Off-farm Work, Technical Efficiency, and Production Risk: Empirical Evidence from a National Farmer Survey in Taiwan

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Abstract

The objective of this paper is to investigate the differences in yield production, production efficiency, and yield risk for farmers with and without off-farm work. Using a nationwide survey of Taiwanese rice farmers, we estimate a stochastic production frontier model accommodating the technical inefficiency and the production risk simultaneously. Applying the stochastic dominance criterion to rank the estimated technical efficiency and yield risk between professional farmers and farmers with off-farm jobs, our empirical analysis shows that off-farm work is significantly associated with lower technical efficiency. Additionally, farmers with off-farm work face higher production risks. Comparing the marginal effects of input uses on technical inefficiency and yield risk between these groups of farmers, we found a substantial heterogeneity of input uses between these two groups of farmers.

Key words: Off-farm work, technical efficiency, production risk, Taiwan.

Introduction

Off-farm work by farm households is a persistent phenomenon in most countries, and the dependence of farm families on the income from off-farm work has increased steadily over years. To improve the wellbeing of farm households, it is necessary to have a better understanding of the nonfarm business of farm households. The importance of off-farm work has been widely acknowledged and the empirical evidence has been revealed in many countries. For example, according to the summary of historical data reported by the United States Department of Agriculture (USDA), the rate of U.S farm households that work off-farm is approximately 65% on average (Fernandez-Cornejo, 2007). Income from off-farm activities has been shown as a primary source of total farm household income. Similar evidence has also been found in Taiwan. Based on the statistics summarized from the Agricultural Census data in 2001, approximately 75% of the farm households have reported wages or income from an off-farm job.

In light of the increasing prominence of off-farm labor as a crucial determinant of farm household income, attention has been paid to the interaction between the farm practice and off-farm work. It is expected that the increased reliance on off-farm employment may affect the allocation of family labor, thus have influences on farm productivity. On the other hand, off-farm work provides an opportunity for farm households to stabilize household income and reduce uncertainty associated with agricultural production. It is a generally held belief that engaging in the off-farm labor market provides a risk management tool to reduce the income variability for the farm household.

Some of the previous studies have investigated the impacts of off-farm work on farm productivity. For instance, by estimating a stochastic production frontier model, Kumbhakar *et al.* (1989) examined the effects of off-farm income on farm-level efficiency of dairy farms in the United States. Their results show that off-farm work is negatively associated with the technical efficiency. Using a similar approach to the vegetable farm survey in Florida, Fernandez-Cornejo (1992) found similar results. Also, Goodwin and Mishra (2004) used the gross cash income over the total variable costs as a simple proxy for the farm efficiency and analyzed the relationship between the off-farm labor supply and farm productivity. Their results also show that those farm households who work off the farm are less efficient.

On the other hand, past studies have pointed out that farm households may treat off-farm work as a vehicle to stabilize their income (i.e. Mishra and Goodwin, 1997). This is due to the fact that farm commodity prices are more variable than off-farm wages. As predicted by the economic theory, a risk averse farmer will allocate labor and other resources to the less risky income sources (i.e. the off-farm work) until the expected marginal returns are equal between available activities. As a result, the reduction of the income risk of farm production may drive farmers to engage in the off-farm labor market.

Our study contributes to the previous studies of the off-farm work in several aspects. Unlike the previous studies on the examination of the effects of off-farm work on farm efficiency, we consider both technical efficiency and production risk simultaneously. As we have stated earlier, off-farm work may provide a useful tool for risk management. Incorporating production risk into the stochastic production frontier framework is crucial since the main purpose of this type analysis is to predict the technical efficiency of each individual farmer, which measures the ability of the farmer to adopt technology, and production risk may affect the decision making of this process. Therefore, ignoring production risks may result in misleading policy implications. The second objective of this paper is to highlight the potential farm heterogeneity by examining the marginal effects of exogenous variables on inefficiency and risk functions. We investigate if the marginal effects of input use on efficiency are monotonically increasing, and how it may differ between farmers with and without off-farm work.

Using the nationwide survey of the rice farmers in Taiwan, we first estimate two stochastic production frontier functions accounting for production risk for two groups of farmers: those without off-farm work, and those whose income from the off-farm work dominates the income from farming. With the consistent estimates of the production parameters, we then calculate the technical efficiencies and risk terms for these two groups of farmers. Instead of comparing the technical efficiencies and risk on the mean values between these two groups of farmers, we compare the *distributions* of these two indexes (i.e., efficiency and risk) by the stochastic dominance criterion. By doing so, we are able to examine the extent to which efficiencies and risk may be associated with farmer's off-farm work.

This paper is structured as follows. We first outline the econometric strategy and the following section introduces the data used in this study. The presentation of results includes: the estimations of the production functions, the marginal effects of the factors on the inefficiency and risk functions, and a discussion of the distributional differences of efficiency and risk between two groups of farmers. The conclusions from this study are the final section in this paper.

Econometric Strategy

The empirical strategy proposed in this study includes two steps. In the first step, we estimate two stochastic production frontier models for two groups of rice farmers. The first group of farmers is those without off-farm work, while the second group of farmers is those who engage in part-time jobs. Given the consistent estimates of the technical efficiency and risk terms of farmers in each group, we then compare the distributions of the technical efficiency and risk by group based on the stochastic dominance criterion.

<u>*Estimating the Stochastic Frontier Model with Risk*</u>

The stochastic frontier model we estimated is an extension of the standard frontier model by allowing heterogeneity risk terms (Battese, Rambaldi, and Wan, 1997; Kumbhakar and Lovell, 2000; Wang, 2002). Following the approach in Wang (2002), the econometric specification of the production function can be shown as:

(1) $y_i = x_i\beta_1 + v_i - u_i$;

$$v_i \sim N(0, \sigma_{v_i}^2); \qquad u_i \sim N^+(\overline{u}_i, \sigma_{u_i}^2)$$

$$\overline{u}_i = h_i\alpha ; \quad \sigma_{u_i}^2 = \exp(k_i l); \quad \sigma_{v_i}^2 = \exp(z_i r)$$

where y_i is production yield, and v_i and u_i are random error and inefficiency term, respectively. Following the conventional set-up in the stochastic production frontier models, the inefficient term u_i follows the truncated-normal distribution with mean $\bar{u}$ and variance σ_u^2, and the random error v_i follows the normal distribution with zero mean and variance σ_v^2. To capture the heterogeneity of the efficiency and risk terms, the mean and variance functions of the efficiency and risk term are determined by exogenous factors. Furthermore, consistent with Wang (2002) and Battese, Rambaldi, and Wan (1997), the variance functions are assumed to be an exponential functional form. The exponential specification is also widely used in the Just-Pope production function (Just and Pope, 1979). The vector x_i, z_i, h_i, k_i are exogenous variables that affect the deterministic frontier, unobservable variance (i.e. risk), and the mean and variance of the technical inefficiency, respectively. The consistent estimators of equation (1) can be obtained by using the maximum likelihood method on the following log-likelihood function:

$$(2) \quad \ln L = constant - \frac{1}{2}\sum_i \ln[\exp(z_i\gamma) + \exp(k_i l)] + \sum_i \ln\Phi\left(\frac{h_i\alpha}{\sigma_i\lambda_i} - \frac{\varepsilon_i\lambda_i}{\sigma_i}\right) - \frac{1}{2}\sum_i \frac{(\varepsilon_i + h_i\alpha)^2}{\sigma_i^2}$$

where $\sigma_i^2 = \sigma_{v_i}^2 + \sigma_{u_i}^2$; $\varepsilon_i = y_i - x_i\beta$; $\lambda_i = [\exp(k_i l - z_i r)]^{0.5}$.

