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Off-farm work, technical efficiency, and rice production risk in Taiwan

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Abstract

This article investigates the differences in yield production, production efficiency, and yield risk for farmers both with and without off-farm work. Using a nationwide survey of rice farmers in Taiwan, we estimate two stochastic production frontier models that accommodate technical inefficiency and production risk simultaneously for farmers both with and without off-farm work. The stochastic dominance criterion is then applied to compare the differences in the distributions of the estimated technical efficiency and yield risk between groups. The empirical results indicate that these two groups of farmers use resources in different ways, and off-farm work is not necessarily associated with lower technical efficiency. For farmers in the lower percentiles of the efficiency distribution, those with off-farm work are more efficient than their counterparts without off-farm work. In addition, farmers with off-farm work face higher production risk and this result is robust for the entire distribution.

JEL classifications: J21, Q12

Keywords: Off-farm work; Technical efficiency; Production risk; Stochastic dominance criterion; Taiwan

1. Introduction

Off-farm work by farm households is a persistent phenomenon throughout the world, both in less developed and developing countries, and the dependence of farm families on the income from off-farm work has increased steadily over the years. The importance of off-farm work has also been acknowledged in many countries. For example, by using a random farmer survey in rural Ghana, Jolliffe (2004) reported that approximately 74% of the farm households engaged in some form of nonfarm work. According to the historical data reported by the U.S. Department of Agriculture, the proportion of U.S. farm households that work off-farm is approximately 65% on average (Fernandez-Cornejo, 2007). 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 off-farm salaries.

In light of the increasing importance of off-farm income as a crucial determinant of farm household well-being, a considerable body of literature has examined the roles of household characteristics, the human capital of the farm operator and spouse, as well as farm programs related to off-farm labor participation (e.g., El-Osta and Morehart, 2008; El-Osta et al., 2007, 2008; Huffman and Lange, 1989; Lass et al., 1991; Mishra and Goodwin, 1997). Attention has also been paid to the interaction between the farm practice and the off-farm work of the farm household (e.g., Phimister and Roberts, 2006). It is expected that the increased reliance on off-farm employment affects the allocation of family labor, and thus exerts an influence on farm productivity. On the other hand, off-farm work provides an opportunity for farm households to stabilize household income and reduce the uncertainty associated with agricultural production. It is a generally held belief that off-farm employment provides a risk management tool to reduce the income variability associated with the farm household (e.g., El-Osta and Morehart, 2008; El-Osta et al., 2007).

Some studies have also documented the impacts of off-farm work on farm productivity (e.g., Bagi, 1984; Kumbhakar et al., 1989; Sherlund et al., 2002; Smith, 2002). For instance, by

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article. Please note: Wiley-Blackwell, Inc. is not responsible for the content or functionality of any supporting information supplied by the author. Any queries (other than missing material) should be directed to the corresponding author for the article.

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estimating a stochastic production frontier model, Kumbhakar et al. (1989) examined the effects of off-farm work on the farm-level efficiency of dairy farms in the state of Utah. Their results show that off-farm work is negatively associated with technical efficiency. Using a similar approach to the vegetable farm survey in Florida, Fernandez-Cornejo (1992) obtained similar results. In addition, Goodwin and Mishra (2004) used the gross cash income over the total variable costs as a simple proxy for the farm's efficiency and analyzed the relationship between the off-farm labor supply and farm productivity. Their results show that those farm households that work off the farm are less efficient.

On the other hand, studies on production risk in agricultural production have been extensive over several decades and research interest in agricultural risk continues to grow. The relationship between farmers' off-farm work and production risks has also been examined. Mishra and Goodwin (1997), for example, have demonstrated that farm households may treat off-farm work as a vehicle to stabilize their income due to farm commodity prices being more variable than off-farm wages. As predicted by production 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 between available activities are equal to each other. As a result, the reduction in farm production risk may lead farmers to participate in the off-farm labor market.

The objective of this study is to compare the production behavior of rice farmers both with and without off-farm work in Taiwan. Our study contributes to previous studies on off-farm work by accommodating technical efficiency and production risk simultaneously. Since uncertain weather conditions (such as temperature and rainfall) are associated with production risk in relation to rice growing in Taiwan (Chen and Chang, 2005), and other factors such as the use of pesticide, fertilizer, and capital may give rise to yield uncertainties as well (Dai, 2006), the joint consideration of risk and efficiency in off-farm work is important since the technical efficiency of each farmer, which measures the ability of the farmer to adopt technology, as well as production risk, may affect the output response of crop production.

By using a national survey of rice farmers in Taiwan, we first estimate two stochastic production frontier functions that account for the production risk of two groups of farmers: those who report off-farm income, and those who do not. With the consistent estimates of the production parameters, we then calculate and compare the technical efficiencies and risk terms for these two groups of farmers. In addition to comparing the technical efficiencies and risk at the mean levels between these two groups of farmers, we also compare the *distributions* of these two indexes (i.e., efficiency and risk) according to the stochastic dominance criterion. In doing so, we are able to examine the extent to which efficiencies and risk may be associated with farmer's off-farm work in different locations of the distributions.

