Impact of Financial variables on the production efficiency of Pangasius farms in An Giang province, Vietnam

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CONTENTS

LIST OF TABLES

ABSTRACT

This research provides the first analysis of the relationship between farm financial exposure and technical efficiency in the Pangasius farming in An Giang province, in the Mekong Delta of Vietnam. A nonparametric DEA approach has been applied to estimate technical and scale efficiency scores of 61 Pangasius farms in An Giang province in the year 2008. The mean technical efficiencies under assumption of constant returns to scale and variable returns to scale and scale efficiency were measured to be 0.595, 1.058 and 0.58 respectively. The decomposition of the technical efficiency measure shows that scale inefficiency is the primary cause of technical inefficiency in the the case of Pangasius farming as about 92% of the sample Pangasius farms exhibits increasing returns to scale (IRS). Then, estimated technical efficiency (TE) scores under assumption of variable returns to scale are used in a regression analysis to investigate the relationship between the efficiency measures and different farm characteristics, including financial considerations. Research results suggest that technical efficiency is influenced by investment level of farms as well as by farm operator's experience. The farms are invested more will be more efficient. The experience measured as the years of operator in farming Pangasius also suggests that the farmers having more experience may have better decisions in farm operating and more efficient in using inputs, thus, their farms are more efficient. Technical efficiency is positively influenced by the debt-to-asset ratio and also by the debt-to-equity ratio, while no statistically significant relationship is found between technical efficiency and the bank debt-to asset ratio. The other factors (age and education levels of the houshlod head) are found to have no effects on the technical efficiency in the sample farms.

***Key words**: Pangasius farms, Data envelopment analysis, Technical efficiency, Scale efficiency, Farm debt, Financial variables.*

CHAPTER 1: INTRODUCTION

Pangasius is one of species of fish that have economic value raised popularly in the Mekong delta of Vietnam and some countries in Asian (i.e., Cambodia, Thailan, Indonesia). In recent years, Pangasius is becoming one of the main sectors of the Vietnam aquaculture and seafood export industry. In ten years, from 1997 to 2006, the farming areas increased only 7 times, but the annual commercial production of raw fish increased by 36 times from 22,500 to 825,000 metric tones and the volume of exported Pangasius fillets jumped up more than 40 times, from 7,000 to 286,000 metric tones. In the year 2008, the raw fish production was 1.65 million M.T and contribute to 657 thousands tons proccessing products to export to 117 countries and territories and got US$ 1.48 billions of export turn-over.

In Vietnam, farm-raised Pangasius now are produced in most of provinces in the Mekong Delta with two species which are Pangasius Bocourti (*Basa*) and Pangasius Hypophthalmus (*Tra*). The water surface areas under Pangasius production totaled about 6,000 hectares at the end of the year 2008 and created 16 millions jobs relating to the Pangasius industry. This contributes considerably in the reforms and economic developing in the Mekong Delta in general. Three provinces of An Giang, Can Tho and Dong Thap are leading culture regions for Pangasius in the Mekong Delta, accounted for 80% of entire Pangasius production. An Giang province is the leading with 1.600ha of ponds areas and the production estimated to the end of October 2008 is 282,000 tons and export turn-over is about US$ 347 millions.

However, challenges remain. Some problems relating to this industry are out of controlling in term of zoning and planning from government of different levels, unsustainable development of this industry relating to environmental impact, crises and fluctuations of price - production, price competition, conflicts between farmers and producers, and lack of sustainable financing for farmers.

Nowadays, besides the four countries Thailand, Cambodia, Laos and Vietnam where Pangasius has raised traditionally, this kind of fish is continued raising in the other countries and becoming one of the most important rased-fishes in the Southest Asisa. Assume that the seafood market demand of the world to Pangasius is still large and the imports of aquacultural products are expected to grow, in the long run, the survival of Vietnam Pangasius may depend firstly on farmer's abilities to produce raw fish efficiently.

Pangasius farming requires the huge cultivating and investment costs. Most of Pangasius farmers have to base their activity on the debt which is mainly bank debt to operate their farms. Assess to credit has been one of the main constraints to farm operating, restructuring and technological improvement. Due to this constraint, it may lead to be unsustainable financing for Pangasius production system and hence decrease the productive efficiency of Pangasius farming in The Mekong Delta of Vietnam.

OBJECTIVES OF THE THESIS:

The objectives of this research are twofold: to understand the existing Pangasius farming system in An Giang province, in the Mekong Delta of Vietnam and to investigate how financial variables affect production efficiency in the case of Pangasius farming.

The specific objectives are:

- to estimate technical and scale efficiency for a selection of Pangasius farms in An Giang province, to know what are the exhibitions of returns to scale for this sector.
- to examine which factors play an important role in determining farm technical efficiency.
- and to identify whether there is a relationship between a farm's financial variables and Pangasius production efficiency.

HYPOTHESES

- The variation in technical efficiency scores is considerable among farms with different input use and technology.

- The variation in technical efficiency scores between the different regions and different group of pnd sizes.

- There is scale inefficiency of the existing Pangasius farming. This hypothesis is supported by the statistical follwing information from the Departments of Agriculture and Rural Development of An Giang province. Pangasius farming areas enlarged and there is farm integration trend, number of bigger farms with farm size 20-40 ha and production of 5,000 to 15,000 metric tones increased in recent time.

- Farm – specific factors are significant factors affecting the efficiency of Pangasius production.

- There is a positive relationship between a farm's technical and scale efficiency and farm financial variables.

PROCEDURE AND METHODOLOGY:

- Data for conducting research is cross-sectional data (61 samples for the crop in year 2008). Primary data are collected by interviewing directly operators of Pangasius ponds farms in An Giang province in January 2009. Secondary data are obtained from Department of Aquaculture of An Giang province.

- A Data Envelopment Analysis (DEA) input-oriented model is employed to measure pure technical and scale efficiencies of each farm. Resulting estimates of farm technical efficiency scores are regressed by Ordinary Least Square (OLS) on some financial variables (*Debt - to - asset ratio; Bank debt - to - asset ratio; Debt - to - asset ratio* in addition to other specific factors hypothesized to affect farm efficiency (Investment level of farm, Age of household head (operator), Education level of household head; household head; in order to determine the importance of those different factors in explaining efficiency levels.

EXPECTED RESULTS:

- The technical best practice levels of Pangasius production system in An Giang province of Vietnam.
- The positive effects of financial variables on the production efficiency.
- Policy implications for efficiency improvement on Pangasius farming in Vietnam.