It is worth mentioning that the general specification of equation (2) is testable for several special cases. Testing the null hypothesis H_0: $\alpha = 0$; H_0: $l = 0$, and H_0: $\gamma = 0$ provides the statistical justification if technical inefficiency and risk functions exhibit heteroscedasticity. These hypotheses can be empirically tested on the null hypothesis.

Since equation (2) is estimated by the maximum likelihood estimation method, likelihood ratio test can be used for testing the null hypothesis.

Based on the consistent estimates of equation (2), the marginal effects of the exogenous factors on the technical efficiency and the risk term can be further derived. The marginal effects, which measure the changes of exogenous factors on the mean and variance functions of the inefficiency, can be derived as (see Wang, 2002):

(3) $$\frac{\partial E(u_i)}{\partial h_i} = \alpha\{1-\xi\frac{\phi(\xi)}{\Phi(\xi)} - [\frac{\phi(\xi)}{\Phi(\xi)}]^2\} + \frac{\sigma_{ui} * l}{2}\{(1+\xi^2)\frac{\phi(\xi)}{\Phi(\xi)} + \xi[\frac{\phi(\xi)}{\Phi(\xi)}]^2\}$$

(4) $$\frac{\partial Var(u_i)}{\partial h_i} = \frac{\alpha}{\sigma_{ui}}\frac{\phi(\xi)}{\Phi(\xi)}(m_1^{\ 2} - m_2) + l * \sigma_{ui}^2\{1 - \frac{\phi(\xi)}{2\Phi(\xi)}[\xi + \xi^3 + (2+3\xi^2)\frac{\phi(\xi)}{\Phi(\xi)} + 2\xi(\frac{\phi(\xi)}{\Phi(\xi)})^2]\}$$

where $\xi = z_i\gamma / \sigma_{ui}$, m_1 and m_2 are the first two moments of u_i.

One of the advantages utilizing the general version of the stochastic production frontier model can be easily seen in equation (3)-(4). The marginal effects of the exogenous factors on the mean and variance functions are not restricted to be necessarily monotonic. Instead, both the positive and negative effects on the production efficiency may exist. The signs and magnitudes of the marginal effects depend on the value of the exogenous determinants. On the other hand, the effect of the exogenous variables on the risk term is relatively simple. It can be shown as:

(5) $$\frac{\partial \sigma_{vi}^2}{\partial z_i} = \exp(z_i\gamma) * \gamma$$

Stochastic Dominance Criterion

Since one of the primary objectives of this paper is to see whether yield risk or production efficiency drives the farmers to work off the farm, we compare the estimated technical efficiency and risk term between these two groups of farmers (professional farmers and farmers working off the farm). Regarding the technical efficiency estimates of each group as a distribution, the differences in distributions of these two technical efficiencies/risk variances can be compared based on the stochastic dominance criterion.

The stochastic dominance analysis has been developed to compare and rank the outcomes of alternative distributions. The comparison and ranking is based on cumulative density functions (CDFs). The two dominance rules discussed below are first order stochastic dominance (FSD) and second order stochastic dominance (SSD) analysis. Assume off-farm work is associated with the distribution of technical efficiency and risk, and the cumulative distribution functions of these two technical efficiencies are given by *P(TE)* and *NP(TE)* for professional farmers and off-farm farmers, respectively. The technical efficiency of the professional farmer group dominates non-participant group in the sense of the FSD *iff*

(6) $NP(TE) - P(TE) \geq 0\,, \quad \forall TE \subseteq R$

with inequality for some $TE \subseteq R$.If equation (6) stands, it implies that the CDF of technical efficiency of professional farmers is greater than the CDF of technical efficiency of the part-time farmer group for all range of the technical efficiency levels. (Chavas, 2004). In graph, the *NP(TE)* is on the left to the *P(TE)*. Alternatively, if these two CDF of technical efficiencies/risk intersect, FSD cannot discriminate between these two alternatives.

If there is no FSD relation between these two distributions, a choice between distributions could be made by the Second Order Stochastic Dominance (SSD) criterion (Hien et al. 1997). Formally, *NP(TE)* dominates *P(TE)* in the SSD sense *iff*

$$(7) \qquad \int_{-\infty}^{TE} (NP(TE) - P(TE))dTE \geq 0, \quad \forall TE \subseteq R$$

with strict inequality for some $TE \subseteq R$. In the graph, SSD test requires a comparison of the area under these two CDF (*NP(TE)* and *P(TE)*). If equation (7) holds, SSD requires that the area under *P(TE)* is always smaller than the area under *NP(TE)*.

Data

Data used in this analysis were taken from the rice farmer survey in Taiwan. This survey is conducted by the Counsel of Agriculture (CoA) in Taiwan annually since 1980. In each year, approximately 1,000 farmers are randomly selected and interviewed. The primary focus of this survey is to understand the production and cost structure of the rice production, and each individual farmer in this survey is requested to report details of the production input use. Although the information of production input and output are revealed, the socio-economic characteristics of farmer or farm household are not investigated. In the recent two waves conducted in year 2005 and 2006, in addition to the input uses of rice production, each individual farmer is asked if he engages in any off-farm job during the production seasons. This information allows us to distinguish two groups of rice farmers: those without off-farm work, and those whose incomes from off-farm jobs are more than their farm revenues.[1]

To increase sample size and validation of the empirical analysis, we combine the recently available waves in year 2005 and 2006. The total sample includes 2,073 rice farmers, but not all of the selected farmers provide full information of input uses. After deleting these missing values, the final sample account for 1,848 rice farmers. Among these rice farmers, 1,326 of them reported that their incomes from other off-farm jobs are larger than their farm revenues. In other words, 72% of the rice farmers are involving in the part-time job, and only 28% of them don't work off the farm. The high proportion of farmers that involve in the off-farm labor market is consistent with the findings in other countries.

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[1] Detail information of each rice farmer's income is confidential, the only available information we have related to off-farm work is whether the incomes from off-farm work are larger than their incomes from the farm revenues. Therefore, we can only category the entire sample into two groups of farmers.

Output variable is defined as the production yield (i.e. production per hectare), and production inputs are categorized into several groups. Labor inputs are measured by the hours spending on the rice production. Consistent with Dhungana, Nuthall, and Nartea (2004) and Audibert (1997), we distinguish the self-provided labor hours and the working hours of hired labor to control for labor quality on yield production. The input expenses per acre for machinery and equipments are measured as the flow value of capital. Per acre expenses of fertilizer and pesticides are also specified. We distinguish the fertilizer and pesticide expenses due to the fact that these two inputs have different implications for yield risk. In addition to the production input, environmental characteristics are also included in the analysis. To take the environmental characteristics into account is important since it is a general belief that environmental factors are significant determinants or sources of production risk. Three variables are specified to represent local environmental characteristics: the average rainfall, temperature and soil quality. These variables are aggregated on the county level. The quality of soil is identified by the Geographic Information System, conducted by the Agricultural Engineering Research Center in Taiwan. A higher score of the soil quality represents a better land quality. The sample statistics of the selected variables, separated by two groups of farmers, are exhibited in Table 1.

