Economic effects of organic farming in Taiwan: Empirical evidence from population-based farm household data

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Abstract

Organic farming has been viewed as one of the promising farming practices of sustainable agricultural production. Evaluating the economic effects of organic farming is important while promoting environmental-friendly policies. Considering the four major components of the cropping system and spatial agglomeration effects, this study looks into three kinds of economic performances-sales revenue, cost and profit, for rice farm households in Taiwan using large-scale national data drawn from the 2015 agriculture census. We apply the analysis of local indicators of spatial associations to gain a better understanding of the patterns of organic farming clusters. The spatial clusters are then incorporated into the Probit-2SLS instrumental variable model, finding that organic farming adoption leads to a significantly positive effect on rice farms' economic performances in turns of cost reduction and profit increase. This positive treatment effect can be further increased through spatial agglomeration. Moreover, the treatment effect of organic farming is found to vary with the farm characteristics such as farmland area and the number of hired workers. For practical implications, establishing organic agriculture specialized zones or providing economic incentives to small farms to expand their scale may be a more effective policy means to promote sustainable agri-food production.

Keywords Organic farming, Causal effect, Farm household analysis, Spatial agglomeration, Heterogeneous treatment effects

JEL code Sustainable Development Q01; Micro Analysis of Farm Firms, Farm Households, and Farm Input Markets Q12

1. Background

Organic farming has been viewed as one of the promising farming practices that provide the building blocks for a sustainable food production system. While the benefits of organic farming including environmental conservation and human health are obvious from the society’s perspectives, the financial consideration, i.e., whether organic farming can sustain or even result in higher returns, plays an important role in farmers’ decision-making for adoption. As stated by Feder (1985), farmers would tend to adopt new technology when the innovation is more likely to be profitable. Hence, in this study, we focus on evaluating the economic effects, including that of sales revenue, cost, and net returns, for the farmers producing the major staple food, rice, in Taiwan.

Addressing the economic effects of organic farming has been one of the major streams of research studying the benefits of organic agriculture. Previous studies examined the effect of organic farming on production, cost or profit controlling for factors like labor hiring, price premium, or farm management (Uematsu and Mishra, 2012; Offermann and Nieberg, 2000; Luh et al., 2016; Nemes, 2009; Froehlich et al., 2018). Most of the studies in the past found the negative association between organic farming and the output level; but the results concerning costs or profits have been mixed. Based on a study of the western states in the U.S., it was found that organic farms in Washington and California in general needed more labor and longer on-farm worktime (Finley et al., 2018). However, the cases in developing countries indicated that the cost for organic farms is usually lower (Nemes, 2009). As for profit, Nemes (2009) found that organic farms made more profit in a study targeting the United States and European countries while another study by Uematsu and Mishra (2012) showed insignificant differences between organic and conventional farms. Uematsu and Mishra (2012) indicated that the higher revenues resulting from the adoption of organic farming are offset by the higher costs for organic certificated farms due to certification fees, labor costs and expenditure on aversion to risks. Similar results were also found in the study of Offermann and Nieberg (2000), in which the profitability of European organic farms is not statistically different from that of conventional farms. Moreover, some found that organic farming exhibited negative economic effects such as the studies of Brazil and Taiwan (Froehlich et al., 2018; Luh, et al., 2016). Specifically, Luh, et al. (2016) investigated the economic effects of organic farming using data from 168 rice farmers in Fuli, Hualian, a township in the east coast of Taiwan. Based on an in-depth questionnaire survey, the results showed that organic farms’ profits were usually lower than that of conventional farms.

The cropping system is composed of four major components, including climate, genotypes, management, and soil (Liu and Basso, 2020). Accordingly, all of the four major components should be featured or controlled for in a comprehensive analysis of the performance of farming practices. It has been brought to our attention that most previous studies concerning the economic outcomes of organic farming did not take into consideration all four key components in their empirical evaluation.

Therefore, our first contribution to the literature is to examine the economic effects of organic agriculture while controlling for all four major components of the cropping system. By providing empirical evidence of the economic effects of organic farming through a comprehensive analysis, this study complements the extant body of knowledge by drawing on the agriculture census data which is composed of more than 700,000 farm households. To the best of our knowledge, there were few studies examining the economic impact of organic farming with large-scale or national census data despite the popularity of the economic analyses of organic adoption. One of the few studies is Froehlich et al. (2018) which studied more than four million family farms in Brazil with their census data, and another is the study by Uematsu and Mishra (2012), which is based on 2698 large farm businesses drawn from the U.S. agriculture census data.

Another goal of this research is to investigate whether the economic effects of organic farming are dependent on spatial agglomeration. Organic farming has been found to exhibit some spatial patterns due to neighboring effect in the studies from many countries, and spatial analyses often help to assess the effect of knowledge/awareness spillover (Beauchesne and Bryant, 1999; Schmidtner et al., 2012; Läpple and Cullinan, 2012; Wollni and Andersson, 2014; Läpple and Kelley, 2015; Yang et al., 2022). One strand of spatial analyses of organic farming focused on factors affecting the formation of organic clusters. For example, Läpple and Cullinan (2012) found that organic clusters existed in Ireland, and some factors like external support and information promote clustering. Based on a spatial analysis of the certified organic frarms in Taiwan, Lu and Cheng (2019) found that the areas with a lower risk of inundation or located on the landslides are more likely to form spatial clusters of organic farming. To examine the economic effect of the organic clusters, Vogt et al. (2022) investigated the effect at the municipal level and found that identifying the organic hotspot could provide policy inferences concerning the township-level economic development and agricultural upgrading. In Marasteanu and Jaenicke (2019), it was found that the organic clusters help reduce regional poverty, and thus serve as an indicator of the economic impacts of organic farming. The agglomeration of organic production and processing was also found to improve the local economy to achieve the goal of rural development. Even so, as Cainelli (2008) indicated, the patterns of organic clusters are different from agricultural clusters. Agricultural clusters are usually located in rural areas where consumers have lower purchasing power and are more price incentive whereas organic agriculture is usually clustered in more urbanized regions with more green buyers. Part of the economic effect of organic agglomeration found in previous studies therefore may be due to the correlation between consumers' purchasing power and farmers' sales revenue. Therefore, we aim to examine whether the economic effects of organic farming vary with the location of the farm in the hotspots in this study. As the two key elements to cropping systems, climatic conditions and soil qualities may be spatially correlated to economic outcomes, we construct an analysis framework by controlling for seasonal weather conditions and land productivity in this study to provide more accurate estimates of the heterogeneous treatment effect due to geographic locations.

