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Pattern of investment allocation to chemical inputs and technical efficiency:

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Abstract

This study focuses on the pattern between investment in chemical inputs such as fertilizer, pesticides and herbicides and technical efficiency of farm households in Laguna, Philippines. Using a one-stage maximum likelihood estimation procedure, the stochastic production frontier model was estimated simultaneously with the determinants of efficiency. Results show that farmers with a low technical efficiency score have a high investment share in chemical inputs. Farmers who invested more in chemical inputs relative to other variable inputs attained the same or even lower output and were less efficient than those farmers who invested less. The result shows that farmers who invested wisely in chemical inputs can encourage farmers to apply chemical inputs more optimally.

Keywords: Agricultural Management, Agricultural Productivity, Farm Household, Fertilizer Use, Rice

JEL Classification (Q12) – Micro-Analysis of Farm Firms, Farm Households, and Farm Input Markets

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1. Introduction

Farmers invest in chemical inputs such as fertilizer, pesticides and herbicides in rice farming to improve crop yield by enhancing soil nutrients and protecting crops from infestation. Since the recommended amount of chemical inputs varies from farm to farm and is considered to be site-specific, crop care management practices among farmers also vary. Some farmers apply fertilizer on a crop more than it can absorb, resulting in the same yield as that of farmers who apply less. Similarly, the amount of pesticides and herbicides applied will also depend on the level of infestation. Farmers apply more pesticides than what is required to mitigate pests and diseases as well as for herbicides to reduce or prevent weed growth. Thus, farmers end up spending more on chemical inputs, which leads to a lower net cash return after harvest.

This study will measure the level of technical efficiency of the sampled farm households in Laguna, Philippines. The analysis will identify the socioeconomic factors that affect the efficiency of farmers such as age, education, household size and farm size as well as factors such as market distance and farm ownership. In addition, the share of chemical input cost in total variable cost is used to identify the pattern of use of chemical inputs in relation to technical efficiency. Chemical inputs refer to inorganic fertilizer, pesticide and herbicide.

2. Review of literature

Production frontier analysis has been widely used in the Philippine literature to measure and identify the factors that affect the technical efficiency of rice farmers. Inputs in rice farming such as seeds, chemical inputs, source of power and labor were commonly used as the explanatory variables in the production function model. Socioeconomic factors such as age, farming experience, household size, education and training, on the other hand, have been used in determining the sources of inefficiency. Villano and Fleming (2004) listed farm-specific studies from 1983 to 2003 across locations in the Philippines. These studies were also extensive and used various methods in analyzing the production frontier of farmers such as the use of covariance and deterministic analysis, and Malmquist index and stochastic models. In addition, these studies conducted production frontier analysis in reference to the rice production ecosystem, i.e., rainfed and irrigated; geographic region (most of which are in the northern regions of the country); and across cropping seasons (panel data). Some of the latest studies on production frontier analysis such as by Yao and Shively (2007) focus on the role of the rice production ecosystem wherein it shows the positive effect of irrigation on the technical efficiency of rice farmers. Using panel data, Villano and Fleming (2004) and Abedullah, Pandey and Jabeen (2009) conducted technical efficiency studies that both focus on the rainfed lowland ecosystem in Central Luzon in the Philippines. The former explained that the high degree of variation across farmers should be taken into consideration in specifying a production function model in this type of ecosystem. The latter, on the other hand, showed that development in technical efficiency is time invariant and does not depend significantly on technological change. In addition, Mariano, Villano and Fleming (2010) conducted a comparative analysis of technical efficiency between the rainfed and irrigated ecosystem using panel data from 1996 to 2006. Using a stochastic metafrontier model, the study concluded that a marginal variation in efficiency between two production ecosystems exists and an absence of technological change was also observed across periods. Most of these analyses focused on the estimates and existence of technical efficiency and methods used. Some studies looked into determining the sources of efficiency aside from the socioeconomic factors that were mentioned earlier. Luis *et al.* (2010) analyzed the effect of rural outmigration on farmers' technical efficiency and concluded that remittances from family members who work far from home contributed to technical efficiency.