Since the primary focus of this study is to examine the differences in rice production between farmers who work off the farm and those who don't, we first look at the differences in production yields. The average yields of production for professional farmers and part-time farmers are 5,773 kg/ha and 5,547 kg/ha respectively. This shows that rice farmers who don't work off the farm have higher yield. It also appears that off-farm work is negatively associated with the variance of the production yield since the standard errors of yields of professional and part-time farmers are 1,324 and 1,228 kg/ha, respectively. This finding can be reinforced in Figure 1 in that the yield distribution for farmers who work off the farm is more flat. With respect to the differences of input uses between these two groups of farmers, it appears that farmers who work off the farm use less labor, fertilizer, pesticides, and capital (Table 1). Also, the average values of rainfall and temperature around the area that these groups of farmers located are higher than the other groups of farmers.

Empirical Results

The empirical results are presented in several sets. First, the estimations of the stochastic production frontier model are discussed (Table 2). Table 3 and 4 present the marginal effects of the exogenous factors on the technical inefficiency and risk functions. The distributional statistics of the estimated technical efficiencies and the risk terms are exhibited in Table 5.

Specification Tests of the Inefficiency and Risk functions

We begin our discussion of the results on the specification tests of interests (the bottom in Table 2). Two null hypotheses are tested to justify if the distinction between technical inefficiency and risk term are appropriate in the rice production function. The first null hypothesis tests if the effects of the exogenous determinants on the mean and variance functions are statistically equal to zero. If the null hypothesis holds, the model is identical to the Just-Pope risk production function. The test statistics of the likelihood ratio test are 41 and 135 for the professional farmer and off-farm farmer groups, respectively. Since both of them are higher than the critical values in the conventional significant level ($x^2(0.95,10)=18.3$), our results provide statistical evidence for the heteroskedasticity of the inefficiency functions. On the other hand, the appropriate accommodation of the risk function can be justified by testing the null hypothesis if the effects of the exogenous variables on the risk function are statistically equal to zero. If the null hypothesis holds, the model is identical to the conventional stochastic production frontier specification. The test statistics of the likelihood ratio test are 127, 170 for groups of professional farmers and off-farm farmers, respectively. Since both of the null hypotheses are rejected at the 5% level or higher (x^2(0.95,8)=15.5), empirical results are supportive to consider the risk function in the empirical analysis.

Estimations of the Production Frontier Model

The deterministic parts of the rice production function are specified as the Cobb-Douglas functional form.[2] As Cobb-Douglas forms were used to illustrate farmers' production behavior, the estimated parameters represent the input-output elasticities of the rice production in Taiwan. All coefficients are positive in the deterministic frontier function, but different elasticities of labor and capital inputs are found for these two groups of farmers. Although self-labor variables for both professional and off-farm farmers are statistically significant at 5% level or higher, the elasticity of the rice yields with respective to self-labor is 5.5% higher for professional farmers than its counterparts. With respect to the effects from the hired-labor, results show that the employment of the hired-labor has positive and significant effects on rice yields for off-farm farmers while the estimation results cannot reject the hypothesis that the corresponding coefficient is zero for professional farmers. In

[2] In the preliminary analysis, we estimated the more general translog production functions. However, most of the second order terms are not significant. Additionally, the calculated input elasticities calculated based on the estimates of the translog forms are negative for some input at certain data points. Therefore, the Cobb-Douglas production functions are chosen.

addition to the effects of the self-labor and the hired-labor input, the yields of rice production for professional and off-farm farmers also response differently to machinery and equipments uses. The coefficient of capital shows that the use of machinery has positive and significant impact on rice production for professional farmers; the rice yield raises 18% when the farmer increases 1% of money investments in machinery and equipment use. Therefore, we may conclude that the rice yields of off-farm farmers are more responsive to the hired-labor variable and the professional farmers benefit more from the use of machinery and equipments, while both professional and off-farm rice farmers in Taiwan relies significantly on the employment of self-labor.

The estimated input elasticities are also compared to the empirical evidence of the rice production of the previous studies (e.g., Audibert, 1997; Huang and Kalirajan, 1997; Fuwa et al. 2007). Our results show that the output elasticity of self-labor is higher than that of hired-labor (0.189 versus 0.011 for professional farmers; 0.134 versus 0.037 for off-farm farmers), which is consistent with Audibert (1997). When comparing the input elasticities for professional farmers in our research with previous studies, the output elasticity with respect to machinery use in our study (0.188) is larger than the findings in Huang and Kalirajan (1997). In addition, the elasticity of fertilizer in our study (0.083) is within the elasticity range reported in Huang and Kalirajan (1997) and Fuwa et al. (2007)[3].

Estimation Results for Technical Inefficiency and Risk Functions

The estimation results of the mean and variance functions of technical inefficiencies and the variance function of risks are reported in Table 2 as well. The coefficients in mean and variance functions of inefficiency indicate how exogenous variables influence the expected level and the stability of technical inefficiencies, respectively.

For the professional farmers, the positive coefficient of self-labor in the mean function indicates that it has negative impact on production efficiency while its positive coefficient in the variance function (of inefficiency) suggests that the employment of self-labor decreases the variance of technical inefficiency. The hired-labor, however, provides opposite impacts. When the professional farmers increase the employment of hired-labor, the expected efficiency as well as the

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[3] Huang and Kalirajan (1997) applied a stochastic varying coefficients frontier approach to estimate the household survey data in China from 1993 to 1995. The GLS results showed that the elasticities of machinery vary between 0.11 (rice farmers in Sichuan in 1994) and 0.16 (rice farmers in Guangdong in 1993 and 1994), while the elasticities of fertilizer are between 0.08 (rice farmers in Sichuan in 1993) and 0.15 (rice farmers in Sichuan in 1995). Fuwa et al. (2007) estimated stochastic frontier production functions using the farm-level and plot-level rice data in eastern India. The empirical results found that the elasticity of fertilizer ranges from 0.004 (lowland, traditional variety) to 0.0947 (upland, traditional variety).

variance of efficiency will increase at the same time.

For off-farm farmers, the impacts from self-labor and hired-labor on the expected level and the stability of technical inefficiency have similar implications to what have been found in the professional farmers model. Additionally, the use of capital (pesticide) has a significant positive (negative) impact on the expected technical efficiency, and the use of fertilizer decreases the stability of technical efficiency of the off-farm farmers.

The parameter estimates in the variance function of risks indicate how exogenous variables may influence production risks. In addition to the production inputs, rainfall, temperature, and soil quality are included in the risk function to accommodate the impacts of environmental conditions on production risks. Results indicate that capital, pesticide, and soil quality are found to be risk-decreasing factors for professional farmers while the hired-labor and rainfalls have significant positive effect on the production risks. As for the off-farm farmers, temperature level and the use of pesticide are statistically significant, but have opposite signs. Pesticide expenditure is a risk-decreasing factor for the off-farm farmers while the production risks goes up as temperature increase.

Marginal Effects of the Inefficiency and Risk Functions

The relationship between technical efficiency and exogenous variables can be discussed in details by measuring the marginal effects of each variable at different percentiles of sample data. The estimation results of marginal effects are presented in Table 4. For the sake of illustration, the marginal effects are depicted in Figures 2-3 by percentiles. Investigating the changes of the marginal effects by percentiles helps to understand if the exogenous variables can have both positive and negative impacts on production efficiency as the value of concerned variable varies (i.e. the "non-monotonic efficiency effects", see Wang, 2002)

Due to the limited space, we only discuss the marginal effects of the exogenous variables that are statistically significant in Table 2. For professional farmers, self-labor and hired-labor are found to have non-monotonic efficiency effects. The use of the first 50% percentile of self-labor is negatively associated with expected inefficiency (i.e., efficiency-enhancing) but the sign of marginal effect turns positive after that. The results for the hired-labor variable have a similar pattern except that the use of first quartile of hired-labor has negative impacts on the expected inefficiency. This implies that the use of excessive labor leads to disadvantages in the production efficiency. The implication is also applicable to off-farm farmers.