Methodologically speaking, organic adoption and economic performance are influenced by observed farm characteristics and environmental factors, and some unobservable factors such as farmers' attitudes, risk aversion, and other psychological factors. As the psychological factors related to farmers' adoption and economic outcomes of organic farming adoption are unobservable in the census data used in this study, there is a potential "selection bias" problem to deal with. To address the selection bias problem, we apply Probit-2SLS instrumental variable (IV) method in the binary treatment model under homogenous and heterogeneous assumptions. Since the organic adoption decision is a binary treatment, the use of the liner instrumental variable method represents some kind of misspecification and thus leads to inefficiency (Manning, 2004; Wooldridge, 2010). Moreover, we consider the possibility that the treatment effect of organic farming may differ depending on some factors like land scale, farming experience, etc. To our knowledge, none of the previous research evaluating the economic effect of organic farming considered this kind of heterogeneous treatment response in the estimation of treatment effect, despite such heterogeneous effects have been modeled and analyzed in other applications. For example, in Sebaggala and Matovu (2015), the farm production effects of extension service which vary with farm characteristics were examined for Uganda's farms. Similarly, Pradhan and Ranjan (2016) found the heterogeneous average treatment effects of farm programs associated with group characteristics.

Furthermore, this study provides empirical evidence of the economic outcomes of organic farming for the agriculture sector dominated by small-scale farms that are less than 1 hectare such as in Taiwan. The Council of Agriculture (COA) in Taiwan set a target to achieve in 2018 that a total of 15,000 hectares of farmland are devoted to organic farming and environmentally-friendly agriculture. Under the governmental efforts in promoting organic agriculture, the area of organic and environmental-friendly farmland has been increasing rapidly during the past three decades, and up until 2020, the organic-alike area has grown from around 1,250 hectares in 2004 to approximately around 18,000 hectares (Taiwan Organic Information Portal, 2019). Despite the observed success in organic development, there is a lack of empirical evidence and study assessing the economic effects of organic farming based on large-scale census data. The findings in this study render important policy implications concerning the design of farm programs aiming at promoting the development of organic agriculture in the future.

The following section will first introduce the data used and the variable definition in details. Section 3 describes the framework for our empirical analyses, and Section 4 presents the results and major findings. The last section is the conclusion of this paper.

2. Data and Sample

Our farm household data are taken from the 2015 Census of Agriculture, Forestry, Fishery and Animal Husbandry (hereafter, the 2015 agriculture census) which contains their socio-economic characteristics and an indicator of whether chemical inputs including fertilizers and pesticides were used in farmers' production. Following the definition by Tsai et al. (2021) and Luh et al. (2023), organic farm households are identified as those who do not use any of the chemical inputs, both synthetic fertilizers and pesticides, in the entire cultivation process of paddy rice. Rice farms are chosen in this study because the farm households with a major commodity focus on rice take the highest share in Taiwan's agriculture census, around 36.3% in the 2015 agriculture census. After deleting the farm household which does not produce any crops or just produces crops for household members' own consumption, there are in total 213,470 rice farm households in this research.

Township-level weather data in this study include seasonal average temperature and precipitation data constructed from the data drawn from Central Weather Bureau Observation Data (Central Weather Bureau, 2015) and the crop suitability index representing soil productivity. Since this research focuses on paddy rice which has only two growing seasons, we construct the weather data for the two growing seasons. The first growing season is from early March to June, and the second growing season is from the end of July to November. Within the growth cycle of rice, heading time is important for its quality and quantity, therefore we further divide each season into two periods by the time to heading following Yang and Chang (1999). Since the standard deviation between months in each growing season is influential to the rice yield (Maggio et al., 2022), seasonal standard deviations of temperature and rainfall are also included in our empirical analysis. On a scale from 1 to 10, soil productivity scores represent whether land soil is suitable for growing crops, the lower score indicates the higher land fertility, by evaluating the characteristics of soil like land slope, drainage, pH level, etc. (National Land Resources Conservation Society, 2015). Average township income is used to control for the consumption ability in the town where the rice farm household is located. It is hypothesized that the richer the residents, the more likely to purchase organic products. Therefore, farms located in high-income township are hypothesized to earn more through the adoption of organic farming.

Table 1 and Appendix A are, respectively, the descriptive statistics and the variable definitions. The average revenue of rice farms is around 211,250 NTD/ha and the average cost accounts for a little more than half of the revenue. Rice farm households' adoption rate of organic farming is on average 4%, which suggests that there are 8,259 farm households that cultivate part of their land using organic farming practices. According to the descriptive statistics in Table 1, the principal operators of the rice farm households are mostly male, elder and attained a lower educational level. There are around 80% of the farm operators worked on the farm for less than 3 months, implying that the majority of the rice farms in Taiwan did not take farm income as the main source of their livelihood. Also, more than half of the farm operators had more than 20 years of farming experience. The socioeconomic characteristics of the rice farm households indicate that on average there are 3 working-age members in the rice farm households. The average percentages of working-age members' educational level are in order elementary school (34%), senior high school (27%), college and above (23%) and junior high school (16%). There is on average less than 1 farm worker in the farm households.

The hotspot is the cluster area of organic farming which is identified from local indices of spatial autocorrelation (LISA) analysis (Marasteanu and Jaenicke, 2019) which will be discuss detailed in section 4.3. In the present study, the hotspot is a dummy variable that takes the value of 1 if the farm is in the high-high cluster area and 0 otherwise. The descriptive statistics of temperature for the two growing seasons are as the following: the average temperature of growing season 1 is lower in before-heading time (Temp_avg11) than after (Temp_avg12); the average temperature of growing season 2 is higher before-heading time (Temp_avg21) than after (Temp_avg22). The statistics of rainfall indicate that the before-heading average (Rainfall_ave11/21) is more than after-heading (Rainfall_ave21/22) in both two seasons, whereas the rainfall is more in season 2. The statistics reported in Table 1 also indicate that while standard deviations from seasonal means are larger in season 1 than in season 2 for temperature, standard variations for precipitation are larger in season 2.