ORGANIZATION OF THE THESIS:

Chapter 2 provides an overview of the existing literature on production efficiency and measurement, Data Envelopment Analysis (DEA) method to measure the efficiency and applications of DEA in aquaculture. This chapter also present the summay and results of the recent studies relating to the relationship between financial eposure and production efficiency.

Chapter 3 desribes methods used to analysis the technical and scale efficiency of selected farms of Pangasius in An Giang province and to estimate the effects of farm-specific factors including the farm's financial variables on the productive efficiency. The data used in two steps of analysis also are described fully in this chapter.

Chapter 4 presents results of the thesis.

Chapter 5 includes the summary, discussions and conclusions of the thesis.

CHAPTER 2: LITERATURE REVIEW

2.1. Basic efficiency concepts:

Economic efficiency has technical and allocative components. The technical component refers to the ability to avoid waste, either by producing as much output as technology and input usage allow or by using as little input as required by technology and output production. Therefore, the analysis of technical efficiency can have an output-augmenting orientation or input-conserving orientation.

Koopmans (1951) provided a formal definition of technical efficiency: A producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduciton in in at least one output. Thus, a technically inefficiency producer could produce the same output with less of at least one input or could ues the same inputs to produce more of at least one output.

The preceding definition is replaced by emphasizing its uses with only the information that is empirically available as in the following definition: (Relative efficiency): A decision making unit is to be rated as fully (100%) efficiency on the basis of available evidence if and only if the performances of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs (Cooper, Seiford, and Zhu (2004)).

Farrell (1957) introduced a measure of technical efficiency. With an input-conserving orientation, this measure is defined as one minus the maximum equiproportionare reduction in all inputs that is feasible with given technology and outputs. With an output-augmenting orientation, this measure is defined as the maximum radial expansion in all outputs that is feasible with given technology and inputs. In both orientations, a score of unity means a firm is technical efficient and a value different from unity indicates the extent of a firm's technical inefficiency.

2.2. Techniques of efficiency measurement

The measurement of productive efficiency is based on deviation of observed performance from optimal performance located on the efficient frontier. If a firm belongs to the frontier, it is considered perfectly efficient. In contrast, if a firm is beneath the efficiency frontier, then it is considered inefficient. Because the true frontier is unknown, an empirical approximation is needed. We estimate a hypothetical frontier that defines the position of hypothetical most efficinent firms against which positions of actual observations can be estimated (or calculated). The hypothetical frontier has been estimated using many different methods over the past 40 years, under different assumptions and implications. The two principal methods that have been used are data envelopment analysis (DEA) and stochastic frontier analysis (SFA), which involve mathematical programming and econometric methods, respectively, according to their assumptions about the functional form of production (or cost) frontier.

The DEA method is computationally simple and has the advantage that it can be implemented without knowing the algebraic form of the relationship between outputs and inputs (i.e., we can estimate the frontier without knowing whether output is a linear, quadratic, exponential or some other function of inputs).

The second approach (SFA), the contribution of Aigner, Lovell and Schmidt (1977), simultaneously Meeusen and van den Broeck (1977) and Battese and Corra (1977) is the introduction of the composed error model, where both stochastic and error components can be included separately in the error term. This method involves the estimation of a stochastic function, where besides incorporating the efficiency term into the analysis (as do the deterministic approaches) also captures the effects of exogenous shocks beyond the control of the analysed units. When the functional form is specificed then the unknown parameters of the function need to be estimated using econometric techniques.

The two approaches use different techniques to envelop data in different ways. The differences between the two approaches can be seen in two essential characteristics and also the sources of advantages of one approach to the other:

* The econometric is stochastic. This enables it to attempt to distinguish the effects of noise from those of inefficiency, thereby providing the basis for statistical inference.

* The mathematical programming approach is nonparametric. This enables it to avoid confounding of effects of misspecification of the functional form (of both technology and inefficiency) with those of inefficiency.

2.3. The DEA approach to efficiency measurement.

The DEA technique uses the linear programming methods to construct a non-parametric piece-wise surface (or frontier envelopment) for all sample observations, which provides a yardstick for all DMUs in a sample. This surface is determined by those units that lie on it, that is the efficient DMUs. Efficiency measures are then calculated relative to this surface. A unit on the efficient frontier is given a score of 1. Units that do not lie on that surface can be considered as inefficient and an individual inefficiency score will be calculated for each one of them, given a score between 0 and 1.

The piece-wise-linear convex hull approach to frontier estimation, proposed by Farrell (1957), was considered by only a few authors in the two decades following Farrell's paper. The mathematical programming method did not receive wide attention until the paper by Charnes, Cooper and Rhodes (1978), in which the term Data envelopment analysis (DEA) was first used. These authors proposed a model that had an input orientation and output orientation under assumption of constant returns to scale (CRS) and how both models follows from different fractional programming models.

Since the initial study by Charnes, Cooper and Rhodes, some 2000 articles have appeared in the literature. Such rapid growth and widespread of DEA is testimony to its strengths and applicability. At present, DEA actually encompasses a variety of alternative (but related) approaches to evaluating performance. Some popular extensions of the basic DEA (CRS and VRS) models so far involve non-discretionary variables, environmental variables, weights restrictions, super efficiency and bootstrap methods.

The uncontrolled or discretionary variables are an important weakness of model developed in Charnes, Cooper, and Rhodes (1978). Some variables are outside the control of manager. Maximization of equi-proportionate contraction should be made by omitting these variables to obtain more precise efficiency scores. However, in order to get more realistic individual efficiency scores, one might isolate in some way this type of variable, known as non-discretionary variables, and their effects on the final performance of the observed units. Banker and Morey (1986) adapt the mathematical programming treatment of DEA models to allow a partial analysis of efficiency on the basis of what they initially termed exogenously and non-exogenously fixed inputs and outputs.

Adjusting for the environmetal variables is another extensions of the basic DEA model to evaluate some factors that could influence the efficiency of a firm, where such factors are not traditional inputs and are assumed not under the control of the manager. There are a number of possible approaches to the consideration of environmental variables such as the “three stages” method proposed by Charnes, Cooper and Rhodes (1981), the possible method is to include the environmental variable(s) directly into the linear programming formulation (Ferrier and Lovell (1990). The two-stage approach involving a DEA problem in the first stage analysis and regressing the efficiency score from the first stage in the second stage by OLS or Tobit regression is recommended in most cases. Some considerable advantages of this approach are that both continuous and categorical variables can be easily accommodated in the second step and hypothesis test to see if the variables have a significant influence upon efficiencis can be conducted.