For the off-farm farmers, capital is an efficiency-enhancing factor while the pesticide is efficiency-impeding. According to Figure 2, the magnitude of the marginal effect of capital increases from the 5 percentile to the 95 percentile. This indicates that the expected efficiency increases with the use of machinery and equipments; however, the benefit diminishes as the use of machinery increases. The marginal effect of pesticide, on the other hand, has an opposite pattern. The use of pesticide has negative impact on the technical efficiency for off-farm farmers, and the negative influence increases with the use of pesticide.

As for the marginal effects on the variance of technical inefficiency, Table 3 shows that, for professional farmers, the employment of the first 75 percentile of self-labor and the first 10 percentile of hired-labor decreases the variance of technical inefficiency; the self-labor and hired-labor increase the variance of inefficiency when they are outside the above range. For off-farm farmers, the negative marginal effect of self-labor on the variance of inefficiency indicate that the employment of self-labor increase the stability of production efficiency, even though the stability benefit decreases with the number of self-labor employees (Figure 3). Additionally, hired-labor and fertilizer uses lead to an increase in the variance of efficiency, and the magnitude of the marginal effect increases as the number of hired-labor or the use of fertilizer increases.

The marginal effects of the risk function are also calculated and the results are reported in Table 4. The marginal effect on the risk function is monotonic since the sign of the marginal effect depends on the sign of parameter estimates in the risk function. For professional farmers, production risks decrease as the farmers use more machinery and pesticide, or the soil of cultivated land has better quality. However, the risk-reducing benefit of these three inputs decreases when the input use of the concerned variable goes up. On the contrary, hired-labor and rainfall are risk-increasing factors for professional farmers, and an increase in the employment of hired-labor or the amount of rainfall will enhance the risk-increasing effect.

As for the off-farm farmers, pesticide is a risk-reducing factor while temperature has significant positive impact on production risks. The results reported in table 4 and the marginal effect pattern illustrated in Figure 4 point out that the risk-reducing benefit from pesticide decrease as it is used more intensively; the risk-increasing effect from the temperature increases as the temperature goes up.

Comparing the distributions of technical efficiency and risk between groups

The technical efficiency level of each farmer can be measured by comparing its actual rice yields to the reference production frontier. Table 5 reports the sample statistics of technical efficiency by percentiles for professional and off-farm farmers.

The average efficiency level is 0.835 for professional farmers and 0.791 for off-farm farmers. At every selected percentile, professional farmers are generally more efficient than off-farm farmers. For example, the average technical efficiency for the first 25% of the professional farmers is 0.778, which is larger than that of the off-farm farmers (0.704). This indicates a first-order stochastic dominance of the professional farmers over the off-farm farmers. The relationship of the technical efficiency between these two groups of farmers can be better understood using the cumulated density functions (CDF) illustrated in Figure 5. It is obvious that the CDF of professional farmers lies entirely below the CDF of off-farm farmers. Let $\tilde{e}$ denotes an arbitrary efficiency level, and Figure 5 demonstrates an inequality relationship that the proportion of off-farm farmers with efficiency level less than or equal to $\tilde{e}$ is no less than the proportion of such professional farmers. For example, the proportion of off-farm farmers with efficiency level less than or equal to 0.8 is larger than the proportion of professional farmers with the same criteria. That is, there is always more production inefficiency in off-farm farmers than in professional farmers. As such, the conclusion that the technical efficiency of professional farmers dominates that of off-farm farmers can be drawn.

The distribution of risk terms for professional farmers and off-farm farmers is also reported in Table 5. The average risk variance is 0.018 for the professional rice farmers and 0.011 for the off-farm farmers. For the first 25 percentile of professional farmers and off-farm farmers, the risk variance has higher value for off-farm farmers than it is for professional farmers, but the direction of inequality reverses as we move from the 25 percentile to the 95 percentile. Although the values of the risk variance are small for both professional and off-farm farmers, the characteristics of the second-order stochastic dominance can be observed from here. The CDFs for professional and off-farm farmers are illustrated in Figure 6. We can see that the CDF of off-farm farmers cross the CDF of professional farmers when the risk variance is around 0.01. The CDF of professional farmers is higher before the crossing point and then become lower after that. We can say that the risk variance of off-farm farmers dominates that of professional farms according to the second-order stochastic dominance. In this case, although the first 25% percentile of off-farm farmers face more production risks than that of professional farmers, the distribution of risk variance for off-farm farmers are more concentrated and skewed to the right, meaning that in general the off-farm farmers in Taiwan face less production risks than the professional farmers.

Concluding Remarks

It is a general belief that the off-farm salary account for a high proportion of the total farm household income, and empirical evidence has been provided by studies in many countries. The primary objective of this paper is to examine the differences of yield production between two groups of farmers: those who don't work off the farm, and those whose incomes from off-farm salary are higher than farm revenues. Specifically, we examine the differences in input use, the technical inefficiency and production risk between these two groups of farmers.

In contrast to previous studies on the similar topic, our study can be distinguished in several aspects. First, we distinguish the effects of technical inefficiency and production risk on yield production function. Additionally, by specifying the heteroskedasticity form of the inefficiency and risk functions, we investigate if the marginal effects of the input uses and other environmental characteristics on the mean, variance function of inefficiency, and the risk function are monotonic. Finally, we also rank the estimated technical efficiencies and risk distributions of these two groups of farmers by applying the stochastic dominance criterion.

Using national survey of Taiwanese rice farmers in 2005 and 2006, our results reveal some interesting findings. First, different patterns of input uses are found for these two groups of farmers. Input elasticities of part-time farmers are higher for hired labors and pesticide expenditures. The marginal effects of exogenous variables on inefficiency and risk terms also differ. The non-monotonic efficiency is found of self-labor and hired-labor uses for professional farmers. For farmers who work off the farm, capital is an efficiency-enhancing factor while the pesticide is efficiency-impeding. The marginal effect of pesticide, on the other hand, has an opposite pattern. With respect to the risk functions, the effects of input uses on yields are also different between farmers with and without off-farm work. For professional farmers, machinery and pesticide uses are risk decreasing, but hired-labor and rainfall are risk increasing. However, the story is somehow different for the off-farm farmers. Pesticide expenditure is associated with risk reducing while temperature has significant positive impact on production risks.

With respect to the differences in the distributions of technical efficiency and risk, results indicate that the technical efficiencies of the farmers working off the farm are lower than farmers without off-farm work. This result is robust across the entire distribution. However, the story is somehow different for yield risk. When facing minor yield risk, there is no significant difference between these two groups of farmers. Instead, for the relatively low yield risk, farmers with off-farm work face less risk than those without off-farm work. As a result, we may conclude that technical inefficiencies are more significant that drive farmers to work off the farm.