3. Empirical Method

The problem of endogeneity due to selection bias is potentially present when measuring the economic effects of organic farming. This problem arises from the correlation between the decision of organic farming adoption and the unobservable characteristics that may also affect farm's economic outcomes. To address the endogeneity issue involved in investigating the economic effects of organic farming, we use the two-stage least squares method (2SLS) with binary instrumental variable to correct for the problem. The outcome equation is specified as equation (1):

$$Y_i = \alpha D_i + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \text{ , where } E[\varepsilon_i|X_i] = 0,\ cov(D_i, \varepsilon_i) \neq 0 \quad (1)$$

In the above equation, the outcome variable, Y_i, is the economic performance of the rice farm households including sales revenue, cost, and profit per farmland unit (ha). The vector of farm and farmer socioeconomic characteristics and the associated coefficient vector are denoted by $\mathbf{X}_i$ and $\boldsymbol{\beta}$ respectively. The treatment variable, D_i, adoption of the organic farming takes the value of 1 if some of the farmland are cultivated without using any synthetic inputs and 0 otherwise, and α is the bias estimated coefficient due to the endogeneity in equation (1).

Fallowing the 2SLS method proposed by Cerulli (2012; 2014), we use the “ivtreatreg” STATA module to estimate the treatment model to eliminate the correlation between treatment variable and the error term in the outcome model. The rationale of the 2SLS method in Cerulli (2012; 2014) is that in the case of a binary treatment, the traditional instrumental variable approach is not efficient due to the fact that the predicted treatment is not limited to (0, 1). To deal with this problem, the first stage of the 2SLS method ought to be carried out in two steps (Adams et al., 2009; Cerulli, 2012, 2014). The first-stage regression is to estimate the probability of organic adoption via the Probit model. The Probit model specified as the following uses the cumulative standard distribution function to ensure probabilities lying between 0 and 1.

$$\Pr\,(D_i = 1) = \Phi(\gamma z_i + \boldsymbol{\kappa}\mathbf{X}_i + \upsilon_i) \tag{2}$$

A valid instrumental variable needs to be correlated with the endogenous explanatory variable but not with the outcome variable (or the error term), that is, the instrument affects the outcome only through its influence on the endogenous regressor. The instrumental variable to correct for the endogeneity of organic adoption is denoted by z_i, and its estimated coefficient is denoted by γ.

Following previous research using friends and neighbors’ organic adoption status (e.g., Dhakal and Escalante) or the proportion of neighboring (either spatial closeness or social proximity) farmers’ adoption rate (Birthal et al., 2015, Arslan et al., 2017; Asfaw et al., 2019; Marasteanu and Jaenicke, 2019), the instrumental variable used in the present study is the township-level average organic adoption rate conducted with leave-out-mean management. The neighboring effect was used as a valid instrument which affects the individual farm’s behavior through the neighboring effect while having no influence on the farm’s economic performance. In Yang et al. (2022) and Marasteanu and Jaenicke (2019), for example, the existence of neighboring effect in organic farming had been verified. Like the study of Maggio et al. (2022), the proportion of households within 30 kilometers from the focal household that applied organic fertilizer and intercropping system was used as an instrumental variable to examine the causal effects of organic fertilizer and intercropping system on crop production.

By using the probability predicted from Probit regression, this should be used as the instrument for treatment variable, D_i, in an ordinary least-squares regression, which regress probability and covariates on D(Cerulli, 2012, 2014). The probability is the orthogonal projection of D, making the smallest projection error in the vector space generated by $(z, \mathbf{X})$. This way can keep the efficiency if interested treatment variable is binary (Wooldridge, 2010). The predicted probability for each individual i is denoted by p_i.

$$p_i = \Pr(D = 1|\, z_i, \mathbf{X}_i) = E[D|z_i, \mathbf{X}_i] \tag{3}$$

Let θ, $\boldsymbol{\kappa}'$ and ν_i' be the estimated coefficients and the error term, second step of the first-stage regression to predict treatment variable is specified as following:

$$D_i = \theta p_i + \boldsymbol{\kappa}'\mathbf{X}_i + \nu_i' \tag{4}$$

We then specify the second stage estimation as in (5):

$$Y_i = \alpha\widehat{D_i} + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{5}$$

Since the predicted value of D_i from first stage estimation, is not correlated with the error term, ε_i, the causal effect is thus identified by the coefficient of $\widehat{D_i}$, which measures the local average treatment effects.

4. Results and Discussions

4.1. Economic effects of adoption

Our primary goal is to identify the causal effect of organic adoption on economic outcomes, including revenue, cost and profit, for rice farms in Taiwan. The results of Probit 2SLS estimation are presented in Table 2. In Table 2, we only report selected coefficients to facilitate discussion. The full set of coefficient estimates are listed in Appendix B.

As shown in column (1) of Table 2, the treatment effect of organic farming adoption on the sales revenue of paddy rice is not statistically significant. The result is different from the finding of Luh et al. (2020) which found negative economic effects of organic farming for 167 rice farmers in Fuli, Hualian of Taiwan. The result in the present study suggests that the price premium for organic rice balances the reduction of output level, resulting in revenues from organic similar to conventional rice farming on average. In column (2), we list the results taking the production cost as the outcome variable. The coefficient estimate indicates that the adoption of organic farming lowers the production cost by about 44,890 NTD/ha on average, which is significant at a 1% level of significance. The reduction in production costs for organic farming is likely to be due to cutting the use of chemical fertilizers and pesticides. Even though the price of organic fertilizers in Taiwan is much higher compared with that of chemical ones, the result implies that the adoption of organic rice farming likely leads to a lower tendency for farmers to use fewer organic fertilizers. According to past observation (Hsiao, 2008), the majority of farms in Taiwan are family farms which tend to rely on labor supply from the family members, rather than hired workers. The economic cost of family labor input is not explicitly accounted for when reporting the production cost in the agriculture census. Therefore, the result reported in column (2) reveals the increase in labor cost associated with organic farming is modest due to the family farm structure of Taiwan’s agricultural sector. In column (3) we report the estimates of the determinants to rice farmers' profitability measured in net revenue. The result indicates that the adoption of organic farming leads to a significant positive outcome in terms of profitability differential by around 50,780 NTD/ha, which suggests that the economic incentives may be the major motivating factor driving the adoption of organic farming.