3. Data and methodology

The data used in this analysis came from the farm household survey conducted in 2012 under IRRI's Green Super Rice (GSR) project. The information collected was based on the 2010-11 dry season and 2011 wet season in Laguna Province, located in the Southern Luzon region of the country. Larger rice area, irrigated farms and rural areas were the main criteria used in selecting the study sites. A site should have a relatively larger rice area to permit better tracking of varietal dissemination for future study of adoption. Rice varieties that were provided for a farm trial are best suited in the irrigated ecosystem; thus, access to irrigation is a primary consideration. In addition, rice communities in rural areas have fewer chances to be converted into an industrial zone than those in urban settings. Five districts, Famy, Mabitac, Majayjay, Santa Maria and Siniloan, were purposively selected based on the criteria mentioned above and 200 respondents were randomly drawn from the list of farmers belonging to these districts. The respondents were the farmers who managed the farm and not necessarily the household head. A structured questionnaire was used in the survey to collect information on farmers' resource endowment, rice varieties grown, rice yield, rice production, income structure and other related information. The survey also collected detailed information on input, power and labor use and costs of rice production for the 2011 wet season. However, only 184 respondents were able to cultivate and harvest rice in this season. This was the sub-sample used in this study since the analysis requires details on the quantity of inputs applied such as seeds, fertilizer, pesticides, herbicides, machinery, draft animals and labor to represent the production function of rice farming.

1.1. Frontier model

Details on the amount of inputs of rice production were selected to fit the stochastic production frontier using the Cobb-Douglas functional form to specify the production function model based on the framework developed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van Den Broeck (1977). Using the maximum-likelihood method, the parameters of the stochastic production function and technical inefficiency effects will be estimated simultaneously in a single-stage procedure as proposed by Kumbhakar, Ghosh and McGuckin (1991), which was used in cross-sectional data and later applied using panel data from Battese and Coelli (1995).

Thus, the stochastic frontier model is given as:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ji} + V_i - U_i \qquad (1)$$

where

i	=	observation of the ith farm household
ln	=	natural logarithmic form
Y	=	rice production yield
β	=	parameters to be estimated
X	=	vector of production inputs
V	=	independent and identically distributed N $(0, \sigma_v^2)$ random error term
U	=	non-negative random variables associated with technical inefficiency of production

while the technical inefficiency model is given as:

$$U_i = \delta + \sum_{j=1}^{n} \delta_i Z_{ji} + \varepsilon_i \qquad (2)$$

where

U	=	technical inefficiency
δ	=	parameters to be estimated
Z	=	determinants of inefficiency
ε	=	random variable defined by the truncation of the normal distribution with zero mean and variance σ_ε^2

Assuming that the random variable U_i has variance σ_u^2 and is independent of V_i, the total variance is given as

$\sigma^2 = \sigma_v^2 + \sigma_u^2$ and the technical inefficiency parameter as $\gamma = \sigma_u^2/\sigma^2$.

The technical efficiency score is defined as the ratio of observed output to the maximum or potential output.

1.2. Variable specification

Table 1 lists the variables specified in the production function model (equation 1) and in the determinants of inefficiency (equation 2).

Table 1. Variables in the production function and inefficiency model

Production function	Determinants of inefficiency
Yield (kg per ha)	Distance to the nearest market (km)
Seed (kg per ha)	Household size
Fertilizer (kg per ha)	Age of the farmer
Herbicide (g per ha)	Years of education of the farmer
Pesticide (g per ha)	Farm size (ha)
Power (cost per ha)	Lease only (dummy for land tenure)
Draft animal (dummy)	Site dummy (dummy for Majayjay District)
Hired labor (person-days per ha)	
Family labor (person-days per ha)	

