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Is land consolidation policy a solution for rice production and agricultural transformation in Vietnam?

Manh Hung Do [1], Trung Thanh Nguyen [1,*], Ulrike Grote [1]

Abstract

Since the global food price crisis between 2007 and 2008, governments in developing countries such as Vietnam have paid more attention to food security issues. The government of Vietnam has issued policies to sustain rice land and imposed restrictions upon the transformation of rice land to ensure food security. Land consolidation is important to increase the economies of scale in farming, and understanding its determinants and effects is useful for policy-makers to support agricultural transformation. In this study, we investigate factors affecting the voluntary participation of rice growers in land consolidation and examine the impacts of this participation on crop production costs, poverty, and rural transformation. Our results show that land consolidation is driven by farming efficiency. It significantly decreases land preparation and harvest costs, increases farm income, and reduces poverty. We conclude that land consolidation should be promoted to facilitate the redistribution of farm land from farmers who want to leave agriculture to those who continue to work in agriculture. The redistribution of farmland promotes agricultural transformation by reallocating labor from farm to non-farm sectors.

Keywords: Rural transformation, land fragmentation, non-farm income, poverty reduction, simultaneous regression

JEL: D01, O12, Q12

RePEc:tvs:wpaper:wp-028

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1. Introduction

Agricultural transformation is an integral part of economic growth and characterized by the reallocation of labor from farm to non-farm sectors, and the redistribution of agricultural land from farmers who want to leave agriculture to those who continue to work in agriculture (Johnston and Mellor, 1961; Lewis, 1954; Nguyen et al., 2021). There are several factors of agricultural transformation such as farming ability, the availability and development of non-farm sectors that provide non-farm employment, and the operation of land markets for land exchange to facilitate land consolidation (Adamopoulos and Restuccia, 2014; Gollin et al., 2002; Hansen and Prescott, 2002; Hüttel et al., 2013; Üngör, 2013; Wang et al., 2016).

One of the constraints for farmers in some developing countries to increase their economies of scale is land fragmentation (Niroula and Thapa, 2005). It increases farm labor and crop production costs (Ho et al., 2017; Van Hung et al., 2007). Consequently, it reduces crop and farm incomes (Tran and Van Vu, 2019). In some densely populated countries in Asia where average farm size is smaller than one hectare (ha) with several small land parcels (Eastwood et al., 2010), land consolidation is even more critical because, without it, farmers cannot apply advanced production technologies for improved productivity, such as agricultural mechanization (Diao et al., 2016). In this regard, understanding the determinants and impacts of land consolidation is important to support farmers to increase their income and to facilitate rural transformation.

Vietnam is an appropriate case to examine this issue. Due to the egalitarian distribution of farmland from a collective system to rural households during the renovation (*Doi Moi*) process in the 1980s, farmland is highly fragmented. The average number of farmland plots per household in rural Vietnam is 3.9 and the average plot size is 0.19 ha (Ayala-Cantu et al., 2017). To address the issue of land fragmentation, the

Congress of Vietnam formally introduced the amended Land Law in 2013, and the government issued Decree No. 43/2014/ND-CP dated 15/05/2014 to facilitate land consolidation by legalizing it and simplifying the administration and registration procedure (Article 78). This 2014 land consolidation policy aimed to improve economies of scale in agricultural production. It was expected that the policy would enhance agricultural transformation as it could enable rural households to decide whether to stick to farming or to move out of agriculture to non-farm activities for example. However, there is no available assessment of this land consolidation policy, the impact, therefore, is unknown.

So far, there are few studies on land consolidation in developing countries (see, for example, Niroula and Thapa, 2005; Wang et al., 2021) and particularly in Vietnam (Nguyen and Warr, 2020; Tu et al., 2021). Hence, this paper aims at (i) identifying the factors that determine the participation of farm households in a land consolidation program, and (ii) investigating the impacts of land consolidation on crop production costs, poverty and rural transformation. Our findings are expected to provide solid evidence in support of land consolidation and agricultural transformation policies in Vietnam in particular and in developing countries in general.

We focus on rice farm households as rice is the main food crop in Vietnam and the main staple food for the Vietnamese people. Since the global food price crisis in 2007 and 2008, governments in many developing countries have paid more attention to food self-sufficiency issues (Clapp, 2017). Although different policy instruments have been applied in rice-exporting and rice-importing countries during and after the crisis, they all aim to ensure food security in domestic markets (FAO, 2010). As a net rice exporter, Vietnam is no exception. In 2009, the Vietnamese government issued Resolution No. 63/NQ-CP on Ensuring National Food Security dated 23/12/2009 with the aim of conserving 3.8 million ha of rice land and restricting the conversion of rice land to other land uses (Hoang et al., 2021). In addition, the occurrence of extraordinary events such as the Covid-19 Pandemic has raised awareness of food self-sufficiency in developing countries (Udmale et al., 2020). In fact, despite the surplus of rice production for domestic consumption, the Vietnamese government is aiming to maintain the rice land area of 3.5 million ha through Resolution No. 34/NQ-CP of 25/03/2021 (amendment of Resolution No. 63/NQ-CP). Such policy instruments put rice farmers at a disadvantage as income from rice is lower than income from other crops (Hoang and Vu, 2021; Markussen et al., 2011).

The rest of the paper is structured as follows. Section 2 provides background information and reviews the literature. Section 3 introduces the data. Section 4 describes the methodology. Section 5 presents the results and discusses the key findings. Section 6 concludes.

2. Background information and literature review

Land fragmentation is defined as the spatial distribution of landholders' plots that are widely separated and intermingled with the plots of other farmers (King and Burton, 1982). Apparently the purpose of land consolidation is to defragment land. The most popular evidence against land fragmentation is higher production costs (Ali et al., 2019; Jabarin and Epplin, 1994; Kawasaki, 2010; Niroula and Thapa, 2005; Rahman and Rahman, 2009; Tran and Van Vu, 2019; Van Hung et al., 2007). This negative impact decreases farming efficiency. Also, increasing land fragmentation could be an important cause of land tenure insecurity, which could lead to land degradation (Sklenicka, 2016). Furthermore, it reduces farm mechanization (Deininger et al., 2017; Nguyen and Warr, 2020). However, land fragmentation also has some positive effects, including crop diversification to reduce the risk of pests/diseases and price volatility (Deininger et al., 2017; Kawasaki, 2010), and improving food security through crop diversification in rural areas (Ciaian et al., 2018). Faces with limited land resources, households diversify crop production as a coping strategy for vulnerable situations (Nguyen et al., 2017b).

In Vietnam, one of the main causes of land fragmentation was land redistribution during the government's decollectivization process in the late 1980s. During this decollectivization, each household was granted an amount of land according to the number of household members in different geographical locations to ensure equality of land area and soil quality between households (Van Hung et al., 2007). Later, land fragmentation also occurred through land inheritance, as parents divided their land into smaller plots for their children.

After the introduction of the National Food Security Strategy in 2009, farmers can officially convert their rice land to land for other crops by applying to local authorities at the district level for a land use purpose change if the changes do not violate the existing land use plan approved by both local and central authorities. The land use plan approved by the district and higher administrative levels is strictly administered and implemented by communal authorities. If the land use changes requested by farmers are not consistent with the approved land use plan, the request will rarely be approved. Therefore, the choice of crops for rice farmers is practically limited (Markussen et al., 2011).

The current literature has some research gaps that require further investigation. First, previous studies on land consolidation have not paid enough attention to the simultaneity of farming efficiency and land consolidation. On the one hand, farming efficiency is considered a key determinant of land consolidation (Deininger and Jin, 2008; Nguyen et al., 2021). On the other hand, empirical evidence shows that land consolidation increases farming efficiency (Nguyen and Warr, 2020). This simultaneity of land consolidation and farming efficiency has not been discussed in the literature. Therefore, our study employs a simultaneous equation modelling approach to address these concerns between land consolidation and farming efficiency.

Second, there is little evidence of the impact of land consolidation on rural transformation at the farm (micro) level. Empirically, land fragmentation directly affects crop income by increasing production costs and limiting the use of mechanization (Deininger et al., 2017). In other words, land fragmentation also has negative implications for technological change (Nguyen and Warr, 2020). Poor mechanization also leads to slower rural transformation (Diao et al., 2016). To illustrate the effects of land consolidation on agricultural transformation, we consider both farm and non-farm incomes and their shares in household income.

Third, one of the limitations of previous studies assessing the impact of land consolidation is that no counterfactual analysis was performed. In this regard, our study is the first attempt to apply a counterfactual assessment to examine the effects of land consolidation between participants (the treatment group) and non-participants (the control group) over time.

Finally, in the case of Vietnam, the question of whether land consolidation effectively lowers production costs and improves farm income of rice households to help them escape poverty has not been answered, as income from rice is often lower than that from other crops. It is noted that rice consumption is decreasing in Vietnam (Timmer, 2014), and non-farm employment is becoming more popular and playing a more important role in rural transformation (Nguyen at al., 2017b; Nguyen et al., 2019a; Tran and Van Vu, 2020). We enrich the current literature by assessing the impact of land consolidation on crop production costs and poverty reduction.

3. Data and descriptive statistics

3.1. Research sites and data

In this study, we focus on the central region of Vietnam. This region is one of the poorest regions that heavily depends on crop production (Nguyen and Tran, 2018), has a diverse population in terms of ethnic groups (Nguyen et al., 2019b), and suffers from land fragmentation problems more seriously than southern provinces (Ayala-Cantu et al., 2017). To address our research questions, we rely on the data from the *"Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam (www.tvsep.de)"* funded by the German Research Foundation (DFG – FOR 756/2). Thus far, the TVSEP database of Vietnam consists of seven household waves. In each wave, the panel includes about 2,200 rural households in three provinces in central Vietnam namely Ha Tinh, Thua Thien Hue, and Dak Lak (see Figure 1 for the study sites of the TVSEP project in Vietnam).