2. Conceptual framework

A simple conceptual framework is built on the conventional agricultural household production model that examines the labor allocation decisions (e.g., El-Osta et al., 2007, 2008; Hallberg et al., 1991) by accommodating production risk and technology. There are fixed endowments of operator time ($\bar{E}$), and time is allocated to leisure (l), farm production (L), and off-farm work (L_m). The household receives income from agricultural sales as well as the paid salaries from the off-farm jobs. Following Kumbhakar (2002), the production function is a function of farm labor and is specified as: $F(L) = f(L) + g(L)\varepsilon - h(L)u$. The functions $f(.)$ and $g(.)$ specify the effects of inputs on the mean level of output and production risk, respectively. The error associated with output risks, ε, is assumed to follow an arbitrary distribution of $\varepsilon \sim i.i.d.(0, \sigma_\varepsilon^2)$. An input is regarded as risk increasing (decreasing) if $g'(.)$ is positive (negative). Production efficiency is reflected in $h(.)u$, where $u \sim i.i.d.(\bar{u}, \sigma_u^2)$ is the random noise on a stochastic production frontier function. The utility of the farm household depends on the consumption (C) and leisure (l), and the farm households maximize their expected utility subject to the total available income and a time constraint

$$\operatorname*{Max}_{C,l} = EU(C, l) \tag{1}$$

s.t.

$$C = P * [f(L) + g(L)\varepsilon - h(L)u] + w * L_m \tag{2}$$

$$\bar{E} = L + l + L_m, \tag{3}$$

where $EU(.)$ is the expected utility of each farm, and P and w represent the price of the agricultural product and the equilibrium off-farm wage rate, respectively. To solve the model, we first substitute Eqs. (2) and (3) into Eq. (1), and this yields

$$\begin{aligned}\operatorname*{Max}_{L,L_m} = EU\{\{P * [f(L) + g(L)\varepsilon - h(L)u]\\ +w * L_m\}, \{\bar{E} - L - L_m\}\}.\end{aligned} \tag{4}$$

The first-order necessary Kuhn-Tucker conditions for the optimal locations of time allocated in farm production and off-farm work are

$$\frac{\partial EU(.)}{\partial L} = \frac{\partial EU(.)}{\partial C} * P * (f_L + g_L\varepsilon - h_L u) - \frac{\partial EU(.)}{\partial l} = 0; \tag{5}$$

$$\begin{aligned}&\frac{\partial EU(.)}{\partial L_m} = \frac{\partial EU(.)}{\partial C} * w - \frac{\partial EU(.)}{\partial l} \leq 0; \quad L_m \geq 0;\\ &\frac{\partial EU(.)}{\partial L_m} * L_m = 0.\end{aligned} \tag{6}$$

Equation (6) determines the optimal time allocation of the farm household to off-farm work. Two optimal conditions possibly occur: the inequality constraint holds if the farmers do not work off the farm, while the equality constraint holds if the farmers participate in the off-farm labor market. Solving Eqs. (5) and (6) simultaneously yields two possible optimal labor allocations: (L_1^*, L_m^*) for farmers who work off the farm, and $(L_0^*, 0)$ for farmers who do not engage in off-farm work. If the optimal use of labor is further plugged into the production function, this yields two possible optimal agricultural supply functions

$$F(L_1^*) = f(L_1^*) + g(L_1^*)\varepsilon - h(L_1^*)u \quad \text{if } \mathrm{L}_\mathrm{m}^* > 0, \tag{7}$$

$$F(L_0^*) = f(L_0^*) + g(L_0^*)\varepsilon - h(L_0^*)u \quad \text{if } \mathrm{L}_\mathrm{m}^* = 0. \tag{8}$$

Equations (7) and (8) guide our empirical analysis. To link the theoretical framework to the empirical analysis, several econometric issues have to be addressed. First, it is likely that the off-farm work decision may be correlated with the farm productivity due to some unobservable characteristics (such as pride, the preference of the farm operator to work, etc.), which may cause the potential endogeneity or self-selection bias problem. A conventional way of correcting the endogeneity problem is to apply Heckman's method by adding the Inverse Mills Ratio (IMR) to the production function (Heckman, 1979). While this approach is theoretically sound, deriving the symbolic forms of the correction terms is not obvious because the production functions contain a composited error in our case. To derive the IMR (i.e., the truncated mean function) given the complicated error structure in our case is not as straightforward as that in the original Heckman model.[1] Moreover, even if the symbolic forms of the IMR can be derived with any luck, one still needs to empirically find some valid instruments, which are assumed to directly affect the off-farm work decision of the operator and which affect the farm production in an indirect way, to econometrically identify the model (i.e., the exclusion condition, as in Wooldridge, 2002). Finding a good instrument is also empirically challenging, and using invalid instruments can lead to worse estimations when compared to the case where there is no correction for self-selection bias (Wooldridge, 2002).

Given the constraints of using cross-sectional data with limited information of the socioeconomic characteristics of the farm operator and the farm household, finding appropriate instruments is not trivial. In addition, due to the lack of a tractable empirical method to handle the endogeneity between a binary choice model and the stochastic production frontier model with production risk, in our empirical analysis, we simply separate the farmers into two groups (those with and those without off-farm work), and estimate the production function for each group of farmers.