Yield is the rice production output measured in kg per hectare and it represents the dependent variable of the production function. Seed is one of the input variables measured in kg per hectare. Fertilizer is also measured in kg per ha and considered to be only inorganic or chemical fertilizer. Although 13 out of 184 farmers applied organic fertilizer, this variable was not included in the model since the unit of measurement used for this input is not standardized. For herbicide and pesticide, farmers applied either liquid or powder types or both and with different concentrations across types. To standardize the unit of measurement, the concentration of the active ingredient of each chemical type was used. The concentration is measured in grams per kg if the chemical is powder-based and in grams per liter if it is liquid-based. Given this conversion equivalent, the units used for pesticide and herbicide were standardized and converted to grams per ha. The use of power or energy from a draft animal or hand tractor, particularly for land preparation, was also included as an input variable. Both power sources (draft animal and hand tractor) were combined and represented as a variable power measured in cost per ha. The use of a draft animal is a lot cheaper than a hand tractor, which includes the cost of fuel and oil. Disaggregating these power sources into two will lead to zero values for some observations since few farmers used only one of the two power sources. Instead, combining the power sources using total power cost was chosen since it can already represent the type of power used. The higher the power cost, the more a hand tractor and less a draft animal was used by farmers. However, the use of a hand tractor and draft animal also affects the productivity of farmers. This factor has been considered by the use of a dummy variable for draft animal. The value of the dummy variable is equal to one if the farmer used a draft animal only and not a hand tractor. Otherwise, it is equal to zero if the farmer used a hand tractor only or combined it with a draft animal. Aside from animal and machine power, human power also contributes to farm productivity. Some farmers used their own family members as part of the labor force on top of laborers hired for the farm. Family and hired labor are two separate variables measured in person-days per ha.

In the second equation representing the inefficiency model, the chosen variables can be categorized into demographic characteristics and farm landholding. Demographic characteristics are the distance from the farmer's house to the nearest market measured in km, household size, age of the farmer and years of education. Farm size and land tenure status describe the landholding information of the farmer. Farm size is measured in hectares while land tenure status is represented by a dummy variable. Land tenure status is either own, leased or sharecropping[1]. In the survey, some farmers have a combination of these land tenure types. Even though some farmers have their own farm, they still lease a parcel of land to cultivate. However, some farmers do not own land and rely only on a land leasehold agreement. Under this arrangement, farmers shoulder the cost of farm inputs, machinery and labor. Farmers pay the landlord a fixed portion from the harvest. The number of cavans[2] paid from the harvest depends on farm size and season but it is usually around 10 cavans or 500 kg per ha based on the surveyed plots. In addition, leasehold farmers make all the decisions in managing the farm and they have the economic incentive to maximize profit since the land rent payment is fixed regardless of their harvest. The dummy variable "lease only" represents the farmers who do not own land but cultivate a farm under a leasehold agreement. A site dummy is also included that refers to the district of Majayjay. Majayjay is located at higher elevation whereas the other four districts are located on the plain and are more prone to flooding. However, in terms of production ecosystem, the five districts belong to the same category, which is lowland irrigated area.

4. Results and discussion

The cost of farming inputs can be divided into fixed and variable costs. Fixed costs include land rent and irrigation. Farmers whose landholding is under a leasehold agreement pay a fixed amount of harvest, which is equivalent to an average of USD158 per ha. The land rent should be paid every cropping season whether the harvest is good or bad. Similarly, the irrigation fee is also fixed and is usually based on farm size. Farmers can get as much water for irrigation as they need and pay the same amount; however, farmers still pay the same irrigation

[1] Farmers who have only a sharecropping type of tenure were not included in the sample selection.

[2] The cavan is a local unit used to measure the amount of rice harvest. Its equivalence in kilograms varies across farmers because the size of the cavan or sack also varies among farmers. In this survey, one cavan ranged from 50 to 55 kg.

fee even when water is scarce. In the survey, the irrigation fee is about USD14 per ha although farmers have the option to pay in either cash or its equivalent amount of harvest. The national irrigation system collects the irrigation fee for the maintenance of canals. However, farmers, who have access to rivers and natural stream like in Majayjay and Famy, don't have to pay irrigation fee.