Table 1: Sample statistics

Farm type		Professional		Off-farm	
Sample		522		1326	
Labels	Definitions	Mean	Std Dev.	Mean	Std Dev.
Output and input variables					
yield	yield (kg/ha)	5773	1324	5547	1228
hour_selflabor	hours of self-labor (hr/ha)	135	31	130	32
hour_hirelabor	hours of hired labor (hr/ha)	4.02	2.49	3.80	3.19
capital	machinery and equipment (NT$/ha)	253	45	251	47
pesticide	pesticide per ha (NT$/ha)	8088	3570	6985	3532
fertilizer	fertilizer expense per ha (NT$/ha)	8337	2629	7704	2535
Environmental characteristics (county level)					
rainfall	average rainfall	170	30	173	31
temperature	average temperature	22.23	1.76	22.56	1.55
soil	soil quality	3.59	0.07	3.63	0.08

Table 2: Estimations of the rice production functions

	Professional farmers		**Off-farm farmers**	
	Deterministic Frontier			
	Coefficient	Std. Dev.	Coefficient	Std. Dev.
log(hour_selflabor)	**0.189**	0.066	**0.134**	0.059
log(hour_hirelabor)	0.011	0.007	**0.037**	0.012
log(capital)	**0.188**	0.037	0.009	0.031
log(pesticide)	**0.113**	0.021	**0.137**	0.017
log(fertilizer)	**0.083**	0.036	**0.061**	0.031
constant	**4.343**	0.528	6.341	0.445
	Mean Function of Inefficiency			
log(hour_selflabor)	**2.249**	0.728	**0.640**	0.162
log(hour_hirelabor)	**-0.269**	0.122	**-0.073**	0.031
log(capital)	0.359	0.330	**-0.326**	0.076
log(pesticide)	0.275	0.212	**0.272**	0.069
log(fertilizer)	0.669	0.431	-0.011	0.070
constant	**-23.491**	9.145	**-2.156**	1.071
	Variance Function of Inefficiency			
log(hour_selflabor)	**-2.571**	0.390	**-2.277**	0.393
log(hour_hirelabor)	**0.278**	0.112	**0.351**	0.090
log(capital)	-0.049	0.413	0.076	0.227
log(pesticide)	0.195	0.249	-0.015	0.152
log(fertilizer)	-0.345	0.421	**0.511**	0.223
constant	**12.461**	5.650	3.017	3.244
	Risk Function			
log(hour_selflabor)	0.908	1.062	1.287	0.753
log(hour_hirelabor)	**1.383**	0.320	-0.128	0.150
log(capital)	**-1.744**	0.538	-0.152	0.453
log(pesticide)	**-0.918**	0.348	**-0.799**	0.183
log(fertilizer)	0.036	0.507	-0.404	0.385
rain_ave	**4.178**	1.062	0.248	0.633
temp_ave	2.600	1.513	**10.180**	2.069
soil	**-11.054**	2.798	2.283	1.434
constant	**46.986**	12.193	-17.628	9.080
Log-likelihood	120		262	
Specification tests	test value		test value	
H_0: α= l =0*	41		135	
$H_{0:}\gamma$=0**	127		170	

BOLD are significant at 5% level.

*All coefficients (except constant) in the mean and variance of inefficiency functions are zero. Critical value is $x^2(0.95,10)=18.3$

**All coefficients (except constant) in the risk function are zero. Critical value is $x^2(0.95,8)=15.5$

Table 3: Distributional marginal effects of the inefficiency functions

	Mean Function		Variance Function		Mean Function		Variance Function	
Percentile	Professional	Off-farm	Professional	Off-farm	Professional	Off-farm	Professional	Off-farm
	log(hour_selflabor)				log(fertilizer)			
5%	-0.349	-0.205	-0.147	-0.078	-0.019	0.011	-0.009	0.006
10%	-0.277	-0.164	-0.099	-0.065	-0.008	0.023	-0.004	0.007
25%	-0.148	-0.107	-0.048	-0.047	0.013	0.038	0.002	0.011
50%	-0.065	-0.033	-0.024	-0.032	0.037	0.050	0.007	0.015
75%	0.025	0.122	-0.008	-0.019	0.064	0.062	0.012	0.019
90%	0.191	0.331	0.019	-0.011	0.113	0.071	0.021	0.024
95%	0.590	0.445	0.056	-0.007	0.228	0.077	0.031	0.027
	log(hour_hirelabor)				log(capital)			
5%	-0.074	-0.047	-0.008	0.002	0.016	-0.268	0.004	-0.025
10%	-0.027	-0.032	-0.003	0.003	0.018	-0.234	0.005	-0.024
25%	-0.007	-0.005	0.000	0.004	0.025	-0.169	0.006	-0.021
50%	0.004	0.014	0.002	0.007	0.039	-0.109	0.009	-0.017
75%	0.013	0.023	0.004	0.009	0.054	-0.072	0.012	-0.012
90%	0.028	0.032	0.010	0.012	0.079356	-0.051	0.017	-0.008
95%	0.036	0.037	0.015	0.014	0.139	-0.041	0.021	-0.006
	log(pesticide)							
5%	0.043	0.040	0.009	0.006				
10%	0.047	0.048	0.010	0.007				
25%	0.055	0.066	0.013	0.011				
50%	0.062	0.097	0.016	0.015				
75%	0.074	0.145	0.020	0.019				
90%	0.095	0.198	0.025	0.022				
95%	0.139	0.225	0.028	0.023				

Table 4: Distributional marginal effects on risk function

	Professional	*Off-farm*	*Professional*	*Off-farm*
Percentile	log(hour_selflabor)		log(capital)	
5%	0.001	0.002	-0.088	-0.004
10%	0.002	0.004	-0.060	-0.003
25%	0.005	0.007	-0.038	-0.002
50%	0.010	0.013	-0.020	-0.002
75%	0.020	0.019	-0.009	-0.001
90%	0.031	0.028	-0.003	-0.001
95%	0.046	0.034	-0.002	0.000
	log(hour_hirelabor)		rainfall	
5%	0.001	-0.003	0.004	0.000
10%	0.003	-0.003	0.008	0.001
25%	0.007	-0.002	0.021	0.001
50%	0.016	-0.001	0.048	0.003
75%	0.030	-0.001	0.090	0.004
90%	0.048	0.000	0.144	0.005
95%	0.070	0.000	0.211	0.007
	log(pesticide)		temperature	
5%	-0.046	-0.021	0.002	0.014
10%	-0.032	-0.017	0.005	0.034
25%	-0.020	-0.012	0.013	0.059
50%	-0.010	-0.008	0.030	0.105
75%	-0.005	-0.005	0.056	0.151
90%	-0.002	-0.003	0.090	0.219
95%	-0.001	-0.001	0.131	0.267
	log(fertilizer)		soil	
5%	0.000	-0.011	-0.558	0.003
10%	0.000	-0.009	-0.382	0.008
25%	0.000	-0.006	-0.238	0.013
50%	0.000	-0.004	-0.126	0.024
75%	0.001	-0.002	-0.056	0.034
90%	0.001	-0.001	-0.021	0.049
95%	0.002	-0.001	-0.010	0.060

Table 5: Distributions of technical efficiency and risk terms

	Technical Efficiency		*Risk Term*	
	Professional	Off-farm	Professional	Off-farm
Mean	0.835	0.791	0.018	0.011
Std. Dev.	0.116	0.131	0.030	0.008
Percentile				
1%	0.471	0.441	0.000	0.001
5%	0.575	0.537	0.001	0.001
10%	0.680	0.599	0.002	0.003
25%	0.778	0.704	0.005	0.006
50%	0.872	0.824	0.011	0.010
75%	0.916	0.899	0.022	0.015
90%	0.941	0.933	0.035	0.022
95%	0.954	0.945	0.051	0.026

