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An Investigation of Production Risk, Risk Preferences and Technical Efficiency: Evidence from Rainfed Lowland Rice Farms in the Philippines *

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Abstract

Risk plays a vital role in farmers' decisions on input allocations and, therefore, output supply. This paper provides empirical evidence on the estimation of production risk, risk preferences and technical inefficiency. An eight-year panel data set is used for 46 rice farmers from a representative rainfed lowland environment in Central Luzon, Philippines. The heteroskedastic and stochastic frontier frameworks are reconciled and extended to accommodate the risk preferences of farmers in an analysis of production risk. Results show that technical inefficiency is overstated in risky production environments where farmers are risk-averse.

Key Words: production risk, risk preferences, technical efficiency.

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1. Introduction

Studies of technical inefficiency in agricultural production in developing countries have proliferated in recent years, contributing to a much better understanding of its causes and extent. The accuracy of the estimates of technical inefficiency may nevertheless have been compromised by an inability to distinguish between technical inefficiency due to shortcomings in farming practices and sub-optimal outcomes brought about by the risk-reducing behaviour of risk-averse farmers. As a result, the extent of technical inefficiency may have been substantially overstated in studies of farm performance in risky production environments.

The rainfed lowland farming system, in which rice smallholders operate in the Philippines, exemplifies such a production environment. Production risk is pervasive and potent in its effect on farming practices. This farming system provides an excellent testing ground to assess the relative contributions by technical inefficiency and risk to farm performance that is below what would be expected in a risk-free environment.

The existence of risk in production environments affects decision making by farmers in terms of their input-allocation decisions and, therefore, output supply. The degree of riskiness of an outcome or event depends on the decision-makers' attitudes towards risk. It is therefore important to analyse how risk affects farmers' decisions on input allocations and, likewise, how it affects farmers' efforts to achieve technical efficiency.

The technical sources of production inefficiency and variability in rice production are well studied and well known (Anderson and Hazell, (1989)). Most empirical studies have been devoted to understanding the causes of low productivity, and explaining technical inefficiency effects and the causes of variability of outputs. The pioneering work of Just and Pope (1978) paved the way for understanding production under risk through the estimation of a heteroskedastic model of production. A shortcoming of their approach is that they examined the marginal effects of inputs on production risk independently of the effects of inputs on mean output and took no account of the risk preferences of decision makers. Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) laid the foundation for accounting for technical inefficiency in a stochastic frontier production framework. Research in this framework generally ignores the marginal effects on the risk component, despite the fact that the stochastic frontier model is consistent with the heteroskedastic model (Jaenicke and Larson, 2001).

In this paper, we investigate production risk and technical inefficiency in rice production in the rainfed lowland environment in the Philippines by reconciling these two frameworks and extending them to accommodate the risk preferences of farmers. The risk preference function developed by Kumbhakar (2002) is used. Kumbhakar's model allows us to examine production risk by simultaneously estimating production risk, risk preferences and technical efficiency in rice production. We provide precise estimates of technical inefficiency and production risk, which should prove useful for research managers and policy makers.

The paper is organised as follows. A review of the methodological issues is presented in Section 2. In Section 3, the study area is described, the data set is discussed, and the empirical model and estimation procedures are outlined. The results are presented in Section 4 and concluding remarks are made in Section 5.

2. Review of Conceptual Issues

2.1 A stochastic frontier production function with flexible risk properties

The flexible risk and stochastic frontier production frameworks are now well known, and are not described here. We review work related to the Kumbhakar (2002) model.

Few empirical studies have attempted to combine the analysis of production risk and technical inefficiency in a single framework. Kumbhakar (1993) demonstrated a method to estimate production risk and technical inefficiency using a flexible production function to represent the production technology. The model was estimated using panel data and the risk function appears multiplicatively to accommodate negative and positive marginal risks with respect to output. The estimation of the individual technical efficiencies was also considered.

Battese, Rambaldi and Wan (1997) specified a stochastic frontier production function with an additive heteroskedastic error structure. Their model allows for negative or positive marginal production risks of inputs, consistent with the Just and Pope (1978) framework. Their model is described below.

Let the production process be characterised by

$$Y_i = f(X_i;\alpha) + \varepsilon_i \tag{1}$$

where:

Y_i is the scalar output for the *i*-th farmer;

X_i is a vector of functions of the levels of *K* inputs used by farmer *i*;

$f(X_i;\alpha)$ is the deterministic part of the production frontier;

α is a vector of technology parameters to be estimated; and

ε_i is the error term that can take different specifications depending on the nature of the analytical model.