Aside from the fixed cost incurred in rice production, farmers also spend on variable inputs such as seed, fertilizer, herbicide, pesticide, tractor, draft animal and hired labor. Table 2 shows the distribution of costs of variable and fixed inputs as well as the average net returns that farmers earn from farming. In terms of the share in total cost, farmers spent mostly on hired labor followed by fertilizer and the combined cost of a tractor and draft animal.

Table 2. Costs and returns of rice production in the wet season of 2011

Costs and returns	Values in USD per ha	% share in total cost
Variable costs		
Seed	39	4.9
Organic fertilizer	2	0.3
Fertilizer	140	18.0
Herbicide	14	1.8
Pesticide	43	5.4
Tractor and draft animal	125	16.0
Hired labor	325	41.0
Fixed costs		
Irrigation	14	1.8
Land rent	90	11.0
Gross income	1182	
Total cost	793	
Net income	389	

Source: IRRI GSR Project, household survey 2012.

Total inputs, which include fixed and variable inputs, were used to calculate the amount of cash income that farmers obtain. However, in determining the contribution of inputs to productivity measured in yield, fixed inputs were not included. Only the variable inputs were used and identified in the production function model. The descriptive statistics of the variables used in the production function model and determinants of inefficiency are presented in Table 3. The production inputs described in the table are only for the wet season of the 2011 crop year. The average yield is about 3.8 tons per ha. Sampled farmers in the survey used 70 kg per ha of seed and applied 219 kg per ha of chemical fertilizer, on average. The application of herbicide and pesticide in terms of concentration was similar across districts at around 500 grams per ha. The use of a tractor and draft animal cost

PhP 3,771 per ha while only 14% of the sample used an animal as the only source of power. Hiring farm laborers was dominant over using own family labor. About two laborers were being hired for every one family member working on the farm.

Table 3. Descriptive statistics of the variables in the production function and inefficiency model

Variable	Unit	Mean	SD
Production function			
Yield (dependent variable)	kg/ha	3793	1519
Seed	kg/ha	70	35
Fertilizer	kg/ha	219	114
Herbicide	g/ha	534	318
Pesticide	g/ha	480	433
Power source	cost/ha	3771	3097
Draft animal (1=draft animal only; 0=otherwise)	Dummy	14%	
Hired labor	person-days/ha	24	12
Family labor	person-days/ha	10	13
Inefficiency factors			
Market distance	km	3.0	2.2
Household size		4.5	2.3
Age of the farmer	years	55	12
Years of education of the farmer	years	8.1	3.3
Farm size	ha	1.44	1.2
Land tenure (1=leased land only; 0=otherwise)	Dummy	55%	
Site dummy (1=Majayjay; 0=otherwise)		15%	

Source: IRRI GSR project, household survey 2012.

Socioeconomic indicators are also presented in Table 3 and will be considered as determinants of the technical inefficiency of farmers. On average, the household has 4.5 members and their residence is about 3 km from the nearest marketplace. The average age of the farmer-respondent is about 55 and their level of education is around 8 years, which is equivalent to the sixth grade plus two years in secondary school. Farmers cultivate about 1.44 ha of farmland; however, 55% of the farmers do not own a farm and the land they cultivate is under a leasehold agreement.

A single-stage procedure using the maximum likelihood method was applied using the program STATA 10.1 with the assumption of half-normal distribution for the inefficiency term. The Cobb-Douglas production function model was also used to represent the data. In addition, this was also the adequate model based on the generalized likelihood ratio test conducted between Cobb-Douglas and Translog models. The generalized likelihood ratio test statistics is 36.51, which is less than the chi-square critical value of 38.93 with 21 degrees of freedom at the 1% level of significance. Further diagnostic tests using the generalized likelihood ratio test were also conducted to test three basic hypotheses. First, the test of the hypothesis that technical inefficiency is not present in the model. Based on the test statistics in Table 4, the null hypothesis, i.e., technical inefficiency is not present in the model, is rejected. In other words, the test proves statistically that the production frontier model should have an inefficiency component. Second, the test of the hypothesis that observed parameters of the inefficiency model have no random component. If this is true, an OLS regression model combining production frontier and inefficiency variables would be appropriate to conduct an analysis. However, the test statistics show that the hypothesis is rejected; hence, the parameters of the inefficiency model have a random component or it is stochastic. Third, the test of the hypothesis that the selected inefficiency variables have no significant effect on technical inefficiency. In this case, the inefficiency variables should be replaced in the technical inefficiency model. This hypothesis is also rejected based on test statistics. This means that the explanatory variables significantly affect the technical inefficiency model.