The flexibility of the frontier that is constructed using DEA is one of the advantages of this method. However, this aspect of the method can also create problems, especially when dealing with small data sets. One can find that the weights assigned to the various input and output variables are not realistic for some firms since they are too large or too small. A variety of methods have been proposed to remedy this. Among them, the most relevant are the Assurance Region (AR) method developed by Thompson, Singleton, Thrall and Smith (1986) and the Cone-Ratio (CR) method developed by Charnes, Cooper, Wei and Huang (1989) and Charnes, Cooper, Sun and Huang (1990). The AR approach deals with the existence of large differences in input/output weights from DMU to another by imposing additional constraints on the relative magnitude of the weights for some particular inputs/outputs into the initial DEA model. More general than the AR method, the cone-ratio approach extends the Charnes, Cooper and Rhodes (1978) model by using constrained multipliers, which are constrained to belong to closed cones (Murillo-Zamorano, 2004).

Supere fficiency relaten to an DEA model which firms can obtain efficiency scores greater than one. To calculate a super efficiency score for the *i*- th firm, the data for the *i*- th firm is removed from matrixes of inputs and outputs. Thus, when running the LP, if the *i*- th firm was a fully-efficient frontier firm in the original standard DEA model, it may not have an efficiency score greater than one. This method was originally proposed by Andersen and Petersen (1993). The problem of infeasibility in that model has been discussed and removed by Lovell and Rouse (2003), Zhu (2004) and Chen (2004).

Other extensions to the DEA basic model include the measurement of allocative efficiency on the basis of price information and the assumption of a behavioural objective such as cost minimization in Ferrier and Lovell (1990), revenue maximisation in Fare, Grosskopf and Lovell (1985) or profit maximization in Fare, Grosskopf and Weber (1997); the treatment of panel data by means of the window analysis developed in Charnes, Clark, Cooper, and Golany (1985) or the Malmquist index approach of Fare, Grosskopf, Lindgren and Roos (1994).

2.4. DEA applications in Aquaculture

A great variety of applications of DEA have been conducted in many of studies to investigate technical, allocative, cost and scale efficiency by applying input and output oriented models in many different activities in many different contexts in many different countries. Areas where DEA applied can be mentioned as hospitals, universities, cities, courts, business firms, banks and others, including the performance of countries, regions, etc.

There are a number of efficiency studies applying DEA conducted on agricultural sector in many countries. However, DEA applications on aquaculture are relatively low in comparison to the other areas.

Sharma et al. (1999) applied a nonparametric DEA technique for multiple outputs to measure economic or “revenue” efficiency and its technical and allocative components for a sample of Chinese polyculture fish farms and to derive the optimum stocking densities for different fish species for Chinese polyculture farms.

Using a weight-restricted DEA technique, Kaliba and Engle (2006) estimate technical, allocative and cost efficiency of a sample of small- and medium-sized catfish farms in Chicot County, Arkansas. These authors then regress the cost efficiency score in Tobit model on operator characteristics, farm practices, and institutional support services to determine whether these factors lead to a higher level of efficiency. An important finding of this research is the authors found that higher cost efficiency of catfish farm efficiency in Chicot County, Arkansas, can be achieved by adjusting inputs used in production to optimal levels rather than by adjusting the scale of operation.

Also using a two-step procedure, Cinemre et al. (2006) measured the cost efficiency of trout farms and explored determinants of cost inefficiencies in the Black Sea Region, Turkey. The decomposition of the technical efficiency measure showed that pure technical inefficiency was the primary cause of technical inefficiency in the sample of trout farms. Research results also suggested that there were positive relationships between cost efficiency and pond tenure, farm ownership, experiences of the operators, education level of the operators, contact with extension services, off-farm income and credit availability while feeding intensity, pond size, and capital intensity had negative effects on cost efficiency.

Ferdous Alam, Murshed-e-Jahan, K. (2008) employed DEA technique in evaluating the resource allocation efficiency of prawn-carp polyculture systems by making use of the data of 105 farmers of Bangladesh. The results showed that 50 percent of prawn-carp farmers displayed full technical efficiency whereas only 9 percent were cost efficiency. Technical and allocative efficiencies showed a positive and negative correlation with pond size, respectively. Labor, fingerlings and feed were overused while organic and inorganic fertilizers were underused in general.

In Vietnam, DEA has been applied in several studies in rice farms of the Mekong Delta, the construction firms, aquaculture processing and food processing companies. So far no study has been conducted in Vietnam that addressed the aquaculture in general and the Pangasius farming to evaluate TE, AE, CE and SE.

2.5. The relationship of Financial variables and technical efficiency:

*** *Theoretical approach*:**

The seminal work of Modigliani and Miller (1958) on the irrelevance of debt structure to firm value has prompted numerous continuations in the literature addressing its strong assumption of perfect capital markets. Under the hypothesis of perfect financial markets, investment and financing decisions are separable. Thus, a firm should have the same efficiency level regardless of the way it is capitalized and, consequently, there should not be any significant statistical impact of leverage on technical efficiency.

Alternatively, economics literature provides arguments for a negative as well as positive impact of high indebtedness on firm performance. Several hypotheses have been advanced to explain the positive relationship between efficiency and indebtedness.

The agency theory approach, is based on Jensen and Meckling's (1976) agency cost concept. They defined an agency relationship as a contract under which one or more persons (the principal (s)) engage another person (the agent) to perform some service on their behalf which involves delegating some decision making authority to the agent. In most agency relationship, the principal and the agent will incur positive monitoring and bonding costs and in addition there will be some divergence between the agent's decisions and those decisions which would maximize the welfare of the principal. The agency cost concept implies that because of the asymmetric information and misaligned incentives between lenders and borrowers, it requires the monitoring of borrowers by lenders. Lenders may pass on the monitoring and adverse incentive costs (e.g., high risk taking or unintended use of loans by the borrower) to the farmers in the form of higher interest rates adjustments, collateral requirements, etc. (Ellinger and Barry, 1991). As a result, highly indebted farmers might incur higher costs and, thus, be less technically efficient. Therefore, the agency theory implies the negative impact of indebtedness on technical efficiency.

The free cash flow concept, developed by Jensen (1986), proposes that issuing large amounts of debt sets up the required organizational incentives to motivate managers and to help them overcome normal organizational resistance to retrenchment which the payout of free cash flow often requires. Debt raise the pressure of managers and serves as an effective motivating force to make such organizations more efficient. Applied to the agricultural sector, this concept suggests that farmers with higher debt obligations will be motivated to improved their efficiency in order to pay their financial obligations. Therefore, the free cash flow concept implies a positive relationship between technical efficiency and indebtedness.