Following the standard stochastic frontier framework, the error specification in equation (1) is assumed to have the form:

$$\varepsilon_i = g(X_i;\beta)V_i - h(X_i;\delta)U_i \tag{2}$$

where:

$g(X_i;\beta)V_i$ is the risk function;

$h(X_i;\beta)U_i$ is the inefficiency function;

β and δ are parameter vectors;

the $V_i s$ are error terms that are assumed to be independent and identically distributed standard normal random variables, representing production uncertainty; and

the $U_i s$ are non-negative random variables associated with the technical inefficiency of the farmers, and are assumed to be independent and identically distributed truncations of the $N(\mu,\sigma^2)$ distribution, independently distributed of the $V_i s$.

Given that $h(X_i;\beta) = g(X_i;\beta)$ in the specification of equation (2), we obtain the stochastic frontier production function with flexible risk properties that was proposed by Battese, Rambaldi and Wan (1997, p. 270), defined by equation (3):

$$Y_i = f(X_i;\alpha) + g(X_i;\beta)[V_i - U_i]. \tag{3}$$

Given the values of the inputs and the technical inefficiency effect, U_i, the mean and variance of output for the *i*-th farmer are:

$$E(Y_i \mid X_i, U_i) = f(X_i;\alpha) - g(X_i;\beta)U_i \tag{4}$$

$$Var(Y_i \mid X_i, U_i) = g^2(X_i;\beta). \tag{5}$$

The marginal production risk with respect to the *j*-th input is defined to be the partial derivative of the variance of production with respect to X_j. This can be either positive or negative:

$$\frac{\partial Var(Y_i | X_i, U_i)}{\partial X_{ij}} > 0 \text{ or } < 0. \tag{6}$$

Accordingly, the technical efficiency of the *i*-th farmer, denoted by TE_i, is defined by the ratio of the mean production for the *i*-th farmer, given the values of the inputs, X_i, and its technical inefficiency effect, U_i, to the corresponding mean production if there were no technical inefficiency of production (Battese and Coelli, 1988, p. 389). It is specified as:

$$TE_i = \frac{E(Y_i \mid X_i, U_i)}{E(Y_i \mid X_i, U_i = 0)} = 1 - \frac{U_i \cdot g(X_i;\beta)}{f(X_i;\alpha)} \tag{7}$$

We follow Battese, Rambaldi and Wan (1997) in estimating technical efficiency assuming that the V_is are independent and identically distributed (i.i.d.) as $N(0,1)$ and the U_is are i.i.d. half-normals, $N(0, \sigma_U^2)$, $U_i \geq 0$. If the parameters of the stochastic frontier production function were known, then the best estimator of U_i would be the conditional expectation of TE_i, given the realised values of the random variable $E_i = V_i - U_i$ (Jondrow et al. 1982). It can be shown that the conditional distribution of U_i given $V_i - U_i$ is distributed as $N(\mu_i^*, \sigma_*^2)$, where μ^* and σ_*^2 are defined by:

$$\mu_i^* = \frac{-(V_i - U_i)\sigma_U^2}{(1+\sigma_U^2)} \tag{8}$$

$$\sigma_*^2 = \frac{\sigma_U^2}{(1+\sigma_U^2)}. \tag{9}$$

It can also be shown that *E[U*$_i$*|(V*$_i$*-U*$_i$*)]*, denoted by $\hat{U}_i$, is given as:

$$\hat{U}_i = \mu_i^* + \sigma_* \left[\frac{\phi(\mu_i^* / \sigma_*)}{\Phi(\mu_i^* / \sigma_*)} \right] \tag{10}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ represent the density and distribution functions of the standard normal random variable. Equation (10) can be estimated by using the corresponding predictors for the random variable E_i given by

$$\hat{E}_i = \frac{Y_i - \hat{f}(X_i, \hat{\alpha})}{\hat{g}(X_i, \hat{\beta})}. \tag{11}$$

After equation (101) is estimated, then the technical efficiency of the i-th farmer can be predicted by

$$\overset{\wedge}{TE}_i = 1 - \frac{\hat{U}_i \cdot \hat{g}(X_i, \hat{\beta})}{\hat{f}(X_i, \hat{\alpha})}. \tag{12}$$

2.2 A model with risk preferences

Neither the stochastic frontier production function defined by equation (3) nor the Just and Pope (1978) flexible risk model takes into account the risk preferences of individual farmers. While several attempts have been made to estimate production risk and technical efficiency in a single framework, a stumbling block has been how to incorporate the risk attitudes of producers in the model. The traditional approach to modelling behaviour under risk is based on the expected utility hypothesis. Most studies have sought to identify farmers' risk preferences without estimating the source of randomness, or to estimate the sources of randomness without simultaneously estimating the risk preference structure (Moschini and Hennessy, 2001).