Figure 1: Empirical yield distribution of these two group rice farmers

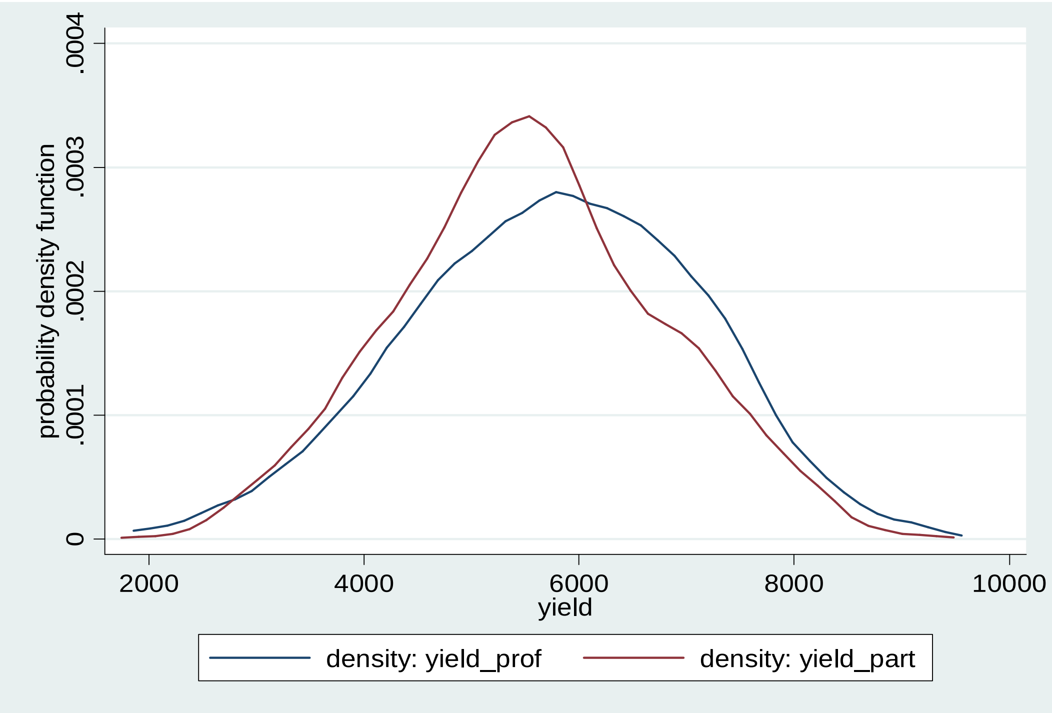
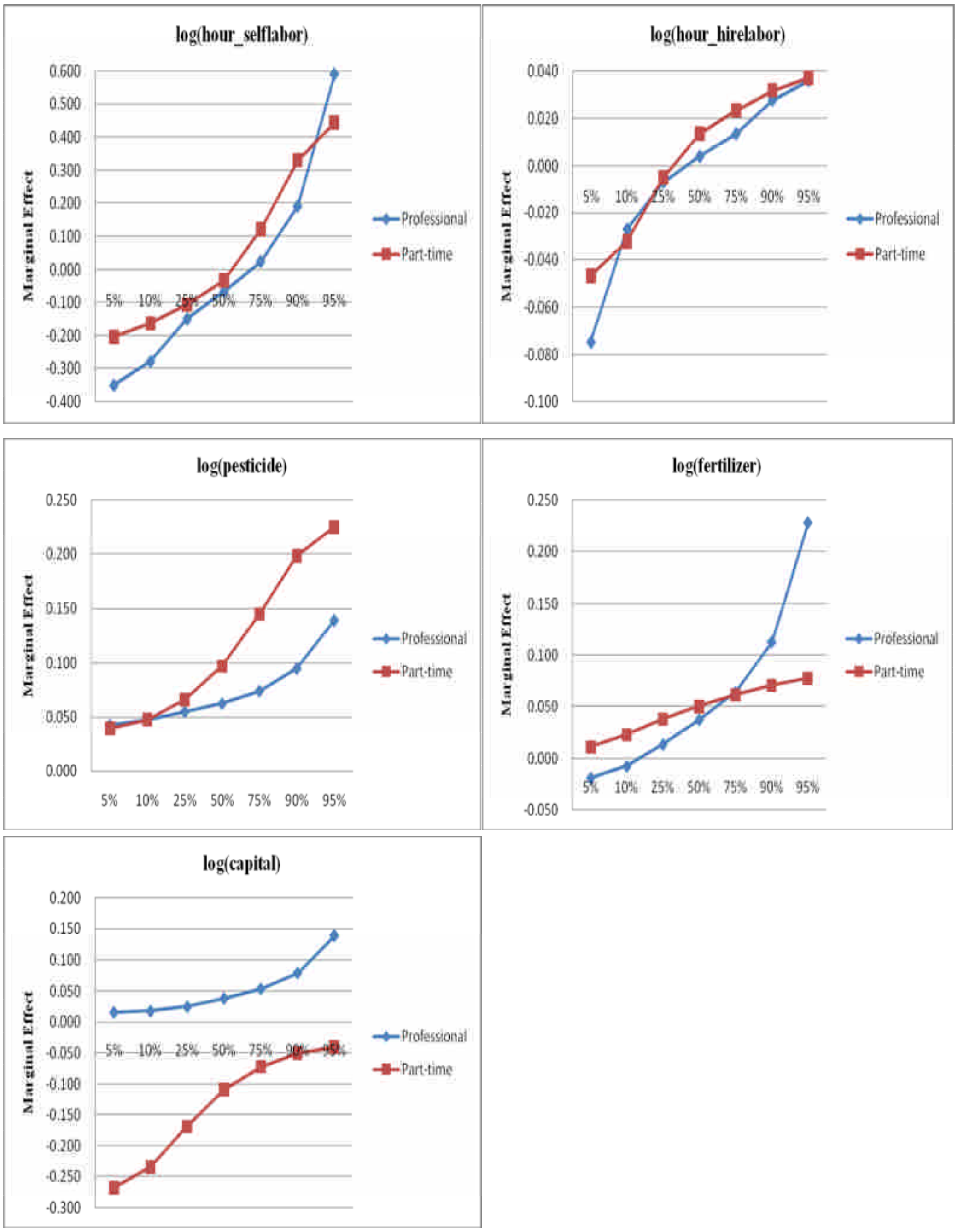
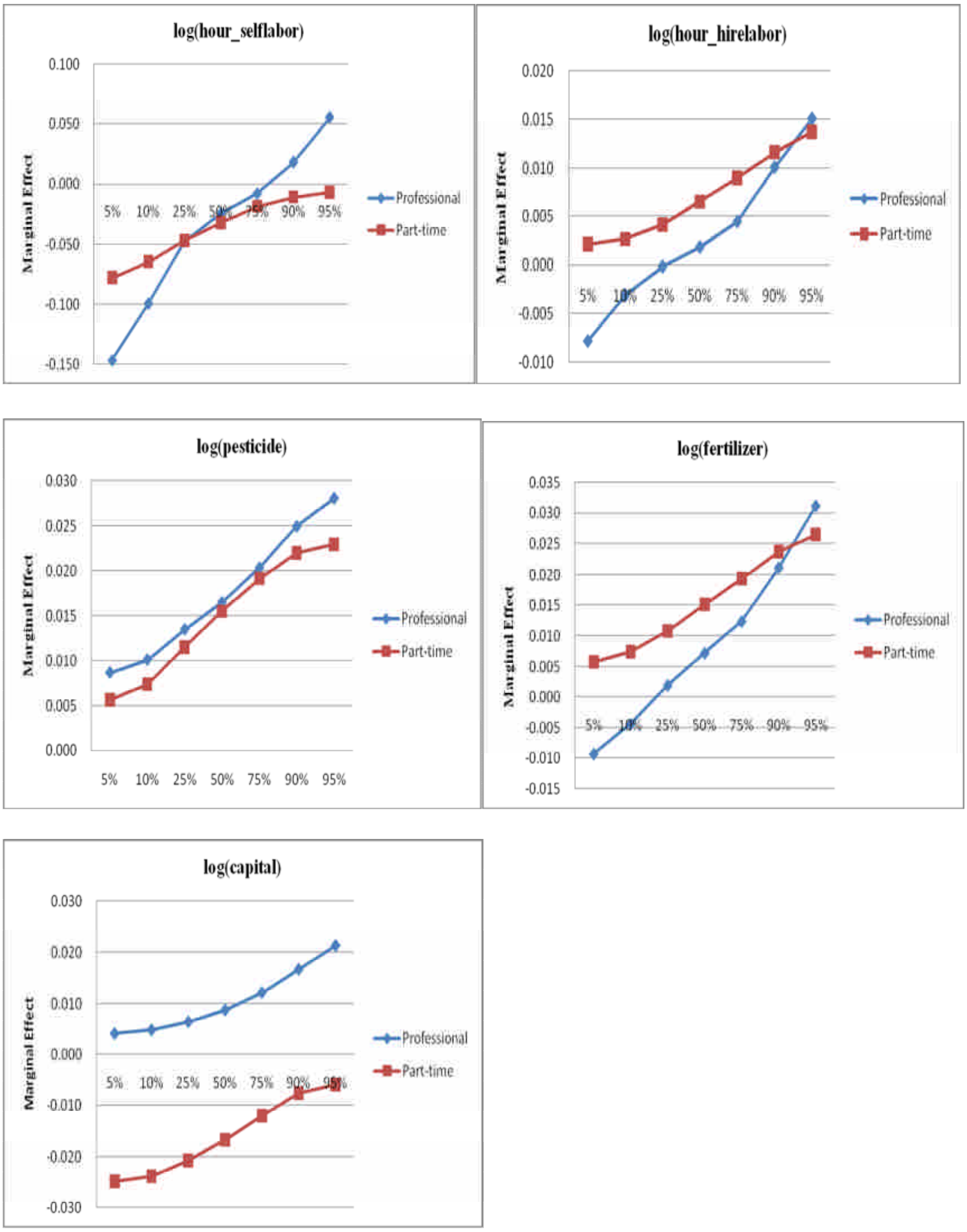


