Crop diversification, economic performance and household's behaviours Evidence from Vietnam

Nguyen, Huy

Arndt-Corden Department of Economics, Australian National University

30 September 2014

Crop diversification, economic performance and household's behaviours Evidence from Vietnam

Huy Nguyen*

Abstract

This study examines economic performances and household's behaviours in multiple crops farming in Vietnam. Smallholder farming systems in Vietnam is being transformed by integration between cash cropping and main food cropping operations. This transformation into diversified farming systems can affect the economies of scope, technical efficiency, and performances of farms. By using the approach of input distance function, we find the first evidence of both scale and scope economies that have important economic performance implications. There is an existence of substantial technical inefficiency in multiple crops farming, which implies that there may be opportunities to expand crop outputs by eliminating technical inefficiency. Enhancing education and further land reforms are main technical efficiency shifters. We also find the complementarity evidence between family labour and other inputs, except hired labour. Thus, policies that lead to more incentives to invest in crop faming activities should focus on the reduction of input costs.

Key words: crop diversification, input distance function, elasticity of substitution, stochastic frontier, and technical efficiency

---

* PhD student at Arndt-Corden Department of Economics, Crawford School of Public Policy, Australian National University, huy.nguyen@anu.edu.au

I am highly indebted to Professor Peter Warr and Dr. Robert Sparrow for their constant encouragement and generous support. I also acknowledge Associate Professor Sanzidur Rahman for useful communications.

1. Introduction

The Vietnam agricultural sector is experiencing significant structural change. Although agricultural systems are dominant by rice production, a large number of rice farmers grow other annual crops in conjunction with rice to improve their livelihoods (World Bank 2007; Dao & Lewis, 2013). Similarly, Minot et al. (2006) show that farm households in poor areas are converting some paddy land to other annual cropland so that they can earn higher income. As a result, diversification of smallholder crop production is one of crucial steps in food and nutrition security strategies in Vietnam[1]. FAO (2012) suggest that diversifying production to include horticulture and high value crops allows smallholders to broaden sources of food in local diets and enter domestic markets for higher- value products. It also strengthens resilience to economic and climate risks.

It has long been recognised that the economic performance of diversified farm households seems also to be increasingly influenced by output-input jointness or complementary. Scope economies arise when diversification implies a cost reduction associated with multi-output production processes (Baumol et al., 1982). There is empirical evidence that economies of scope are prevalent in farming (Chavas and Aliber 1993; Fernandez-Cornejo et al. 1992; Paul and Nehring 2005; Rahman 2010). Similarly, Fleming and Hardaker (1994) show that smallholders have been most successful in increasing productivity when diversifying their activities through an adaptive growth strategy..

The objective of this paper is to explore the economic performance of crop diversified farms in Vietnam. It gives an analysis of diversification economies and efficiency of small production in a farming system characterised by a combination of cash cropping and food crop production, mainly rice. The dynamics processes of change in integrated farming sub-systems can affect the potential for productivity gains and technical efficiency in their activities. We mainly concentrate on measuring the influence of crop diversity on the production system as scope economies, technical efficiency, and the behaviours of rice-based farms in Vietnam by estimating input distance function by stochastic production frontier methods[2]. We are also interested in examining the response of households and investigate

[1] According to Bloomberg News (2012), The Ministry of Agriculture and Rural Development of Vietnam has planned to convert 200,000 ha of paddy land into the land for growing other crops in the Mekong River Delta, where is the biggest rice-growing region in Vietnam. In addition, other rice growing regions also start crop conversion.

[2] In this paper, we ignore risks and uncertainties despite the fact that risks and uncertainties are likely to influence on jointness and crop diversification. Nevertheless, the behavioural motivation for observed input and output composition is not a direct focus of the input distance function. The issues of risks and uncertainties are not main focus in this paper and will be explored in further research.

how farm households adjust output and input jointness in an environment of increasing cost stress. Understanding the economic performance of crop diversification is important in redesigning of food security policies related to crop diversity polices in Vietnam.

Most of existing papers only focus on rice instead of multi-output and multi-input patterns, and none has addressed the efficiency of crop diversification in Vietnam's agricultural production[3]. Moreover, using the framework of multi-output multi-input production enable us to estimate the elasticity of substitution and complementarity which cannot be estimated from direct cost functions and overcome the limitation of household surveys due to the lack of information on input prices.

This study contributes to literature in several ways. Firstly, to the best of the author's knowledge, this research provides the first investigation of the economic performance of annual crop diversified farms in Vietnam using parametric regression. The investigation of economic performance on rice-based diversified farm households should inform the Government's agricultural policy and provide a better understanding of household behaviours for annual crops. Secondly, it also provides the evidence of the elasticity of substitution and complementarity between inputs, particularly the response of farm labour to changes in other inputs such as an increase in costs of fertilizer, pesticide and capital, which is ignored in Vietnam. Finally, understanding technical efficiency enables us to uncover the reasons that hinder productivity growth of annual crop farming in Vietnam in light of declining trends of agricultural growth in recent years and rising abandon of rice fields in many provinces. Kompas et al. (2012) provided evidence on the role of further land reform on improving technical efficiency in Vietnamese rice production. The analysis of technical efficiency in multi-crop environment, however, is an empirical question.

The paper is organized as follows. Section 2 introduces the conceptual frameworks for the distance function, empirical models and the performance measures of production process. These performance measures act as performance indicators that can be constructed from the estimated model. Section 3 describes the dataset and the construction of variables. Section 4 discusses the empirical results and finally the results and policy implications conclude.

2. Research methodology

2.1. Analytical framework

[3]Papers that study the efficiency in rice production include Kompas et al. (2004, 2012); Vu (2012)

In the study of Paul and Nehring (2005), the authors used both input and output distance functions to evaluate the economic performance of the US farms. Although we use the approach developed by Paul and Nehring (2005), an input-oriented stochastic distance function is our main interest instead of output oriented distance function. This is because, inputs are scare and scattered, especially land, and rising costs of agricultural production due to high inflation over the past decade. Fertilizer expenditure has tended to increase in recent years. Thus, it is logical to assume that the main concern is cost minimization. In addition, the choice of a stochastic input distance function approach can allow separating the random noise from technical inefficiency effects that is ignored in the data envelopment analysis. Using the parameters of the estimated input distance function allows us to measure scale economies, technical efficiency and elasticity of substitution in crop-diversified farms (Grosskopf et. al. 1995; Stern 2008, 2010; Rahman 2010).

In the study of stochastic frontier analysis, Kumbhakar and Lovell (2003) introduce the overview of input distance function[4]. This function describes how much an input vector may be proportionally contracted with the output vector that is held fixed. In this paper, we use the theoretical framework introduced by Paul and Nehring (2005, p. 529). The input distance function D is formally defined as:

$$D(x,y) = \max\{\lambda; \lambda > 0, x/\lambda \in L(y)\} \qquad (1)$$

$$L(y) = \{x \in R_+^N : x\}, \text{ x can produce y given r} \qquad (2)$$

where x is a scalar, L(y) is the set of input requirement x, which is used to produce the output vector y. D(x, y) is non-decreasing, positively linearly homogenous and concave in x, and increasing in y. Paul and Nehring (2005) show that the input distance function can provide a measure of technical efficiency because it allows for deviation (distance) from the frontier. Finally, there is a dual relationship between input distance function and cost function, which allow us to relate the derivatives of the input distance function to the cost function (Färe and Primon 1995).

To empirically estimate the distance function, a functional form must be specified. we select the translog functional form used by previous studies (Lovell et al., 1994; Grosskopf et al., 1995; Coelli et al., 1998; Paul et al., 2000; Irz and Thirtle, 2004; Paul and Nehring, 2005; Rasmussen, 2010; Rahman, 2010). The translog is a flexible function and it has some advantages that it allows the elasticity of scale to change for various farm

[4]See further details of properties of input distance function in Kumbhakar and Lovell (2003).

sizes. In addition, a flexible technology also allows for substitution effects in the function (Paul et al., 2000).

The translog input distance function with M outputs, N inputs of the farm household i is given by:

$$\ln D_i = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N} \beta_{nk} \ln x_n \ln x_k + \sum_{m=1}^{M} \alpha_m \ln y_m + \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M} \alpha_{ml} \ln y_m \ln y_l + \sum_{m=1}^{M}\sum_{n=1}^{N} \gamma_{mn} \ln y_m \ln x_n \quad (3)$$

where D_i measures the radical distance from (x,y) to the production. As the input distance function is linear homogenous in inputs, the parameters in equation (3) must satisfy the following regulatory restrictions:

$$\sum\nolimits_n \beta_n = 1, \sum\nolimits_k \beta_{nk} = 0, \sum\nolimits_n \gamma_{mn} = 0 (m = 1,...,M), \sum\nolimits_n \theta_{rn} = 0 (r = 1,...,C)$$

$$\beta_{nk} = \beta_{kn} (n,k = 1,...,N), \alpha_{ml} = \alpha_{lm} (m,l = 1,...M)$$

We use the approach of Lovell et al. (1994) in imposing these restrictions by normalizing the function by one of the input. As a result, the equation (3) is expressed as follows:

$$\frac{\ln D_i}{x_{1i}} = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n^* + \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N} \beta_{nk} \ln x_n^* \ln x_k^* + \sum_{m=1}^{M} \alpha_m \ln y_m + \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M} \alpha_{ml} \ln y_m \ln y_l + \sum_{m=1}^{M}\sum_{n=1}^{N} \gamma_{mn} \ln y_m \ln x_n^* = \ln D(x^*, y) \quad (4)$$

where $x_{ni}^* = x_{ni} / x_{1i} (\forall n, i)$ i.e. summing only N-1 inputs are not used for normalization.