The rural household surveys of TVSEP followed a three-stage random sampling method from commune, village, and household levels. The enumerators who conducted these surveys were selected for their experience in conducting rural household surveys. They were intensively trained and practiced before the surveys. During the surveys, each enumerator conducted face-to-face interviews at respondents' homes. The average duration of each interview was about two and a half hours. The data collected were checked by the survey team leaders for contradictory and plausible information.

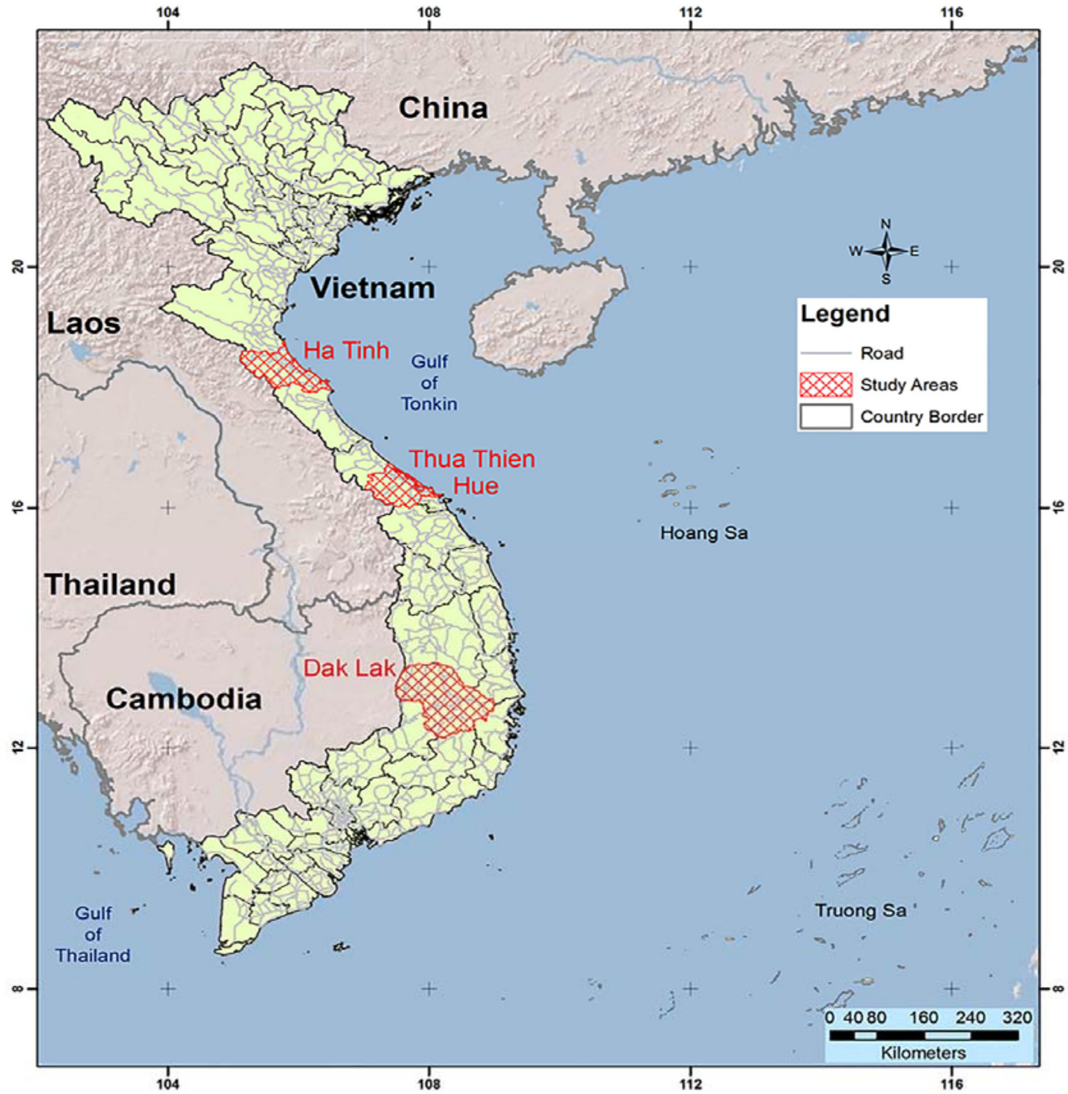

Figure 1: Our studied sites under the TVSEP project in Vietnam (Source: Nguyen et al., 2021)

In TVSEP data, crop information captured various aspects of production, such as production costs, productivity, and output values. Production costs include a wide range of categories such as land preparation, seedling, irrigation, weeding, fertilizers, pesticides, and harvesting costs. However, data on input intensity (e.g. amount of fertilizers or pesticides) is insufficient. We form a panel dataset of identical rice producers to establish a balanced panel of households that participated in the survey in all three most recent waves of 2010, 2013, and 2017. The successful interviews in the 2010, 2013, and 2017 waves of the TVSEP project in Vietnam were 2,099, 2,010, and 1,989, respectively.

The number of households with rice land was 1,379 in 2010, 1,282 in 2013, and 1,168 in 2017. We keep only those households (i) having rice land, (ii) participating in the three waves of the TVSEP survey, and (iii) not having missing data. Our final sample for analysis includes data from 995 rice households collected in these three waves, totaling some 2,985 observations. Compared to the number of households with rice land in 2017, our reduced sample accounts for 85% of households with rice land in the 2017 wave (995 out of 1,168 households).

3.2. Measurement of land fragmentation

We use an indicator of land fragmentation to determine whether a household has participated in land consolidation. There are several indicators to measure land fragmentation, such as the number of land plots, the distance to parcels, and the Simpson index (Kawasaki, 2010; Nguyen and Warr, 2020; Van Hung et al., 2007). Among these indicators, the Simpson index has been widely used because of its better ability to capture the extent of land fragmentation, both in terms of fragment size and distance (Deininger et al., 2017). We therefore use the Simpson index to represent land fragmentation. We also control for the distance between fragments by including the location of all plots. The Simpson index is calculated as follows:

$$Simpson\ index = 1 - \sum (a_i^2)/(A)^2 \qquad (1)$$

In equation (1), a_i is the area of the i-th farmland plot and A is the total area of all farmland plots ($A = \sum a_i$). The Simpson index ranges from zero indicating a complete land consolidation (households only have one farmland plot) to one representing a severe fragmentation (households have many small farmland plots).

To identify which households have consolidated their land, we construct a subsample of households that have a decreasing Simpson index over time or otherwise.

The decreasing Simpson index denotes that households decrease the number of land parcels or increase the land area of each parcel, or both. In other words, they consolidate land. In addition to including the location of all plots, constructing these subsamples helps reflect more accurately the land consolidation process than directly using the largest parcel, the number of plots, and Simpson index (Nguyen and Warr, 2020; Tu et al., 2021).

Table 1: Changes of land fragmentation and poverty indices in central Vietnam

	Whole sample (n = 2985)	2010 (n = 995)	2013 (n = 995)	2017 (n = 995)
A. Land fragmentation				
Average farmland area (ha)	1.024	0.887	1.083	1.103
	(1.776)	(1.038)	(1.576)	(2.425)
Land plots (number of plots)	4.958	3.944	5.594	5.337
	(2.473)	(1.561)	(2.724)	(2.632)
All plots in village (yes = 1)	0.752	0.708	0.596	0.953
	(0.431)	(0.455)	(0.491)	(0.212)
Simpson's index	0.622	0.533	0.681	0.651
	(0.193)	(0.190)	(0.168)	(0.186)
B. Poverty indices				
Absolute poverty head-count at daily per capita income of PPP$ 2.05	0.296	0.389	0.338	0.163
	(0.457)	(0.488)	(0.473)	(0.369)
Absolute poverty gap at daily per capita income of PPP$ 2.05	0.157	0.198	0.192	0.081
	(0.375)	(0.339)	(0.426)	(0.343)
Absolute poverty severity at daily per capita income of PPP$ 2.05	0.165	0.154	0.218	0.124
	(1.327)	(0.438)	(1.640)	(1.549)
Absolute poverty head-count at daily per capita income of PPP$ 3.20	0.467	0.611	0.506	0.283
	(0.499)	(0.488)	(0.500)	(0.451)
Absolute poverty gap at daily per capita income of PPP$ 3.20	0.239	0.307	0.278	0.132
	(0.359)	(0.346)	(0.391)	(0.312)
Absolute poverty severity at daily per capita income of PPP$ 3.20	0.186	0.214	0.230	0.114
	(0.703)	(0.362)	(0.851)	(0.788)

Note: Standard deviations in parentheses; PPP$: Purchasing Power Parity dollars adjusted to 2005 prices.

Panel A in Table 1 shows the general information of land fragmentation in central Vietnam from the TVSEP data. The farmland area per rice household increased between 2010 and 2017, while the number of plots fluctuated significantly. Before 2014, the number of plots per household had increased from about 3.9 plots in 2010 to 5.6 plots in 2013 but then decreased to 5.3 after 2014. Consequently, the average values of the Simpson index varied from 0.53 in 2010, to 0.68 in 2013, and 0.65 in 2017. There is a significant change of farmland indicators after the introduction of the land consolidation policy in 2014.

3.3. Measurement of poverty indices

To measure poverty, we use the method proposed by Foster et al. (1984) (or the FGT method) with different income thresholds as follows:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{H}\left[\frac{Z - Y_i}{Z}\right]^{\alpha} \quad (2)$$

In equation (2), P_α is a poverty index; α is a parameter which receives the values of 0, 1, and 2 that denote the poverty headcount ratio, the poverty gap, and the poverty severity, respectively; Z is the poverty threshold and Y_i is the daily income per capita of household i. We use two different poverty thresholds, the Vietnam's national poverty level at Purchasing Power Parity (PPP) $ 2.05 per capita a day, and the World Bank's poverty threshold for middle-income countries at PPP$ 3.20 per capita a day (World Bank, 2018).