Farm management is another major component in the crop production system. Labor (counted in accumulated times monthly) and the number of family members doing farm work, are found to have a significant positive effect on sales revenue, cost and profit. In this study, township average income per capita (*Income_town*) is used to capture the size of potential consumers for organic food, which however has a moderate negative effect in all three outcome models. This result implies the consumption ability in the township does not promote local sales or profit of rice farms. This finding might be due to the transportation system and other factors in the distribution of agricultural products in Taiwan. As for the climatic factors, we control for seasonal average temperature and rainfall and their variations (standard deviations) within each growing season. We find that the higher temperature in the hot season (summer, June to September) increases the farm sales revenue and profit, but the higher temperature in October to November, which is around the fall in Taiwan, leads to a negative effect. This may be attributed to the phenomenon of the prolonged hot seasons resulting from climate change which makes the temperature higher during the traditional planting time. The effects of rainfalls are mostly in the same direction as the temperatures. Specifically, the negative effects in March to May and October to November on the economic outcomes might also be associated with the damages from excess rainfalls in the rainy season and the higher frequency of typhoons in those periods. As for the deviations of climatic factors, it is found that the corresponding coefficient estimates are negative in the second growing season, indicating the degree of temperature variations is harmful to crop production. As for the results of soil productivity, we found that worse fertility contributes to better economic performances. The results might indicate that instead of relying on the original soil fertility, farmers tend to increase the productivity of the land from other resources, especially on poor land.

To validate the use of the instrumental variable in this study, we perform the endogeneity Wu-Hausman test in Table 3. The statistics of Wu-Hausman test in the profit regression equation are significantly different from zero, suggesting that the IV approach should be used in the estimation of all three models. Also, models pass the weak instrumental variable test (F statistics are larger than 10). The test results confirm the validity of using the township average adoption rate of organic farming as an instrument in our empirical analysis.

4.2. Hotspot of organic adoption

In this section, we discuss the spatial effects focusing on the clusters identified through the local indicators of spatial associations (LISA) proposed by Anselin (1995). LISA is also named as local Moran's I, which is calculated as the following:

$$I_i = \frac{y_i - \bar{y}}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y}), i \neq j \tag{6}$$

In the above equation, y_i stands for the township-level adoption rate, and w_{ij} is the element in the ith row and jth column of the spatial weight matrix. We use the towns as the basic units of our spatial analysis, i.e., the polygons, and the neighborhood is defined by the common boundaries of towns. Generally speaking, there are four types of spatial autocorrelation: high-high, high-low, low-high, and low-low (Anselin, 1995). Each of the spatial patterns implies that when the chosen polygon is the former, then its neighbors tend to be the latter. The clustering or agglomeration of organic adoption is portrayed by the "high-high" relationships, which is also termed a hotspot in spatial analysis. The fourth type of spatial autocorrelation, the "low-low" polygons, indicate the gathering of lower organic adoption, which is termed coldspot. In Figure 1 we portrayed the four patterns of spatial autocorrelation of organic adoption by testing the statistical significance after simulating the random permutation 999 times. The gray areas in Figure 1 are undefined in the spatial autocorrelation analysis due to the absence of rice farms in the town or the town being isolated without any neighboring towns.

In the left panel of Figure 1, the spatial patterns indicate that the hotspots are located in northern and eastern Taiwan. The two regions are not the major rice production areas in Taiwan, suggesting that organic rice is less prevalent in the major rice production regions. Similar findings can be found for the low-low areas. We also present the global Moran's I in Figure 1(b). The global Moran's I can be used as a test for the existence of an overall spatial autocorrelation. The global Moran's I statistic is 0.366 which is significant at a 1% significance level. The positive slope of the scatterplots shows the positive correlation between polygons and its neighbors, indicating that the neighborhood effect at the township level is positive from an overall perspective. The agglomeration of organic adoption is expected to moderate the economic effects of organic farming. There, as below we examine if hotspots or coldspots make a difference in the outcomes of organic farming.

In Table 4, we find the treatment effects of organic adoption to be dependent on whether the farm is in the hotspot, non-hotspot (includes coldspot and neither), or coldspot. Although the coefficient estimates of organic adoption in sales revenue are negative for all three groups including hotspot, coldspot and non-hotspot, the size of the effect on reduced sales revenue becomes much smaller in the hotspot than the non-hotspot and coldspot groups in the first row. The reduction in sales revenue varies from approximately 24,260 NTD/ha in hotspots to 65,040 NTD/ha in the non-hotspot townships, and further to 1,485,640 NTD/ha in the coldspots. This result suggests that farms in hotspots might receive a higher price premium or have higher productivity due to the agglomeration.

In the second row, the negative treatment effect of organic farming on the production costs is smaller in the hotspot group than in the coldspot group. Comparing column (1) and (3), the organic farms in the hotspot might spend more on organic input or invest on farming facilities to help increasing their yield. However, in terms of the most important outcome for farmers—profitability—the coefficients of organic adoption are, respectively, negative in coldspot, not significantly different from zero in non-hotspot, and positive in hotspot areas. We also found the positive treatment effect in the hotspot group is larger than the average treatment effects of the entire rice population listed in Table 2. These results indicate that organic agglomeration exerts a positive impact on organic farms' economic performance.

Tests for the nine models (three performance indicators for three groups of farms) are also performed and listed in Table 5. The IV regression endogeneity Wu-Hausman tests for sales revenue in the hotspot group is insignificant, suggesting that the issue of endogeneity is not a critical concern. Therefore, we use the OLS (ordinary least squares) model in estimating the revenue model in column (2) of Table 4 (model types are presented at the bottom of the tables). As shown in Table 5, all models pass the weak instrumental variable test with F statistics greater than 10.