Paul and Nehring (2005) find that coefficient estimates from the equation (4) have the opposite signs from those for a standard production or input requirement function. The authors introduce a method by reversing their signs of the equation in order to interpret the measures from (4) more similarly to those from more familiar functions in the literature review[5]:

$$\ln x_1 = -\ln D(x_{ni}^*, y) - u + v \quad (5)$$

The equation (5) is expressed in a standard stochastic production frontier model, which includes two error terms representing deviations from the frontier and random error. On the basic of a parameterisation of the distance function and distributional assumptions of

[5]In the studies of Paul et al. (2000), Paul and Nehring (2005), Rahman (2010), and Rasmussen (2010), they only reverse the signs of coefficient estimates from the $\ln D(x^*, y, r)$. We follow the same step and keep the signs of the random statistical noise v and technical inefficiency u unchanged.

error terms, the equation (5) can be estimated by the maximum likelihood methods, which have been extensively used in the stochastic frontier literature[6].

2.2. The econometric specification and identification

The production structure of annual crops in Vietnam is modelled using a multi-output multi-input stochastic distance function. One of issues that arise for implementing the distance function estimation is which of the inputs might be used as normalizing factors. As Collie and Perelman (2000) argue, any input can be chosen and this should not present econometric problems because the results are invariant to this choice. However, there could still be economic reasons for selecting x_1. Because we mainly focus on rice-based annual crop farms in Vietnam, so all other inputs are represented relative to land as x_1 in this study[7].

We desire the following empirical model:

$$-\ln x_{1i} = \beta_0 + \sum_{n=2}^{7}\beta_n \ln x_n^* + \frac{1}{2}\sum_{n=2}^{7}\sum_{k=2}^{7}\beta_{nk}\ln x_n^* \ln x_k^* + \sum_{m=1}^{4}\alpha_m \ln y_m + \frac{1}{2}\sum_{m=1}^{4}\sum_{l=1}^{4}\alpha_{ml}\ln y_m \ln y_n$$
$$+\sum_{m=1}^{4}\sum_{n=2}^{7}\gamma_{mn}\ln y_m \ln x_n^* + \sum_{k=1}^{8}\rho_k REG_k + v_i - u_i \qquad (6)$$

According to Battese and Coelli (1995), the parameter in the inefficiency distribution is expressed as $u_i = \eta_0 + \sum_{s=1}^{9}\eta_s M_{is} + \zeta_i^*$ (6a)

Where x_1 is land cultivated per farm as the normalizing input; v_i is the two-sided random error and u is the one-sided error in model (6); M in equation (6a) introduces variables that represent farm household characteristics that affect technical inefficiencies. The difference of equation (11) compared with the equation (7) is that a new variable. We add dummy variables that controls for regional differences, REG_k. The model (6) includes seven production inputs (X), four outputs and nine variables of M_{is} in the technical inefficiencies model. There is no environmental condition in the model due to lack of data that captures this variable.

As regards the endogeneity problem, there is a criticism that parameter estimates of the distance functions may be affected by simultaneous equations bias (Atkinson et al., 1999). These authors went to correct this criticism by use of instrumental variables, although

[6] See the summary of the stochastic frontier literature by Coelli, Rao and Battese (1998).

[7] Using land as a normalizing variable in the input distance function has been widely applied in many studies in agricultural economics (Irz and Thirle, 2004; Paul and Nehring, 2005; Rahman, 2010; Rasmussen, 2010). This choice is consistent with the typical agricultural economics approach to production modelling in terms of yields, and inputs per acre. Different choices for the normalizing input variable (x_1) such as fertilizer were tried, with slight difference in results.

they did not clearly specify the source of suspected simultaneous equations bias (Coelli, 2000). Coelli (2000) clearly demonstrated that ordinary least squares provide consistent estimates of the parameters of the input distance function under an assumption of cost minimizing behavior. In fact as Coelli (2000) concludes 'distance functions are no more subject to possible endogeneity criticisms than production functions ... when cost minimizing behavior is a reasonable assumption, the input distance function has a clear advantage over the production function, because the distance function has an endogenous dependent variable and exogenous regressors, while the production function has the converse' (p. 20–21).

Estimates of the parameters in the equations (6) and (6a) were implemented by using maximum likelihood estimation in a single state shown in Coelli and Perelman (2000) or Rahman (2010). We use STATA 13 to estimate the models. In addition, we solved the problem of zero values in the translog input distance function by applying the approach of Conerjo et al. (1992) and Paul et al. (2000).

2.3. The performance measures

2.3.1. Scale and scope economies

Willig (1979) developed the concept of economies of scope in multiproduct firms. He finds that with economies of scope, joint production of two goods by one firm is less costly than combined costs of production of two firms. The reason for economies of scope, according to Willig (1979), comes from inputs that are shared and jointly utilized without complete congestion. This concept measures cost savings due to simultaneous production. Moreover, economies of scope arise from the presence of public inputs, which means that once inputs purchased to produce certain products can be used to produce other product free of cost (Baumol et al., 1982).

Based on the above ideas, scale and scope economies can be derived in farming production. Färe and Primont (1995) and Paul and Nehring (2005) find that the combination of the first-order input elasticities representing scale economies shows the positive correlation between productivity and input growth. Moreover, these studies conclude that the relationship between input and output scale economy is defined as the sum of individual input elasticities and reflects how much overall input use must increase to support a 1 per cent increase in all outputs, which is the same as a cost function-based scale economy measure. Based on the development in Paul and Nehring (2005), the individual input elasticity summarizing the input expansion that is required for a 1 per cent increase in Y_m is expressed as follows:

$$-\varepsilon_{D,y_m} = -\frac{\partial \ln D}{\partial \ln y_m} = \frac{\partial \ln x_1}{\partial \ln y_m} = \frac{\partial x_1}{\partial y_m}\frac{y_m}{x_1} = \varepsilon_{x,y_m} \tag{12}$$

The measure in the equation (12) can be considered as an "input share" of y_m that is relative to x_1. It is expected to be negative for all desirable outputs. Summarizing all elasticities in equation (12) results in a measurement of scale economies shown by:

$$-\varepsilon_{D,y} = -\sum_m \frac{\partial \ln D}{\partial \ln y_m} = \sum_m \frac{\partial \ln x_1}{\partial \ln y_m} = \varepsilon_{x,y_m} = \varepsilon_{x,y} \tag{12a}$$

Paul and Nehring (2005) indicates that the extent of scale economies (for proportional changes in all inputs) is implied by the shortfall of $\varepsilon_{x,y}$ from 1. In addition, we can decompose the first-order elasticities $\varepsilon_{x,ym}$ and $\varepsilon_{x,y}$ into the second-order effects capturing the changes in output composition as scale expands. This decomposition is implied by technological bias measures showing how the y_m input elasticity or the share $\varepsilon_{x,ym}$ reflects to a change in another output. Thus, these measures provide insights about the output jointness of the agricultural production system. The increase in y_m as y_l increases can be represented by $\varepsilon_{y_m,y_l} = \partial\varepsilon_{x,y_m} / \partial \ln y_l$. If $\varepsilon_{y_m,y_l} < 0$, output jointness or complementarity is implied. As a result, there is an existence of economies of scope in farm production. In this case, input uses do not have to increase as much to expand y_m if the y_l level is greater. With economies of scopes, the cost of adding the production of y_l to the production of y_m is smaller than the production of y_l alone. As a result, this elasticity is represented by the cross-output coefficient estimate α_{ml}, $\varepsilon_{y_m,y_l} = \alpha_{ml} = \varepsilon_{y_l,y_m}$. If the complementarity between outputs is satisfied, an increase in one output expands the contribution of other outputs and thus performance and cost savings.