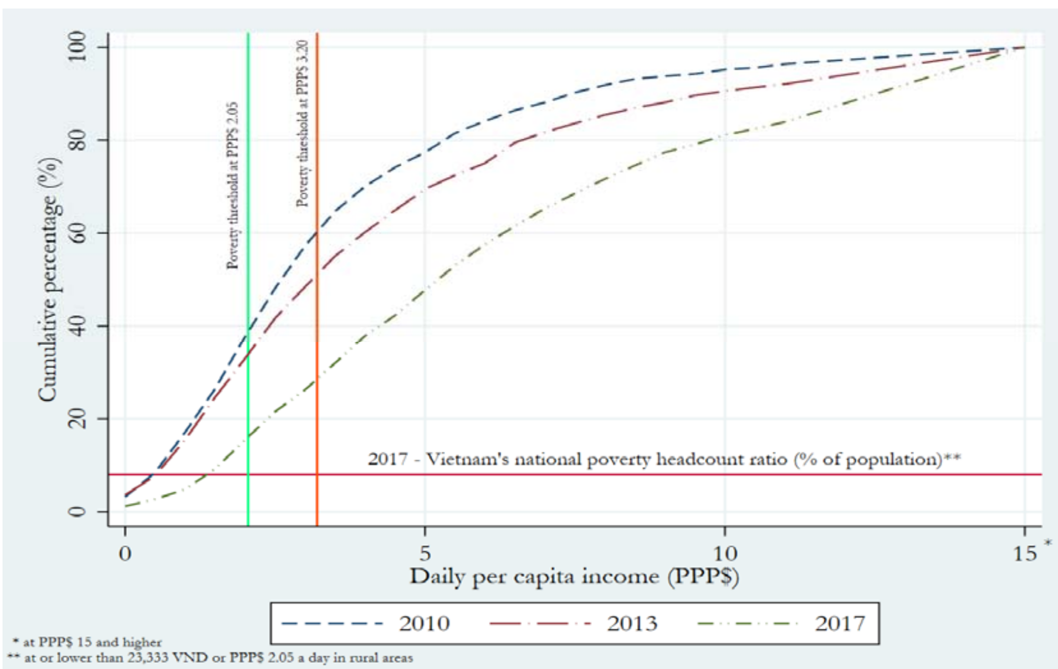

Figure 2: Daily per capita income of rice households in central Vietnam

Panel B in Table 1 presents the description of the poverty indicators at the poverty threshold of PPP$ 2.05 per capita a day and PPP$ 3.20 per capita a day. Overall, there is a decreasing trend of these poverty indicators in 2010, 2013, and 2017. Although the poverty indicators have shown a significant improvement in 2017, the number of rice households living under poverty is still relatively high. Figure 2 shows the income distribution of rice households and income development over time. According to the General Statistics Office of Vietnam (GSO) (2017), the poverty headcount ratio (based on Vietnam's national poverty line) was about 8% of the population. In comparison, our data shows that about 16% of all rice households live in poverty with a daily per capita income of PPP$ 2.05 and about 28% with a daily per capita income of PPP$ 3.20. In addition, the income inequality of rice households is decreasing over time.

3.4. Summary of rice production, household income and characteristics

Table 2 stacks the descriptive summary of rice production and household income between the treatment (households conducted land consolidation) and the control group (households did not conduct land consolidation) and between the pre- and post-intervention periods (see Appendix 1 for the name and measurement of variables). It appears that most rice production and income indicators have increased over time, except for irrigation costs, and farm laborers. Comparing the two household groups, those from the treatment group tend to have higher rice yields, more farm laborers, and a larger farmland area. Regarding production costs, the difference between the two groups is significant in terms of seedling, fertilizer, and pesticides costs, while land preparation, irrigation, and harvest costs are not significantly different. From the average number of farm laborers and average land area, it can be derived that farm households who conduct land consolidation are more likely to specialize in agricultural activities than those in the control group. These households have more members engaged in agricultural activities and a larger farmland area.

Table 2: Rice production and income

	Whole sample	By group		By period	
	(n = 2985)	Control (n = 1236)	Treated (n=1749)	Before (2010-2013) (n = 1990)	After (2017) (n = 995)
Rice production					
Rice yield (kg/ha)	3779.18	3554.46	3937.98^{***,a}	3492.31	4352.91^{***,a}
	(1625.37)	(1469.81)	(1709.56)	(1601.77)	(1517.45)
Land preparation cost (PPP$/ha)	185.56	185.60	185.53^{a}	169.39	217.88^{***,a}
	(159.01)	(149.58)	(165.39)	(165.44)	(139.87)
Seedling cost (PPP$/ha)	145.37	134.99	152.70^{***,a}	126.19	183.73^{***,a}
	(154.38)	(138.72)	(164.19)	(165.19)	(121.37)
Fertilizer cost (PPP$/ha)	469.27	453.89	480.13^{**,a}	457.61	492.58^{***,a}
	(291.30)	(260.85)	(310.63)	(315.71)	(233.37)
Pesticide cost (PPP$/ha)	109.53	105.22	112.59^{*,a}	98.07	132.47^{***,a}
	(103.11)	(90.47)	(111.10)	(100.86)	(103.78)
Irrigation cost (PPP$/ha)	31.74	30.77	32.42^{a}	32.8	29.60^{a}
	(73.47)	(64.73)	(79.07)	(80.86)	(55.81)
Harvest cost (PPP$/ha)	173.06	171.78	173.97^{a}	153.24	212.7^{***,a}
	(164.02)	(139.91)	(179.15)	(173.42)	(135.01)
Farm laborers (persons)	2.19	2.07	2.27^{***,a}	2.17	2.23^{a}
	(1.01)	(0.89)	(1.07)	(1.02)	(0.97)
Farmland area (ha)	1.02	0.78	1.20^{***,a}	0.99	1.10^{*,a}
	(1.78)	(1.01)	(2.14)	(1.34)	(2.42)
Income indicators					
Non-farm income per laborer	6.10	5.96	6.21^{a}	5.39	7.40^{***,a}
(PPP$ per day)	(8.08)	(7.49)	(8.51)	(7.66)	(8.67)
Share of non-farm income in	34.73	35.74	34.01^{a}	33.79	36.61^{**,a}
household income (%)	(32.81)	(32.60)	(32.94)	(32.53)	(33.29)
Farm income per laborer	3.00	2.89	3.07^{a}	2.75	3.49^{***,a}
(PPP$ per day)	(5.45)	(4.92)	(5.79)	(4.65)	(6.73)
Share of farm income in	40.32	38.21	41.81^{***,a}	42.80	35.35^{***,a}
household income (%)	(31.72)	(30.49)	(32.49)	(31.92)	(30.74)

Note: Standard deviations in parentheses; PPP$: Purchasing Power Parity dollars adjusted to 2005 prices; Statistic tests between groups and periods; ^{a}: Two-sample t-test; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

The income from non-farm and farm sources of the treatment group is relatively higher compared to the control group, but these differences are not statistically significant. In relative terms, the share of farm income in the treatment group is significantly higher than in the control group, while the share of non-farm income is not significantly different. Over time and measured in household income, there is a significant rural transformation towards higher non-farm incomes. Non-farm income per laborer increased from PPP$ 5.39 a day in the before period to PPP$ 7.40 a day in the after period. Their share of total household income also rose from about 34% to 37%. Income from farm sources also increased, but at a slower pace, and the share of farm income fell over the same period.

Table 3: Household and farm characteristics

	Whole sample	By group		By period	
	(n = 2985)	Control (n = 1236)	Treated (n=1749)	Before (2010-2013) (n = 1990)	After (2017) (n = 995)
Household's characteristics					
Male head†	0.85	0.87	0.83***, b	0.86	0.82***, b
	(0.36)	(0.34)	(0.38)	(0.35)	(0.39)
Age of head (years)	51.71	51.74	51.70 a	50.19	54.75***, a
	(11.71)	(11.59)	(11.79)	(11.66)	(11.2)
Ethnicity of head†	0.77	0.86	0.71***, b	0.77	0.77 b
	(0.42)	(0.35)	(0.46)	(0.42)	(0.42)
Schooling years of head (years)	7.53	7.74	7.39***, a	7.61	7.38**, a
	(2.91)	(2.93)	(2.89)	(2.96)	(2.81)
Household size (persons)	5.05	5.03	5.06 a	5.23	4.69***, a
	(1.77)	(1.71)	(1.81)	(1.77)	(1.71)
Dependency ratio	1.49	1.50	1.48 a	1.57	1.32***, a
	(0.65)	(0.66)	(0.64)	(0.64)	(0.64)
Health of head†	0.75	0.76	0.74 b	0.72	0.81***, b
	(0.43)	(0.43)	(0.44)	(0.45)	(0.39)
Head born in the village†	0.75	0.84	0.69***, b	0.74	0.76 b
	(0.43)	(0.37)	(0.46)	(0.44)	(0.43)
Farm characteristics					
Land location†	0.75	0.79	0.73***, b	0.65	0.95***, b
	(0.43)	(0.41)	(0.45)	(0.48)	(0.21)
No of agro-machines	0.51	0.56	0.48***, a	0.60	0.33***, a
	(0.74)	(0.75)	(0.73)	(0.76)	(0.66)
No of agro-equipment	1.51	1.53	1.49 a	1.38	1.76***, a
	(0.97)	(0.90)	(1.01)	(0.91)	(1.03)
Physical capital					
No of motorcycles	1.21	1.22	1.21 a	1.05	1.54***, a
	(0.92)	(0.94)	(0.91)	(0.83)	(1.01)
No of phones	1.52	1.53	1.51 a	1.45	1.66***, a
	(1.22)	(1.20)	(1.23)	(1.28)	(1.06)
No of pushcarts	0.25	0.30	0.22***, a	0.12	0.50***, a
	(0.53)	(0.57)	(0.50)	(0.35)	(0.71)
Asset value per capita (PPP$)	635.71	653.87	622.88 a	478.61	949.91***, a
	(920.47)	(879.13)	(948.65)	(606.08)	(1288.52)

Note: Standard deviations in parentheses; PPP$: Purchasing Power Parity dollars adjusted to 2005 prices; Statistical tests between groups and periods; a: Two-sample t-test; b: Non-parametric rank-sum test; †: Dummy variable; *** p<0.01, ** p<0.05, * p<0.1.