4.3 Heterogeneous effects

Considering that the treatment effect may vary with the farm and farmers' socioeconomic characteristics, we conduct further analyses of heterogeneous (or idiosyncratic) average treatment effects following the procedures outlined in Cerulli (2014). When the heterogeneous response is present, the treatment effect is correlated with the deviation of the farm from the whole sample. In this study, we take all explanatory variables into consideration, and portray the heterogeneous effects based on the distribution of the average treatment effects.

Figure 2 presents the distribution of the heterogeneous average treatment effects by three outcome indicators. It is found that the average treatment effect differs substantially with the characteristics of individual farms. In Figure 3, we present the distribution of treatment effects by some farm characteristics in x-axis, including land size, number of hired labors, and the characteristics of the farm operator. These factors have been found to be important factors affecting a farm's economic performance and the adoption of organic farming in the literature. The first row in Figure 3 shows the average treatment effect on profit per hectare increases with the farmland areas or the number of hired labor. The results suggest that more land area and hired labors will result in more sizable economic effects of organic farming. We also present the distribution of average treatment effects by farm operator's characteristics, including age, educational level, on-farm work days and farm experiences. As shown in Figure 3, the average treatment effects exhibit modest variations with farm operators' characteristics either by the scatter plots or the fitted lines. However, in general, the treatment effect is found to be more sizable when the principal operators are younger, more experienced, have a higher educational level, or devote more on-farm work days.

5. Conclusion

This paper examined the causal effect of organic farming on rice farms' economic performance. The results in this study indicate that organic farms outperform their conventional counterparts either in terms of production cost or profitability. The reduction in the production cost is likely to be due to cutting the use of chemical fertilizers and pesticides, while the higher demand for labor is complemented by family labor. It is worth mentioning that the adoption of organic farming has larger positive impact on organic farms' economic performances in the hotspot areas. This result may be considered some evidence supporting the economic benefits of the cluster of organic farming. The findings in this study have important policy implications for the promotion of organic farming. First, since spatial spillovers of organic farming generate positive externality as the agglomeration theory predicts, the establishment of the specialized organic agriculture park/production areas in Taiwan is expected to benefit farmers adopting the environmentally-friendly practices and the development of rural economy. Furthermore, the heterogeneous treatment response identified in this study indicate that the treatment effects of organic farming vary with the farm's characteristics such as land size and the number of hired labors. Both land size and number of hired workers can be used to indicate the scale of farms, the findings in this study thus suggest that instead of providing flat-rate subsidies to encourage the adoption of organic farming, providing economic incentives to small farms to expand their scale may be more effective policy means to promote organic agriculture.

Due to the limitation of data, this study did not control the use of organic fertilizers. The appropriate use of organic fertilizers plays an important role in the organic farming system. However, it is also costly due to higher prices. Furthermore, due to its importance in Taiwan's agriculture, we limit our study focus to the rice farms in this research. Since the economic effects of organic farming are likely to vary by crop, a promising avenue of future extension of our work is to explore the treatment effects for other crops like vegetables, fruits, grains, and so on.

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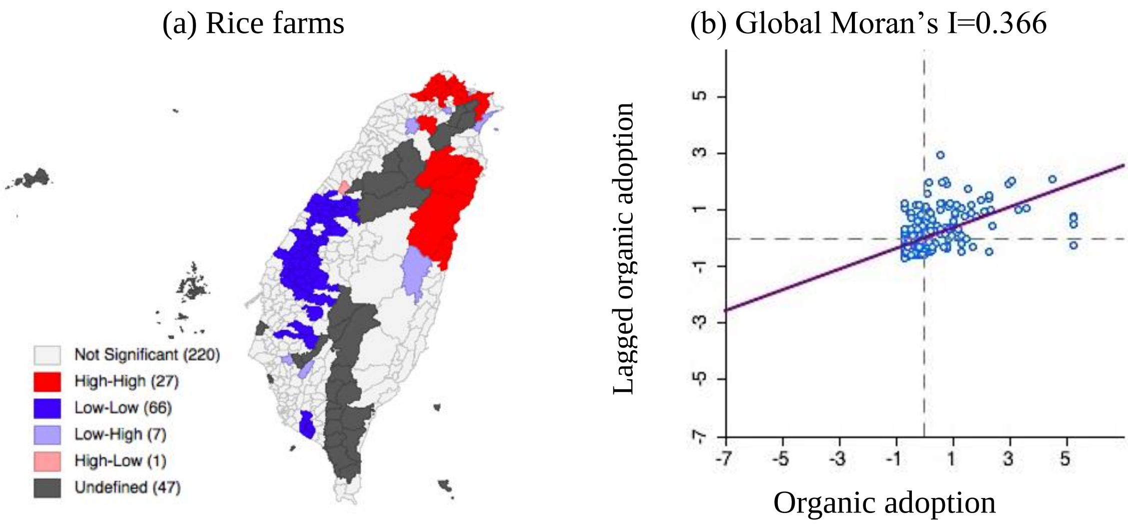

Figure 1 Spatial patterns (left) and Moran scatterplot (right) of organic farming