2.3.2. Elasticity of substitution

This section provides insights into input contribution obtained from the input distance function using the duality between the cost function and input distance function (Färe and Primont, 1995). We measure the elasticity of substitution between inputs, which has been ignored in Vietnam's agricultural production. One of the advantages of the input distance function over the cost function is that no information on input prices is required, nor the maintained hypothesis of cost minimization. Grosskopf et al. (1995) find that there is no specific behavioural goal in the input distance function. We use estimated parameters of the input distance function to calculate the Morishima elasticity of substitution (MES), Allen-Uzawa elasticity of substitution (AES). Blackorby and Russell (1989) convincingly argue that the Morishima elasticity of substitution is more appropriate measure than the Allen one when there are more than two inputs in the production process. This approach has been applied in several studies (Grosskopf et al., 1995 for MES and AES; Kumar, 2006 for MES and AES; Rahman, 2010 for MES, AES).

Grosskopf et al. (1995, p. 281) claim that due to complete description of the production technology, parameters of the input distance function may be used to describe the characteristics of the frontier technology, including curvature, which captures the degree of substitutability along the surface technology. Hence, the indirect Morishima elasticity of substitution as denoted by Blackorby and Russel (1989) can be calculated as:

$$MES_{x,nk} = -\frac{d\ln[D_n(x,y)/D_k(x,y)]}{d\ln[x_n/x_k]} = x_n\left(\frac{D_{nk}(x,y)}{D_k(x,y)}\right) - x_n\left(\frac{D_{kk}(x,y)}{D_n(x,y)}\right) \tag{13}$$

where the subscripts in the input distance function indicates partial derivatives with respect to inputs, e.g. $D_{nn}(x,y)$ represents the second order derivative of the distance function with respect to x_n. Kumar (2006) notes that the first derivatives of the input distance function with respect to inputs obtain the normalized shadow price of that input due to the dual property between cost function and the input distance function. The first component of the definition, thus, can be considered as the ratio of percentage change in the shadow prices resulted from one per cent change in the ratio of inputs. This represents the change in relative marginal products and input prices needed to affect substitution under cost minimization. Grosskopf et al. (1995) suggest a simplified method to calculate the indirect Morishima elasticity as follow:

$$MES_{x,nk} = \varepsilon_{x,nk}(x,y) - \varepsilon_{x,nn}(x,y) \tag{14}$$

Where $\varepsilon_{x,nk}(x,y)$ and $\varepsilon_{x,nn}(x,y)$ are the constant output cross and own elasticity of shadow prices with respect to input quantities. The first term gives information on whether pairs of inputs are net substitutes or net complements, and the second term is the own price elasticity of demand for the inputs. In addition, Kumar (2006) further adds that if $\varepsilon_{x,nk}(x,y)$ is greater than zero, net complements are implied. If $\varepsilon_{x,nk}(x,y)$ is less than zero, net substitutes are indicated. The indirect MES has opposite patterns to the direct one. In the case of indirect MES, if more input x_n were used for a given level of x_k, a higher value of MES suggests lower substitutability and the relative shadow price of x_n to x_k would increase substantially. Conversely, lower values reflect relative ease of substitution between the inputs. In addition, the Morishima elasticity is not symmetric.

Using the parameters from the translog estimating equation (11), $\varepsilon_{x,nk}(x,y)$ and $\varepsilon_{x,nn}(x,y)$ are obtained as follows:

$$\varepsilon_{x,nk}(x,y) = [\beta_{nk} + S_n S_k]/S_k \text{ if } n \neq k \text{ and } \varepsilon_{x,nn}(x,y) = [\beta_{nn} + S_n(S_n - 1)]/S_n \text{ if n=n} \quad (15)$$

Where S_n is the first order derivative of the translog input distance function with respect to x_n as: $S_n = \partial \ln D / \partial \ln x_n = -\partial \ln x_1 / \partial \ln x_n^*$ (16)

As regards the AES, Grosskopf et al. (1995) suggest a method to derive the AES from the input distance function as follows:

$$AES_{x,nk} = \left[D(x,y)D_{nk}(x,y)/D_n(x,y)D_k(x,y)\right] \quad (17)$$

If we follow the method used by Kumar (2006), the AES is not symmetric. Theoretically, this is inaccurate[8]. Therefore, the empirical method developed by Grosskopf et al. (1995) is applied in this chapter. From the parameters of the equation (11), the AES can be estimated as:

$$AES_{x,nk} = \frac{\beta_{nk}}{(x_n x_k)D_n D_k} \text{ where } D_n = (1/x_n)[\hat{\beta}_n + \sum_n \hat{\beta}_{nk} \ln x_k^* + \sum_m \hat{\gamma}_{mn} \ln y_m + \hat{\theta} \ln P_i] \quad (17a)$$

2.3.4. Technical efficiency

Technical efficiency (TE) refers to the ability to minimize input use in the production of a given output vector, or the ability to obtain maximum output from a given input vector (Kumbhakar and Lovell, 2003). In general, $0<TE<1$, where $TE = 1$ reflects that farms are producing on the production frontier and are said to be technically efficient. Alternatively, $TE <1$ implies that farms are technically inefficient, which means that (1-TE) captures the proportional reduction in inputs, x that can be gained to produce output, y. The equation (6a) provides the model to estimate the determinants of technical inefficiency in annual crop farms. From the one-sided error term u_i from the equation (6), we can qualify the levels of technical efficiency.

3. Data

Rice is the traditional and most important crop in Vietnam's agriculture. Most of the production comes from family-operated small-scale farms. Rice growing area in 2006 was 4.1 million of hectares (ha), accounting for 43.77 per cent of total agricultural land and 65 per cent of annual cropping land (Agricensus, 2006). Similarly, the number of rice growing households was 9,330,490, which represents 64.27% of 10,245,080 total annual crop farm households. Land area was only 0.4 ha on average in 2006.

[8]In the studies of Rahman (2010) and Kumar (2006), both studies use the formula as $AES=\varepsilon_{x,nk}/S_n$, which results in the asymmetric outcomes of the AES. However, Blackorby and Russel (1989) found that the Allen and Uzawa elasticity of substitution is symmetric. Therefore, in this paper, we use the method suggested by Grosskopf et al. (1995) to estimate the AES. This method will create results that are consistent with theoretical framework of the AES.

The paper uses the Vietnam Household Living Standard Survey (VHLSS) in 2006 for empirical analysis. This survey is nationally representative, and consists of questionnaires at both household and communal levels. The Vietnamese General Statistics Office undertook them with technical support from the World Bank and UNDP since 1997/1998. Since our empirical analysis focuses on rice-based farms that mainly grow rice, starchy crops, vegetables and industrial annual crops in land for annual crops. We only select rice-based annual cropping farms.

In this paper, there are four outputs including rice (y_1), vegetables (y_2), starchy outputs (y_3) and annual industrial outputs (y_4). In addition, the seven inputs used in the model (11) are: x_1: land, x_2: family labour, x_3: fertilizer, x_4: pesticide, x_5: hired labour, x_6: hired capital[9], x_7: seeds. Family labour (x_2) is the number of working hours of the family. There were a large number of observations that had zero value for the input variable x_5 (hired labour) and x_6 (hired capital). After dropping zero values of inputs and outliers, the final sample for empirical analysis is 1970 farm households[10].

(Table 1 here)

Table 1 describes a summary of statistics on the variables used in the analysis. The output measures include rice production and other annual crop production (aggregation of starchy crops, vegetables and annual industrial crops). It should be noted that average farm size of multiple crop-growing households is small (0.41 hectare per farm), in which 95 per cent of farmers have land area less than 1 hectare. In light of high land fragmentation in rural Vietnam (average 6.32 plots per farm), diversification can be a solution to reduce risk for small farms when income from rice production is low. Chavas and Di Falco (2012) found that small-scale farms tend to diversify to stabilize returns of different crops and reduce risk. On the contrary, large farms focus on specialization.

[9]Hired capital includes land rental or contracting, rental of assets, machinery, equipment and means of transport, and rental of cattle for ploughing.

[10]From 9189 households in the VHLSS 2006, we selected households with positive rice outputs (4824 households). Of 4824 rice households, we then selected all household with positive other outputs (aggregating starchy, vegetables, and annual industrial crops) to obtain 3388 farm households. We also dropped observations of 3388 farmers with zero values of land, fertilizer, pesticides and seed, i.e. no input. The remaining sample for empirical analysis was 1970 farm households. There were 61% of farm households without hired labour and 30% without hired capital. We applied the approach used by Paul et al. (2000, p. 332) for variables with several zero values.

For rice-based farm households in the sample, households that grow vegetables, account for 78.68%. The number of households that produce starchy crops represents 73.35% of total households, which reflects an increasing trend of crop switching. There are only 38.12 per cent of households growing annual industrial crops. According to VHLSS 2006, there are 70.2 per cent of households that diversify their crops among rice farmers. There are 29.8 per cent that only produce rice.