Table 3 shows the household characteristics, farm characteristics, and physical capital of rice households in central Vietnam. Rice households are more often headed by men and the average age of household heads is almost the same for both groups at 51.7 years. The mean values of household size, dependency ratio, and health status of household heads are not statistically different between the control and treatment groups.

Nearly 80% of the households in the sample belong to the Kinh majority. The number of schooling years of households in the control group is relatively higher than in the treatment group.

We include additional farm characteristics and physical capital that may have an influence on rice production in Table 3. In case of farm characteristics, both groups have a similar number of agricultural equipment, while the control group has more agricultural machines. Households in the control group have all of their farmland plots in the village they live in (79%) compared with those in the treatment group (73%). This difference is statistically significant. With regard to physical capital, those in the control group have more pushcarts, while the numbers of motorcycles and phones are not significantly different between the two groups. Although there is no significant difference between the two groups in terms of asset value per capita, the physical capital shows significant improvements over time.

4. Methods

4.1. Identifying factors of participation in land consolidation

In the first step, we estimate the farming efficiency in rice production by applying the time-variant stochastic frontier model suggested by Greene (2005) with the true random-effects model because this model can differentiate between the inefficiency component and unobserved heterogeneity. We follow the translog specification from Nguyen et al. (2021) to estimate farming efficiency. The true random-effects model from Greene (2005) with translog specification is as follows:

$$ln\, rice\_output_{it} = \alpha + \omega_i + \sum_m \beta_m \, lnX_{itm} + \frac{1}{2}\sum_m \sum_n \beta_{mn} \, lnX_{itm} lnX_{itn} - u_{it} + v_{it} \quad (3)$$

In equation (3), $ln\, rice\_output_{it}$ is the rice yield (kilograms per hectare) of household i at time t in natural logarithm; lnX_{it} are the vectors of inputs of household i

at time t in natural logarithm which include farmland area, family farm laborers, and production costs (measured in PPP$ and adjusted to 2005 prices) for land preparation, seedlings, fertilizers, pesticides, irrigation, and harvesting; ω_i is the time-invariant and farm-specific heterogeneity.

We employ the correlated random-effects (CRE) approach suggested by Mundlak (1978) to address potential endogeneity problems of omitted relevant variables (e.g, unobserved characteristics) and reverse causality because input and output are jointly determined (Gautam and Ahmed, 2019; Lien et al., 2018). Furthermore, all input variables are normalized as $\ln(X^*_{itm}) = \ln(\frac{X_{itm}}{\bar{x}_m})$ by their respective means to allow the interpretation of estimated coefficients to be elasticities at means (see Holtkamp and Brümmer, 2017; Nguyen et al., 2021). We run the true random-effects stochastic frontier model using the maximum likelihood method proposed by Belotti et al. (2013) and estimate the farming efficiency of household i at time t as:

$$\Gamma_{it} = \mathrm{E}[\exp(-u_{it})|(v_{it} - u_{it}) \quad (4)$$

In the second step, we examine the inter-relationship between farming efficiency and participation in land consolidation. The model is specified as:

$$LC_{it} = \varphi_1 + \varphi_2\Gamma_{it} + \varphi_3 X_{it} + \varepsilon_{it} \quad (5)$$

$$\Gamma_{it} = \mu_1 + \mu_2 \mathrm{LC}_{it} + \mu_3 X_{it} + \varsigma_{it} \quad (6)$$

In equation (5) and (6), LC_{it} is a binomial variable for land consolidation (LC) of household i at time t. This decision is captured by a decreasing Simpson index (land consolidation or $LC_i = 1$) or otherwise an increasing Simpson index between 2013 and 2017 (land fragmentation or $LC_i = 0$). Γ_{it} is farming efficiency in rice production of household i at time t. X_{it} are key factors affecting rice production/livelihood such as (i) household's characteristics, (ii) farm characteristics, and (iii) physical capital (Panel C, D, and E in Appendix 1, respectively). These factors have been found to be significant in defining household's livelihood strategies and production efficiency (Gebre et al., 2021; Nguyen et al., 2017a; Nguyen et al., 2020; Tran et al., 2019; Van Hon and Khuong Ninh, 2020). Finally, ε_{it} and $\varsigma_{it}$are the error terms.

There are two problems in regressing equations (5) and (6). First, the available method for the simultaneous regression model is the three-stage least squares (3SLS) method (Greene, 2018). Estimations using this method with binary dependent variables might be biased. Therefore, we address this problem by including the predicted probabilities of household's participation in land consolidation. We use the heteroscedasticity-based (or heteroscedasticity-based estimation) approach with internal instrumental variables proposed by Lewbel (2012) to estimate the probabilities. Assume that we have the impact of household's characteristics on farming efficiency as:

$$\Gamma_{it} = \Psi + \psi X_{it} + \xi_{it} \tag{7}$$

Lewbel (2012) proposes to use $[X_{it} - E(X_{it})]\hat{\xi}_{it}$ as an internal IV for Γ_{it} in regressing equation (5), where $\hat{\xi}_{it}$ is predicted residuals obtained from the estimation of equation (7). This estimation method can be used with both binary and continuous outcomes and regressors (Lewbel, 2018). In addition, Baum et al. (2012) suggest employing external instrumental variables (IV) to improve effectiveness of this heteroscedasticity-based IV method. Hence, we use two additional external instruments at commune levels, namely, the average number of household's member engaged in farming and the average distance from house to all land plots. The intuition behind the use of these variables is that the number of people engaged in farming might affect the efficiency since more people can share their knowledge or they may have more experiences. Besides, further distance to land plots results in higher costs and lower efficiency. We conduct several quality tests, namely the under-identification test (Cragg and Donald, 1993), the weak identification test (Stock and Yogo, 2005), and the Sargan-

Hansen test for over-identifying restrictions (Sargan, 1958) of the IV estimation. The results of these tests confirm the appropriateness of these IVs in the heteroscedasticity-based estimation (results of heteroscedasticity-based estimation and post-estimation tests are presented in Appendix 2). Besides, the VIF values show that there are no serious multicollinearity problems from our independent variables (see VIF values in Appendix 3).

The second problem of conducting the simultaneous regression model using the 3SLS method is that it requires additional instrumental variables in each equation to address the simultaneity. Hence, we specify our simultaneous equation model as follows:

$$\overline{\mathrm{LC}}_{it} = \delta_0 + \delta_1\Gamma_{it} + \delta_2 R_{jt} + \delta_3 X_{it} + \mu_{it} \tag{8}$$

$$\Gamma_{it} = \theta_0 + \theta_1\overline{LC}_{it} + \theta_2 Z_{jt} + \theta_3 X_{it} + \vartheta_{it} \tag{9}$$

In equation (8) and equation (9), $\overline{LC}_{it}$ is the predicted probability of household's participation in land consolidation and Γ_{it} is the farming efficiency of household i from village j in year t, respectively; X_{it} captures household's characteristics, farm characteristics, and physical capital (as in equation (5); μ_{it} and ϑ_{it} are the error terms of land consolidation and farming efficiency estimation, respectively.

We include R_{jt} as the IVs in the equation on land consolidation and Z_{jt} as the IVs in the equation on farm efficiency. We use exogenous variables at village level, namely the number of enterprises in the village and having made roads instead of dirt roads in the village as IVs in the estimation on land consolidation (as R_{jt} in equation (8)). The intuition for using these village variables is that they might reflect the available opportunities for off-farm employment and these opportunities might affect households' participation in non-farm activities rather than land consolidation. For Z_{jt} in equation (9), we employ exogenous variables at village level, namely the share of households with internet access and the share of households working in own farm as the IVs. There is significant evidence on the effect of these variables on crop production and efficiency (Kaila and Tarp, 2019; Nguyen et al., 2018). Additionally, the average distance to all land plots at commune level is also used as an IV in the estimation of farming efficiency.

We run several quality checks for validating the simultaneous estimation and independent variables. First, the results of the VIF values show no significant problem of multicollinearity from variables in equations (8) and (9) (see Appendix 4). Second, the results of the four additional tests, namely the Hansen-Sargan over-identification test, Breusch-Pagan Lagrange Multiplier test for independent equations, the Likelihood Ratio LR test and the Wald test for overall system heteroscedasticity validate our simultaneous equation model (see Appendix 5). Lastly, to prevent spatial autocorrelation and in order to have robust standard errors, we bootstrap these estimations with 1000 replications and cluster the standard errors at the village level.

4.2. Examining the association between land consolidation and rural transformation

The reallocation of farm labor to non-farm labor is an indicator of agricultural transformation during economic growth (Nguyen at al., 2021). This process emphasizes the role of agriculture in releasing labor for industrial employment (Johnston and Mellor, 1961). Since the allocations of household labor into farm and non-farm employment are not dependent but interrelated, the error terms in the estimations of non-farm income and farm income or the share of non-farm labor and farm labor are correlated. Thus, we use the seemingly (un)related regression to control for this interdependence (Nguyen et al., 2017a). This seemingly (un)related model is specified as:

$$\mathrm{N}_{it} = \varphi_0 + \varphi_1 LC_{it} + \phi_2 X_{it} + \eta_{it} \tag{10}$$

$$\mathrm{F}_{it} = \phi_0 + \phi_1 LC_{it} + \phi_2 X_{it} + \eta_{it} \tag{11}$$

In equation (10) and equation (11), N_{it} and F_{it} refer to the rural transformation indicators: (i) non-farm income per laborer and (ii) the share of non-farm income in household income, (iii) farm income per laborer and (iv) the share of farm income in household income of household i in year t, respectively; LC_{it} indicates whether the household consolidate farmland. Since LC_{it} is endogenous, we address this problem with the same procedure as before when estimating the equations (8) and (9). X_{it} captures household characteristics, farm characteristics, and physical capital as mentioned in section 4.1; and η_{it} is the error terms. The VIF values of independent variables in this seemingly (un)related regression model show no signs of multicollinearity problem (see Appendix 6).