The third main approach, the credit evaluation concept suggests that lenders will prefer to finance more efficient farmers because these borrowers are lower credit risks. In addition to collateral requirements, agricultural bankers often use efficiency variables along with financial variables in evaluating a farmer's creditworthiness. Thus, the more efficient farmers might have higher indebtedness because they are selected by banks as good risks.

*** *Empirical works:***

The previous theories are test in the empirical literature by both parametric and nonparametric approaches that are usual in applications. Following are summarizations and the main results of recent studies research on the relationship between efficiency and indebtedness.

DEA one stage model was applied in the research of *Andreu et al.* (2006) which establishes the cost-efficiency frontier and its variation over time for a sample of 610 farms in Kansas for ten consecutive years (1995 to 2004) to examine how financially constrained firms affect cost efficiency and its components, allocatice, technical and scale efficiency. They employed an output-oriented analysis for model 1 uses DEA in the basic multi-output/multi-input (7 outputs, 10 inputs) cost minimization problem to estimate TE, AE,SE and CE. Model 2 and model 3 use DEA in the same context as model 1, except that a financial constraint is added by the total amount of annual debt and the amount of working capital for each farm, respectively. Each of the three models were estimated seperately for each year and then the efficiency scores were compared for each model each year to investigate if any the two financial constraints imposed are binding. These authors also compared the efficiency scores each year in terms of farm size and determine if the difference is statistically significant. The results showed that the farms appear to achieve the same level of cost efficiency and scale efficiency despite being debt constrained or working capital constrained in any of the years from 1995 to 2004. However, financially constrained model 2 and 3 differ in the estimates of technical efficiency and allocative efficiency. The results for the statistically significant difference in technical efficiency and allocative efficiency scores between financially-constrained models 2 and 3 and base model 1 suggest that there exists a negative relationship between technical efficiency and the cost structure of a farm.In contrast, allocative efficiency seems to be positively related to more indebted farms or those with negative working capital. The results suggest that for farms in the sample, the financial constraints did not prevent farm from achieving overall cost efficiency. The authors explained that when farms were constrained by debt or negative working capital, they compensated the level of technical efficiency and allocative efficiency to maintain the level of cost efficiency. On the relationships of farm size with cost and production efficiency measures, there appears a pattern of change for Kansas farms between 1995 and 2004, where larger farms score higher in the most efficiency scores except for scale efficiency.

Another group of applications use nonparametric methods to calculate efficiency of firms in the first stage, and then these values are regressed on various explicative variables. In the second stage, the tobit regression is used more extensively since it overcome the problems of data censoring and truncation from DEA analysis. *Chavas and Aliber* (1993) use information on 545 Wisconsin farms (two output and seven inputs in 1987) and run different nonparametric models to obtain technical, allocative, scale and scope efficiency scores. The tobit regression indicate that short-run debt to-asset ratios have no significant effect on any of the efficiency indexes whereas intermediate and long-run debt to-asset ratios present positive and significant effects on technical and allocative efficiency. The results also showed that intermediate and long-run debt to-asset ratios have the effects on scale efficiency but more complex when such ratios are found to have no significant relationship with scale efficiency under decreasing returns to scale but have a significant negative (positive) relationship with scale efficiency under increasing returns to scale. Those results indicate that there is no statiscal evidence that the financial structure of the larger farms affects their scale efficiency, however, the financial structure of the smaller farms affects their ability to attain an efficient scale. In this line, *Bezlepina et al.* (2004) examine the impact of debts on managerial performance by using a panel of 144 dairy farms in the Moscow region over the period 1996-2000. This research considered different sources of debts (banks, state, suppliers) as well as the different role of debts in poorly and well performing enterprises. The results suggested that debts, which were mainly the loans from suppliers in the form of trade credit, were positively related to manageral efficiency. In addition, a positive effect of debt payables on manageral efficiency was observed. Also to determine the relationship between farm efficiency and farm debt, *Lambert and Bayda* (2005) studied in a panel of 54 North Dakota crop farms in seven years (1995 to 2001). Farm technical efficiency was found to be influenced by debt structure. A significant negative relationship was found between technical efficiency and the current debt-to-asset ratio. The negative relationship supports the agency-cost concept, in which technically inefficient farmers may not able to generate internal financial resourses to cover operating expenses so are forced to increase borrowing. At the same time, lenders may impose a higher proportion of collateral and adverse incentive costs (higher interest rate, servicing fees) on those producers, therefore, increases their operating costs and lowers their technical efficiency. The positive relationship between the intermediate debt-to-asset ratio and technical efficiency supports the credit-evaluation concept, indicating that bankers may prefer to extend intermediate-term capital to more-efficient farmers. These authors also examine the effects of farm-specific factors on scale efficiency for farms. Similar to the results found by Chavas and Aliber, nostatiscally significant relationship existed between debt structure and scale efficiency for the 205 observations exhibiting decreasing returns to scale. For the 94 observations characterized by increasing returns to scale, there was also no significant relationship between intermediate- or long-term debt and scale efficiency, however, current debt-toasset ratio was negatively related to scale efficiency.

Other empirical studies use a stochastic parametric function in the “one stage procedure” proposed by Battese and Coelli (1995) that include explicative variables to model the error term and it is estimated by using maximum likelihood techniques. *Weill* (2001) provided new empirical evidence on a major corporate governance issue: the relationship between leverage and corporate performance. The author applied frontier efficiency techniques to measure performance of medium-sized firms from seven European countries and observed a positive and significant relationship between leverage and efficiency in four countries (Belgium, France, Germany, and Norway), while it is negative and significant in Italy and Spain, and finally not significant in Portugal. He concludes that institutional factors influence the relationship between leverage and performance. Considering the role of the access to bank credit on the relationship between leverage and performance, Weill found that the countries with the lowest access-to-credit-ratio do not have a significantly positive relationship between leverage and performance. Furthermore, the country with the highest access-to-credit-ratio, Germany, has the highest significantly positive coefficient for the Leverage variables. Within agricultural economics, *Hadley et al.* (2001) contribute to empirical literature regarding to relationship of financial exposure and farm efficiency by a study of the England and Wales dairy sector on a panel of 601 dairy farms covering the production years from 1984 to 1997. A translog distance function is employed representing one output (revenue) and multiple inputs (rent and land charges, family labour hours, hired labour hours, feed costs, vet and med costs, crop input costs, misc costs,capital and dairy hezd size) to study the efficiency. As determinants of technical inefficiency, a number of variables are incorporated the ratio of total debt to total assets, short-term loans and debt to total assets and the ratio of long and and medium term loans and debts to total assets were hypothesised as possibly having a role in explaining differences in levels of technical efficiency among farms. The results point out that negative estimated coefficients are related to increases in levels of technical inefficiency, so that increases in the size of the various debt ratio are all likely to decrease the technical efficiency of farms.