In an attempt to estimate production risk and producers' risk preferences simultaneously, Love and Buccola (1991, 1999), Chavas and Holt (1996), and Saha, Shumway and Talpaz (1994) considered the risk preferences of producers in a joint analysis of input allocations and output supply decisions. Love and Buccola (1991) proposed a primal model that allows the preferences of firms and their technology to be estimated jointly in the presence of risk. They followed Just and Pope (1978) in using a heteroskedastic technology specification with Cobb-Douglas mean and variance functions, a constant absolute risk aversion risk preference structure, cross-equation restrictions and a nonlinear three-stage least-squares estimator. Their approach is restrictive in the sense that constant absolute risk aversion is imposed (Moschini and Hennessy, 2001). Saha, Shumway and Talpaz (1994), on the other hand, developed a method using an expo-power utility function that imposes no restrictions on the risk preference structure. Their results showed that the combined estimation of production function parameters with the utility function parameters is more efficient than estimating them separately. Chavas and Holt (1996) developed a joint estimation method that is able to test for constant or decreasing absolute risk aversion.

One of the immediate problems of the empirical analysis of producers' attitudes towards risk is that an explicit form of the utility function has generally been assumed. Another drawback is that it is necessary to impose distributional assumptions on the errors that represent production risk. Even with these assumptions, the main problem for an applied researcher is that there are only a few utility functions and probability distributions that can be used to derive the risk preference function analytically. They are difficult to estimate and the model becomes quite complicated (Kumbhakar, 2002).

Because the risk preferences of producers have an important bearing on input allocation decisions, it is fundamental to consider a model that permits the simultaneous estimation of the risk attitudes of producers, production risk and technical inefficiency. Kumbhakar (2002) proposed a method that meets this challenge. We introduce a risk preference function in a model that follows Kumbhakar's method and is consistent with the Just and Pope flexible risk and stochastic frontier production models.

Assume that farmers maximise expected utility of profit:

$$Max\, E[U(\pi)] \tag{13}$$

where $U(.)$ is assumed to be a continuous and differentiable utility function of expected profit (π), normalised by the output price, p, and defined as:

$$\pi = Y_i - W.X_i \tag{14}$$

where W is the column vector of the prices of variable inputs relative to the output price. Recall from equation (3) that uncertainty in variable profit comes from production uncertainty, given by V_i, as well as technical inefficiency, U_i.

The first-order condition for the maximisation of $E[U(\pi)]$ can be expressed as:

$$f_j(X_i,\alpha) = w_j - \theta \cdot g_j(X_i,\beta) + \lambda \cdot g_j(X_i,\delta) + \eta_j \tag{15}$$

where:

$f_j(X_i,\alpha) = \dfrac{\partial f(X_i,\alpha)}{\partial X_{ij}}$ is interpreted as the marginal product of input j, defined as the change in mean output for a unit change in the variable input, X_j;

$g_j(X_i,\alpha) = \dfrac{\partial g(X_i,\beta)}{\partial X_{ij}}$ measures the effect of input, X_j, on output such that X_j is risk-increasing if $g_j(X_i,\alpha) > 0$, risk-decreasing if $g_j(X_i,\alpha) > 0$, and neither risk-increasing nor risk-decreasing if $g_j(X_i,\alpha) = 0$;

$\theta = \dfrac{E[U'(\pi)V]}{E[U'(\pi)]}$ and $\lambda = \dfrac{E[U'(\pi)U]}{E[U'(\pi)]}$ capture the risk preferences of the producers, such that $\theta < 0$ and $\lambda > 0$ if producers are risk-averse (the effect of an increase of U_i on profit is the opposite of an increase in V_i) and risk-neutral if θ and λ are both zero; and

η_j represents allocative inefficiency associated with optimisation error.

Producers are said to be fully efficient if $U_i = 0$, in which case the risk preference function is given only by θ.