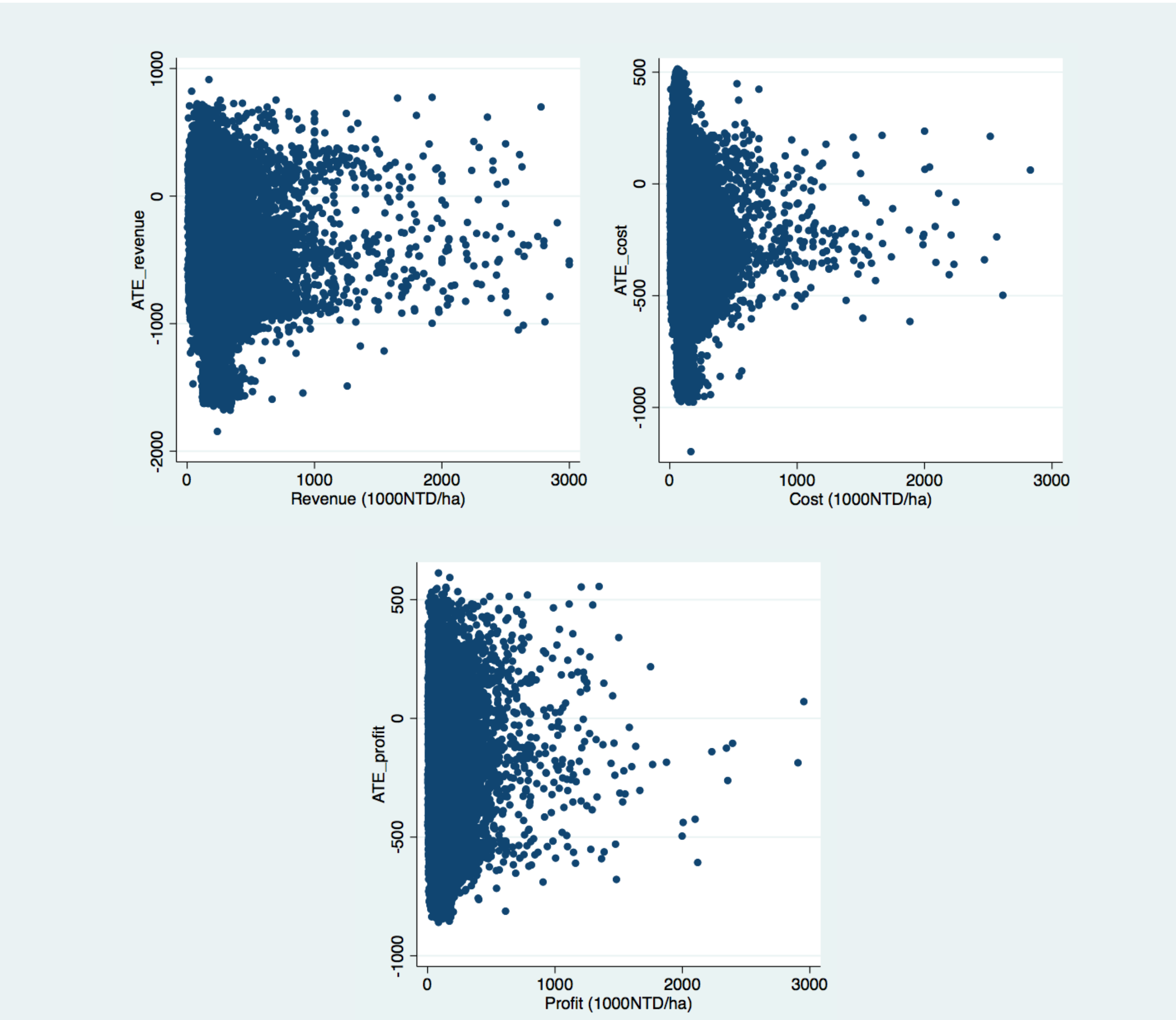

Figure 2. Distribution of heterogeneous average treatment effects on revenue, cost, and profit

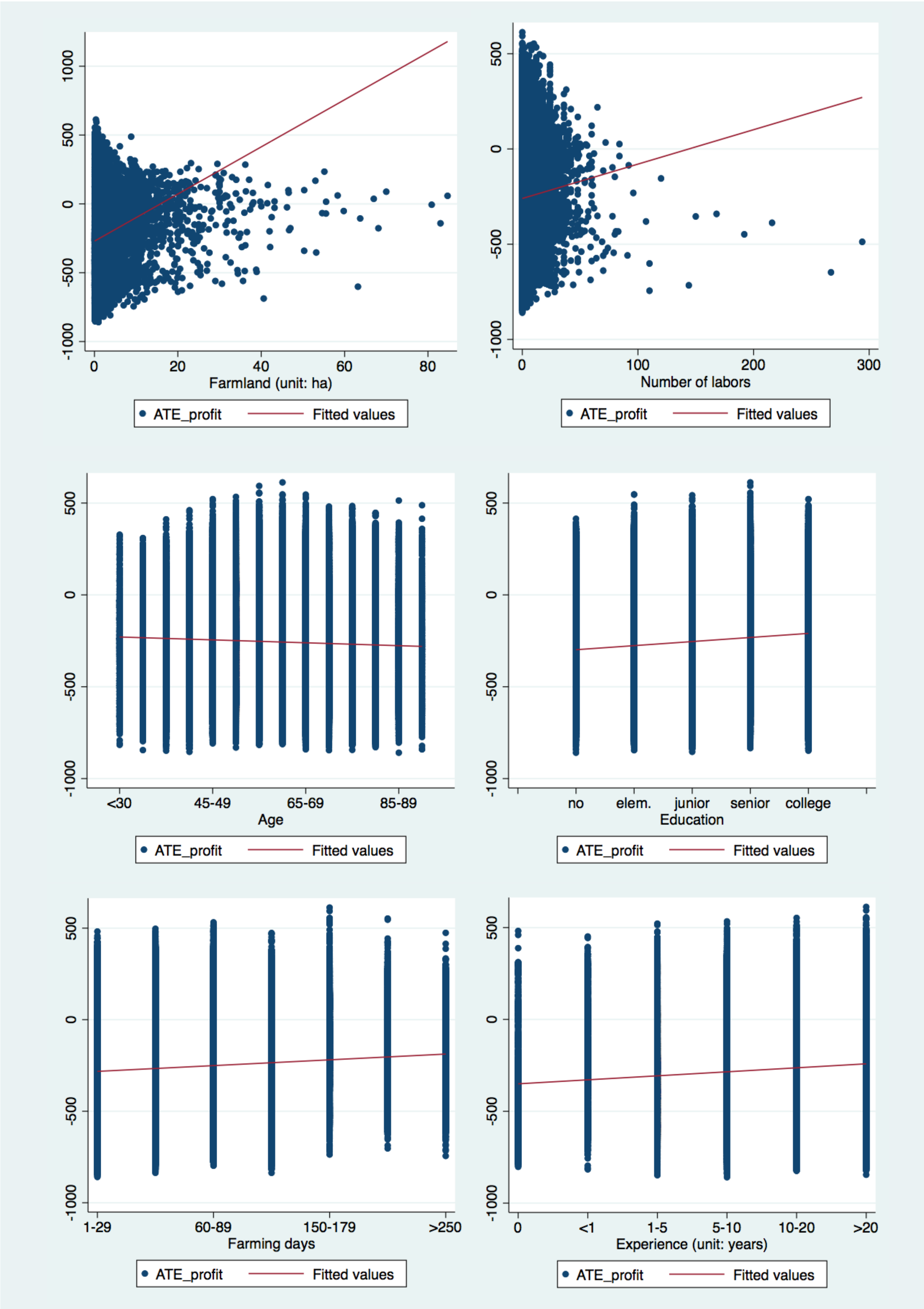

Figure 3. distribution of heterogeneous average treatment effects on farm’s characteristics