4.3. Evaluating land consolidation's impacts on production costs and poverty

To assess the impact of land consolidation, we apply the propensity score matching (PSM) with Difference-in-Differences (DD). Both PSM and DD are popular impact evaluation methods (Ali and Rahut, 2020; Gertler et al., 2016). The PSM method is used to balance the treatment and control groups to ensure the similarity of the groups in terms of observed baseline characteristics (Stuart et al., 2014). The propensity scores generated from the PSM method produce more robust inferences by reducing extrapolation and subsequent dependence on the specification of the outcome models (Ho et al., 2007). These scores are taken into the estimations of the DD method. The two methods are combined to reduce the risk of biases from observed characteristics and the effects of unobserved variables on outcome variables (Smith and Todd, 2005). The propensity scores are generated from a Probit regression as follows:

$$P(X) = Pr(LC_{it} = 1 | \Gamma_{it}, X_{it}) \tag{12}$$

We apply the kernel PSM-DD as it is able to produce the best performance among matching estimators (Smith and Todd, 2005). The concept of DD design (Card and Krueger, 1993) is estimated from the model:

$$f(Y_{it}) = \alpha + \lambda LC_i + \gamma Time_t + \delta LC_i Time_t + \nu_{it} \tag{13}$$

When integrating with the PSM, the estimator of PSM-DD requires:

$$E[Y_{0(post)} - Y_{0(pre)} | P(\Gamma_{it}, X_{it}), LC = 1] = E[Y_{0(post)} - Y_{0(pre)} | P(\Gamma_{it}, X_{it}), LC = 0] \tag{14}$$

In equation (13), Y_{it} is the observed outcome of household *i* at time *t;* LC_i is an indicator of household *i* being in the land consolidation LC (treatment) group or non-land consolidation (control) group, and time denotes the pre- (t = 0) or post-intervention (t = 1) period. Parameter δ is the estimator of DD and the estimate of δ generated from this model is analogous to the non-parametric approach that includes the differences in the changes of the two groups over time or the treatment effect of the LC.

We take into account two groups of outcome variables including rice production costs and poverty indicators to evaluate the impacts of land consolidation. The first group of dependent variables includes six major cost categories of rice production, namely land, seedlings, fertilizers, pesticides, irrigation, and harvest costs. The second group includes six poverty indices, namely the poverty headcount ratio, the poverty gap index, and the poverty severity at two poverty thresholds of PPP$ 2.05 and PPP$ 3.20 per capita a day. We evaluate the changes of production costs and poverty indices between the control and treatment groups over time. Finally, we apply the kernel-based matching and bootstrapping method for estimating standard errors and PSM-DD estimators with 1,000 replications.

5. Results and discussion

5.1. Factors affecting participation in land consolidation

To validate the appropriateness of the translog functional form compared with the Cobb-Douglas model, we run the likelihood ratio test using the critical value from Kodde and Palm (1986). The result of the ratio test indicates that the translog functional form is more appropriate than the Cobb-Douglas (see Appendix 7). The results of the translog stochastic frontier production estimation from true random-effects with Mundlak's adjustments (CRE) show that four (out of eight) mean variables of CRE have a statistical significance in our estimation (see Appendix 8). This implies the presence of time-invariant unobservable characteristic effects (Gautam and Ahmed, 2019; Nguyen et al., 2021). The results also denote that fertilizer is the most important input, while irrigation is the least important input of rice production in Vietnam. Figure 3 shows the distribution of predicted farming efficiency scores from rice production over time. The mean scores are 0.669 in the previous period (2010 and 2013) and 0.748 in the post period (2017). The all-time average of farming efficiency is about 0.696. This score from our estimation is relatively higher than the score of 0.63 for rice farmers in northern and north-eastern Thailand (Rahman et al., 2009) and the scores of 0.60 from Cambodia (Mishra et al., 2018) and 0.57 from Bangladesh (Mishra et al., 2015).

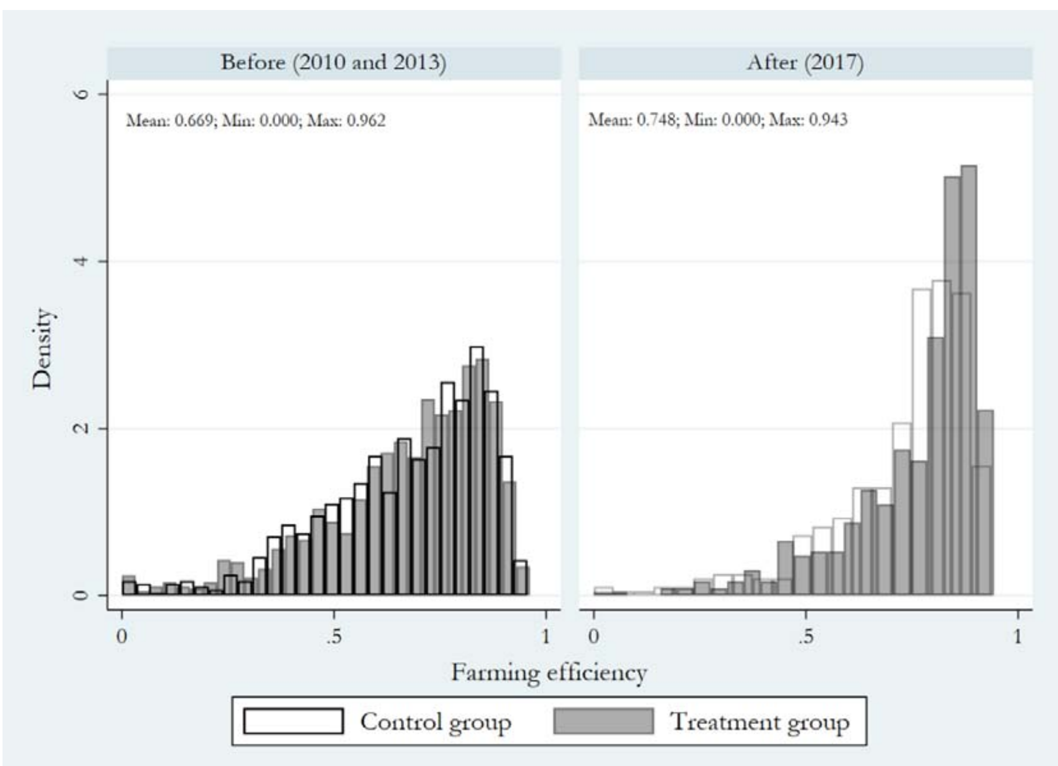

Figure 3: Farming efficiency of rice production in central Vietnam

Table 4 shows the results of the interrelationship between land consolidation and farming efficiency from the simultaneous estimation which shows that farming efficiency positively and significantly affects the participation in consolidation. This result is, however, different from that of Nguyen and Warr (2020) and Tu et al. (2021). The reasons could be differences in measuring land consolidation and econometric approaches. Our results further show that roads and the number of enterprises with at least nine employers negatively and significantly affect household's participation in a land consolidation scheme. These results are reasonable because these variables represent the available opportunities for non-farm activities. Therefore, these opportunities can discourage farm households to conduct land consolidation and encourage them to participate in non-farm employment. Indeed, better road quality has a positive effect on households' participation in non-farm activities in rural areas (Do et al., 2022).

Table 4: Interrelationship between land consolidation and farming efficiency (simultaneous regressions)

	Participation in land consolidation	Farming efficiency
Made road	-0.016**	
	(0.006)	
Enterprises with nine employers	-0.009**	
	(0.004)	
Distance to all land plots (ln)		0.017
		(0.011)
Share of households with cable internet at home		-0.099
		(0.104)
Share of households working in own farm		0.024
		(0.026)
Farming efficiency	0.545*	
	(0.295)	
Participation in land consolidation		-0.814
		(1.081)
Farmland area	0.015***	0.010
	(0.005)	(0.020)
Male head†	-0.044***	-0.004
	(0.010)	(0.034)
Age of head	0.001***	0.002
	(0.000)	(0.001)
Ethnicity of head†	-0.171***	-0.068
	(0.016)	(0.163)
Schooling years of head	-0.001	-0.001
	(0.001)	(0.002)
Household size	-0.001	-0.002
	(0.001)	(0.003)

Dependency ratio	-0.021***	-0.018
	(0.004)	(0.023)
Health of head†	-0.023***	0.017
	(0.009)	(0.014)
Head born in the village†	-0.146***	-0.099
	(0.009)	(0.156)
Land location†	-0.083***	-0.026
	(0.010)	(0.073)
No of agro-machines	-0.026***	-0.026
	(0.003)	(0.031)
No of agro-equipment	-0.007	0.015**
	(0.005)	(0.006)
No of motorcycles	-0.007	0.020***
	(0.006)	(0.006)
No of phones	0.012**	-0.016***
	(0.006)	(0.005)
No of pushcarts	-0.051***	-0.019
	(0.005)	(0.045)
Asset poor†	-0.020**	-0.037
	(0.008)	(0.029)
Constant	0.578***	1.247
	(0.163)	(0.941)
Number of observations	2985	
Wald chi2	2013.920	
Prob > chi2	0.000	

Note: Robust standard errors bootstrapped with 1000 replications and clustered at village levels in parentheses; †: Dummy variable; ln: natural logarithm; *** p<0.01, ** p<0.05, * p<0.1.

Regarding the remaining factors affecting land consolidation, farming area, age of household head, and owning more phones have a positive effect on the participation in land consolidation. In Vietnam, households with larger farm sizes often suffer higher land fragmentation because of historical land allocation. Therefore, households with a larger farmland area tend to implement land consolidation. Male head, ethnicity of head, dependency ratio of household, health of head, head born in the village, the number of agricultural machines, the number of pushcarts, and asset-poor households have a negative influence on the participation. The negative effect of land location (household has all farmland plots in the same village = 1) appears to be reasonable because the impact of land fragmentation on households with all land plots in the same village (their land is fragmented, but in a short distance) is less severe than those with land plots located in different villages. With regard to the farming efficiency, the number of agricultural equipment and the number of motorcycles are positively associated with the efficiency, while owning more phones is negatively associated with the efficiency.