Figure 2: Distributions of the Marginal Effects of the Mean Function



Figrue 3: Distributions of the Marginal Effects of the Variance Function



Figrue 4: Distributions of the Marginal Effects of the Risk Function

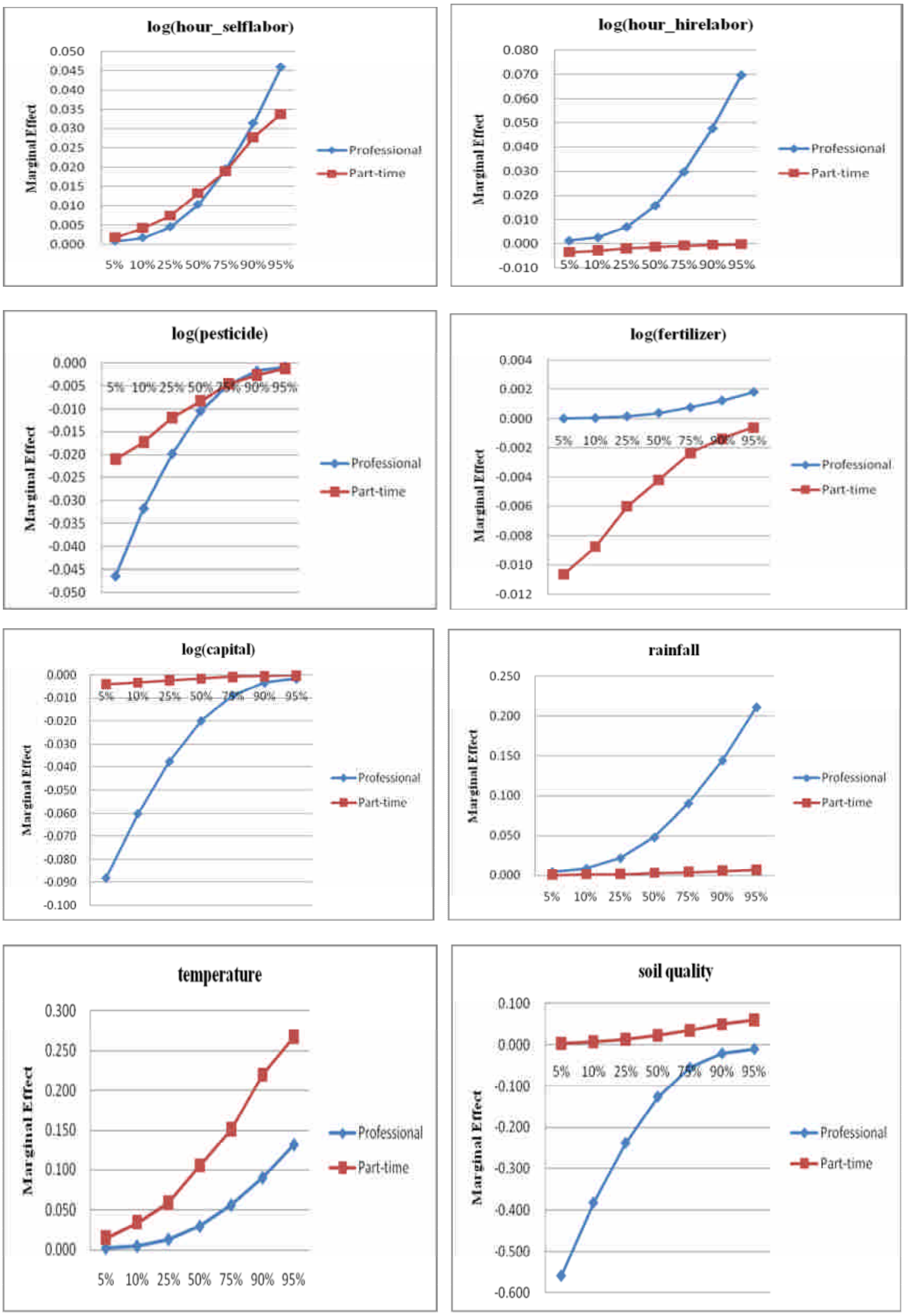


Figure 5: Distributions of technical efficiency scores

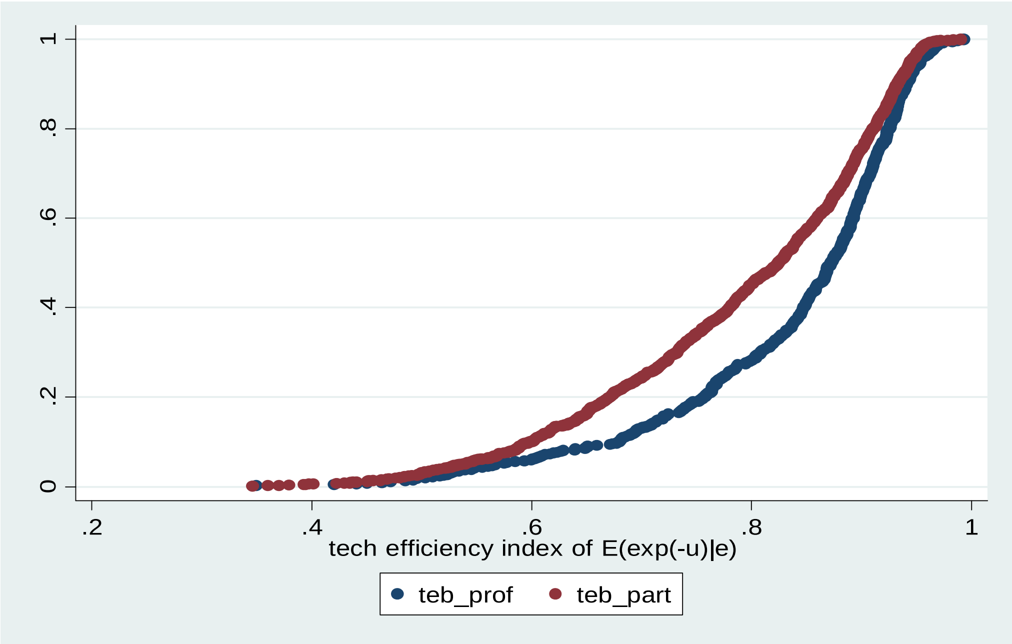
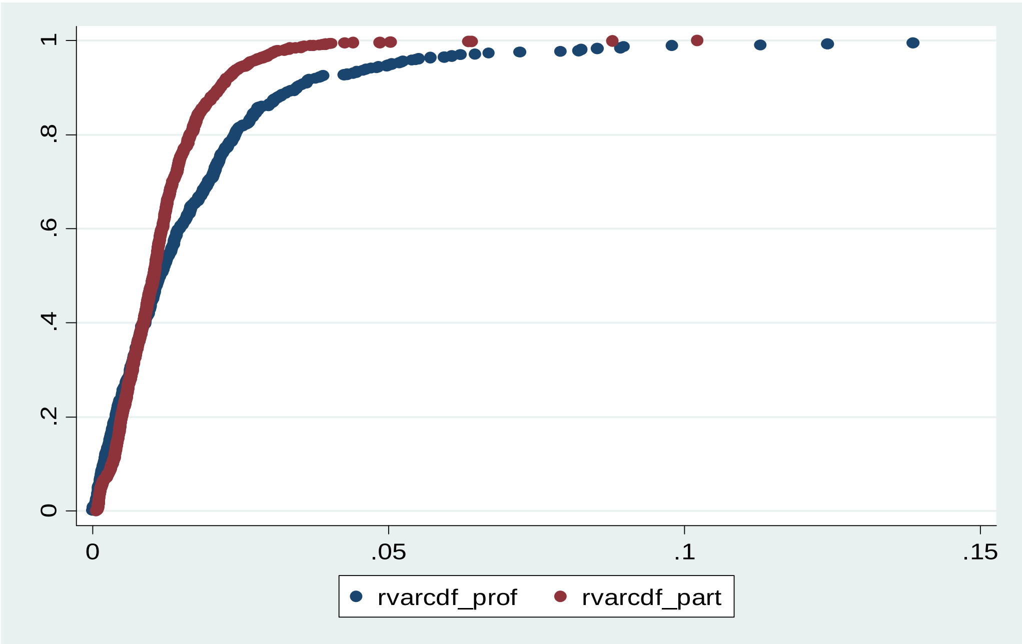


Figure 6: Distributions of the risk terms



References

Abdulai, A., Eberlin, R. (2001). “Technical efficiency during economic reform in Nicaragua: evidence from farm household survey data.” *Economic System* 25:113–125.

Audibert, M. (1997). “Technical inefficiency effects among paddy farmers in the villages of the ‘Office du Niger’, Mali, West Africa.” *Journal of Productivity Analysis* 8:379–394.

Battese, G. (1992). “Frontier production functions and technical efficiency: a survey of empirical application in agricultural economics.” *Agricultural Economics* 7:185–208.

Bagi, F. (1984). “Stochastic frontier production function and farm-level technical efficiency of full-time and part-time farms in West Tennessee.” *North Central Journal of Agricultural Economics* 6: 48-55.

Battese, G., Rambaldi, A., and Wan, G. (1997). “A stochastic frontier production function with flexible risk properties.” *Journal of Productivity Analysis* 8: 269-280.

Chavas, J. P. (2004). *Risk Analysis in Theory and Practice.* Amsterdam; Boston: Elsevier Butterworth-Heinimann Publishers.

Dahl, B., Wilson, W., and Nganje, W. (2004). “Stochastic dominance in wheat variety development and release strategies.” *Journal of Agricultural and Resource Economics* 29: 94-111.

Dhungana, B., Nuthall, P., and Nartea, G. (2004). “Measuring the economic inefficiency of Nepalese rice farms using data envelopment analysis.”*Australian Journal of Agricultural and Resource Economics* 48: 347-369.

Fernandez-Cornejo, J. (2007). “Off-farm income, technology adoption, and farm economic performance.” Economic Research Report No. ERR-36. Economic Research Service, U S. Department of Agriculture, Washington, D. C.

Fuwa, N., Edmonds, C., and Banik, P. (2007). “Are small-scale rice farmers in eastern India really inefficient? examining the effects of microtopography on technical efficiency estimates.” *Agricultural Economics* 36: 335-346.