According to Kumbhakar (2002), the derivation of the risk preference function depends on neither the specific parametric form of the utility function nor any distributional assumption on the error term representing production risk. It is based on the second-order approximation of the marginal utility of profit, $U'(\pi)$, rather than the utility of profit, $U(\pi)$, and the specific probability distribution of production risk. The parameters of the risk preference functions are estimated by assuming a parametric form of the absolute risk aversion function, allowing the identification of increasing, constant and decreasing absolute risk aversion.

For the purpose of understanding the basic framework, the algebraic representation of the risk preference functions, θ and λ, are presented as follows. Let

$$U(\pi) = U(\mu_\pi) + g(X_i, \beta)V_i - g(X_i, \delta)U_i \tag{16}$$

where $\mu_\pi = f(X_i, \alpha) - W_i \cdot X_i$.

A second-order approximation of $U'(\pi)$ at $V_i = U_i = 0$ yields the following forms of risk preference functions (Kumbhakar, 2002, p. 11):

$$\theta = \frac{-AR.g(X_i, \hat{\beta}) - DR.g^2(X_i, \hat{\beta}).a}{1 + AR.g(X_i, \beta)a + \frac{1}{2}DR.g^2(X_i, \beta).(1 + b^2 + a^2)} \tag{17}$$

$$\lambda = \frac{a + AR.g(X_i, \beta)(b^2 + a^2) + \frac{1}{2}DR.g^2(X_i, \beta).[a + c + 3ab^2 + a^3]}{1 + AR.g(X_i, \beta).a + \frac{1}{2}DR.g^2(X_i, \beta).(1 + b^2 + a^2)} \tag{18}$$

where:

$g(X_i, \hat{\beta})$ and $g^2(X_i, \hat{\beta})$ are estimated values from the variance functions; and

a, b and c are the first three central moments of U_i based on the assumptions of the standard frontier model with U_i distributed as half-normal, defined by:

$E(U) = a = \sqrt{2/\pi\sigma_u}$;

$Var(U) = b^2 = \dfrac{\pi - 2}{\pi}\sigma_u^2$; and

$E\{(U - a)^3\} = c = \sqrt{2/\pi}(4/\pi - 1)\sigma_u^3$.

AR is the Arrow-Pratt measure of absolute risk aversion (Arrow 1971; Pratt 1964) defined by:

$$AR = \frac{-U''(\pi)}{U'(\pi)}. \tag{19}$$

A farmer is said to be risk-averse, risk-neutral or a risk taker if $AR>0$, $AR=0$ or $AR<0$, respectively. Absolute risk aversion is useful for comparing the attitudes of farmers towards a given activity at different levels of wealth. Consequently, DR measures the downside risk aversion, which is defined by:

$$DR = \frac{-U'''(\pi)}{U'(\pi)}. \tag{20}$$

If DR is positive, farmers are averse to downside risk, and "generally avoid situations which offer the potential for substantial gains but which also leave them even slightly vulnerable losses below critical level" (Menezes, Geiss and Tressler, 1980, p. 921).

Equations (19) and (20) are related:

$$DR = \frac{-\partial AR}{\partial \pi} + AR^2. \tag{21}$$

In this framework, a parametric form of AR has to be assumed, which subsequently allows testing for different forms of risk preferences.

By expanding (17) and substituting the values of θ and λ, we have:

$$f_j(X_i,\alpha) = W_j - \left[\frac{-AR.g(X_i,\beta) - DR.g^2(X_i,\beta).a}{1 + AR.g(X_i,\beta)a + \frac{1}{2}DR.g^2(X_i,\beta).(1+b^2+a^2)}\right].g_j(X_i,\beta)$$

$$+ \left[\frac{a + AR.g(X_i,\beta)(b^2+a^2) + \frac{1}{2}DR.g^2(X_i,\beta).[a+c+3ab^2+a^3]}{1 + AR.g(X_i,\beta).a + \frac{1}{2}DR.g^2(X_i,\beta).(1+b^2+a^2)}\right] g_j(X_i,\beta) + \eta_j. \tag{22}$$

From equation (22), it can be seen that input allocations are affected by the presence of technical inefficiency and production risk by means of θ and λ. If technical inefficiency were neglected in the model, information on input allocation and predicted values of the risk preference function would be misleading. Thus, the absolute, relative and downside risk aversion measures are invalid (Kumbhakar, 2002). Similarly, neglecting production risk can lead to inaccurate measures of technical efficiency.