Table 1 Descriptive Statistics of variables

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Outcome variables			Labor (person)	0.75	3.42
Revenue (1000 NTD/ha)	211.25	121.92	Organic hotspots (0/1)	0.01	0.11
Cost (1000 NTD/ha)	105.72	65.36	Income_town (1000 NTD)	732.27	110.68
Profit (1000 NTD/ha)	105.53	65.88	*Characteristics of household members*		
Treatment variable			FH_male (%)	0.56	0.25
Organic adoption (0/1)	0.04	0.19	FH_age (<45) (person)	1.39	1.36
Operators & farm's characteristics			FH_age (45-64) (person)	1.1	0.88
Male (0/1)	0.81	0.39	FH_age (>64) (person)	0.89	0.81
Age (<45)	0.05	0.21	FH_elementary (%)	0.34	0.34
Age (45-64)	0.45	0.5	FH_junior (%)	0.16	0.26
Age (>64)	0.5	0.5	FH_senior (%)	0.27	0.3
Elementary (0/1)	0.48	0.5	FH_college (%)	0.23	0.28
Junior (0/1)	0.21	0.41	FH_farm_working (person)	0.72	0.81
Senior (0/1)	0.22	0.42	*Climate & Soil variables*		
College (0/1)	0.08	0.27	Temp_avg11	23.26	1.34
Days (<=29 days)	0.27	0.44	Temp_avg12	29.37	0.97
Days (30-59 days)	0.3	0.46	Temp_avg21	27.93	0.86
Days (60-89 days)	0.22	0.42	Temp_avg22	24.44	1.14
Days (90-149 days)	0.12	0.33	Rainfall_avg11	169.52	37.9
Days (150-179 days)	0.05	0.21	Rainfall_avg12	59.11	39.19
Days (180-249 days)	0.02	0.15	Rainfall_avg21	265.36	96.41
Days (>249 days)	0.01	0.12	Rainfall_avg22	57.81	113.63
Exp (< 5 yrs)	0.1	0.3	Temp_sd1	3.98	0.57
Exp (5-9 yrs)	0.12	0.33	Rainfall_sd1	182.51	57.35
Exp (10-19 yrs)	0.19	0.39	Temp_sd2	1.93	0.31
Exp (>=20 yrs)	0.59	0.49	Rainfall_sd2	193.17	72.09
Land (ha)	0.71	1.44	Soil_score	8.09	0.95

Table 2 Estimation for economic effect of rice farms (selected coefficients)

	Revenue		Cost		Profit	
Variables	(1)		(2)		(3)	
Organic adoption	5.89	(10.99)	-44.89***	(5.13)	50.78***	(6.79)
Farm characteristics						
Labor	4.25***	(0.26)	2.69***	(0.15)	1.56***	(0.12)
FH_farm_working	8.99***	(0.48)	2.87***	(0.25)	6.12***	(0.27)
Income_town	-0.04***	(0.00)	-0.01***	(0.00)	-0.03***	(0.00)
Climate and soil						
Temp_ave11	19.63***	(1.55)	20.29***	(0.89)	-0.66	(0.82)
Temp_ave12	1.35	(1.70)	-11.70***	(0.97)	13.05***	(0.90)
Temp_ave21	51.52***	(3.41)	28.73***	(1.64)	22.79***	(2.07)
Temp_ave22	-64.09***	(2.83)	-34.48***	(1.31)	-29.61***	(1.74)
Rainfall_ave11	-0.68***	(0.02)	-0.32***	(0.01)	-0.36***	(0.01)
Rainfall_ave12	0.26***	(0.01)	0.16***	(0.01)	0.10***	(0.01)
Rainfall_ave21	0.33***	(0.01)	0.23***	(0.01)	0.10***	(0.01)
Rainfall_ave22	-0.17***	(0.01)	-0.12***	(0.00)	-0.05***	(0.00)
Temp_sd1	12.51***	(2.10)	14.85***	(1.20)	-2.34**	(1.11)
Rainfall_sd1	0.68***	(0.01)	0.29***	(0.01)	0.38***	(0.01)
Temp_sd2	-166.88***	(5.93)	-64.17***	(2.75)	-102.71***	(3.63)
Rainfall_sd2	-0.35***	(0.01)	-0.19***	(0.01)	-0.17***	(0.01)
Soil_score	22.36***	(0.61)	9.54***	(0.34)	12.81***	(0.33)
Type	IV		IV		IV	
Observations	213,470		213,470		213,470	

Note: Robust standard errors are in the parentheses, and significant levels are denoted by *, ** and *** at 10%, 5% and 1% respectively.

Table 3 Tests for endogeneity and weak instrumental variable - all rice farm

	Revenue	Cost	Profit
Rice farms (obs=213,470)			
Endogeneity test	significant***	significant ***	significant ***
Weak IV test (F-stat > 10)	F= 9032.18	F= 9032.18	F= 9032.18

Note: Stars here *** denotes significant at 1%.

Table 4 Estimation for economic effect s between non -hotspot and hotspot groups

	Hotspot	Non-hotspot	Coldspot
	(1)	(2)	(3)
Outcome variable			
Revenue	-24.26**	-65.04***	-1,485.64***
	(11.80)	(10.63)	(100.06)
Cost	-209.78**	-59.57***	-403.41***
	(87.50)	(5.41)	(32.25)
Profit	197.13**	-5.47	-1,082.23***
	(99.44)	(5.94)	(71.20)
Type	OLS / IV / IV	IV / IV / IV	IV / IV / IV
Observations	2,464	211,006	94,955

Note: Robust standard errors are in the parentheses, and significant levels are denoted by *, ** and *** at 10%, 5% and 1% respectively.