CHAPTER 3: MODEL DEVELOPMENT AND DATA

The objective of this research is to examine the production efficiency of Pangasius farms in Angiang province and to identify whether there is a relationship between a farm's production efficiency and its financial variables. In the first stage of the analysis, the technical efficiency and scale efficiency of individual farms is assessed by the data envelopment (DEA) super-efficiency approach. The second stage consists of a description of econometric models. A OLS model is employed to assess the influence of selected farm-specific factors including financial variables on estimated technical efficiency scores. Finally, data used in the research is described fully in the final part of the chapter.

3.1. METHODOLOGY

3.1.1. STEP 1: Efficiency measurement

The technique of data envelopment analysis (DEA) introduced by Charnes, Cooper and Rhodes (CCR) (1978) is widely employed for estimation of multiple input, multiple output production correspondences and the evaluation of the productive efficiency of decision making units (DMUs). They provided linear programming formulation to measure the productive efficiency (CCR efficiency) of a DMU relative to a set of referent DMUs.

Banker, Charnes and Cooper (BCC) (1984) showed that the CCR efficiency measure can be regarded as the product of technical efficiency (BCC efficiency) measure and a scale efficiency measure.

Technical efficiency is considered in terms of the optimal combination of inputs to achieve a given level of output (an input-orientation) or the optimal output that can be produced given a set of inputs (an output-orientation). The envelopment surface of the oriented models can be either constant returns-to scale (CRS) or variable returns-to-scale (VRS). Under CRS, the form of the envelopment surface of the constructed production frontier is a conical hull, while under VRS, it is a convex hull.

The input-oriented models is used for this research since in agriculture, farmers have more control over their inputs than their outputs. In the case of Pangasius farming in An Giang province in particular and general, under some certain constraints of financing and the high costs for farming, especially the cost for feed, the choice of the DEA input-oriented models is make sense.

Suppose we have n DMUs (DMU_j : j = 1,2, …, n), which produce s outputs y_{rj} (r = 1,2,…, s) by utilizing m inputs, x_{ij} (I = 1,2,…, m). An input-oriented model which exhibits CRS, developed by Charnes, Cooper and Rhodes (CCR) (1978) and referred to in the literature as the **CCR** model, can be written as

$$
\begin{aligned}
&\text{Min } \theta_o \\
&\text{s.t} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_o x_{io}, \qquad i = 1,2,\dots,m, \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro} \qquad r = 1,2,\dots,s, \\
&\quad \lambda_j \ge 0, \qquad j = 1,\dots,n, \qquad\qquad (3.1)
\end{aligned}
$$

where, x_{io} and y_{ro} are, respectively, the ith input and rth output for a DMU_o under evaluation.

Solving that model n times results in optimal values of the objective function and the elements of intensity variables vector λ for each farm. For the DMU_o the optimal value θ^*_o measures the maximal proportional input reduction without altering the level of outputs. The vector λ^*_j indicates participation of each considered farm in the construction of the virtual reference farm that the DMU_o is compared with.

Solving the CCR model, the total technical efficiency measure θ^*_o *(CCR)* is obtained by comparing small scale units with large scale units and vice versa without considering the economies of scale. This may be inappropriate for all of the farms in the sample. Therefore, the BCC model, developed by Banker, Charnes and Cooper (BCC) (1984) and called the input-oriented BCC model, allows for variations in the returns to scale is considered.

The input-oriented VRS model is obtained from the CRS model by adding a convexity constraint $\sum\lambda = 1$ to the CCR model (3.1), , can be written as

$$
\begin{aligned}
&\text{Min } \theta_o \\
&\text{s.t} \sum^{n} \lambda_j x_{ij} \le \theta_o x_{io}, \qquad i = 1,2,\dots,m,
\end{aligned}
$$

$$j=1$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \qquad r = 1,2, \ldots, s,$$

$$\sum_{j=1}^{n} \lambda_j = 1, \qquad (3.2)$$

$$\lambda_j \geq 0, \qquad j = 1, \ldots, n,$$

The BCC model formulation allows to calculate the pure technical efficiency and decompose the technical efficiency score into pure technical efficiency ands scale efficiency (SE).

The Variable returns to scale input-oriented models is used for this research since in agriculture, farmers have more control over their inputs than their outputs. The CRS assumption is appropriate when all farms are operating at an optimal scale. However, imperfect competition, constraints on finance, government regulations, etc., may cause a farm to be not operating at optimal scale.

The scale efficiency measures is computed as the ratio of the measure of technical efficiency calculated under the assumption of CRS to the measure of technical efficiency calculated under the assumption of VRS (Banker et al., 1984; Fare et al., 1985). The value of the SE is interpreted: if $SE_j = 1$, then DMU_o is considered as a scale efficient unit and this unit shows the constant returns to scale property (CRS); if $SE_j < 1$, then the production mix of DMU_o is not scale efficiency.

One shortcoming of this measure of scale efficiency is that the value does not indicate whether the farm is operating in an area of increasing or decreasing returns to scale. This issue can be determined by running an additional DEA problem with non-increasing returns to scale (NIRS) or non-decreasing returns to scale (NDRS) imposed. This is done by substituting the $\sum\lambda = 1$ restriction in model (3.2) with $\sum\lambda \leq 1$ or $\sum\lambda \geq 1$. By seeing whether the NIRS TE or NDRS TE score is equal to the VRS TE score, one can determined the nature of the scale inefficiencies for a particular farm. If NIRS and VRS scores are unequal then increasing returns to scale exist for that farm. If they are equal then decreasing returns to scale apply. Similarly, if NDRS and VRS are unequal then decreasing returns to scale exist for that farm. If they are equal then increasing returns to scale apply.

Super efficiency: Super-efficiency data envelopment analysis (DEA) model was originally proposed by Andersen and Petersen (1993) to provide a ranking system that would help them discriminate between frontier firms. When a DMU under evaluation is not included in the reference set of the original DEA models, the resulting DEA models are called super-efficiency DEA models. The super-efficiency method has subsequently been used in a number of alternative ways such as for sensitivity testing (Zhu, 2001) or outlier identification (Banker and Chang, 2006). This model also can be used as a method of circumventing the bounded-range problem in a second stage regression methods can be used instead of Tobit regression.