Table 4. Tests of hypotheses for the parameters of the inefficiency model

Null hypothesis	Log-likelihood	Test statistics
$H_0: \gamma = \delta_1 = \delta_2 = \ldots = \delta_9 = 0$	-162.94	117.06*
$H_0: \gamma = 0$	-155.75	102.68*
$H_0: \delta_1 = \delta_2 = \ldots = \delta_9 = 0$	-123.71	38.60*

*Test statistics exceed the chi-square critical value; thus, the null hypotheses are rejected.

The result of the maximum likelihood estimates of the parameters of the production function and inefficiency model is presented in Table 5. The parameters of the production function are the elasticities with respect to yield or output. Fertilizer and hired labor are both positive and statistically significant factors contributing to output. On the other hand, the use of a draft animal as a source of power is negative and significant. This means that farmers who do not have a tractor and rely only on a draft animal have lower output than those who have used a tractor in crop cultivation.

Table 5. ML estimates of the Cobb-Douglas production function and inefficiency model parameters

Variable	Coefficient	z-value
Production function		
Constant	8.11***	15.07
ln(seed)	0.0132	0.26
ln(fertilizer)	0.121***	2.67
ln(herbicide)	0.00760	0.53
ln(pesticide)	-0.0146	-0.76
ln(power source)	-0.0415	-0.84
Draft animal (1=draft animal only; 0=otherwise)	-0.337**	-2.48
ln(hired labor)	0.119**	2.35
ln(family labor)	-0.0294	-1.05
Inefficiency factors		
Constant	-0.875	-0.90
Market distance	-0.184***	-3.19
Household size	0.0609	1.03
Age of the farmer	0.0215*	1.68

Years of education of the farmer	-0.0850**	-1.97
Farm size	0.0765	0.81
Land tenure (1=leased land only; 0=otherwise)	-0.0319	-0.12
Site dummy (1=Majayjay; 0=otherwise)	-0.613	-1.45
Sample size	184	
Log-likehood	-104.41	
Average TE	0.62	
Minimum	0.01	
Maximum	0.95	

* $p < 0.1$, ** $p <0.05$, *** $p <0.01$

The overall technical efficiency score is 0.62 or 62% level of efficiency, which implies that productivity can still be improved by 38%, which is still quite significant. Figure 1 shows that the distribution of farmers with a higher efficiency score is skewed to the right. Most farmers have a relatively high efficiency score but the potential for improving farming remains high and important.