Table 5 Tests for endogeneity and weak instrumental variable -subgroups

	Hotspot			Non-hotspot			Coldspot		
Endogeneity	Revenue	Cost	Profit	Revenue	Cost	Profit	Revenue	Cost	Profit
	N	Y***	Y**	Y*	Y***	Y***	Y***	Y***	Y***
Weak IV(F>10)	F=14.61			F=7303.72			F=558.75		
	obs=2,464			obs=211,006			obs=94,955		

Note: Signal N and Y indicates whether the model pass the test (no/yes) and significant levels are denoted by *, ** and *** at 10%, 5% and 1% respectively.

Appendix A

Variable	Definition
Dependent variable	
Revenue	Farm revenue from agricultural sales per unit farmland (excluding the processed; 1,000NTD/ha)
Cost	Total cost of agricultural production and sales per unit farmland (1,000NTD/ha)
Profit	Total profit of agricultural production and sales per unit farmland (1,000NTD/ha)
Treatment variable	
Organic adoption	Organic rice farming is adopted=1 and 0 otherwise
Principal operator	
Male	Gender of the principal operator
Age (under 45)	Age (less than 45 years old)
Age (45-65)	Age (45-64 years old)
Age (65 and up)	Age (more than 64 years old)
Elementary	Education (elementary school and below)
Junior	Education (junior high school)
Senior	Education (senior high school)
College	Education (college and above)
Days (< 30 days)	On-farm workday (less than 30 days)
Days (30-59 days)	On-farm workday (30-59 days)
Days (60-89 days)	On-farm workday (60-89 days)
Days (90-149 days)	On-farm workday (90-149 days)
Days (150-179 days)	On-farm workday (150-179 days)
Days (180-249 days)	On-farm workday (180-249 days)
Days (>249 days)	On-farm workday (more than 249 days)
Exp (< 5 yrs)	Farming experience less than 5 years
Exp (5-9 yrs)	Farming experience 5-9 years
Exp (10-19 yrs)	Farming experience 10-19 years
Exp (>=20 yrs)	Farming experience more than 20 years
Household members over 15 years old	
FH_male	Share of male members
FH_age (under 45)	Number of members under 45 years old
FH_age (45-65)	Number of members aged 45 to 64
FH_age (65 and up)	Number of members aged 65 and up
FH_elementary	Share of members with elementary school education and below
FH_junior	Share of members with junior high school education
FH_senior	Share of members with senior high school education
FH_college	Share of members with college education and below
FH_farm_working	Number of members who take farm work as their main job
Farm characteristics	
Land	Farmland used for crop production (hectare)
Labor	Total hired labor (calculated by number of labors hired per month)
Income_town	The average income (all sources) per capita in the located town

Climate and soil

Temp(Rainfall)_ave11	The average monthly temperature (rainfall) before heading in growing season 1
Temp(Rainfall)_ave12	The average monthly temperature (rainfall) after heading in growing season 1
Temp(Rainfall)_ave21	The average monthly temperature (rainfall) before heading in growing season 2
Temp(Rainfall)_ave22	The average monthly temperature (rainfall) after heading in growing season 2
Temp(Rainfall)_sd1	Standard deviations from seasonal temperature (rainfall) means in growing season 1
Temp(Rainfall)_sd2	Standard deviations from seasonal temperature (rainfall) means in growing season 2
Soil_score	The score of soil productivity, scaling from 1 to 10 (decreasing fertility)

Appendix B Estimates of operator and household member's characteristics: all rice farms

	Revenue		Cost		Profit	
Variables	(1)		(2)		(3)	
Operator characteristics						
Male	-0.84	(0.76)	-1.18***	(0.40)	0.33	(0.43)
Age (under 45)	6.60***	(1.30)	4.34***	(0.72)	2.26***	(0.71)
Age (65 and up)	-5.91***	(0.99)	-2.10***	(0.53)	-3.81***	(0.57)
Junior	-2.83***	(1.04)	-0.91	(0.59)	-1.92***	(0.56)
Senior	-3.39***	(1.04)	-0.32	(0.56)	-3.07***	(0.58)
College	-0.94	(1.47)	1.49*	(0.79)	-2.43***	(0.84)
Days (30-59 days)	6.67***	(0.59)	7.17***	(0.32)	-0.50	(0.34)
Days (60-89 days)	30.53***	(0.79)	18.95***	(0.42)	11.59***	(0.44)
Days (90-149 days)	41.40***	(1.05)	27.26***	(0.57)	14.14***	(0.58)
Days (150-179 days)	40.17***	(1.59)	26.73***	(0.87)	13.44***	(0.88)
Days (180-249 days)	54.39***	(2.57)	34.01***	(1.32)	20.38***	(1.46)
Days (>249 days)	36.79***	(2.39)	26.00***	(1.34)	10.80***	(1.37)
Exp (5-9 yrs)	3.94***	(0.91)	3.61***	(0.49)	0.34	(0.52)
Exp (10-19 yrs)	4.65***	(0.83)	4.47***	(0.45)	0.17	(0.48)
Exp (>=20 yrs)	3.32***	(0.83)	4.61***	(0.45)	-1.29***	(0.47)
Household members						
FH_male	-0.56	(1.13)	-0.21	(0.62)	-0.35	(0.63)
FH_age (under 45)	-0.31	(0.25)	-0.30**	(0.13)	-0.01	(0.14)
FH_age (45-65)	0.46	(0.34)	0.51***	(0.18)	-0.05	(0.19)
FH_age (65 and up)	0.43	(0.50)	0.53**	(0.26)	-0.10	(0.28)
FH_junior	3.95**	(1.66)	1.31	(0.92)	2.65***	(0.91)
FH_senior	4.58***	(1.51)	1.20	(0.81)	3.39***	(0.85)
FH_college	1.08	(1.81)	0.39	(0.97)	0.68	(1.02)
Constant	-98.45***	(13.73)	-33.95***	(7.07)	-64.51***	(8.08)

Note: Robust standard errors are in the parenthesis, and significant levels are denoted by *, ** and *** at 10%, 5% and 1% respectively.