From (3.2), all the frontier DMUs (efficient DMUs) have $\theta^*_o = 1$. In order to discriminate the performance of efficient DMUs, we use the VRS super-efficiency DEA model where DMU_o is not included in the reference set

$$\begin{aligned}
&\text{Min } \theta_o^{\text{VRS-super}} \\
&\text{s.t } \sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j x_{ij} \leq \theta_o^{\text{VRS-super}} x_{io}, && i = 1,2, \ldots, m, \\
&\sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j y_{rj} \geq y_{ro} && r = 1,2, \ldots, s, \\
&\sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j = 1, && \qquad (3.3) \\
&\lambda_j \geq 0, && j \neq 0
\end{aligned}$$

Adler et al. (2002) showed the three problems with this methodology. Thrall (1996) noted that the super-efficiency CCR model may be infeasible. Zhu (1996), Dula and Hickman (1997), Seiford and Zhu (1999) prove under which conditions various super-efficiency models are infeasible. Despite these drawbacks, due to the simplicity of this concept, many researchers have used this approach. For example, Hashimoto (1997) developed the DEA super-efficiency model with assurance regions in order to rank DMUs completely. Chen (2004) proposed a modified super-efficiency DEA model to overcome the infeasibility problem and to correctly capture the possible super-efficiency existing in forms of the input saving or output surplus.

3.1.2: STEP 2: Sources of Technical Efficiency

Measures of farm technical and scale efficiency obtained from step 1 are used in regression analysis to estimate the relationship between the efficiency and different farm characteristics, including farm financial variables. The following translog model is estimated:

$$\ln TE = \alpha_0 + \alpha_I \ln I + \alpha_{II} \ln I^2 + \alpha_A \ln A + \alpha_{AA} \ln A^2 + \alpha_{ED} \ln ED + \alpha_{EDED} \ln ED^2 + \alpha_{EX} \ln EX + \alpha_{EXEX} \ln EX^2 + \alpha_{DA} \ln DA + \alpha_{DADA} \ln DA^2 + \alpha_{BDA} \ln BDA + \alpha_{BDABDA} \ln BDA^2 + \alpha_{DE} \ln DE + \alpha_{DEDE} \ln DE^2 + \alpha_{IA} \ln I \ln A + \alpha_{IED} \ln I \ln ED + \alpha_{IEX} \ln I \ln EX + \alpha_{IDA} \ln I \ln DA + \alpha_{IBDA} \ln I \ln BDA + \alpha_{IDE} \ln I \ln DE + \alpha_{AED} \ln A \ln ED + \alpha_{AEX} \ln A \ln EX + \alpha_{ADA} \ln A \ln DA + \alpha_{ABDA} \ln A \ln BDA + \alpha_{ADE} \ln A \ln DE + \alpha_{EDEX} \ln ED \ln EX + \alpha_{EDDA} \ln ED \ln DA + \alpha_{EDBDA} \ln ED \ln BDA + \alpha_{EDEX} \ln ED \ln DE + \alpha_{EXDA} \ln EX \ln DA + \alpha_{EXBDA} \ln EX \ln BDA + \alpha_{EXDE} \ln EX \ln DE + \alpha_{DABDA} \ln DA \ln BDA + \alpha_{DADE} \ln DA \ln DE + \alpha_{BDADE} \ln BDA \ln DE$$

where *TE* represents the super efficiency scores obtained from the estimation made in the previous step. Variables hypothesized to influence technical efficiency include farm investment (I); age of the household head (A); schoolings of the household head (ED); experience of the household head, which is measured as a number of years in the farm business (EX); debt-to-asset ratio (DA); bank debt-to-asset ratio (BDA); debt-to-equity ratio (DE)

Variable *I* (Investment) is the capital expenditures to the start of period net physical property, land, ponds, machines and equipment serve for Pangasius farming. The expected sign of this variable on technical efficiency scores is positive.

A is a variable included in the model to estimate the impact of age of the household head on the level of technical efficiency. Age can be a proxy since the Pangasius farming in the Angiang province is a traditional one. The larger the age, the greater the technical performance is.

Variable education (*ED*) measured as the number of years of schooling achieved by the household head. This variable is used as a proxy for input management. The higher level of educational achievement may lead to the better assessment of farming decision such as the efficient use of inputs. The expected sign for education variable is positive.

Farmer experience (*EX*), measured here in terms of years that the producer has been. The farmers that have been farming for a longer period of time may have learned from past experiences and thus would have improved management abilities and be more receptive to innovations, result in a better efficiency

The debt-to-asset ratios (*DA*) in this research is current debt-to-asset ratios, since only current debt is used in all samples, measure the impact of financial leverage on technical efficiency. The debt-to-asset ratios measure the impact of financial leverage on efficiency. As can be seen in the chapter of literature review, there have been different hypotheses of the relationship between financial leverage and technical efficiency**.** This research expect sign of the estimated coefficient is positive because of the fact that most of Pangasius farms need to base on current debt which mostly go to the huge cost for fish feeding everyday. Pangasius farmers have the constraint on operating loans more than capital loans. Most farms in the sample use their debt to operating their farms more than investing or improving their fixed assets. The availability of debt or credit will lose the constraints of farm operating to get the inputs on time and hence is supposed to increase the efficiency of the farmers.

In Vietnam, the interest rates charged by the formal financing system (including state-owned and joint-stock commercial banks, local credit funds) are substantially lower than those charged by moneylenders (including professional moneylenders, relatives and friends, which are among the popular sources of credit in Vietnam). The bank debt-to-asset ratios (*BDA*) was included in the model to explore whether there is a relationship between financing of banks and farm efficiency.

Variable debt-to-equity ratios (*DE*) included in the model to estimate more reliably the impact of Debt on the level of technical efficiency since total assets including the fixed properties (i.e land, houses, equipment) that are not easy to transform to cash in a short time to serve the farm operating. Therefore, debt-to-equity ratios is used as an proxy in this empirical model.

3.2. DATA DESCRIPTION

Data collection was carried out in Chau Phu district, An Phu district and Long Xuyen city of An Giang province. The cross-sectional data was employed in this research with the results of the crop in year 2008 of these three regions. The household survey was carried out during the months of January and February, 2009. The structured questionnaire that meets the objectives of this study was used to collect the primary data. In order to develop the questionnaire, several pilot surveys were conducted to help to correct mistakes, evaluate and select relevant questions and information and eliminate ones.

