant		
Yield (kg ha^{-1})	KBM	7,542	7,510	32	0.15
	NNM	7,544	7,500	44	0.19
Output price (VND kg^{-1})	KBM	5,650	5,131	519	4.83***
	NNM	5,649	5,117	532	4.89***
Return (000' VND ha^{-1})	KBM	23,217	19,895	3,323	2.42**
	NNM	23,297	19,708	3,589	2.58**

Note: [1)]1 USD is taken here as 22,500 VND at the time of the survey.
** and *** denote significant at 0.05 and 0.01 levels, respectively.
Source: Own calculation

households. By contrast, earlier studies by Miyata, Minot and Hu (2009), Maertens and Velde (2017), and Mishra et al. (2018) indicated that contract farming remarkably increases crop yields for participants.

Findings also showed that farmers participating in the outgrower scheme experience positive and significant effects on return and output price. Participants in the outgrower scheme received selling prices that were approximately 519 and 532 VND higher per kilogram for KBM and NNM, respectively, which suggests that outgrower scheme participation may remarkably increase the output price by approximately 9%–10%. This finding is supported by earlier studies (Girma & Gardebroek, 2015; Maertens & Velde, 2017; Michelson et al., 2012). The higher selling price observed in the present case may be due to the commitment of the contract firm to offer a premium over the normal market price for participants' outputs that meet its requirements. Participants in the contract scheme revealed significantly increased returns per hectare of approximately 14% and 15% for KBM and NNM, respectively. This result suggests that the outgrower scheme can raise rice farmers' incomes by an equivalent of 148–159 USD per hectare. This higher return may be driven by tremendous increases in selling price, as discussed above. The present findings are consistent with earlier studies (Birthal et al., 2008; Bolwig et al., 2009; Hu, 2013; Jones & Gibbon, 2011; Wainaina et al., 2014; Mishra et al., 2018). Simmon et al. (2005) found that contract farming participants in maize seed and poultry production in Indonesia report profit increases of 71% and 160%, respectively.

4. Sensitivity Analysis

Table 8 shows the results of simulation-based sensitivity analysis using KM. Here, three types of confounders U were used. First, the neutral confounder U_n, e.g., the confounder with a probability of $p_{ij}=0.5$ with treatment $T=i$ ($=1$ or 0) and outcome $Y=j$ ($j=1$ or 0), may slightly perturb the baseline estimate (Ichino, Mealli, & Nannicini, 2008). Second, the "killer" confounder U_k with probabilities of $p_{11}=0.7$, $p_{10}=0.7$, $p_{01}=0.4$, $p_{00}=0.2$, which has high effects of selection and outcome, reflects that worst-case scenario possibly violating the CIA assumption (Nannicini, 2007). Finally, the "calibrated" confounder U_{fo}, which mimics membership in the farmers' organization variable, is a binary variable that may have exert remarkable effects on selection and outcome (Ichino et al., 2008; Nannicini, 2007).

In terms of rice income or return simulated ATTs, the results in Table 8 indicate that

TABLE 8. SIMULATION-BASED SENSITIVITY ANALYSIS FOR PSM ESTIMATES

		Return (000'VND ha^{-1})	Output price (VND kg^{-1})	Yield (kg ha^{-1})
No simulated confounder	Baseline ATT	3,441	521	30
Neutral confounder $U^{1)}{}_n$	ATT	3,554	527	33
	Outcome effect	1.229	1.186	1.181
	Selection effect	1.152	1.102	1.152
"Killer" confounder $U^{2)}{}_k$	ATT	3,129	498	38
	Outcome effect	4.806	5.189	5.816
	Selection effect	6.377	6.952	6.090
Confounder to mimic member of farmers' organizations U_{fo}	ATT	3,458	529	35
	Outcome effect	2.736	1.091	1.723
	Selection effect	2.570	2.425	2.720

Note: [1)]Un set with probabilities of Treatment (T) and Outcome (Y): p11(T=1; Y=1)=0.5; p10(T=1; Y=0)=0.5; p01(T=0; Y=1)=0.5; p00(T=0; Y=0)=0.5

[2)]Uk set with probabilities of Treatment (T) and Outcome (Y): p11(T=1; Y=1)=0.7; p10(T=1; Y=0)=0.7; p01 (T=0; Y=1)=0.4; p00(T=0; Y=0)=0.2

Outcome effect measures the effect of the binary confounder on the untreated outcome.

Selection effect measures the effect of the binary confounder on the probability of selection into treatment.

Source: Own calculation

differences between the baseline estimate and estimates with U_n, U_k, and U_{fo} are approximately 3%, 9%, and 0.5%, respectively. Similarly, in terms of output price simulated ATTs, deviations between the baseline estimate and estimates with U_n, U_k, and U_{fo} are approximately 1%, 4% and 2%, respectively. Table 8 also shows that differences between baseline estimate and estimates of rice yield for U_n, U_k, and U_{fo} are approximately 10%, 16% and 26%, respectively. These numbers imply that, although unobserved factors of the confounders U_n, U_k, and U_{fo} are present, these factors explain less than 10% and 5% of the baseline estimates for rice income and output price, respectively. In generally, when simulating the confounder U, the estimates remain close to the baseline estimates, even in the presence of U_k. These results suggest that the estimated effect of contractual participation on rice income and output price is more robust, while impact on rice yield is less robust. Thus, the CIA condition holds, and effects estimated by the PSM are plausible.

IV. *Conclusion*

The present study estimates the impact of an outgrower scheme on rice yield, income from rice crops, and output price in Vietnam' Mekong Delta using the PSM approach to correct for selection bias on observable variables. The findings demonstrate that the rice outgrower scheme has a positive and significant impact on rice income and output price for farmers in the Mekong Delta. These results suggest that the outgrower scheme tremendously increases rice incomes for farming households; rice incomes are driven greatly by high prices because outgrower schemes enables rice-farming households to produce better quality outputs, which, in turn, may result in better prices. Hence, expanding the outgrower scheme or contract farming in the rice sector may be an effective measure to achieve the Vietnamese government's target of improving rice quality and rice growers' income in the Delta.

A major policy implication of the findings is that contract farming is unlikely to be suitable for all rice growers and business firms because not all farmers opt to adopt the outgrower scheme and some firms cannot provide certain investments (e.g., seed, agrochemicals, technical assistance) to their contractual farmers owing to human and financial limitations.

This study presents a number of limitations, and further study is required. For example, the impact estimation by PSM relies solely on observable characteristics of households but does not control for unobservable attributes of households in the regression model. Hence, a further study should control unobserved variables in impact evaluation model with other econometric approaches such as switching regression and instrumental variable models. This study only focuses on the outgrower scheme led by one firm; thus, additional studies focusing on comparing the effects of different contract schemes, such as private-led contractual farming and public contractual farming, on the rice sector should be conducted. Incentives for farmers who participate in such schemes may also be implemented in future work.

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