4. Results and discussion

4.1. Tests of hypotheses for model selection

Table 2 provides the results of hypothesis tests. We employ the results of the likelihood ratio tests, which compare the likelihood functions under the null and alternative hypothesis. There are five hypothesis tests that are summarized in Table 2 below. Firstly, testing the selection of a right functional form, the log likelihood specification test rejects the Cobb-Douglas specification in favor of a translog production function. Secondly, we compare the frontier with the mean input distance function estimated by examining that the inefficiency term u is non-stochastic and equal to zero. In this context, the deviation from the frontier of the input requirement set is solely explained by random shocks and the input distance function can be estimated by the ordinary least squares method. The log likelihood ratio test at 5% significant level rejects the null hypothesis. As a result, this indicates that significant technical inefficiencies exist in Vietnam's agriculture.

Next, we test whether the variables in the technical inefficiency model are significant. The null hypothesis is rejected at 5% level, implying that the distribution of inefficiencies is not the same across individual household and is subject to the variable of vector M_i in the equation (11a). This result is consistent with the efficiency model introduced by Battese and Coelli (1995). Then, the hypothesis of input-output separability is also tested. We follow the steps carried out by (Irz and Thirtle, 2004). The hypothesis test is defined mathematically by equating all cross-terms between outputs and inputs (γ_{mn}) to zero. The null hypothesis is strongly rejected, which indicates that it is impossible to aggregate consistently the two outputs into a single index. The final test introduced in Table 2 is the presence of returns to scale in annual crop production in the context of multi-output technology. We test the summary of all regulatory restrictions of all α_m that equal to one. The null hypothesis is also rejected in favor of the existence of scale economy.

(Table 2 here)

We also investigate the monotonicity condition, which suggests that the input distance function is non-decreasing in inputs (i.e. $\partial \ln D / \partial x_n \geq 0$) and non-increasing in outputs (i.e. $\partial \ln D / \partial y_m \leq 0$) (Hailu and Veeman, 2000). The fulfilling curvature (i.e. concave in x_n and quasi-concave in y_m) property in accordance with production theory can be checked by examining the Hessian matrix of the second-order partial differentials of the distance function with respect to outputs and inputs. Monotonicity conditions are not violated if the elasticities of inputs are positive and elasticities of outputs are negative. Table 3 below provides the monotonicity condition check. As can be seen in the Table 3, monotonicity condition is satisfied for all inputs and outputs.

(Table 3 here)

4.2. Measures of economic performance

This section begins by examining the elasticities of inputs and outputs at sample mean, which are derived from the estimation of the equation (11)[11]. All the variables are mean differenced prior to estimation so that elasticities of the input distance function estimated at the sample mean are considered as the first order coefficients.

Table 4 below introduces the elasticities of input distance function at the average values of the variables. As can be seen in the Table 4, the signs on the first order coefficients of outputs and inputs are consistent with prior expectations. The elasticity of the distance function with respect to output corresponds to the negative of the cost elasticity of that output. The values in the Table, as expected, are negative and highly significant ($\varepsilon_{D,y_m} = -\varepsilon_{x_1,y_m}$). The elasticity with respect to rice (ε_{D,y_m}) is -0.574, which is the largest if compared with other outputs. These results also indicate that the cost elasticity of rice output is larger than the corresponding elasticity of other annual crops, which implies that a 10 percent increase in rice output results in a 5.74 per cent in total costs, while the corresponding figure for starchy crops and vegetables are only 1.78 per cent and 0.38 per cent respectively. The estimated parameters, thus, reflect the dominance of rice production in Vietnam's agriculture.

(Table 4 here)

[11]The full estimated results of the input distance function are presented in the appendix. 55% of the coefficients in the distance function are statistically significant. In this chapter, we only report the elasticities computed from the coefficients and the average values of the variables in the data.

The evidence of scale economies also presented in Table 4. The presented measures show significant scale economies ($\varepsilon_{x,y}$=0.896) for input-oriented specification ($\varepsilon_{x,y}$<1 indicates scale economies)[12]. This implies that when total outputs increase by 1 per cent, total costs of production only rice by 0.89 per cent. We also reject the null hypothesis of constant returns to scale ($\varepsilon_{x,y}$=1) introduced in Table 2. This evidence is interesting because other studies used the approach of input distance function share the same finding of significant scale economies in crop farms (Paul and Nehring, 2005, $\varepsilon_{x,y}$=0.653 for the US; Rahman, 2010, $\varepsilon_{x,y}$=0.45 for Bangladesh; Ramsmussen, 2010, $\varepsilon_{x,y}$=0.723 for Denmark). Ogundari and Brümmer (2010) also found the evidence of increasing returns to scale in cassava production in Nigeria using the output distance function. Chavas and Aliber (1993) also found the evidence of economies of scale in small farms using the US farm data.

However, studies that use the data envelopment analysis provide mixed results. Vu (2012) concludes that majority of rice farms are operating with increasing returns to scale in Vietnam. These findings suggest that a large number of rice farms in Vietnam should increase their scale of operations to gain scale efficiency. There has been no study on returns to scale in the context of multi-output farms in Vietnam. Conversely, Wadud and White (2000) had an opposite findings with Rahman (2010) when they supported the decreasing returns to scale in Bangladesh agriculture. Therefore, the results are largely subject to selected methods to measure the scale economies and the context of multi or single output. FAO (2012) finds the evidence of increasing returns to scale in crop diversification.

Similarly, the first order conditions of the input distance function with respect to inputs are equal to cost shares and imply the importance of inputs in annual crop. As can be seen in Table 4, all elasticities are significant at one percent level. Land has the largest elasticity with a value of 0.38, which means that the cost of land represents 36 per cent of total cost at the sample mean[13]. The costs of pesticides, fertilizer and seeds account for 43 per cent of the total costs for the sample. In the report on the rice crisis, FAO (2010) shows that costs of fertilizer, pesticides and seeds represented 43% of total cash costs during the 2008 winter-spring rice crop in Mekong River Delta in Vietnam. All studies

[12]Paul and Nehring (2005) find that the estimated scale economies are lower when off-farm income as another output is included, which reflects the increasing prevalence of off-farm incomes for small landholding farm households combats their scale disadvantages from only farming activities. We also find a similar result but the estimate is insignificant so we do not report in this chapter.

[13]Due to regulatory restrictions, $\sum_n \beta_n = 1$ in the equation (11), the elasticity of land is computed by taking the difference between 1 and summary of the coefficients of all other inputs. Thus, the significance cannot be reported in Table 3.

related cost structure in Vietnam focus on rice production, not for multiple crops. The family labour cost accounts for 16.1% of total costs, reflecting the importance of family labour in the production process. It should be noted that the markets for land and labour in developing countries are not sufficiently developed. As a result, there is no information on prices of land or family labour input in the household data surveys[14], which cannot provide the information on the cost share of land and family labour.

To further investigate the implications of estimated parameters of output jointness, we use the argument of Paul and Nehring (2005) which shows that if $\varepsilon_{x,y_m,y_l} = \partial\varepsilon_{x,y_m} / \partial \ln y_l < 0$, output jointness or complementary is implied. It means that input uses do not increase as much to expand y_m if the y_l is higher. In the estimated input distance function, ε_{x,y_m,y_l} is represented by the cross-parameter (α_{ml}) in the equation (11) and introduced in Table 4. There is a complementary between rice and other crops, which implies that the input uses expanding other annual crops do not have to increase as much. This finding is interesting because it indicates that significant scope economies exist in crop diversification in Vietnam. Average costs for a farm household in producing more than two outputs are lower and cost savings arisen from byproducts in the production process. Increasing the production of other annual products reduce the input share of rice. Since there have been no studies on crop diversification in Vietnam, we cannot verify this result in the context of Vietnam's agriculture. We have the same finding with Rahman (2010) for Bangladesh and Ogundari and Brümmer (2011) for Nigeria.

4.3. Elasticity of substitution and complementarity

In this paper, we extend the approach of Rahman (2010) by introducing Table 5. It should be noted that they are indirect elasticities. Moreover, if $\varepsilon_{x,nk}(x,y)$ is less than zero, net substitutes are implied. Conversely, $\varepsilon_{x,nk}(x,y)$ is greater than zero, net complements are indicated (Grosskopf et al. 1995). The substitutability between inputs implies that as the shadow price (or cost share) of an input increases, farm households employ more of another input (Kumar 2006; Rahman, 2010).

(Table 5 here)

[14] Many studies find that perfect labour and land markets are rarely found in developing countries (Benjamin, 1992; Urdy, 1996; Jolliffe, 2004). Le (2010) also rejected the perfect market assumptions in the sample of Vietnamese farmers. World Bank (2006) has the same conclusion for land market in Vietnam when the government controls land prices and ownership.