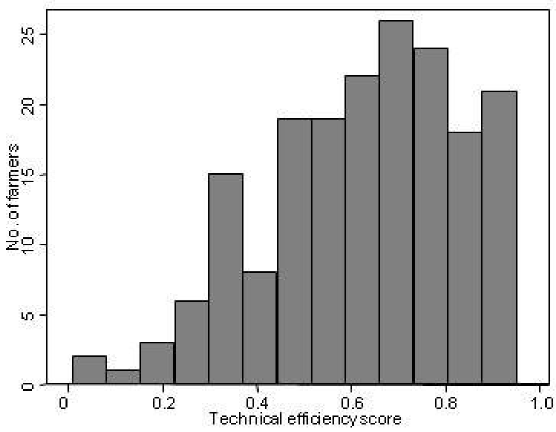

Figure 1. Distribution of technical efficiency score

Several factors can affect the inefficiency of farmers. Some of these factors are included in the inefficiency model shown in Table 5. The positive sign in the observed parameters refers to its direct relationship with inefficiency. It means that a positive coefficient contributes to inefficiency whereas a negative coefficient reduces inefficiency. The coefficient of market distance is negative and significant. This implies that the farther the market is from the farmer's residence, the less inefficient the farmer is. The result is in contrast to other findings in the literature on the role of market distance from a farmer's residence or farm (Ahmad, Chaudhry and Iqbal 2002; Alene and Hassan 2003; Marinda, Bangura and Heidhues 2006; Javed *et al.* 2008). The positive effect of market distance on farmers' efficiency has been connected to the easy access of farmers to the latest technology and information, availability of farm inputs and connection to trade. In the case of Laguna farmers, the negative relationship of market distance to farmers' efficiency can be associated with farm management, resource allocation and labor supply. The market is not only a place for trading goods and services but also a place of leisure among townsfolk. Being away from this place also encourages farmers to focus on direct farm management since distraction from any other non-farm activities is limited. Allocation of resources will also be maximized and well planned to save farmers from the additional transportation cost of procuring inputs in farming. Availability of labor, particularly farm labor, is relatively abundant compared with farm labor near the market, because the market encourages the labor force to move to non-farm opportunities. Meanwhile, the coefficient of the age of the farmer is significant and positive. This implies that older farmers are less efficient than younger farmers. Physical strength, which is important in carrying out farm activities, can explain the efficiency of young farmers. More years of education is another factor that significantly reduces inefficiency. Educated farmers, measured in terms of years of attendance in formal education, are less inefficient, which can be attributed to the knowledge they gain from educational institutions.

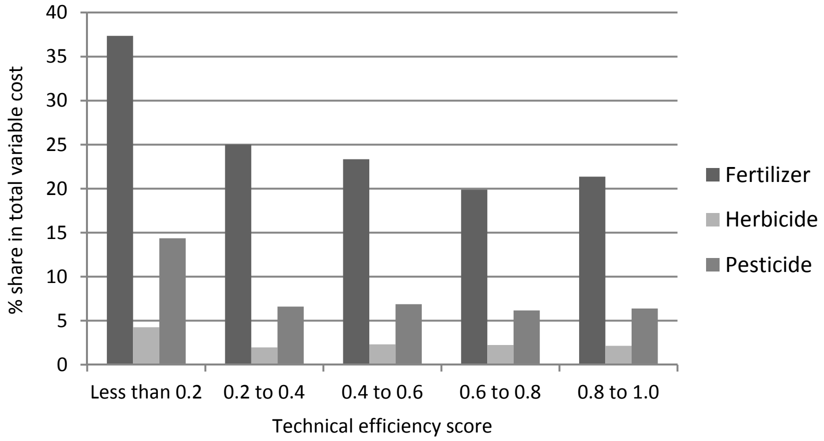

Figure 2. Share of chemical input cost and technical efficiency score

In terms of the pattern of the technical efficiency score across farmers in relation to the share of spending on chemical inputs, Figure 2 shows a clear pattern in which farmers with a higher efficiency score allocated smaller share of investment to chemical inputs. This observation can be attributed to the distance of the market from the farmer's residence since chemical inputs are usually purchased from the market. Unlike other inputs such as power source and labor, which are locally available and easily accessible, a farmer needs to travel and spend on transportation to buy chemical inputs. By being far from the market, farmers tend to spend wisely on the amount of chemical inputs they need. In addition, efficient farmers in the sample are more educated; thus, knowing the cost of frequent visits to the market, they will plan more carefully on how much should be allocated and spent on chemical inputs.

5. Conclusions

Farming has to be improved either by providing farmers with new technology or introducing them to better crop management practices. Estimating farmers' technical efficiency is one way to measure whether room for improvement exists. This study showed that an opportunity for improving efficiency still exists among the sampled farmers in Laguna. Although chemical inputs as factors of production contributed significantly to output, technical efficiency may be affected by the investment allocation for chemical inputs indirectly. This implies that farmers who invested more in chemical inputs relative to other variable inputs attained the same or even lower output as those farmers who invested less. The result shows that farmers who invested wisely in chemical inputs can encourage farmers to apply chemical inputs more optimally.

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