3. 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 farmers. In what follows, we compare the distributions of the estimated technical efficiency and risk between groups based on the stochastic dominance criterion.

3.1. Estimating the stochastic frontier model with risk

The estimated model is an extension of the standard frontier model that allows heterogeneous risk terms (Battese et al., 1997; Wang, 2002). Following Wang (2002), the econometric specification of the production function can be shown as

$$\begin{aligned} &y_i = x_i\beta + v_i - u_i;\\ &v_i \sim N\big(0, \sigma_{v_i}^2\big); \quad u_i \sim N^+\big(\bar{u}_i, \sigma_u^2\big)\\ &\sigma_{v_i}^2 = \exp(z_i r); \quad \bar{u}_i = w_i\alpha, \end{aligned} \tag{9}$$

where y_i and x_i are the logarithm of the production yield and inputs, respectively, and β is a vector of coefficients that characterize the production frontier. The notations v_i and u_i are the random error and inefficiency terms, respectively. Following the conventional specification in the stochastic production frontier model, the random error v_i follows a normal distribution with zero mean and variance σ_{vi}^2, and the inefficiency term u_i follows a truncated-normal distribution with mean $\bar{u}$ and variance σ_u^2. To capture the heterogeneity of the efficiency and risk terms, the mean efficiency and risk functions are determined by exogenous factors. The vector w_i denotes exogenous variables that have influences on the mean value of production inefficiency. The risk function is assumed to have an exponential functional form with the vector of the exogenous determinants z_i (Battese et al., 1997; Just and Pope, 1979). The notation α is a vector of parameters associated with the mean of the production inefficiency while the notation γ is the vector of parameters associated with the production risk. The consistent estimators of Eq. (9) can be obtained by using the maximum likelihood estimation method on the following log-likelihood function

[1] Conceptually, it is possible to accommodate the binary probit choice mechanism and the production function that contains efficiency and risk. However, to accommodate the sample selection problem directly, one has to specify the conditional distributions for the components (v_i-u_i | *given the off-farm work decision*), and estimate Eqs. (7) and (8) along with the off-farm work binary choice equation simultaneously. This is empirically challenging because the random variable u is assumed to be a one-sided error, and the joint distribution is multivariate. For estimation purposes, it is necessary to derive the symbolic form of the correction terms (i.e., the truncated mean function with a composite error). The previous literature is silent on this topic and only one study has proposed a way of estimating the sample selection model using a stochastic production frontier model (Kumbhakar et al., 2008). Their method involves a complicated simulated MLE estimation due to the lack of a closed form solution. Our model is more complicated than that of Kumbhakar et al. (2008) since we consider not only the technical efficiency but also the production risk. To the best of our knowledge, no one has developed a tractable empirical method to solve this particular problem.

$$\ln L = \text{cons}\tan t - \frac{1}{2}\sum_i \ln\left[\exp(z_i\gamma) + \sigma_u^2\right] + \sum_i \ln\Phi\left(\frac{w_i\alpha}{\sigma_i\lambda_i} - \frac{\varepsilon_i\lambda_i}{\sigma_i}\right) - \frac{1}{2}\sum_i \frac{(\varepsilon_i + w_i\alpha)^2}{\sigma_i^2}, \quad (10)$$

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

The general specification of Eq. (10) is testable for several special cases. Testing the null hypotheses $H_0{:}\alpha = 0$, and $H_0{:}\gamma = 0$ provides the statistical justification if the technical inefficiency and risk functions are heteroskedastic. If the parameters $\alpha = 0$, then Eq. (9) is simply a Just-Pope type of production risk function (Just and Pope, 1979). By contrast, Eq. (9) becomes the conventional stochastic production frontier model without the consideration of risk if the parameter $\gamma = 0$ (Aigner et al., 1977). The likelihood ratio test can be conducted for each null hypothesis. The technical efficiency of each farmer can be then calculated as $TE_i = E[\exp(-u_i)|\hat{\varepsilon}_i]$ (see Battese and Coelli, 1988), and the risk term of each farmer is the exponential function of the vector specified in the risk functions, that is, $\exp(z_i\hat{\gamma})$.

3.2. Stochastic dominance criterion

The next step of the analysis is to compare the estimated technical efficiencies and risk terms between these two groups of farmers (i.e., with and without off-farm work). Two statistical tests are used. The first method is based on the conventional method of moments to test if the means and the variances between these two groups of farmers are statistically equal by applying the *t*-test and the *F*-test, respectively. To further compare the differences in the distributions of these two technical efficiencies/risk distributions, the stochastic dominance criterion is then applied following Sherlund et al. (2002).[2] The stochastic dominance analysis is developed to rank the outcomes of alternative distributions. The ranking is based on cumulative density functions (CDFs). The two dominance rules discussed below are the first-order stochastic dominance (FSD) criterion and the second-order stochastic dominance (SSD) criterion. It is assumed that the off-farm work is associated with the distribution of technical efficiency and production risk, and that the cumulative density functions of these two technical efficiencies are given by *P(TE)* and *NP(TE)* for farmers with and without off-farm work, respectively. The technical efficiency of the farmers with off-farm work dominates its counterpart in the sense of the FSD *iff*

$$NP(TE) - P(TE) \geq 0, \quad \forall\, TE \subseteq R. \quad (11)$$

If Eq. (11) stands, the CDF of the technical efficiency of the farmers with off-farm work is greater than the CDF of the technical efficiency of their counterparts throughout the whole range of the technical efficiency levels (Chavas, 2004). In graphical terms, *NP(TE)* is to the left of *P(TE)*. Alternatively, if these two CDFs of the technical efficiencies/risk intersect, the FSD cannot discriminate between these two alternatives.