Households were selected randomly. We went to the sites selected beforehand and approach the farmers and asked if their household heads were willing to co-operate. If they said "yes", we started conducting the questionnaire.

The interviewers were selected among the staffs of the Departments of Agriculture and Rural Development of Chau Phu and An Phu districts. Most of them had the experiences on collecting data and knowledge of Pangasius farming operations. The selected interviewers were trained prior conducting the questionnaire to make them acquainted with the questionnaire.

The survey experienced several problems common to some agricultural sectors experiences. It took times to approach directly the household head who can supply correctly the information we need in the questionnaire. Although questionnaire was prepared carefully, the data collected can be affected by some perception bias of the respondents. Farmers usually do not keep standard accounting books. Therefore, when asked for some detailed information about past activities they had to recall what already happened. However, we feel confident that the answers of he respondents do reflect the characteristics of Pangasius farming in a sufficient way that warrants us to do empirical analyses because cross-checking the data during and after the survey did not reveal any extremely incorrect or impossible answers.

Table 3.1: Summary Statistics of Input and Output Variables for Pangasius farms in An Giang province

Name	Mean	ST. DEV	Minimum	Maximum
Labor (persons)	4.0328	2.6455	1.00	15.00
Fuel (million VND)	24.853	40.357	1.50	210.00
Electricity (million VND)	21.939	29.831	1.00	160.00
Chemicals (million VND)	36.656	47.259	5.00	265.00
Seed (units)	259590	275640	35000.00	1200000.00
Feed (tons)	523.89	717.73	50.00	3330.00
Pangasius Production (tons)	285.31	390.90	30.000	2000.00

Table 3.1 summarizes the descriptive statistics of used inputs and output. To estimate farm technical efficiency, data of farm households and the enterprises were aggregated to obtain six inputs and one output. Output is Pangasius production. Inputs consist of: Labor, Fuel and oil, Electricity, Chemicals, Seed and Feed.

Labor includes both full time family and hired labor in pangasius production and is measured by persons. Only the large farms are mechanized in their operating, the others need to base on very high labor intensity. Labor is mainly used to prepare the fish feed, feed pangasius everyday and harvest in the end of crop. In the last months of mature pangasius, it eat a lot and the number of feeding times everyday also increase. Therefore, labor is also the important input in pangasius farming. Regarding to labor using, the minimum value is 1 and maximum arise to 15 which is depended on the scale of farms.

Fuel and oil and *Chemicals (including veterinary drugs)* and *Electricity* are aggregated inputs, and they are measured in monetary value since it was not possible to ask farmers about these inputs in number. Farmers usually do not remember exactly the amount of these inputs in comparison to the information of Feed and Seed.

Seed is measured in number of fingerlings and *Feed* is measured in tons, are the most important inputs in the model. In practice, the cost of feed and seed are the highest ones among the costs for all inputs in pangasius farming.

Table 3.2 provides summary-descriptive statistics for variables that were used in the estimation of the relationship between the farm-specific variables that were hypothesized to influence technical efficiency and the technical efficiency scores.

Table 3.2: Summary Statistics of data of Farm characteristics Variables for Pangasius farms in AnGiang province

NAME	Explain	Mean	ST. DEV	Min	Max
SUPERVRS	Super efficiency scores under VRS	1.0767	0.44426	0.35124	2.6667
I (million VND)	Investment	216.86	144.04	35.00	670.00
A (years)	Age of household head	43.721	8.7352	22.0	62.00
ED (years)	Education of household head	9.623	2.7335	4.00	12.00
EX (years)	Experience of household head	5.6230	2.5243	2.00	15.00
DA	Debt to Assets ratio	0.57471	0.11938	0.3	0.8
BDA	Bank debt to Assets ratio	0.41042	0.18092	0.00	0.75
DE	Debt to Equity ratio	1.5861	0.73620	0.44828	3.7619

Investment, being an aggregate input, is measured in monetary value. It is calculated as a sum of machinery and equipment, buildings, warehouses and improvements, and other fixed assets (which are valued more than 5 million VND regarding the laws of Vietnam) which were calculated as a sum of beginning and ending inventories divided by two. Given large variation in the data of this variable, it is expected that there would also be the effect of it on individual farm efficiency.

All farms in this research sample need to use the debts in their farming. Debt for pangasius farming includes bank debt and the debts from other moneylenders. Some farms did not approach the formal financing and just borrow money from the moneylenders. Therefore, their bank debt is described by zero.

Equity is the capital of the farmers which can cover all or a certain amount of the total cost for paganisms farming. Equity is measured by total cost minus the debt used in pangasius farming. Assets is measured by the money value of the sum of equity and other assets of household or enterprise. Because of the certain risks in agriculture, an informal regulation of Vietnam banks is that the maximum loans is equal to 80% value of total assets as collateral for the banks. Therefore, the DA ratio and BDA ratio have more small variations in comparison to DE ratio in this research since they are all less than 1. DE ratio is expected to have the effect on individual farm efficiency since it has larger variation in the data of this variable.

CHAPTER 4: RESULTS

This chapter consists of two sections. First, the distribution of farm technical and scale efficiency scores and characteristics of efficiency scores by each region and by pond size are presented. Then, the relationship between farm super efficiency scores under the assumption of variable returns-to-scale and farm-specific factors including farm financial variables are estimated using the OLS model in Shazam. In addition, this chapter present the results from testing of heteroscedasticity of the errors, test for omitted regressors and/or wrong functional form and hypothesis testing,

4.1. Efficiency Scores

Farm technical efficiency (TE) scores under the assumptions of CRS and VRS and scale efficiency (SE) scores were estimated using super DEA input oriented model. The distributions of the scores are presented in Tables 4.1. Mean, standard deviation, minimum, and maximum levels of TE and SE scores by regions are reported in Tables 4.2, 4.3, and 4.4 and by pond sizes are presented in Tables 4.5, 4.6 and 4.7.

From Table 4.1, Mean total technical efficiency for all farms is 0.595. It can be said that, on average, pangasius farmers in An Giang province are producing pangasius at about 59.5% of the potential frontier production levels at the present state of technology and input levels. It also means that farms can reduce their inputs by 40.5% and still produce the same level of output. The number of super technically efficient farms (i.e., farms operating on the production frontier) under the assumption of CRS was 8 (13.12%). Approximately 32.8% of the farms exhibited TE scores less than 0.40, and 24.6% of the farms exhibited TE scores from larger than 0.60 to less than 1.