The parameters of the mean function, risk function, inefficiency function and *AR* functions can be estimated using a multi-step procedure or maximum-likelihood estimation. Kumbhakar (2002) proposed a multi-step procedure to estimate a model with production risk and risk preferences that is followed in this paper.

3. Empirical Application

3.1 The study area and data

The data consist of an eight-year panel of 46 farms. They were collected by the International Rice Research Institute (IRRI) as part of a research activity undertaken by the Rainfed Lowland Rice Research Consortium. A farm survey was conducted to gather information on the resource base of farmers, rice crop management, including the amounts of inputs and output, and general characteristics of farm households residing in four villages (Calibungan, Canarem, Mangolago and Masalasa) within the municipality of Victoria in the province of Tarlac, Philippines. The farmers were randomly selected in each village from a total list of farmers obtained from the municipality of Victoria. Monitoring rice production practices of the 46 sample farmers was initiated in 1990 and continued until 1997. For each year, crop production data were obtained for all fields that were operated by the sample farmers.

The agricultural sector is dominant in the economy of Tarlac. Rice is the main crop planted during the wet season, accounting for almost 90 per cent of the total cropped area. In 1997, the total area planted to rice was approximately 103,000 hectares with a total output of 389,000 tonnes. The average rice yield was 3.8 tonnes per hectare.

There are two distinct seasons in the province. The wet season usually starts in late May and ends quite abruptly in mid-October. The average annual rainfall in Tarlac from 1977 to 1997 was about 1,620 mm, with most of the rains occurring during July to September. Overall, the rainy season provides four months of more than 200 mm per month. The dry season occurs from November to April, with an average rainfall of less than 100 mm per month.

There are two major land types in the study area. In this study, we use the farmers' classification of land type. In Tarlac, land type can be classified into *upper bantog* (upper fields), *lower bantog* (medium fields) and *lubog* (lower fields). The *bantog* fields are drought-prone on the upper part of the toposequence while the *lubog* fields are generally prone to flood and submergence. Overall, *bantog* is the most common land type, accounting for about 76 per cent of the total area under rice. Soil types are classified as *Panaratin, Kadagaan* and *Pila*, which are sandy, clay and heavy clay soils, respectively. Of the total operational landholdings, clay soils covered about 50 per cent of the area monitored. Sandy soils are most dominant in the upper fields while clay soils are dominant on the medium and lower fields.

The average operational holding of the sampled farms during 1990 to 1997 was about 2.7 hectares. Landholdings are fragmented, with more than three parcels per household, on average, and an average area per parcel of almost 0.8 hectare. Eighty per cent of the land was planted to rice in the first season. As rainfall is inadequate for a second crop of rice, rainfed fields are left fallow in the second season.

The major inputs used in rice production are fertiliser, labour and chemicals. Fertilisers are applied in both the seedbeds and the main fields. The main sources of labour are family, hired and exchange labour. Herbicides are applied in the main fields to control weeds, especially in the upper land types.

3.2 Empirical model

Following the Kumbhakar (2002) approach outlined in Section 2.2, we specify a model for panel data:

$$Y_{it} = f(X_{it};\alpha) + g(X_{it};\beta)[V_{it} - U_{it}] \tag{23}$$

where:

Y_{it} represents the quantity of freshly threshed rice paddy (in tonnes) of the i-th farmer in the t-th year; and

$f(X_{it};\alpha)$ and $g(X_{it};\beta)$ are the quadratic mean production function and the risk function, where, for example, $f(X_{it};\alpha)$ is defined by

$$f(X_{it};\alpha) = \alpha_0 + \sum_{j=1}^{5}\alpha_j X_{jit} + 0.5\sum_{j\leq}^{5}\sum_{k}^{5}\alpha_{jk}X_{jit}X_{kit}. \tag{24}$$

There are five input variables that are defined as follows:

X_1 is the total area planted to rice (in hectares);

X_2 is fertiliser (as nitrogen, phosphorus and potassium, or NPK) (in kilograms);

X_3 is total family, exchanged and hired labourers growing, harvesting and threshing rice (in person-days);

X_4 is herbicide applied (in grams of active ingredients); and

X_5 denotes the year in which the observation on rice production is obtained.