As can be seen in Table 5, among the cross elasticity between inputs, family labour appears to be complement to all other inputs, except hired labour. Hired labour can be a substitute for family labour. The complementarity between family labour and fertilizer, pesticides, capitals and seeds implies that if the shadow prices or cost shares of fertilizers, pesticides, seeds and capital increase, there is a reduction of family labour supply[15]. Therefore, the increasing burden of high costs of farm production results in increasing inefficiency in farm production. Household members seek off-farm opportunities to smooth income and consumption in light of the uncertainties of farm incomes as push factors (Reardon et al. 2001). Interestingly, there have been no studies explaining the reasons why farmers have abandoned their fields in the past few years in Vietnam[16]. Using the approach of the elasticity of substitution can explain this story partly. Hence, Vietnam government should change the approach of designing food security policies. Instead of only focusing on rice price policy, the reduction of costs of production such as fertilizer, pesticides, seeds and hired capitals plays a vital role to create more incentives for farmers to stay and invest in agricultural production.

The elasticity of substitution between family labour and hired labour is also our interest in this chapter. In the light of rising landlessness in Vietnam, the substitutability between family labour and hired labour can provide policy implications. In 2004, landlessness rate was 13.55%, which led to increasing rural stratification. More farm households hired labour for farming activities and participated in off-farm jobs Vietnam (Akram-Lodhi, 2005; Ravallion and van de Walle, 2006).

Table 5 provides the evidence of net substitutes between family labour and hired labour, which implies that the increase of farm labour supply depends on the shadow price of hired labour as well as other inputs. As the cost share of hired labour rises, households increase labour supply. Conversely, households reduce family labour required for farming activities. As the degree of substitutability between family and hired labour increases, farm operators can more easily hire replacement workers on the farm. The family labour

---

[15]Kumar (2006) shows that the absolute shadow price reflects the actual proportion of inputs used by an inefficient producer. Hence, the shadow price means the cost share of an input. He also assumed that the observed price of one input is equal to its shadow price. Similarly, Rahman (2010, p335) applies the same method used in Kumar (2006) to compute elasticities in Bangladesh agricultural production.

[16]Vietnamese rice farmers are abandoning their paddy fields. In 2013, 42,785 families left over 6,882 hectares of fields untouched. Moreover, 3,407 families returned over 433 hectares of land. Some farmers state that the income they receive from growing rice has shrunk. A few hundred square meters of land can only provide them $2.37 to $3.79 a month on average. (http://thediplomat.com/2013/12/vietnamese-rice-farmers-abandon-their-fields/).

can then allocate more hours to off-farm activities or migrate to urban areas (D'Antoni et al. 2014). This can result in increasing inequality and social stratification within rural areas as shown by Akram-Lodhi (2005).

As regards the relationship between fertilizer and family labour, the increase in cost share of fertilizer reduces family labour supply on farm. Gilbert (2014) finds that the fertilizer subsidy programs have positive impacts of the probability that a household demands agricultural labour. The reduction of cost share of fertilizer enables to relieve credit constraints and increases labour demand for hired and family labour.

(Table 6 and 7 here)

The indirect Morishima and Allen elasticities of substitution are computed from input distance function and they are presented in Tables 6 and 7, respectively[17]. The Morishima elasticities of substitution are not symmetric. These results are consistent with Table 5. There is a complementary between family labour and other inputs, except hired labour. Households are sensitive to input price changes. This implies that an increase in input prices such as fertilizer and capital should cause a significant reduction in farm labour demand. Overall, the estimated elasticities indicate that family labour can be relatively easily substituted for hired labour. There is a complementarity between family labour and other inputs, which partly explain increasing trends of farmers abandoning their fields to seek better opportunities of incomes in rural Vietnam.

4.4. Technical efficiency

Prior studies mainly focused on technical efficiency in rice production in Vietnam. Dao and Lewis (2013) found that the mean of technical efficiency for rice-based multiple crop farms was 0.83. In this paper, the mean technical efficiency is 0.82, which indicates that opportunity may exist to expand crop outputs without using more inputs or the application of improved production technology. There is a wide range of production inefficiency of farm households ranging from 17 per cent to 96 per cent in multiple crop farming. The mean technical efficiency of multiple crop farming is higher than other estimates of studies producing only rice. Kompas et al. (2012) and Vu (2012) estimated the mean technical efficiency to be 0.77 and 0.78 respectively.

[17] See further procedures about how to calculate elasticities in Grosskopf et al. (1995, p. 293).

As regards the determinants of technical inefficiency in multiple crops farming, Table 9 provides the effects of farm characteristics on technical inefficiency. It can be seen in Table 8, education plays a vital role in reducing technical inefficiency, particularly women education compared with men education. The level of impact on the reduction of technical inefficiency of female education is two times that of male education. This also reflects the role of women in crop diversity. This result is consistent with the findings of Rahman (2010). The significant role of education on reducing technical inefficiency in Vietnam is also reported by Kompas et al. (2012). In addition, household size at working age also significantly improves technical efficiency. Households who diversify their crops have small and fragmented landholdings. As a result, the application of mechanization in farming activities is hindered. Mafoua-Koukebe et al. (1996) indicates that when production is labour intensive, farms tend to be more diversified. More supply of family labour at working age, thus, reduces technical inefficiency in crop production.

(Table 8 here)

Table 9 also shows the effect of land fragmentation on agricultural efficiency. We use the number of plots instead of the Simpson index[18]. This result is consistent with the conclusions of studies in case of Vietnam (Hung et al. 2007; Kompas et al. 2012). It means that the less fragmented is a farm, the higher is efficiency. In previous chapter, we also found that land reforms related to the reduction of land fragmentation could result in labor allocation of farm households. In this chapter, land reforms can improve efficiency in crop diversification. Crop diversity significantly reduces technical inefficiency with a coefficient value of 2.05. The lower Herfindahl index implies higher crop diversification. The finding in this study is consistent with the one of Coelli and Fleming (2004) for Papua New Guinea, Rahman (2010) for Bangladesh, and Ogundari (2013) for Nigeria.

5. Conclusion and policy implications

This study has reported on an analysis of economies of diversification, scale and scope economies, and efficiency in farming system comprising cropping activities of subsistence food and other annual cash crops in rural Vietnam. It also provides the information on elasticities of substitution between inputs and responses of small farm households to

[18] The coefficient of the Simpson index is not statistically significant even though it shows a positive sign. Therefore, we only report the number of plots.

increasing cost stress in multi-crop production. Scale and scope economies were found to exist in crop production. The significant scale economies is 0.89 which implies that when total outputs increase by 1 per cent, total costs of production only rise by 0.89 per cent. There is a complementary between rice and other crops, which show that there are considerable scope economies in farm production as a result of crop diversification.

Results also show that households with smallholder production substantially respond to cost stress in multiple crop environment. Complementary exists between family labour and fertilizers, pesticides and capitals, which means that farm labour may fall when cost share of these input increase. This finding contributes to the literature on push factors of labour allocation in a small holder. Due to small scale of annual crop production, farms are sensitive to costs of inputs. Since fertilizer, pesticide and seeds accounted for the largest share of total production costs, policies that lead to more incentives to invest in crop faming activities should focus on the reduction of input costs. The government should spend more resources on reducing fertilizer price for farmers such as increasing subsidy programs. The evidence of elasticity of substitution between farm labour and fertilizer and pesticides indicates that subsidy programs on fertilizer and pesticides can has a positive effect the probability that a household demand family labour, which can reduce increasing trends of the abandon of agricultural production in rural Vietnam.

However, the adjustments of cost structure also impacts on rural labour market when rural stratification is taking place and more farm households have worked as farm wages. The result shows that there is a substitute between family labour and hired labour. With increased participation in off-farm activities of smallholders, the reliance of hired labour is more important for producers. The farm household can allocate more hours to off-farm works by easily hiring replacement workers on the farm. Therefore, it would be expected that large increase in government input subsidy would have significant impact on the flow of labour into farming activities, mainly on the reduction of demand for hired labour. Warr and Yusuf (2014) find that input subsidy such as fertilizer has large and positive impacts on unskilled wages in Indonesia. We may find a similar conclusion in the case of Vietnam by using the estimates of elasticity of substitution in multi-crop farming.

Another finding is that there is an existence of substantial technical inefficiency in multiple crops farming, which implies that there may be opportunities to expand crop outputs without resort to greater uses of inputs or improved technologies in farm production (about 18 per cent of the loss in potential outputs). There were seven variables, which significantly affect technical inefficiency. The improvement of education, particularly for women and reduction of dependency ratio contribute to improving technical efficiency. Furthermore, land reforms toward the reduction of land fragmentation should be strengthened to improve efficiency.

The final policy implication of this research emphasizes the design of policies to promote crop diversification, which is found to improve productivity through scope economies and technical efficiency. There has been no specific policy on crop diversification. Vietnamese government seems to give priority to rice self-sufficient policies rather than income of farmers. Kompas et al. (2012) also conclude that the mandate to grow rice all provinces, at least in term of defined efficiency criteria, is not appropriate. Therefore, crop diversity should be expanded. As part of an FAO nutrition-sensitive food systems approach, crop diversification improves the nutritional health status of low-income households, through increased production of nutrient-rich foods for direct consumption and generation of the income needed to procure the amount and variety of food families need (FAO, 2012).