Goodwin, B., and Mishra, A. (2004). “Farming efficiency and the determinants of multiple job holding by farm operators.” *American Journal of Agricultural Economics* 86: 722-729.

Huang, Y., and Kalirajan, K. (1997). “Potential of China’s grain production: evidence from the household data.” *Agricultural Economics* 17:191–199.

Just, R., and Pope, R. (1979). “Stochastic specification of production functions and economic implications.” *Journal of Econometrics* 7: 67-86.

Kalirajan, K., and Shand, R. (1986). “Estimating location-specific and firm-specific technical efficiency: an analysis of Malaysian agriculture.” *Journal of Economic Development* 11:147–160.

Kwon, O., and Lee, H. (2004). “Productivity improvement in Korean rice farming: parametric and non-parametric analysis. *Australian Journal of Agricultural and Resource Economics* 48:323–346.

Kumbhakar, S. (2002). “Specification and estimation of production risk, risk preference, and technical efficiency.” *American Journal of Agricultural Economics* 84: 8-22.

Kumbhakar, S., and C. A. K. Lovell. (2000). *Stochastic Frontier Analysis*. New York: Cambridge University Press.

Mishra, A., and Goodwin, B. (1997). “Farm income variability and the supply of off-farm labor.” *American Journal of Agricultural Economics* 79: 880-887.

Paxton, J. (2007). “Technical efficiencies in a semi-formal financial sector: the case of Mexico.” *Oxford Bulletin of Economics and Statistics* 69: 57-74.

Phimister, E., and Roberts, D. (2006). “The effect of off-farm work on the intensity of agricultural production.” *Environmental and Resource Economics* 34: 493-515.

Sherlund, S., Barrett, C., and Adesina, A. (2002). "Smallholder technical efficiency controlling for environmental production conditions." *Journal of Development Economics* 69: 85-101.

Smith, K. (2002). "Does off-farm work hinder smart farming?" *Agricultural Outlook* 294:28-30, Economics Research Service, U.S Department of Agriculture.

Surendra, P., and Williamson, Jr. H. (1981). "Part-time farming: productivity and some implications of off-farm work by farmers." *Southern Journal of Agricultural Economics* 13: 61-67.

Tadesse, B., and Krishnamoorthy, S. (1997). "Technical efficiency in paddy farms of Tamil Nadu: an analysis based on farm size and Ecological zone." *Agricultural Economics* 16:185–192.

Wang, H. (2002). "Heteroskedasticity and non-monotonic efficiency effects of a stochastic frontier model." *Journal of Productivity Analysis* 18: 241-253.