5.2. Association between land consolidation and rural transformation

Table 5 presents the results of the seemingly (un)related regression, which show that land consolidation is positively associated with farm income per laborer, but insignificantly associated with non-farm income per laborer. Since land consolidation enhances the mechanization in crop production (Deininger et al., 2017), it could reduce production costs and increase households' farm income. Further, the results from the estimation on income shares show that land consolidation is negatively associated with the share of non-farm income and positively associated with the share of farm income. This finding implies that land consolidation plays an important role in stimulating rural transformation. For households participating in land consolidation, the share of farm income accounts for a larger proportion, while for those not participating, the income from non-farm sources comprises a larger proportion. In addition, the share of non-farm income is rising in both groups of participating and non-participating households. Hence, the implementation of land consolidation policy should be enhanced to facilitate the redistribution of agricultural land from farmers who want to leave agriculture to those who continue to work in agriculture.

Table 5: Effects of land consolidation on farm income and non-farm income (seemingly (un)related regressions)

	Income per laborer		Income share	
	Non-farm sources (ln)	Farm sources (ln)	Non-farm sources (%)	Farm sources (%)
Participation in land consolidation	-1.285	1.141**	-0.443***	0.518***
	(0.852)	(0.512)	(0.134)	(0.126)
Farmland area	-0.044	0.080*	-0.014	0.015
	(0.062)	(0.048)	(0.010)	(0.009)
Male head†	0.061	0.091	-0.023	0.058***
	(0.142)	(0.069)	(0.020)	(0.020)
Age of head	0.000	-0.004*	-0.003***	-0.002**
	(0.004)	(0.002)	(0.001)	(0.001)
Ethnicity of head†	0.034	0.385***	-0.024	-0.007
	(0.189)	(0.112)	(0.030)	(0.031)
Schooling years of head	-0.005	0.013	0.002	-0.003
	(0.019)	(0.008)	(0.002)	(0.002)
Household size	-0.025	-0.046***	0.015***	-0.015***
	(0.033)	(0.014)	(0.004)	(0.004)
Dependency ratio	0.398***	0.060	0.017	-0.011
	(0.068)	(0.036)	(0.010)	(0.010)

Health of head†	0.268**	0.064	0.026*	-0.021
	(0.116)	(0.051)	(0.014)	(0.013)
Head born in the village†	-0.031	0.084	-0.032	0.003
	(0.179)	(0.093)	(0.025)	(0.027)
Land location†	-0.103	0.010	-0.022	0.018
	(0.116)	(0.058)	(0.015)	(0.015)
No of agro-machines	-0.254***	0.254***	-0.068***	0.096***
	(0.079)	(0.038)	(0.010)	(0.010)
No of agro-equipment	-0.160**	0.242***	-0.047***	0.060***
	(0.069)	(0.030)	(0.009)	(0.010)
No of motorcycles	0.493***	0.040	0.094***	-0.063***
	(0.069)	(0.031)	(0.009)	(0.008)
No of phones	0.133***	0.016	0.011**	-0.006
	(0.044)	(0.019)	(0.006)	(0.005)
No of pushcarts	-0.204*	0.221***	-0.038***	0.020
	(0.107)	(0.055)	(0.012)	(0.013)
Asset poor†	-0.320**	-0.195***	-0.013	0.008
	(0.147)	(0.068)	(0.018)	(0.019)
Constant	-0.243	-1.010**	0.699***	0.171
	(0.869)	(0.498)	(0.129)	(0.125)
Number of observations	2985		2985	
Wald chi2	184.140		394.840	
Prob > chi2	0.000		0.000	

Note: Robust standard errors bootstrapped with 1000 replications and clustered at village levels in parentheses; †: Dummy variable; ln: natural logarithm; *** p<0.01, ** p<0.05, * p<0.1.

With regard to the results of the estimation on farm income and its share, farmland area, male head, head belonging to the ethnic majority group, number of pushcarts, and households with more agriculture-related productive equipment are positively associated, while age of head, household size, number of motorcycles, and asset-poor households are negatively associated with farm income. Our finding is consistent with that from Nguyen et al. (2021). For non-farm income, household size, dependency ratio, health of head, and owning motorcycles and phones are positively associated with non-farm income. The finding on phone ownership is in a similar vein with Nguyen et al. (2022) that the increase in smartphone and internet use has a positive impact on household income. The effect of household size on non-farm income from our study is in line with that from Do et al. (2019). Poor households and those owning agro-machines and agro-equipment are negatively associated with non-farm income. Apparently, the influence of owning more agricultural machines and equipment is reasonable because households with more agricultural machines and equipment are more likely to specialize in farm work. The sign of the asset poor variable is acceptable because farmers need certain levels of capital to participate in non-farm activities (Do et al., 2019).

5.3. Impacts of land consolidation on production costs and poverty

Impacts of land consolidation on production costs and poverty are presented in Table 6 (estimated propensity scores in Appendix 9, covariate-balancing tests conducted after matching in Appendices 10 and 11). The PSM-DD estimators for rice production costs and poverty indices show some clear results. First, regarding the production costs, the land preparation costs are significantly different after land consolidation. In the pre-intervention period, the costs of land preparation in the treatment group is higher than in the control group, however, in the post-intervention period, the costs of the treated group are slightly lower with a gap of PPP$ 18.88 per ha. This difference is significant at the 10% level of significance. Consequently, the DD estimator shows a difference of about PPP$ 24.35 per ha and is significant at the same significant level. Indeed, land fragmentation reduces the average plot size below the threshold for farm mechanization (Deininger et al., 2017; Diao et al., 2016).

Second, the advantage of mechanization in rice production is also reflected in the harvesting costs. The average harvest costs of the control group are lower than those of the treatment group before the land consolidation, but are higher after the land consolidation. Both the post-difference and the PSM-DD estimator are significant at the 1% level of significance. The gap is only about PPP$ 9.54 per ha in the previous period, but widens to PPP$ 32.29 per ha in the postperiod, resulting in a difference of PPP$ 41.82 per ha between the two groups. The reason for this is that the consolidation of land results in a larger farmland area, which allows rice farmers to use combine harvesters instead of hand harvesters or rice reapers. The use of combine harvesters can bring benefits to rice farmers, such as reducing harvest costs by combining cutting, threshing, and bagging in one process (Jabarin and Epplin, 1994) and increasing production by reducing post-harvest quality losses and quantity (Fukai et al., 2019).

Finally, land consolidation significantly improves farm income and thus helps prevent rural households from falling into poverty. The results of the PSM-DD estimation for FGT poverty indices at commune levels do not show significant differences in the post-period, however the DD estimators (δ) indicate that households in the treatment group have made progress in reducing poverty. Our results are consistent with those from Wang et al. (2021) that land consolidation contributes to poverty reduction. Indeed, in the pre-period, households in the treatment group have a higher poverty headcount ratio, a higher poverty gap index, and a higher poverty severity evaluated at two poverty thresholds of PPP$ 2.05 and PPP$ 3.20 per capita a day. In the post-period, the poverty indices are relatively reduced in the two groups. As a result, the DD estimators therefore differ significantly over time.

Table 6: Impacts of land consolidation on rice production cost and poverty (PSM-Kernel matching with difference-in-differences estimations)

Outcome variables	Before				After				Diff-in-Diff (δ)	Robust S. E. [a]
	Control (C)	Treated (T)	Diff (T-C)	Robust S. E.[a]	Control (C)	Treated (T)	Diff (T-C)	Robust S. E. [a]		
Rice production costs										
Land preparation cost (PPP$/ha)	168.736	174.205	5.470	8.149	227.052	208.170	-18.882*	10.716	-24.352*	13.037
Seedling cost (PPP$/ha)	118.051	137.668	19.618**	8.583	182.512	182.773	0.261	9.133	-19.357	12.706
Fertilizer cost (PPP$/ha)	441.853	469.796	27.943*	15.505	485.837	500.791	14.954	19.216	-12.989	23.667
Pesticide cost (PPP$/ha)	95.039	102.882	7.843	4.972	134.840	131.994	-2.846	7.678	-10.689	9.140
Irrigation cost (PPP$/ha)	34.546	33.745	-0.801	5.021	27.564	29.761	2.197	3.729	2.998	6.247
Harvest cost (PPP$/ha)	152.005	161.540	9.535	9.066	231.124	198.837	-32.287***	10.464	-41.822***	13.943
Poverty indices										
Poverty head-count ratio at PPP$ 2.05 per capita a day	0.356	0.383	0.027**	0.014	0.178	0.172	-0.006	0.014	-0.033*	0.020
Poverty gap index at PPP$ 2.05 per capita a day	0.176	0.220	0.044***	0.009	0.073	0.092	0.020**	0.009	-0.025*	0.013
Poverty severity at PPP$ 2.05 per capita a day	0.126	0.236	0.111***	0.018	0.126	0.129	0.003	0.052	-0.108**	0.054
Poverty head count ratio at PPP$ 3.20 per capita a day	0.568	0.574	0.005	0.013	0.286	0.304	0.017	0.018	0.012	0.023
Poverty gap index at PPP$ 3.20 per capita a day	0.281	0.316	0.036***	0.010	0.136	0.144	0.008	0.011	-0.027*	0.015
Poverty severity at PPP$ 3.20 per capita a day	0.188	0.257	0.069***	0.011	0.121	0.123	0.002	0.027	-0.067**	0.030

Note: Kernel Matching (Gaussian kernel; bwidth = 0.06; and common support); Means and standard errors are estimated by linear regressions; [a]: Standard errors bootstrapped with 1000 replications; PPP$: Purchasing Power Parity dollars adjusted to 2005 prices; Inference: *** p<0.01, ** p<0.05, * p<0.1

6. Summary and conclusion

This research aimed to answer two research questions related to land consolidation measures and their impacts on rural transformation. The specific questions were to examine which factors influence participation in land consolidation and how this participation affects the costs of crop production, poverty, and rural transformation. We used data of 995 rice farm households from 2010, 2013, and 2017. Using an econometric approach to account for the potential simultaneity of land consolidation and farming efficiency, the result shows that farm households with higher farming efficiency are more likely to participate in land consolidation, while the inverse correlation is less pronounced.