The elasticity of mean output with respect to input X_j, given U_i=0, is given by

$$E_j = \frac{\partial f(X_{it};\alpha)}{\partial X_{jit}} \frac{X_{jit}}{f(X_{it};\alpha)} = \left[\left(\alpha_j + \sum_{k=1}^{5} \alpha_{jk} X_{kit} \right) \frac{X_{jit}}{f(X_{it};\alpha)} \right]. \qquad (254)$$

Descriptive statistics of the variables included in the model are presented in Table 1. The average production of rice was approximately 6.5 tonnes per household, which translates to a mean yield of about 3.1 tonnes per hectare. Rice production is highly variable, with output per household ranging from 92 kilograms to 31.1 tonnes. Average fertiliser use was 187 kilograms per household, which is equivalent to approximately 89 kilograms per hectare. The average labour use was approximately 51 person-days per hectare.

[TABLE 1 HERE]

The marginal production risk at the frontier is given by

$$\frac{\partial Var(Y_{it} \mid U_{it} = 0)}{X_{jit}} = 2 \times g(X_{it};\beta) \left(\beta_j + \sum_{k=1}^{5} \beta_{jk} X_{kit} \right). \qquad (26)$$

Equations (15), (24) and (26) are used to express the first-order conditions for input X_j:

$$\alpha_j + \sum_{k=1}^{5} \alpha_{jk} X_{kit} = w_j - \theta \left(\beta_j + \sum_{k=1}^{5} \beta_{jk} X_{kit} \right) + \lambda \left(\beta_j + \sum_{k=1}^{5} \beta_{jk} X_{kit} \right) + \eta_j \qquad (27)$$

where θ and λ, as previously defined, contain the estimated values of $g(X_{it};\beta)$, values of the first, second and third central moments of U_i, and the AR and DR functions. We choose a linear form of the absolute risk aversion function:

$$AR = \gamma_0 + \gamma_1 \Pi^* \tag{29}$$

where Π* is the initial wealth plus mean profit. The value of non-farm income and the estimated value of household assets are used as a proxy for initial wealth. An explicit form of the downside risk aversion function of the producers can also be estimated. Equation (28) is estimated using non-linear three-stage least squares regression to obtain estimates of the mean function, variance functions and risk preference functions. The corresponding estimates of technical efficiencies are obtained using equation (12). The estimates are presented in the following section.

4. Results

In this section, results are presented for the empirical model that is specified above. Table 2 contains elasticity results for the generalised flexible risk frontier model, defined by equation (3). It shows that the elasticities for area and labour are significant at the five per cent level.

[TABLE 2 HERE]

The mean values of the output elasticities for area, fertiliser, labour and herbicide are about 0.38, 0.14, 0.34 and 0.01, respectively. In calculating elasticities for individual farmers at their input values, we found that some elasticity estimates were negative for a few farmers, implying some excessive use of inputs.

The marginal output risk estimates of the inputs are presented in Table 3. On average, it can be seen that fertiliser and labour are risk-increasing while herbicide is risk-decreasing. This implies that fertiliser and labour are estimated to increase the variance of the value of output.

[TABLE 3 HERE]

We examined the risk preferences of each farmer based on the predicted values of the risk preference functions, θ and λ, in equation (15). The risk preference estimates of each farmer are presented in Table 4. Results show that all farmers are risk-averse, indicated by the negative values of θ and positive values of λ. The mean value of θ estimated over the eight-year period is -0.453. The magnitude of the estimates varies across farms, with a range of 0.609. The estimated mean value of the λ-parameter is 0.556, with all estimates positive. The magnitudes of the risk preference functions are found to vary from year to year.

[TABLE 4 HERE]

It can also be seen from the Table 4 that the values of θ are larger than the values of λ. This implies that the risk component has greater influence on decisions on input use than the inefficiency component, although the difference is not great.

The estimated AR function is given as

$$
\begin{aligned}
AR = &-0.059 - 0.0027\,\Pi^{*} \\
&(0.069) \quad (0.0016)
\end{aligned}
$$

where the figures in parentheses are the corresponding standard errors correct to two significant digits. The estimated coefficient, γ_1, is negative and is significant at the five per cent level. This implies that the rice farmers exhibit decreasing absolute risk aversion.

The predicted values of absolute and downside risk aversion for each farmer are presented in Table 5. The average degree of absolute risk aversion is 0.394 with a standard deviation of 0.028. A larger value of *AR* implies a stronger aversion to risk. The predicted values of downside risk aversion are all positive, indicating aversion to downside risk. Again, a larger value of *DR* shows greater downside risk aversion. The average value of *DR* is 0.156 with a standard deviation of 0.021.