If there is no FSD relationship between these two distributions, a choice between distributions could be made based on the SSD criterion (Chavas, 2004). Formally, *NP(TE)* dominates *P(TE)* in the SSD *iff*

$$\int_{-\infty}^{TE} (NP(TE) - P(TE))\, dTE \geq 0, \quad \forall\, TE \subseteq R, \quad (12)$$

with strict inequality for some $TE \subseteq R$. Graphically, the SSD test requires a comparison of the area under these two CDFs. If Eq. (12) holds, the SSD requires that the area under *P(TE)* be always smaller than the area under *NP(TE)*.

4. Data sources

The data used in this analysis were drawn from the rice farmer survey, which has been conducted by the Council of Agriculture (CoA) in Taiwan since 1980. In each year, approximately 1,000 farmers are selected and interviewed.[3] The sample selection criterion is based on the proportion of the rice farms in each administrative region, and thus it is representative of the rice farmers in Taiwan. The primary focus of this survey is to understand the production and cost structure in rice production, and each individual farmer in this survey is requested to report details regarding the production output and inputs used. However, the socioeconomic characteristics of the farmers or farm households are not documented. In the most recent two surveys (for the years 2005 and 2006), in addition to the detailed information of rice production, each individual farmer was asked if he engaged in any off-farm job during the production season. This information allows us to distinguish two groups of rice farmers: those with and those without off-farm jobs.[4] The two recent data sets of 2,073 rice farmers in 2005 and 2006 were combined for the analysis. After deleting those with missing values, the final sample accounted for 1,848 rice farmers. Of this total, 1,326 farmers reported receiving income from off-farm jobs (72%).

Similar to the empirical specification of rice production found in previous studies (e.g., Audibert, 1997; Dhungana et al., 2004; Fu et al., 1992; Fuwa et al., 2007; Kwon and Lee, 2004), the output variable is defined as the production yield (i.e., production per hectare). Production inputs are categorized into several groups. Labor inputs are measured by the hours spent on rice production. Following Dhungana et al. (2004) and Audibert

[2] The stochastic dominance criterion had been applied by Sherlund et al. (2002) to compare the distribution of the technical efficiency using the smallholder rice farmer data in West Africa.

[3] Although this data set is compiled annually, it is difficult to match the same farmer across different years. Therefore constructing a panel data structure is infeasible.

[4] Detailed information regarding each rice farmer's income is not available; the only information we have related to off-farm work is whether he/she works off the farm.

Table 1
Sample statistics

Sample (%) Labels	Definitions	Without off-farm work 522 (28%) Mean	Std dev.	Off-farm work 1326 (72%) Mean	Std dev.	P-value*
Production and farm characteristics variables						
yield	yield (kg/ha)	5,773	1,324	5,547	1,228	0.005
hourselflabor	hours of self-labor	135.15	30.55	130.13	31.57	<0.001
hourhirelabor	hours of hired labor	4.02	2.49	3.80	3.19	0.130
capital	mechinary and equipment (NT$/ha)	252.97	44.65	250.60	46.73	0.155
pesticide	pesticide per ha (NT$/ha)	8,088	3,570	6,985	3,532	<0.001
fertilizer	fertilizer expense per ha (NT$/ha)	8,337	2,629	7,704	2,535	<0.001
farmsize1	If operated land <0.5 ha.	0.23	0.42	0.26	0.44	0.047
farmsize2	If operated land > = 0.5 and <1.0 ha.	0.29	0.45	0.32	0.47$	–
farmsize3	If operated land > = 1.0 and <1.5 ha.	0.19	0.39	0.23	0.42	–
farmsize4	If operated land > = 1.5 ha.	0.29	0.45	0.20	0.40	–
r_selflabor	Ratio of self-labor over the total labor	0.97	0.02	0.97	0.02	0.417
class	Number of production-marketing teams (divided by 10)	1.92	1.21	1.50	1.23	<0.001
member	Number of farmers per production-marketing team (divided by 100)	1.98	0.89	2.06	0.97	0.360
Environmental characteristics (county level)						
rain ave	average of rainfall	170.29	29.82	173.22	30.69	0.002
temp ave	average temperature	22.23	1.76	22.56	1.55	0.009
soil	soil quality	3.59	0.07	3.63	0.08	<0.001

Data were drawn from the national survey of rice farmers in Taiwan in 2005 and 2006.
*Conducted in t-test to test the equality of the two sample means.
$The chi-square test is used for the four category of the farmsize variables.