The impact of land consolidation on farming efficiency is not statistically significant. It appears to have a positive effect on reducing land preparation and harvesting costs for rice households. The results of the PSM-DD estimators show that households participating in land consolidation have lower land preparation costs by PPP$ 24.35 per ha and lower harvesting costs by PPP$ 41.82 per ha. Furthermore, the results of the counterfactual assessment also show that land consolidation has a significant impact on poverty reduction at the poverty line of PPP$ 2.05 and PPP$ 3.20 per capita per day. Land consolidation is found to have a positive effect on farm income per laborer but an insignificant impact on non-farm income per laborer. In addition, land consolidation has a negative and significant effect on the non-farm income share, while it has a positive and significant influence on the farm income share. As land consolidation helps to address several rice household problems, it should be improved to facilitate the redistribution of agricultural land from farmers who want to give up farming to those who continue to work in agriculture.

Although rice is in surplus in Vietnam, relaxing the restrictions on land use for rice growing to crop diversification should be considered. The restrictions could be relaxed in the communes where rice production is not efficient (i.e. lower farming efficiency). We recommend future research to focus on identifying the level of farming efficiency at which the farmers should conduct land consolidation. At the village level, rural development policies aiming at accelerating rural transformation should encourage rural enterprises and invest more in rural infrastructure (e.g., better road quality and internet). At the household level, households who are more efficient should be encouraged and facilitated to consolidate farmland.

Declaration of Competing Interest

The authors declare that they have no conflict of interest in this research.

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Appendices

Appendix 1: Name, measurement, and definition of variables

Name	Measurement	Definition
A. Rice production		
Rice yield	Kilograms per hectare (ha)	Rice harvest per crop season
Land preparation cost	PPP$ (adjusted to 2005 prices) per ha	Expenditure on land preparations per hectare per crop season
Seedling cost	PPP$ (adjusted to 2005 prices) per ha	Expenditure on seedlings per hectare per crop season
Fertilizer cost	PPP$ (adjusted to 2005 prices) per ha	Expenditure on fertilizers per hectare per crop season
Pesticide cost	PPP$ (adjusted to 2005 prices) per ha	Expenditure on pesticides per hectare per crop season
Irrigation cost	PPP$ (adjusted to 2005 prices) per ha	Expenditure on irrigation including fuels/electricity per hectare per crop season
Harvest cost	PPP$ (adjusted to 2005 prices) per ha	Expenditure on harvest including fuels/electricity per hectare per crop season
Farm laborers	Persons	Total household's members engaging in agricultural activities
Farmland area	hectares	Total land area of the household for farming
B. Indicators of farm and non-farm income		
Non-farm income per laborer	PPP$ adjusted to 2005 prices	Daily income per laborer from non-farm activities such as wage- and self-employment
Share of non-farm income	Percentage	Share of income from non-farm activities such as wage- and self-employment in total income
Farm income per laborer	PPP$ adjusted to 2005 prices	Daily income per laborer from crop, livestock, and other farm activities
Share of farm income	Percentage	Share of income from farm activities such as crop, livestock, and other farm activities in total income
C. Household's characteristics		
Male head	Dummy	Gender of the household's head. Male = 1; otherwise = 0
Age of head	Years	Ages of the household's head
Ethnicity of head	Dummy	The ethnic group of the household. Kinh majority = 1; otherwise = 0
Schooling years of head	Years of schooling	Number of schooling years of the household's head
Household size	Persons	Number of members in the household
Dependency ratio	Continuous	The ratio of nucleus size and independent members (15-64 years) in the household
Health of head	Dummy	Health condition of the household's head. Healthy or still able to work = 1; otherwise = 0
Head born in the village	Dummy	If the household's head was born in the same (as current) village. Yes = 1; otherwise = 0

D. Farm characteristics		
Land location	Dummy	If all land plots owned by the household in the same (as current) village. Yes = 1; otherwise = 0
No of agro-machines	Quantity	The number of agricultural machines such as 2-wheel tractors, 4-wheel tractors, rice milling machines, and rice threshing machines that the household owns
No of agro-equipment	Quantity	The number of agricultural equipment such as knapsack sprayers, engine sprayers, and pumps that the household owns
Simpson index	Continuous	Indicator of household's land fragmentation. The Simpson indexes vary from 0 to 1
E. Physical capital		
No of motorcycles	Quantity	The number of motorcycles that the household owns
No of phones	Quantity	The number of phones that the household owns
No of pushcarts	Quantity	The number of pushcarts that the household owns
Asset value per capita	PPP$ (adjusted to 2005 prices)	Per capita value of durable goods of the household; Saving, home and land values are not included
Asset poor	Dummy	Households belong to the first quintile group (20% of the poorest) of asset value per capita
F. Village variables		
Enterprises with nine employers	Enterprises	Average number of enterprises having at least nine employers in the village
Made road	Dummy	If the village has made roads instead of dirt roads. Yes = 1; otherwise = 0
Share of households with cable internet at home	Continuous	The share of households having cable internet access at home at village level
Share of households working in own farm	Continuous	The share of households working in their own farm at village level
G. Commune variables		
Average farm laborers	Continuous	Average number of household's members engaged in farming in each village at commune level
Average distance to land plots	km	Average distance from house to all land plots in each village at commune level

Appendix 2: Estimation results of the probability of farmers' participation in land consolidation

	Probit estimation				Heteroscedasticity-based IV estimation	
	Coefficient	Robust Std. Err.[a]	Marginal effect	Robust Std. Err.[a]	Coefficient	Robust Std. Err.[a]
Farming efficiency	0.604***	0.141	0.222***	0.051	0.292**	0.149
Farmland area	0.083**	0.039	0.031**	0.014	0.016**	0.007
Male head†	-0.106	0.108	-0.039	0.040	-0.037	0.038
Age of head	0.003	0.003	0.001	0.001	0.001	0.001
Ethnicity of head†	-0.432***	0.105	-0.159***	0.038	-0.169***	0.036
Schooling years of head	-0.001	0.015	0.000	0.006	-0.001	0.006
Household size	-0.007	0.022	-0.003	0.008	-0.002	0.008
Dependency ratio	-0.052	0.050	-0.019	0.018	-0.021	0.019
Health of head†	-0.045	0.062	-0.017	0.023	-0.016	0.023
Head born in the village†	-0.381***	0.098	-0.140***	0.035	-0.146***	0.034
Land location†	-0.198***	0.063	-0.073***	0.023	-0.077***	0.023
No of agro-machines	-0.070	0.051	-0.026	0.019	-0.026	0.019
No of agro-equipment	-0.010	0.035	-0.004	0.013	-0.003	0.013
No of motorcycles	-0.009	0.045	-0.003	0.016	-0.004	0.017
No of phones	0.018	0.021	0.006	0.008	0.008	0.008
No of pushcarts	-0.124**	0.056	-0.045**	0.021	-0.047**	0.021
Asset poor†	-0.066	0.077	-0.024	0.028	-0.024	0.028
Constant	0.664**	0.311			0.717***	0.132
Number of observations	2985				2985	
Wald chi2(17)	78.720					
Prob > chi2	0.000					
F(18,94)					5.21	
Prob > F					0.000	
Under identification					0.000	
Over identification					0.098	
Weak identification					18.368	

Note: [a]: Robust standard errors clustered at village level; †: Dummy variable; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix 3: Results of Variance Inflation Factor (VIF) values from the estimation on the probability of farmers' participation in land consolidation

Variable	VIF
Farming efficiency	1.06
Farmland areas	1.15
Male head	1.11
Age of head	1.20
Ethnicity of head	1.37
Schooling years of head	1.13
Household size	1.22
Dependency ratio	1.11
Health of head	1.15
Head born in the village	1.13
Land location	1.04
No of agro-machines	1.17
No of agro-equipment	1.42
No of motorcycles	1.66
No of phones	1.34
No of pushcarts	1.12
Asset poor	1.38
Mean VIF	**1.22**

Appendix 4: Results of VIF values from the estimation of simultaneous model on land consolidation and farming efficiency

	Participation in land consolidation	Farming efficiency
Made road	1.18	
Enterprises with nine employers	1.04	
Distance to all land plots		1.19
Share of households with cable internet at home		1.22
Share of households working in own farm		1.34
Farming efficiency	1.06	
Participation in land consolidation		6.66
Farmland area	1.15	1.4
Male head	1.11	1.15
Age of head	1.20	1.32
Ethnicity of head	1.48	2.94
Schooling years of head	1.14	1.15
Household size	1.22	1.27
Dependency ratio	1.11	1.18
Health of head	1.15	1.15
Head born in the village	1.17	2.54
Land location	1.04	1.37
No of agro-machines	1.17	1.35
No of agro-equipment	1.42	1.42
No of motorcycles	1.67	1.73
No of phones	1.34	1.35
No of pushcarts	1.12	1.33
Asset poor	1.38	1.43
Mean VIF	**1.22**	**1.72**

Appendix 5: Quality tests of the simultaneous model of land consolidation and farming efficiency

	chi2	Prob.>chi2
Hansen-Sargan over-identification statistic	2.702	0.440
Tests of independent equations (Breusch-Pagan Lagrange Multiplier Test)	1686.487	0.000
Tests of Overall System Heteroscedasticity (Likelihood Ratio LR Test)	2484.655	0.000
Tests of Overall System Heteroscedasticity (Wald Test)	9.83e+07	0.000

Appendix 6: Results of VIF values from the estimation of seemingly (un)related regression model