[TABLE 5 HERE]

The predicted values of U_{it} are used to estimate the technical efficiencies of individual farmers. The annual averages and ranges of estimated technical efficiencies are presented in Table 6. The mean technical efficiency is 0.88, with the individual technical efficiencies ranging from 0.58 in 1996 (a drought year) to 0.79 in 1993.

The frequency distribution table of the technical efficiencies for individual years is given in Table 7. On average, most of the farmers have technical efficiency levels of more than 0.80 for all years. From the table, it can be seen that the distribution of the levels of technical efficiency of farmers were more dispersed in 1996. About 20 per cent of the farmers had technical efficiencies between 0.71 and 0.80.

[TABLE 7 HERE]

5. Concluding Comments

The primary objective of this paper is to provide an empirical application of the estimation of production risk, risk preferences and technical efficiency. The models used in this paper are consistent with the specification of Just and Pope (1978), Aigner, Lovell and Schmidt (1977), Battese, Rambaldi and Wan (1997) and Kumbhakar (2002).

The empirical application is based on an eight-year panel data of 46 farmers in a rainfed lowland rice environment in the Philippines. Rice production in the rainfed rice environment is inherently risky, because of the highly variable rainfall and heterogeneous production environment. The study area is representative of the rainfed environment in the Philippines.

We estimated a stochastic frontier production function with flexible risk properties. The estimated effects of inputs on the output variance show that labour and fertiliser are risk-increasing while herbicide is risk-decreasing.

We used the technique proposed by Kumbhakar (2002) to estimate the risk preference functions of farmers. All estimates of the risk preference functions and risk aversion coefficients confirmed that farmers are risk-averse. The results show further that the degree of risk aversion varies across farms and over time. The estimates of the risk preference functions imply that the risk component has a slightly greater influence on the input-use decisions than the inefficiency component. Finally, the technical efficiencies of individual farmers were shown to vary over time and across farmers.

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Table 1: Descriptive statistics of the variables

Variable	Mean	Standard deviation	Minimum	Maximum
Rice harvested (tonnes)	6.47	5.08	0.09	31.1
Area (hectares)	2.11	1.45	0.20	7.00
Fertiliser (kilograms)	187.0	168.82	3.36	1030.9
Labour (person-days)	107.0	76.8	7.8	436.9
Herbicide (grams)	0.39	0.62	0.0	4.41

Table 2: Output elasticity estimates at mean input levels

Input	Elasticity	Standard Error
Area	0.383*	0.073
Fertiliser	0.14	0.11
Labour	0.34*	0.15
Herbicide	0.010	0.022

* Denotes significant at the five per cent level.

Table 3: Marginal production risk estimates

Input	Coefficient	Standard Error
Fertiliser	0.0038	0.0055
Labour	0.012	0.020
Herbicide	-0.02	0.75

Table 4: Average risk preference estimates for all sample farmers

	θ		λ	
Farmer	**Mean**	**Std**	**Mean**	**Std**
1	-0.656	0.055	0.524	0.014
2	-0.74	0.16	0.498	0.047
3	-0.75	0.22	0.494	0.061
4	-0.379	0.080	0.583	0.013
5	-0.624	0.030	0.5287	0.0070
6	-0.194	0.037	0.6010	0.00097
7	-0.43	0.12	0.544	0.024
8	-0.536	0.079	0.552	0.017
9	-0.573	0.062	0.542	0.013
10	-0.73	0.13	0.506	0.039
11	-0.301	0.044	0.5935	0.0036
12	-0.151	0.024	0.60057	0.00038
13	-0.377	0.072	0.583	0.011
14	-0.455	0.079	0.570	0.015
15	-0.154	0.039	0.59815	0.00037
16	-0.194	0.060	0.5976	0.0027
17	-0.70	0.18	0.497	0.045
18	-0.73	0.28	0.486	0.067
19	-0.76	0.15	0.490	0.043
20	-0.75	0.13	0.494	0.035
21	-0.64	0.10	0.525	0.025
23	-0.446	0.080	0.572	0.015
24	-0.73	0.26	0.490	0.067
26	-0.59	0.12	0.532	0.028
27	-0.51	0.12	0.528	0.019
28	-0.340	0.043	0.5877	0.0054
29	-0.418	0.075	0.568	0.012
30	-0.41	0.12	0.573	0.017
31	-0.45	0.15	0.563	0.031
32	-0.20	0.13	0.577	0.011
33	-0.214	0.058	0.5993	0.0028
34	-0.242	0.026	0.5871	0.0015
35	-0.29	0.10	0.5825	0.0084
36	-0.227	0.045	0.5989	0.0020
37	-0.60	0.18	0.534	0.039
38	-0.432	0.071	0.575	0.011
39	-0.307	0.056	0.5868	0.0059
40	-0.327	0.093	0.574	0.010
41	-0.58	0.27	0.530	0.054
42	-0.174	0.036	0.59349	0.00073
43	-0.466	0.023	0.5656	0.0044
44	-0.308	0.024	0.5931	0.0024
45	-0.499	0.073	0.554	0.014
46	-0.346	0.075	0.5746	0.0080
All	**-0.45**	**0.22**	**0.556**	**0.045**