(1997), we distinguish the self-provided labor hours and the working hours of hired labor to control for different labor qualities. The input expenses per acre for machinery and equipment 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 (see Just and Pope, 1979). In addition to the production inputs, various variables reflecting farm household characteristics are also defined. These variables include four dummy variables for farm size (farmsize1, farmsize2, farmsize3, farmsize4), and the ratio of the self-labor over the total labor use (r_self-labor).

In addition to the rice farmer's survey, some data on environmental characteristics and local agricultural activities are also collected from additional sources. Three variables are specified to reflect local environmental characteristics, namely, the average rainfall, temperature, and soil quality. These variables are aggregated at the county level. The weather and rainfall data are provided by the census conducted by the Weather Bureau in Taiwan, and the soil quality is identified by the Geographic Information System administered by the Agricultural Engineering Research Center in Taiwan. A higher score for the soil quality represents a better land quality. To capture the effects of the local agricultural activities on rice production, two variables reflecting the total number of the local farmers' cooperatives for production and marketing services, as well as the average number of farms in each cooperative team are specified. These two variables are aggregated at the county level and are based on the official publication of the Council of Agriculture in Taiwan. The sample statistics of the selected variables are exhibited in Table 1.

In Table 1, the average yields of production for farmers without and with off-farm work are 5,773 kg/ha and 5,547 kg/ha, respectively. According to the statistical test results, significant differences in input uses are found between these two groups of farms. Farmers who work off-farm use less self-labor and pesticides, and have smaller farm sizes compared to their counterparts. In addition, the average rainfall and temperature in the areas where the farmers with off-farm work are located are higher than in the areas where the farmers without off-farm work are located.

5. Empirical results

The empirical results are presented in several sets. The estimations of the stochastic production frontier models are exhibited in Table 2, while the sample statistics of the estimated technical efficiencies and the risk terms are provided in Table 3.

5.1. *Specification tests of the inefficiency and risk functions*

We begin our discussion of the results of the specification tests of interest (at the bottom of Table 2). Two null hypotheses are tested to determine whether the distinctions between technical inefficiency and the production risk are appropriate. We first test whether the effects of the exogenous determinants on the mean efficiency function are statistically equal to zero

Table 2
Estimations of the rice production functions

	Without off-farm work		Off-farm work	
	Deterministic frontier			
	Coefficient	Std. err.	Coefficient	Std. err.
log(hour_selflabor)	0.140***	0.049	0.108***	0.028
log(hour_hirelabor)	0.048***	0.011	0.042***	0.011
log(capital)	0.147***	0.027	0.133***	0.019
log(pesticide)	0.071***	0.018	0.067***	0.010
log(fertilizer)	0.080***	0.028	0.026*	0.016
constant	5.368***	0.414	6.149***	0.256
	Mean function of inefficiency			
farmsize1	0.080	0.141	0.138**	0.069
farmsize2	0.001	0.135	0.175**	0.069
farmsize3	0.187	0.163	0.164**	0.070
r_selflabor	−4.273	3.861	−2.574*	1.534
class	−0.081	0.076	−0.047**	0.024
member	−0.178**	0.098	−0.019	0.022
constant	4.118	3.668	2.412*	1.436
	Risk function			
log(hour_selflabor)	−0.835	1.157	−0.397	0.602
log(hour_hirelabor)	0.450**	0.196	−0.009	0.150
log(capital)	−1.869***	0.605	−1.043***	0.309
log(pesticide)	−0.589*	0.346	−0.162	0.182
log(fertilizer)	0.168	0.505	0.280	0.307
rainfall	1.425	1.288	0.602	0.608
temperature	−0.340	1.849	7.804***	1.619
soil	−4.849**	2.393	1.870	1.567
constant	36.947***	11.022	−8.676	8.469
Log-likelihood	111.619		245.582	
Specification tests	Test value		Test value	
H_0: no efficiency ($\alpha = 0$)$^{\$}$	46		146	
H_0: no risk ($\gamma = 0$)$^{\$\$}$	143		115	

***, **, * indicate significance at the 1%, 5%, and 10% level.
$All coefficients (except constant) in the mean and variance of functions are zero. Critical value is $x^2(0.95,6) = 12.6$.
$$All coefficients (except constant) in the risk function are zero. Critical value is $x^2(0.95,8) = 15.5$.

($H_0 : \alpha = 0$). Under the null hypothesis, the model is identical to the Just-Pope production risk function (Just and Pope, 1979). The test statistics of the likelihood ratio test are 46 and 146 for the farmers without and with off-farm work, respectively. Since both values are higher than the critical values at the conventional significance level (chi-square test $\chi^2(0.95, 6) = 18.3$), the empirical specifications of the inefficiency function are appropriate. Similarly, the consideration of production risk can be justified by testing the null hypothesis to determine whether the effects of the exogenous variables on the risk function are statistically equal to zero ($H_0 : \gamma = 0$). If the null hypothesis holds, the model is identical to the conventional stochastic production frontier specification (Aigner et al., 1977). The test statistics of the likelihood ratio test are 143 and 115 for these two groups of farmers, respectively. Since the null hypotheses are rejected at the 5% level or higher (chi-square test $\chi^2(0.95, 8) = 15.5$), the empirical results support the specification of the risk function.