Table 1. Definitions, units of measurement and summary statistics for all variables in the empirical analysis

Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Output variables						
Rice (y_1)	Kg	1970	1876.68	2713.83	53.6	43550
Vegetables (y_2)	Kg	1970 (1550)	410.06	1152.29	0	25200
Starchy crops (y_3)	Kg	1970 (1445)	1025.48	4110.27	0	110000
Annual industrial crops (y_4)	Kg	1970 (751)	71.62	310.94	0	7200
Input variables						
Land area cultivated (x_1)	Ha	1970	0.41	0.54	0.03	11.3
Family labour (x_2)	Hours	1970	2293.65	1616.68	40	12960
Fertilizers (x_3)	Kg	1970	525.93	717.60	6	16963
Pesticides (x_4)	1000 VND	1970	359.74	1071.03	4	31900
Labour hired (x_5)	1000 VND	1970	340.02	1184.20	0	18200
Capital hired (x_6)	1000 VND	1970	546.40	968.83	0	14310
Seeds (x_7)	1000 VND	1970	415.07	597.48	8	9900
Farm specific variables						
Age of the household head	Years	1970	47.72	11.13	19	90
Mean education of working age men	Years	1970	4.08	2.17	0	12.5
Mean education of working age women	Years	1970	3.99	2.16	0	15
Access to formal credit	1 if access	1970	0.37	0.48	0	1

Household members, from 15 to 60	Persons	1970	3.02	1.20	1	9
Dependency ratio (%)	Per cent	1970	0.31	0.22	0	0.833
Days of illness	Days	1970	21.25	43.03	0	440
Number of plots	Plots	1970	6.32	4.26	1	49
Hours of nonfarm wage participation	Hours	1970	988.77	1519.42	0	9888

Note: *starchy crops, vegetables, and annual industrial crops aggregate other outputs of a farm.

Table 2. Tests of hypotheses

Name of tests	Null hypothesis	Likelihood ratio (χ^{2}-calculated)	χ^{2}-critical (0.95)	Decision
1. Functional form (Translog vs Cobb-Douglass)	H_0: $\beta_{nk}=\alpha_{ml}=\gamma_{mn}=0$ for all n, k, m and l	1099.23	73.31	Reject H_0 (selected TL)
2. No inefficiency effect	H_0: $\gamma=\eta_0=\eta_1=\eta_2=\eta_3=\eta_4=\eta_5=\eta_6=\eta_7=\eta_8=\eta_9=0$	41.39	3.84	Reject H_0
3. Farm specific effects do not affect technical inefficiencies	H_0: $\eta_0=\eta_1=\eta_2=\eta_3=\eta_4=\eta_5=\eta_6=\eta_7=\eta_8=\eta_9=0$	39.31	16.92	Reject H_0
4. Input-output separability	H_0: all $\gamma_{mn}=0$ for all m and n	87.34	36.42	Reject H_0
5. Returns to scale (scale economy if $\varepsilon_{x,y}<1$)	H_0: $(\Sigma\alpha_m)=1$ for all m	11.10	3.84	Reject H_0 (scale economy exists)

Table 3. Monotonicity condition check

Inputs $\{(\partial \ln D/\partial x_n)\geq 0\}$ for every input	Value	Outcome	Outputs $\{(\partial \ln D/\partial y_m)\leq 0\}$ for every output	Value	Outcome
Family labor	0.018	Fulfilled	Rice	-0.076	Fulfilled
Fertilizer	0.029	Fulfilled	Vegetables	-0.009	Fulfilled
Pesticide	0.013	Fulfilled	Starchy crops	0.038	Fulfilled
Labor hired	0.008	Fulfilled	Annual industrial crops	0.062	Fulfilled
Capital hired	0.005	Fulfilled			
Seeds	0.022	Fulfilled			

Table 4. Elasticities of input distance function at sample means (First order components)

Variables	Symbol	Value[a]	*t*-ratio
Output elasticities			
Scale economy	$\varepsilon_{x,y}$	0.896	
Rice	$\varepsilon_{x, y1}$	0.574	20.73
Vegetables	$\varepsilon_{x, y2}$	0.038	4.80
Starchy crops	$\varepsilon_{x, y3}$	0.178	4.42
Annual industrial crops	$\varepsilon_{x, y4}$	0.106	1.94
Input elasticities			
Family labour	$\varepsilon_{x, x2}$	-0.161	-7.33
Fertilizer	$\varepsilon_{x, x3}$	-0.205	-6.38
Pesticides	$\varepsilon_{x, x4}$	-0.070	-3.36
Labour hired	$\varepsilon_{x, x5}$	-0.030	-4.74
Capital hired	$\varepsilon_{x, x6}$	-0.027	-3.22
Seeds	$\varepsilon_{x, x7}$	-0.147	-5.18
Land	$\varepsilon_{x, x1}$	-0.360	
Output jointness			
Rice and vegetables	$\varepsilon_{x,y12}$	-0.010	-2.72
Rice and starchy crops	$\varepsilon_{x,y13}$	-0.019	-6.09
Rice and annual industrial crops	$\varepsilon_{x,y14}$	-0.023	-5.40
Vegetables and starchy crops	$\varepsilon_{x,y23}$	-0.003	-3.07
Vegetables and annual industrial crops	$\varepsilon_{x,y23}$	-0.0007	-0.63
Starchy crops and annual industrial crops	$\varepsilon_{x,y34}$	-0.001	-0.88

Notes: [a] evaluated at the means of the data using parameters estimates of (11).

Table 5. Mean of output cross and own indirect elasticity of shadow prices with respect to inputs (ε_{ij})

	Labour	Fertilizer	Pesticide	Hired labour	Capital	Seeds
Labour	-1.136 (-15.92)	0.268 (3.87)	0.116 (0.92)	-0.307 (-2.97)	0.457 (3.78)	0.205 (2.23)
Fertilizer	0.351 (3.87)	-0.889 (-8.40)	0.363 (1.91)	0.348 (2.46)	-0.009 (-0.08)	-0.003 (-0.02)
Pesticide	0.051 (0.92)	0.121 (1.91)	-0.644 (-3.91)	-0.365 (-3.77)	0.051 (0.47)	0.201 (2.82)
Hired labour	-0.058 (-2.97)	0.049 (2.46)	-0.156 (-3.77)	-0.233 (-1.77)	0.067 (1.87)	-0.0741 (-2.56)
Capital	0.077 (3.78)	-0.001 (-0.08)	0.029 (0.71)	0.067 (1.87)	-1.467 (-11.90)	0.077 (2.96)
Seeds	0.179 (2.23)	-0.002 (-0.02)	0.491 (2.82)	-0.333 (-2.56)	0.258 (1.79)	-0.879 (-6.43)

Notes: t-values are in parentheses; evaluated at the means of the data using parameters estimates of (11).

Table 6. The indirect Morishima elasticity of substitution

	Labour	Fertilizer	Pesticide	Hired labour	Capital	Seeds
Labour		1.157 (7.74)	0.760 (3.68)	-0.074 (-2.46)	1.925 (11.07)	1.085 (5.97)
Fertilizer	1.487 (11.51)		1.006 (3.16)	0.582 (3.50)	1.454 (6.56)	0.876 (4.18)
Pesticide	1.187 (12.93)	1.010 (6.59)		-0.131 (-0.87)	1.518 (8.44)	1.081 (6.49)
Hired labour	-1.194 (-14.99)	0.939 (8.48)	0.487 (2.77)		1.534 (11.67)	0.809 (5.67)
Capital	1.213 (17.02)	0.888 (8.35)	0.664 (3.69)	0.300 (2.28)		0.935 (6.84)
Seeds	1.315 (11.11)	0.887 (5.69)	1.135 (4.24)	-0.099 (-0.59)	1.739 (8.07)	

Notes: t-values are in parentheses; evaluated at the means of the data using parameters estimates

Table 7. The indirect Allen-Uzawa elasticity of substitution

	Labour	Fertilizer	Pesticide	Hired labour	Capital	Seeds
Labour						
Fertilizer	0.011 (1.66)					
Pesticide	-0.005 (-0.34)	0.017 (0.81)				
Hired labour	-0.096 (-4.52)	0.029 (0.98)	-0.316 (-4.50)			
Capital	0.038 (2.46)	-0.024 (-1.36)	-0.007 (-0.18)	0.050 (1.03)		
Seeds	0.005 (0.49)	-0.021 (1.63)	0.059 (2.01)	-0.157 (-3.64)	0.018 (0.82)	

Notes:t-values are in parentheses;evaluated at the means of the data using parameters estimates

Table 8. Technical inefficiency model

	Parameters	Coefficients	t value
Age of the household head	η_1	0.0029	-0.06
Mean education of working age men	η_2	-0.073	-2.54
Mean education of working age women	η_3	-0.150	-4.73
Access to formal credit	η_4	0.151	1.37
Household members, from 15 to 60 years old	η_5	0.416	4.76
Dependency ratio (%)	η_6	0.697	2.08
Days of illness	η_7	0.001	0.44
Number of plots	η_8	0.033	2.22
Hours of nonfarm wages	η_9	-0.0002	-3.64
Herfindahl index	η_{10}	2.050	2.74
Constant	η_0	-4.869	-4.57
Number of observations		1970	

References

Agricensus, 2006. *Agricultural census and survey*, General Statistics Office of Vietnam and Ministry of Agriculture and Rural Development.