Table 5: Predicted values of the absolute and downside risk aversion

Farmer	Absolute (AR)		Downside (DR)	
	Mean	**Std**	**Mean**	**Std**
1	0.4073	0.0034	0.1658	0.0028
2	0.4076	0.0063	0.1661	0.0052
3	0.4130	0.0044	0.1706	0.0037
4	0.4150	0.0029	0.1722	0.0025
5	0.3924	0.0071	0.1540	0.0056
6	0.4123	0.0013	0.1699	0.0011
7	0.3009	0.0072	0.0906	0.0044
8	0.4060	0.0050	0.1648	0.0041
9	0.4008	0.0030	0.1606	0.0024
10	0.4240	0.0061	0.1797	0.0052
11	0.4136	0.0024	0.1711	0.0020
12	0.40758	0.00078	0.16612	0.00063
13	0.4128	0.0025	0.1704	0.0021
14	0.4123	0.0010	0.16997	0.00087
15	0.40171	0.00046	0.16137	0.00034
16	0.40471	0.00053	0.16379	0.00043
17	0.3614	0.0053	0.1306	0.0038
18	0.376	0.011	0.1413	0.0084
19	0.3968	0.0082	0.1574	0.0065
20	0.3946	0.0069	0.1558	0.0055
21	0.4013	0.0057	0.1611	0.0046
23	0.4140	0.0044	0.1714	0.0036
24	0.382	0.016	0.146	0.012
26	0.3892	0.0067	0.1515	0.0053
27	0.2797	0.0070	0.0782	0.0039
28	0.4091	0.0021	0.1673	0.0017
29	0.3831	0.0039	0.1467	0.0030
30	0.4045	0.0018	0.1636	0.0015
31	0.3975	0.0052	0.1581	0.0041
32	0.35282	0.00099	0.12448	0.00070
33	0.41178	0.00072	0.16956	0.00059
34	0.3763	0.0019	0.1416	0.0014
35	0.3818	0.0010	0.1457	0.0010
36	0.4116	0.0025	0.1693	0.0020
37	0.4140	0.0055	0.1714	0.0045
38	0.4180	0.0041	0.1748	0.0034
39	0.3952	0.0018	0.1562	0.0014
40	0.36237	0.00152	0.1313	0.0011
41	0.4101	0.0075	0.1682	0.0062
42	0.38858	0.00068	0.15099	0.00053
43	0.4004	0.0043	0.1603	0.0034
44	0.4133	0.0014	0.1708	0.0012
45	0.3867	0.0052	0.1495	0.0041
46	0.3713	0.0031	0.1379	0.0023
All	**0.394**	**0.028**	**0.156**	**0.021**

Table 6: Annual estimates of technical efficiency

Year	Mean	Minimum	Maximum
1990	0.89	0.62	0.97
1991	0.88	0.77	0.98
1992	0.90	0.74	0.96
1993	0.89	0.79	0.97
1994	0.88	0.76	0.97
1995	0.88	0.58	0.97
1996	0.85	0.59	0.95
1997	0.88	0.71	0.96
All years	**0.88**	**0.58**	**0.98**

Table 7: Relative frequency distribution of farmers in different technical efficiency intervals

	Percentage of farmers (%)				
Year	0.51-0.60	0.61-0.70	0.71-0.80	0.81-0.90	0.91-1.00
1990		2.27	15.91	22.73	59.09
1991			11.36	38.64	50.00
1992			9.09	31.82	59.09
1993			2.27	54.55	43.18
1994			4.55	56.82	38.64
1995	2.27		2.27	56.82	38.64
1996	2.27		20.45	56.82	20.45
1997			11.36	40.91	47.73