	VIF
Participation in land consolidation	1.07
Farmland area	1.15
Male head	1.10
Age of head	1.20
Ethnicity of head	1.38
Schooling years of head	1.13
Household size	1.22
Dependency ratio	1.11
Health of head	1.15
Head born in the village	1.15
Land location	1.04
No of agro-machines	1.17
No of agro-equipment	1.41
No of motorcycles	1.65
No of phones	1.32
No of pushcarts	1.12
Asset poor	1.38
Mean VIF	**1.22**

Appendix 7: Likelihood ratio test between Cobb-Douglas and translog functional form

	Likelihood ratio test $\lambda = -2 * (log\widehat{\Omega}_{H0} - log\widehat{\Omega}_{H1})$	P-value [a]
H0: Cobb-Douglas is more appropriate (Translog is not appropriate)	4035.110	0.000

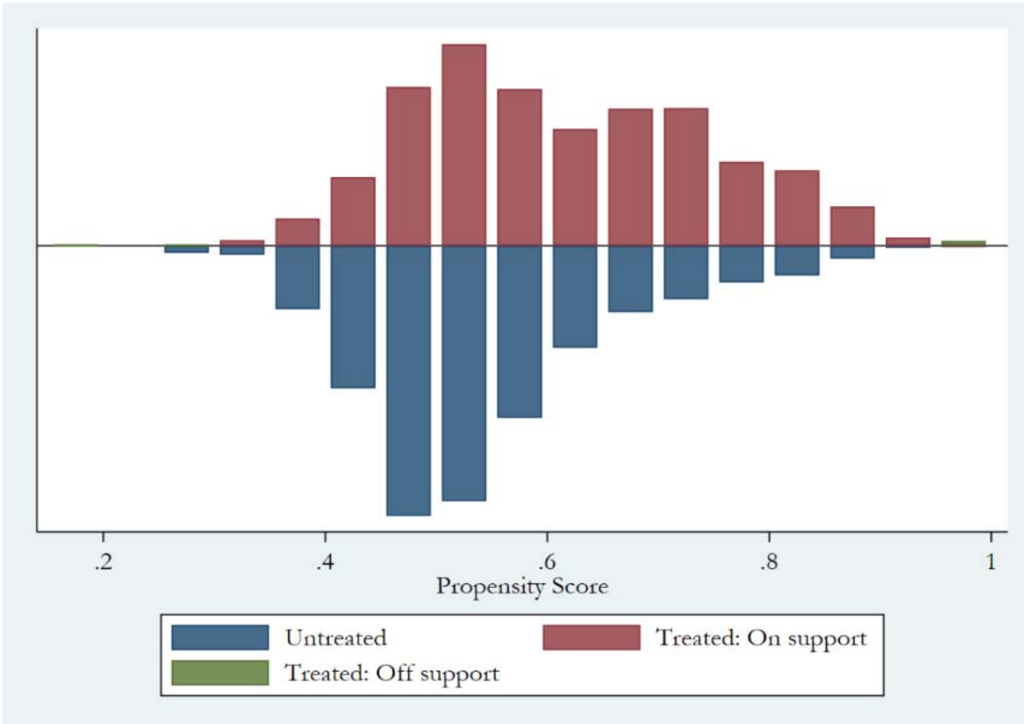
Note: $log\widehat{\Omega}_{H0}$ is the log likelihood of restricted model under the null hypothesis; $log\widehat{\Omega}_{H1}$ is the log likelihood of the alternative hypothesis; [a]: compared with the critical value from Kodde and Palm (1986).

Appendix 8: Results of the translog stochastic frontier production estimation of rice production in Vietnam from the true random-effects with Mundlak's adjustments (CRE)

	Coefficient	Robust Std. Err.[a]
ln farmland area (a)	0.005	0.021
ln land preparation cost (b)	0.038***	0.012
ln seedling cost (c)	0.037***	0.014
ln fertilizer cost (d)	0.167***	0.019
ln pesticide cost (e)	0.074***	0.012
ln irrigation cost (f)	0.016*	0.009
ln harvest cost (g)	0.023**	0.010
ln farm laborers (h)	0.035	0.023
a^2	0.013**	0.007
b^2	0.004***	0.001
c^2	0.002*	0.001
d^2	0.014***	0.001
e^2	0.008***	0.001
f^2	0.002*	0.001
g^2	0.003***	0.001
h^2	0.006*	0.003
a*b	0.000	0.002
a*c	0.003	0.002
a*d	0.012**	0.005
a*e	-0.013**	0.006
a*f	0.001	0.002
a*g	-0.003	0.004
a*h	-0.004	0.009
b*c	0.001***	0.000
b*d	0.001	0.002
b*e	-0.003***	0.001
b*f	0.000	0.000
b*g	-0.001*	0.001
b*h	-0.005	0.004
c*d	0.000	0.001
c*e	0.002	0.001
c*f	0.000	0.000
c*g	-0.001	0.001
c*h	-0.002	0.002
d*e	-0.002	0.002
d*f	-0.001	0.002
d*g	-0.003*	0.002
d*h	0.012	0.011
e*f	0.001	0.001
e*g	0.002	0.001
e*h	0.002	0.010
f*g	0.000	0.001

f*h	-0.002	0.001
g*h	-0.001	0.008
Mean variables of CRE		
ln farm area (time average-CRE)	0.081***	0.022
ln land preparation cost (time average-CRE)	0.013**	0.005
ln seedling cost (time average-CRE)	0.007**	0.004
ln fertilizer cost (time average-CRE)	0.024	0.015
ln pesticide cost (time average-CRE)	0.005	0.010
ln irrigation cost (time average-CRE)	0.005*	0.003
ln harvest cost (time average-CRE)	0.009	0.009
ln farm laborers (time average-CRE)	-0.031	0.026
_constant	8.376***	0.119
No of observations	2985	
Log simulated-likelihood	-1733.053	
Sigma_u; Sigma_v; Lambda	0.454***; 0.156***; 2.914***	
Wald Chi2(75)	933.440	
Prob.	0.000	

Note: [a]: Robust standard errors clustered at village level; ln: natural logarithm; *** p<0.01, ** p<0.05, * p<0.1.



Note: Kernel Matching (Gaussian kernel; bwidth = 0.06; and common support).

Appendix 9: Estimated propensity scores of Kernel matching algorithm

Appendix 10: Covariate balancing test for propensity score matching (average treatment effects)

Sample	Pseudo-R2	LR chi2	p>chi2	Mean Bias	Median Bias	B	R	%concern	%bad
Before matching	0.055	223.770	0.000	11.20	8.60	55.7*	1.63	24	6
After matching	0.003	10.320	0.890	2.10	1.50	12.9	0.79	0	0

Note: Kernel Matching (Gaussian kernel; bwidth = 0.06; and common support); * if B>25%, R outside [0.5; 2];

B is the standardized difference in the means of the propensity scores between consolidated and un-consolidated households

R the ratio of the variances of the propensity scores for consolidated and un-consolidated households

Appendix 11: Covariate balancing test for propensity score matching (average treatment effects)

Variable	Matching	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V_e(T)/ V_e(C)
Farming efficiency	Before	0.70	0.69	8.60		2.30	0.02	1.04
	After	0.70	0.69	6.00	30.10	1.51	0.13	1.00
Farmland areas	Before	1.20	0.77	25.40		6.50	0.00	3.80**
	After	0.82	0.77	2.60	89.90	1.12	0.26	0.84
Male head	Before	0.83	0.87	-9.70		-2.60	0.01	1.21
	After	0.86	0.87	-0.70	93.20	-0.17	0.86	1.01
Age of head	Before	51.70	51.74	-0.30		-0.09	0.93	1.03
	After	52.17	51.74	3.70	-982.00	0.92	0.36	0.96
Ethnicity of head	Before	0.71	0.86	-37.70		-9.93	0.00	1.91*
	After	0.85	0.86	-2.20	94.10	-0.64	0.52	1.09
Schooling years of head	Before	7.39	7.73	-11.80		-3.19	0.00	0.97
	After	7.71	7.73	-0.80	93.10	-0.20	0.84	0.96
Household size	Before	5.06	5.03	1.70		0.45	0.66	1.11
	After	5.02	5.03	-0.90	46.80	-0.22	0.82	1.04
Dependency ratio	Before	1.48	1.50	-3.80		-1.03	0.30	0.93
	After	1.49	1.50	-1.50	61.80	-0.35	0.72	1.02
Health of head	Before	0.74	0.76	-3.60		-0.97	0.33	1.04
	After	0.76	0.76	-0.70	80.40	-0.18	0.86	1.01
Head born in the village	Before	0.69	0.83	-35.30		-9.32	0.00	1.67*
	After	0.83	0.83	-0.40	98.80	-0.11	0.91	1.01
Land location	Before	0.72	0.79	-15.30		-4.09	0.00	1.24
	After	0.78	0.79	-3.20	79.20	-0.82	0.41	1.09
No of agro-machines	Before	0.48	0.56	-10.70		-2.88	0.00	0.98
	After	0.53	0.56	-4.10	61.30	-1.00	0.32	1.07
No of agro-equipment	Before	1.49	1.53	-3.80		-1.01	0.31	1.29*
	After	1.51	1.53	-2.00	48.40	-0.50	0.62	1.13
No of motorcycles	Before	1.21	1.22	-1.10		-0.29	0.77	0.93
	After	1.22	1.22	-0.30	69.60	-0.08	0.94	0.93
No of phones	Before	1.51	1.53	-1.70		-0.47	0.64	1.06
	After	1.54	1.53	0.30	81.20	0.08	0.94	1.02
No of pushcarts	Before	0.21	0.30	-15.50		-4.21	0.00	0.76*
	After	0.27	0.30	-6.00	61.30	-1.48	0.14	0.83
Asset poor	Before	0.21	0.19	3.50		0.95	0.34	1.06
	After	0.19	0.19	0.20	94.10	0.05	0.96	1.01

Note: Kernel Matching (Gaussian kernel; bwidth = 0.06; and common support);

* if 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2];

** if 'bad', i.e. variance ratio <0.5 or >2