Table 3
Distributions of technical efficiency and risk

	Technical efficiency		*Risk*	
	No off-farm work	Off-farm work	No off-farm work	Off-farm work
Mean	0.821#	0.814#	0.013$	0.015$
Std. dev.	0.124##	0.110##	0.011$$	0.010$$
Percentile (%)				
1	0.480	0.513	0.001	0.002
5	0.546	0.591	0.002	0.004
10	0.627	0.651	0.003	0.006
25	0.758	0.744	0.005	0.009
50	0.861	0.844	0.010	0.012
75	0.916	0.900	0.017	0.019
90	0.940	0.931	0.027	0.029
95	0.955	0.941	0.034	0.035

#A *t*-test is conducted to test the equality of the sample mean between the two groups. The *p*-value is 0.012.
$A *t*-test is conducted to test the equality of the sample mean between the two groups. The *p*-value is <0.001.
##A *F*-test is conducted to test if the variances of the two groups is equal. The *p*-value is 0.006.
$$A *F*-test is conducted to test if the variances of the two groups is equal. The *p*-value is 0.031.

5.2. *Estimations of the production frontier model*

The deterministic parts of the rice production function are defined as in the Cobb-Douglas functional form. The Cobb-Douglas functional form is specified because it has been shown to be a good functional form for capturing the deterministic production frontier for rice technology in Taiwan (e.g., Fu et al., 1992; Tsai and Wann, 1995).[5] As presented in Table 2, the empirical results of the deterministic frontier function indicate that the production behaviors of the farmers with and without off-farm work share some common characteristics. For both groups of farmers, machinery use has the highest elasticity among all of the inputs, followed by the use of self-labor. The higher elasticity of self-labor use than that for hired labor (0.140 vs. 0.048 for farmers without off-farm work; 0.108 vs. 0.042 for farmers with off-farm work) is consistent with the finding in Audibert (1997). When comparing our estimates of the input elasticities for farmers without off-farm work with previous studies (e.g., Fuwa et al., 2007; Huang and Kalirajan, 1997; Kwon and Lee, 2004; Tadesse and Krishnamoorthy, 1997), our estimated elasticities of machinery and fertilizer use are in line

[5] For instance, using the same data set in earlier years, Fu et al. (1992) compared the empirical performance between the Cobb-Douglas and translog specifications for rice production in Taiwan, and found that the Cobb-Douglas functional form fit the Taiwanese rice production data better.

with the findings in Huang and Kalirajan (1997) and Fuwa et al. (2007).[6]

While all coefficients in the deterministic frontier function are positive, different input-output responses are found between these two groups of farmers. As exhibited in Table 2, each input elasticity in the deterministic frontier for the farmers without off-farm work is larger than that of their counterpart farmers with off-farm employment. This result may reflect the fact that farmers without off-farm work are likely to pay more attention to farm management and usually have better knowledge regarding the use of inputs in production. Therefore, their use of self-labor, pesticides, and fertilizer are more productive than in the case of the farmers who work off the farm.[7] The differences in input uses due to the off-farm work are also found for hired labor. Our results indicate that the elasticities of the hired labor for farmers without and with off-farm work are 0.048 and 0.042, respectively. Since it is believed that supervision may improve the productivity of hired labor (e.g., Desilva et al., 2006; Eswaram and Kotwal, 1985; Taslim, 1989), our finding of a lower elasticity of the hired labor among the off-farm-work farmers may reflect the fact that this group of farmers may have weaker ability or spend less time supervising their hired workers.

As for the output response to machinery and equipment use, the results show that the production yields of the farmers without off-farm work are more responsive to their investments in the machinery and equipment than those of their counterparts (0.147 vs. 0.133). A possible explanation of this finding may be that, in Taiwan, farmers with off-farm work usually operate smaller farm sizes, and thus they are less likely to benefit from the economies of scale of rice production, especially for machinery use. As a result, the return that machinery investment by farmers with off-farm work has on output is lower than that of the other group of farmers.

5.3. Estimation results for technical inefficiency and risk functions

The estimation results of the mean function for the technical inefficiencies and risks functions are reported in Table 2 as well. For the inefficiency function, the estimated coefficients are qualitatively consistent between farmers without and with off-farm work. While previous studies provide mixed results to the discussion of the relationship between farm sizes and production efficiency (e.g., Carter, 1984; Dyer, 2004; Kumbhakar et al., 1989), Johnson and Le Roux (2007) pointed out that the share of family labor cannot be ignored in studying the effect of farm size on efficiency. In accordance with the finding in Carter (1984), our results show that farm sizes and the share of the family labor in labor used as a whole have positive effects on efficiency. To reflect the economies of scale of farm production, it is not a surprise to see that larger farmers are more efficient. The positive effect of the share of family labor on efficiency is not unexpected either. Previous studies have indicated that family members are more efficient than hired labor because the former usually pay more attention to their own production and are characterized by higher labor quality (Thapa, 2003). The cooperative activities in the local area in which each farm is located also matter for production efficiency. Our results indicate that local cooperative activities improve the technical efficiency of rice production, which is in agreement with the general belief that the local farmers' association usually provides professional advice to farmers in regard to production and enhances the production efficiency of the farmers that belong to it.