Aigner, D.J., Lovell, C.A.K. & Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6, pp.21–37.

Akram-Lodhi, A.H., 2005. Vietnam's agriculture : processes of rich peasant accumulation and mechanisms. *Journal of Agrarian Change*, 5(1), pp.73–116.

Atkinson, S.E. & Cornwell, C., & Honerkamp, O., 1999, *Measuring and decomposing productivity change: stochastic distance function estimation vs DEA*, Working Paper 99-478, Department of Economics, University of Georgia, Athens.

Battese, G.E. & Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data, *Empirical Economics*, 20, pp.325-332.

Baumol, W.J., Panzar, J.C. & Willig, R.D., 1982. *Contestable Markets and the Theory of Industry Structure*, Harcourt Brace Jovanovich Inc, New York.

Benjamin, D., 1992. Household composition, labor markets and labor demand: testing for separation in agricultural household models. *Econometrica*, 60(2), pp.287–322.

Blackorby, B.C. & Russell, R.R., 1989. Will the Real Elasticity of Substitution Please Stand Up ? (a comparison of the Allen / Uzawa and Morishima elasticities). *The American Economic Review*, 79(4), pp.882–888.

Bloomberg News, 2012. http://www.bloomberg.com/news/2013-09-12/vietnam-s-rice-output-faces-slide-on-crop-switch-southeast-asia.html

Brümmer, B., Glauben, T. & Lu, W., 2006. Policy reform and productivity change in Chinese agriculture: A distance function approach. *Journal of Development Economics*, 81(1), pp.61–79.

Chavas, J.-P. & Di Falco, S., 2012. On the Role of Risk Versus Economies of Scope in Farm Diversification With an Application to Ethiopian Farms. *Journal of Agricultural Economics*, 63(1), pp.25–55.

Chavas, J.P. & Aliber, M., 1993. An analysis of economic efficiency in agriculture: a nonparametric approach. *Journal of Agricultural and Resource Economics*, 18, pp.1–16.

Coelli, T. & Fleming, E., 2004. Diversification economies and specialisation efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. *Agricultural Economics*, 31, pp.229–239.

Coelli, T. & Perelman, S., 2000. Technical efficiency of European railways: a distance function approach. *Applied Economics*, 32(15), pp.1967–1976.

Coelli, T.J., 1995. Estimators and hypothesis tests for a stochastic frontier function: A Monte-Carlo analysis. *Journal of Productivity Analysis*, 6, pp.247–268.

Coelli, T.J., 1993. *A stochastic frontier production function incorporating a model for technical inefficiency effects*, Working Paper in Econometrics and Applied Statistics no 69, Department of Econometrics, University of New England, Armidale.

Coelli, T.J., 2000. *On the econometric estimation of the distance function representation of the production technology*, CORE Discussion Paper 2000/42 (Louvain-la-Neuve: Universite Catholique de Louvain).

Coelli, T.J., Prasada, D.S. & Battese, G.E., 1998. *An Introduction to Efficiency and Productivity Analysis*, Kluwer Academic Publishers, Boston

D'Antoni, J.M., Khanal, A.R. & Mishra, A.K., 2014. Examining labor substitution: does family matter for US cash grain farmers? *Journal of Agricultural and Applied Economics*, 2(May), pp.273–284.

Dao, G. & Lewis, P., 2013. *Technical efficiency of annual crop farms in northern Vietnam*, Working Paper, available at: www.murdoch.edu.au

FAO, 2012. *Crop diversification sustainable diets and nutrition*, Plant Production and Protection Division, Rome.

FAO, 2010. *The rice crisis: markets, policies and food security* D. Dawe, ed., London, FAO and Earthscan. Rome.

Fare, R.S. & Primont, D., 1995. *Multi-Output Production and Duality, Theory and Application*, Kluwer Academic Publishers, Boston

Fernandez-Cornejo, J. et al., 1992. Dynamic measures of scope and scale economies: an application to German agriculture. *American Journal of Agricultural Economics*, 74, pp.329–342.

Gilbert, J.R., 2014. Wage and employment effects of Malawi's fertilizer subsidy program, *Agricultural Economics*, 45, pp.337-353.

Grosskopf, S., Hayes, K. & Hirschberg, J., 1995. Fiscal stress and the production of public safety: a distance function approach. *Journal of Public Economics*, 57, pp.277–296.

Hailu, A. & Veeman, T.S., 2000. Environmentally sensitive productivity analysis of the Canadian pulp and paper industry, 1959-1994. *Environmental Economics and Management*, 40, pp.251–274.

Hicks, J.R., 1963. *The Theory of Wages* 2nd eds., MacMilan, London.

Van Hung, P., MacAulay, T.G. & Marsh, S.P., 2007. The economics of land fragmentation in the north of Vietnam. *The Australian Journal of Agricultural and Resource Economics*, 51(2), pp.195–211.

Irz, X. & Thirtle, C., 2004. Dual Technological Development in Botswana Agriculture: A Stochastic Input Distance Function Approach. *Journal of Agricultural Economics*, 55(3), pp.455–478.

Jolliffe, D., 2004. The impact of education in rural Ghana: examining household labour allocation and returns on and off the farm. *Journal of Development Economics*, 73(1), pp.287–314.

Kim, K. et al., 2012. Specialization, diversification, and productivity: a panel data analysis of rice farms in Korea. *Agricultural Economics*, 43(6), pp.687–700.

Kompas, T., 2004. *Market reform, productivity and efficiency in Vietnamese rice production*,

Kompas, T. et al., 2012. Productivity, net returns, and efficiency : land and market reform in Vietnamese rice production. *Land Economics*, 88(3), pp.478–495.

Kumar, S., 2006. Analysing industrial water demand in India : an input distance function approach. *Water Policy*, 8, pp.15–29.

Kumbhakar, S.S. et al., 2007. Do we estimate an input or output distance function? an application of the mixed approach to European Railways. *Journal of Productivity Analysis*, 27, pp.87–100.

Kumbhakar, S.S. & Lovell, C., 2003. *Stochastic Frontier Analysis* 2nd ed., Cambridge, UK: Cambridge University Press.

Le, K.T., 2010. Separation Hypothesis Tests in the Agricultural Household Model. *American Journal of Agricultural Economics*, 92(5), pp.1420–1431.

Lovell, C.A.K. et al., 1994. Resources and functioning: a new view of inequality in Australia. In W. Eichhorn, ed. *Models and Measurement of Welfare Inequality*. Berlin: Springer-Verlag Press.

Mafoua-Koukebene, E., Hornbaker, R.H. & Sherrick, B.J., 1996. Effects of Government program payments on farm portfolio diversification. *Review of Agricultural Economics*, 18, pp.281–291.

Minot, N. et al., 2006. *Income Diversification and Poverty in the Northern Uplands of Vietnam*, Washington, DC: International Food Policy Research Institute.

Ogundari, K., 2013. Crop diversification and technical efficiency in food crop production: A study of peasant farmers in Nigeria. *International Journal of Social Economics*, 40(3), pp.267–287.

Ogundari, K. & Brümmer, B., 2011. Estimating Technical Efficiency, Input substitution and complementary effects using Output Distance Function: A study of Cassava production in Nigeria. *Agricultural Economic Review*, 12(2), pp.62–79.

Paul, C.J.M., Johnston, W.E. & Frengley, G. a. G., 2000. Efficiency in New Zealand Sheep and Beef Farming: The Impacts of Regulatory Reform. *Review of Economics and Statistics*, 82(2), pp.325–337.

Paul, C.J.M. & Nehring, R., 2005. Product diversification, production systems, and economic performance in U.S. agricultural production. *Journal of Econometrics*, 126(2), pp.525–548.

Rahman, S., 2010. Women's Labour Contribution to Productivity and Efficiency in Agriculture: Empirical Evidence From Bangladesh. *Journal of Agricultural Economics*, 61(2), pp.318–342.

Rasmussen, S., 2010. Scale efficiency in Danish agriculture: an input distance-function approach. *European Review of Agricultural Economics*, 37(3), pp.335–367.

Ravallion, M. & van de Walle, D., 2006. Does rising landlessness signal success or failure for Vietnam's agrarian transition? *Journal of Development Economics*, 87(2), pp.191–209.

Robison, L.J. & Barry, P.J., 1987. *The competitive firm's response to risk*, New York: Macmillan Publishing Company.

Shephard, R., 1970. *Theory of cost and production function*, Princeton: Princeton University Press.