Although the estimated coefficients are consistent between farmers without and with off-farm work, the magnitudes of the effects do differ. For instance, among all of the factors, the number of farmers per production-marketing team is the only significant variable related to production efficiency for the farmers without off-farm work. As for their counterparts, however, farm size, the number of production-marketing teams in each country, and the self-labor ratio are significant in terms of the technical inefficiency. This finding implies that, in Taiwan, the production performances of farmers without off-farm work are more homogeneous than of those with off-farm employment.

With regard to production risk, the production inputs and local environmental characteristics are significant. For farmers without off-farm work, hired labor has a positive and significant effect on production risk, meaning that hired labor is a risk-increasing factor.[8] The negative and significant effects of capital on risk are evident for both groups of farmers, which indicate that the investment in machinery and equipment will decrease the production risk in rice production. Such a conclusion is in accordance with the findings in Just and Pope (1979) and Gardebroek et al. (2010) in that the use of agricultural machinery shortens the harvesting period and the exposure time to an uncertain environment, and thus stabilizes crop production.

[6] Huang and Kalirajan (1997) applied a stochastic varying coefficients frontier approach to estimate the household survey data in China from 1993 to 1995. Their generalized least squares (GLS) results showed that the elasticities for 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 for fertilizer lie 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 farm-level and plot-level rice data in eastern India. They found that the elasticity for fertilizer ranges from 0.004 (lowland) to 0.0947 (upland).

[7] The elasticity of the rice yields with respect to self-labor for farmers without off-farm work is higher than that for those farmers with off-farm work (0.140 vs. 0.108). In addition, for farmers without off-farm work, the results show that 1% increases in pesticide and fertilizer use raise the rice output by 0.071% and 0.080%, respectively (compared with 0.067% and 0.026% for farmers with off-farm work).

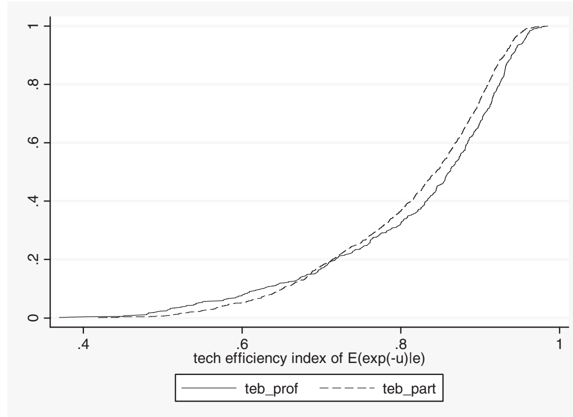
[8] Though it is commonly believed that labor is a risk-decreasing variable in agricultural production (Dai, 2006; Kumbhakar, 2002), Gardebroek et al. (2010) point out that the use of hired labor may increase the risk on organic farms. This might provide some support to our findings.

With respect to the use of pesticide and fertilizer, which are usually assumed to have negative effects on the variance of production, our results show that, only for farmers without off-farm work, the use of pesticide has a decreasing effect on the variance of production, and the estimate is statistically significant at the 10% level. In addition, the use of fertilizer does not have risk-decreasing effects for either group of farmers. The estimates of the soil variable indicate that, for farmers without off-farm work, soil of higher quality will stabilize rice production. However, such a finding does not apply to the off-farm-work farmers. Finally, our results reveal that rainfall does not have a significant effect on production risk while temperature is risk increasing for farmers with off-farm work. Our estimates of the environmental variables in the risk function for the farmers with off-farm work are in agreement with Dai (2006), who found that rice production in Taiwan is more vulnerable to temperature.

It is particularly worth noting that the differences in input uses of the risk function between these two groups of farmers may reinforce our earlier argument about the negative association between off-farm work and farm management. The better skills in terms of input uses, such as pesticides and machinery, enable them to use these inputs properly and to react to the production risks promptly. In addition, the positive and significant estimate of the temperature variable for farmers with off-farm work may imply that this group of farmers relies more on surface water than on irrigation supply, which makes them have less of a response to high temperatures.

5.4. *Comparing the distributions of efficiency and risk between groups*

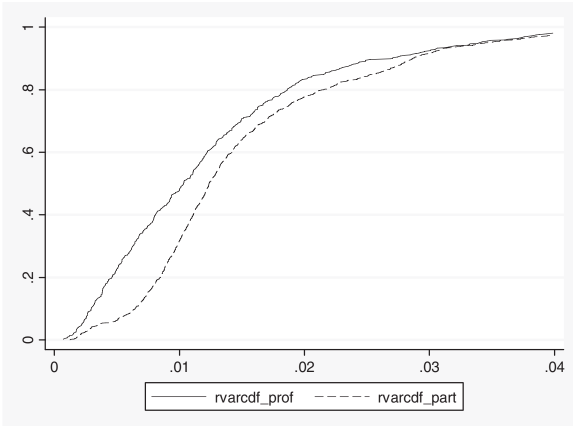
Table 3 reports the sample statistics of technical efficiency in terms of percentiles for these two groups of farmers. A negative impact of off-farm work on farm efficiency was found in previous studies, such as Kumbhakar et al. (1989), Fernandez-Cornejo (1992), and Goodwin and Mishra (2004). Our empirical findings support this conclusion since the average efficiencies are 0.821 and 0.814 for farmers without and with off-farm work, respectively. However, some important findings are revealed when looking at the technical efficiency level for different percentiles (Table 3). From the first to the 10th percentiles, the technical efficiency has a higher value for farmers with off-farm work than their counterparts, but the direction of the inequality reverses as we move from the 25th to the 95th percentiles. The relationship in terms of the technical efficiency between these two groups of farmers can be better understood using the CDFs illustrated in Fig. 1. The CDF for the farmers with off-farm work crosses the CDF for the farmers without off-farm work when the efficiency level is around 0.7. In particular, for the relatively less efficient farms in both groups (i.e., the farmers with technical efficiency levels of less than 0.7 in both groups), that portion of the CDF for farmers with off-farm work lies to the right of that for the group of farmers not working off the farm. Thus, for the relatively inefficient farms, the reallocation of some labor to off-farm jobs seems to improve the technical efficiency. By contrast, for the farmers with an efficiency level higher than 0.7, the farmers without off-farm work are more efficient. It is in this part of the distribution that one might well expect the reduction in technical efficiency due to off-farm work to be the most pronounced.



teb_prof are technical efficiencies for farmers without off-farm work.
teb_part are technical efficiencies for farmers with off-farm work.

Fig. 1. Distributions of technical efficiency scores.

The distribution of estimated risk for these two groups of farmers is also summarized in Table 3. The average values of risk are 0.013 and 0.015 for the farmers without and with off-farm work, respectively. The equality in terms of the mean and variance of the estimated risk distributions between these two groups of farmers is rejected at the 5% significance level based on the *t*-test and *F*-test, respectively. In each selected percentile, farmers with off-farm work generally face higher risk than the other group of farmers. For instance, the average value for the first to the 25th percentiles of the farmers with off-farm work is 0.009, which is larger than that for the farmers without off-farm work (0.005). This result points to a first-order stochastic dominance relationship of the farmers with off-farm work over the other group of farmers. This finding can be graphically presented in Fig. 2. It is obvious that the CDF for farmers with off-farm work lies entirely below the CDF for farmers without off-farm work. To fix the idea and let $\tilde{e}$ denote an arbitrary risk level, Fig. 2 demonstrates an unequal relationship in that the proportion of farmers without off-farm work at the risk level that is less than or equal to $\tilde{e}$ is no smaller than the corresponding proportion for the other group. For example, the proportion of farmers without off-farm work with a risk level less than or equal to 0.2 is larger than the proportion of farmers with off-farm work based on the same criteria. That is to say, in Taiwan, the farmers with off-farm work face higher production risk than their counterparts.



rvarcdf_prof are estimated risk distribution for farmers without off-farm work.
rvarcdf_part are estimated risk distribution for farmers with off-farm work.

Fig. 2. Distributions of the risk terms.

6. Conclusions

Off-farm salaries account for a high proportion of the total farm household income in many countries. While some studies assert that off-farm work stabilizes the uncertainty of agricultural production, others argue that technical inefficiency is the primary factor associated with the farmers' off-farm work. This article aims to examine the differences in production yield between two groups of farmers (those with and without off-farm work) to disentangle the relationships between off-farm work, production risk, and production efficiency. To reach our goal, we estimate a more general stochastic production model that takes both the technical efficiency and production risk into consideration. In addition, we rank the estimated technical efficiencies and risk distributions of these two groups of farmers based on the stochastic dominance criterion.

By using a national rice farmer survey in Taiwan, our results reveal some interesting findings. First, different patterns of input uses are evident for these two groups of farmers. In general, the input elasticities are higher for farmers without off-farm employment. In addition, farm characteristics and local agricultural activities significantly determine the technical efficiency of the rice farmers. However, these effects are more pronounced for farmers with off-farm work. In regard to production risk, the effects of input uses on yields also differ between these two groups of farmers. For farmers without off-farm employment, the use of pesticide is risk decreasing. However, the story is different for farmers with off-farm work. The use of machinery is only significantly associated with a reduction in risk.

With respect to the differences in the distributions of technical efficiency and production risk, our results indicate that the mean level of the technical efficiencies of the farmers with off-farm work is lower than that of the other group of farmers. However, this is not true for farms in the lower tail of the efficiency distribution. Our results show that off-farm work may provide a vehicle for family labor reallocation and thus improve production efficiency. With respect to the production risk, our results show that farmers with off-farm work face higher risk and this result is robust for the entire distribution.

Although some interesting findings are revealed in this study, a few caveats pertain. Since the hours of off-farm work are not available, we are not able to further investigate the extent to which hours of off-farm work may affect farm productivity. In addition, a more sophisticated econometric model should be developed to account for the endogeneity between off-farm work and farm productivity. Some convincing instrumental variables are also needed for model identification. This issue is beyond the scope of the current study and deserves further investigation. Finally, this article only addresses the effect of off-farm work on production risk and efficiency from the labor force allocation standpoint, and ignores the income-stabilization effect of off-farm work. Future studies could further address this issue.

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