Solís, D., Bravo-Ureta, B.E. & Quiroga, R.E., 2009. Technical Efficiency among Peasant Farmers Participating in Natural Resource Management Programmes in Central America. *Journal of Agricultural Economics*, 60(1), pp.202–219.

Timmer, C.P., 2014. Food security in Asia and the Pacific: the rapidly changing role of rice. *Asia & The Pacific Policy Studies*, 1(1), pp.73–90.

The Diplomat, 2013. http://thediplomat.com/2013/12/vietnamese-rice-farmers-abandon-their-fields/

Urdy, C., 1996. Gender, agriculture production, and the theory of the household. *The Journal of Political Economy*, 104(5), pp.1010–1046.

Vu, L., 2012. Efficiency of rice farming households in Vietnam. *International Journal of Development Issues*, 11(1), pp.60–73.

Wadud, A. & White, B., 2000. Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods. *Applied Economics*, 32, pp.1665–1673.

Warr, P. & Yusuf, A.A., 2014. Fertilizer subsidies and food self-sufficiency in Indonesia. *Agricultural Economics*, 45(5), pp.571–588.

Willig, R.D., 1979. Multiproduct Technology and Market Structure. *The American Economic Review*, 69(2), pp.346–351.

Wooldridge, J.M. 2012, *Econometric analysis of cross section and panel data*, 2nd eds, The MIT Press, London.

World Bank, 2006. *Vietnam: business*, Development Report 34474-VN, Hanoi, Vietnam.

World Bank, 2007. *Accelerating rural development in Vietnam*, Hanoi, Vietnam. Available at: www.worldbank.org.vn.

Appendix A1. Parameter estimates of the stochastic input distance function including inefficiency effects

Variables	Parameters	Coefficients	SE	t value
Production variables				
ln(labor/land)	β_2	-0.175	0.143	-1.22
ln(fertilizer/land)	β_3	0.274	0.191	1.44
ln(pesticide/land)	β_4	-0.433	0.127	-3.41
ln(hired labor/land)	β_5	0.02	0.045	0.46
ln(capital/land	β_6	-0.110	0.048	-2.31
ln(seeds/land)	β_7	-0.052	0.189	-0.28
1/2 ln(labor/land)2	β_{22}	-0.047	0.011	-4.15
1/2 ln(fertilizer/land)2	β_{33}	-0.021	0.022	-0.94
1/2 ln(pesticide/land)2	β_{44}	0.020	0.012	1.73
1/2 ln(hired labor/land)2	β_{55}	0.036	0.004	9.13
1/2 ln(capital/land)2	β_{66}	-0.013	0.003	-4.01
1/2 ln(seeds/land)2+A7`	β_{77}	-0.003	0.019	-0.15
ln(labor/land)*ln(fertilizer/land)	β_{23}	0.023	0.015	1.56
ln(labor/land)*ln(pesticide/land)	β_{24}	-0.003	0.009	-0.34
ln(labor/land)* ln(hired_labor/land)	β_{25}	-0.014	0.003	-4.52
ln(labor/land)* ln(capital/land)	β_{26}	0.008	0.003	2.46
ln(labor/land)* ln(seeds/land)	β_{27}	0.006	0.013	0.49
ln(fertilizer/land)* ln(prsticide/land)	β_{34}	0.011	0.013	0.81

ln(fertilizer/land)* ln(hired labor/land)	β_{35}	0.004	0.004	0.98
ln(fertilizer/land)* ln(capital/land)	β_{36}	-0.006	0.004	-1.36
ln(fertilizer/land)* ln(seeds/land)	β_{37}	-0.03	0.018	-1.63
ln(pesticide/land)* ln(hired labor/land)	β_{45}	-0.013	0.003	-4.5
ln(pesticide/land)* ln(capital/land)	β_{46}	-0.001	0.003	-0.18
ln(pesticide/land)* ln(seeds/land)	β_{47}	0.025	0.012	2.01
ln(hired labor/land)* ln(capital/land)	β_{56}	0.001	0.001	1.03
ln(hired labor/land)* ln(seeds/land)	β_{57}	-0.014	0.004	-3.64
ln(capital/land)* ln(seeds/land)	β_{67}	0.004	0.004	0.82
ln(labor/land) * ln(rice output)	γ_{21}	0.037	0.011	3.4
ln(labor/land)* ln(vegetables)	γ_{22}	0.002	0.003	0.5
ln(labor/land)*ln(starchy output)	γ_{23}	-0.006	0.003	-2.1
ln(labor/land)* ln(annual industrial output)	γ_{24}	-0.009	0.004	-2.39
ln(fertilizer/land)* ln(rice output)	γ_{31}	-0.048	0.018	-2.67
ln(fertilizer/land)* ln(vegetables)	γ_{32}	0.002	0.005	0.47
ln(fertilizer/land)*ln(starchy output)	γ_{33}	-0.003	0.005	-0.6
ln(fertilizer.land)*ln(annual industrial output)	γ_{34}	-0.005	0.005	-0.91
ln(pesticide/land) * ln(rice output)	γ_{41}	0.009	0.011	0.83
ln(pesticide/land) * ln(vegetables)	γ_{42}	0.005	0.003	1.41
ln(pesticide/land)*ln(starchy output)	γ_{43}	-0.003	0.003	-1.02
ln(pesticide/land)*ln(annual industrial output)	γ_{44}	0.0016	0.003	-0.05
ln(hired labor/land)* ln(rice output)	γ_{51}	0.010	0.004	2.55
ln(hired labor/land)* ln(vegetables)	γ_{52}	0.001	0.001	0.71
ln(hired labor/land)*ln(starchy output)	γ_{53}	0.002	0.001	2.77
ln(hired labor/land)*ln(annual industrial output)	γ_{54}	-0.001	0.001	-1.41
ln(capital/land)* ln(rice output)	γ_{61}	0.014	0.004	3.49
ln(capital/land)* ln(vegetables)	γ_{62}	-0.001	0.001	-0.55
ln(capital/land)*ln(starchy output)	γ_{63}	0.001	0.001	0.91
ln(capital/land)*ln(annual industrial output)	γ_{64}	-0.001	0.001	-0.85
ln(seeds/land) * ln(rice output)	γ_{71}	-0.002	0.015	-0.16
ln(seeds/land) * ln(vegetables)	γ_{72}	-0.005	0.004	-1.18
ln(seeds/land)*ln(starchy output)	γ_{73}	-0.003	0.004	-0.87
ln(seeds/land)*ln(annual industrial output)	γ_{74}	0.007	0.005	1.31
ln(rice output)	α_{1}	-0.181	0.189	-0.96
ln(vegetables)	α_{2}	0.021	0.049	0.43
ln(starchy output)	α_{3}	0.226	0.042	5.44
ln(annual industrial output)	α_{4}	0.195	0.055	3.52
1/2 ln(rice output)2	α_{11}	0.104	0.017	5.99
1/2 ln(vegetables)2	α_{22}	0.021	0.002	8.48
1/2 ln(starchy output)2	α_{33}	0.019	0.002	9.33
1/2 ln(annual industrial output)2	α_{44}	0.042	0.004	9.5
ln(rice output)* ln(vegetables)	α_{12}	-0.010	0.004	-2.72
ln(rice output)*ln(starchy output)	α_{13}	-0.019	0.003	-6.09
ln(rice output)*ln(annual industrial output)	α_{14}	-0.023	0.004	-5.4
ln(vegetables)*ln(starchy output)	α_{23}	-0.003	0.001	-3.07

ln(vegetables)*ln(annual industrial output)	α_{24}	-0.001	0.001	-0.63
ln(starchy output)*ln(annual industrial output)	α_{34}	-0.001	0.001	-0.88
Region				
North East	ρ_1	0.060	0.018	3.29
North West	ρ_2	0.031	0.032	0.99
North Central Coast	ρ_3	0.110	0.019	5.79
South Central Coast	ρ_4	-0.008	0.026	-0.29
Central Highlands	ρ_5	0.372	0.042	8.78
South East	ρ_6	0.461	0.053	8.75
Mekong River Delta	ρ_7	0.148	0.041	3.63
Constant	β_0	-3.187	0.139	-22.92
Inefficiency effects function				
Age of the household head	η_1	0.0029	0.005	-0.06
Mean education of working age men	η_2	-0.073	0.029	-2.54
Mean education of working age women	η_3	-0.150	0.032	-4.73
Access to formal credit	η_4	0.151	0.110	1.37
Household members, from 15 to 60 years old	η_5	0.416	0.088	4.76
Dependency ratio (%)	η_6	0.697	0.336	2.08
Days of illness	η_7	0.001	0.001	0.44
Number of plots	η_8	0.033	0.015	2.22
Hours of nonfarm wages	η_9	-0.000	0.000	-3.64
HI	η_{10}	2.050	0.748	2.74
Constant	η_0	-4.869	1.066	-4.57
N		1970		