Individual Super TE scores under the assumption of VRS ranged from 0.345 to 2.667 which show considerable variability among farms. Mean total super TE score for all farms is 1.0576 and standard deviation of 0.443 indicates that farms can increase input usage by 5.76% and still be within the technology defined by the other farms in the sample. As can be seen in table 4.1, TE scores under the assumption of variable returns-to-scale (TESVRS) are considerably higher than TESCRS scores. These results suggest that the significant economies of scale should be present among farms in the sample. Approximately 42.62% of the observations were on the production frontier under assumption of VRS (i.e., TE $\geq$ 1).

Table 4.1: Distribution of Farm Technical and Scale Efficiency Scores: DEA input orientation

Distribution of farms	TE scores under CRS		TE scores under VRS		SE scores	
	Number	Frequency (%)	Number	Frequency (%)	Number	Frequency (%)
< 0.2					3	4.92
0.2 to 0.4	20	32.79	1	1.64	13	21.31
0.4 to 0.6	18	29.5	1	1.64	18	29.5
0.6 to 0.8	13	21.31	18	29.5	14	22.95
0.8 to 1	2	3.28	15	24.59	12	19.67
1 to 1.2	4	6.56	10	16.4	1	1.64
1.2 to 1.4	1	1.64	3	4.92		
1.4 to 1.6	1	1.64	6	9.84		
1.6 to 1.8	1	1.64	4	6.56		
1.8 to 2						
2 to 2.2	1	1.64	2	3.28		
2.2 to 2.4						
2.4 to 2.6						
2.6 to 2.8			1	1.64		
Mean SD Minimum Maximum	0.595 0.37 0.22 2.09		1.0576 0.443 0.345 2.667		0.58 0.242 0.127 1.00	

An enlargement of the feasible region for the super BCC model makes the number of the efficient farms under assumption of VRS is expected to be more than under assumption of CRS. In this research, the difference of the number of the efficient farms between these models are considerable, 9 frontier farms under assumption of CRS in comparison to 26 frontier farms under assumption of VRS in total 61 samples. The technical scores of other farms in the sample under VRS also were improved in comparison to those under CRS. There was only 1 farm (1.64%) exhibited TE scores less than 0.4 and 1 farm has score from 0.4 to less than 0.6, which mean 59 on 61 farms exhibited scores from 0.6 to less than 1.

4.1.1. Technical eficiency scores by region

Analyzing TE scores under CRS and VRS by regions are presented in Table 4.2, 4.3 and 4.4. It can be seen that under both CRS and VRS assumption, Region 2 had the highest mean levels of TE scores, while the lowest cores belong to Region 1. Mean technical efficiency scores under the assumption of variable returns-to-scale (TESVRS) with the range goes from 0.945 for Region 1 to 1.036 for Region 3 and 1.2 in Region 2. The number of frontier farms in Region 2 under VRS and CRS are also highest, 11 and 4 farms, respectively, in comparison to those of Region 1, 7 and 1 farms, and Region 3, 7 and 3 farms, respectively. These results indicate that Region 2 and 3 exist the potential gains from improving technical efficiency for farms in the sample, especially for the farms in Region 2, Chau Phu district.

Scale efficiency multiplied by the technical efficiency measured under VRS equals technical efficiency under assumption of CRS Scale efficiency (SE). A farm can thus be scale efficient (SE = 1) but not lie on the TEVRS or TECRS efficiency frontiers. There were differences between TEVRS ands SE in the sample. The correlation coefficient between technical and scale efficiency is – 0.178, indicating only a moderately negative relationship between the two measures. The decomposition of the technical efficiency measure show that pure technical inefficiency was the primary cause of technical inefficiency. Scale efficiency scores varied from 0.127 to 1.00 with an average measure of 0.58 and standard deviation of 0.242. The scale efficiency level of 0.58 indicates that the average farm is 42% scale inefficient of Pangasius farming in the sample. Individual analysis of the farms indicate that 6.56% of the total sample farms had decreasing returns to scale (DRS), indicating that the output levels of these farms would expand by a smaller percentage then their inputs. One important finding is 91.8% of the sample pangasius farms exhibits increasing returns to scale (IRS). This indicates that when these farms expand their input levels by a certain percentage, their output level would expand by a larger percentage. This result also indicate that these IRS farms operated at below optimal scale. The percentage of scale efficient farms were very low : only 1 farm of the farms were fully scale efficient, and 9.84% of the farms had SE scores higher than 0.95. Over all, approximately 78.7% of the observations exhibited scale measures less than 0.80, and about 9.84% of the farms had SE scores 0.8 and 0.95. These above results mean the largest increase in technical efficiency in the sample farms could be obtained by eliminating the problem of increasing return to scales.

Table 4.2: Technical efficiency and Scale efficiency scores of Region 1

DMU	Region 1 – An Phu district					
	TECRS scores	TE VRS Scores and Ranking	Scale efficiency Scores	TE NIRS Scores	TE NDRS Scores	Scale Efficiency
A01	0.46	0.99 (22)	0.47	0.46	0.99	IRS
A02	0.25	0.82 (31)	0.30	0.25	0.82	IRS
A03	0.70	2.14 (2)	0.33	0.70	2.14	IRS
A04	1.14	1.41 (11)	0.81	1.14	1.41	IRS
A05	0.36	1.48 (10)	0.25	0.36	1.48	IRS
A06	0.36	1.13 (18)	0.32	0.36	1.13	IRS
A07	0.41	0.70 (39)	0.59	0.41	0.70	IRS
A08	0.47	0.63 (42)	0.74	0.47	0.63	IRS
A09	0.61	0.61 (44)	1.00	0.61	0.61	**CRS**
A10	0.56	1.16 (17)	0.48	0.56	1.16	IRS
A11	0.81	0.97 (23)	0.83	0.81	0.97	IRS
A12	0.52	1.41 (11)	0.37	0.52	1.41	IRS
A13	0.24	0.71 (38)	0.34	0.24	0.71	IRS
A14	0.51	1.03 (20)	0.50	0.51	1.03	IRS
A15	0.42	0.64 (41)	0.65	0.42	0.64	IRS
A16	0.22	0.61 (44)	0.36	0.22	0.61	IRS
A17	0.63	0.68 (40)	0.93	0.63	0.68	IRS
A18	0.29	0.62 (43)	0.47	0.29	0.62	IRS
A19	0.39	0.53 (45)	0.74	0.39	0.53	IRS
A20	0.47	0.79 (32)	0.59	0.47	0.79	IRS
A21	0.48	0.78 (33)	0.61	0.48	0.78	IRS
Mean	*0.49*	*0.945*	*0.555*	*0.49*	*0.953*	
SD	*0.212*	*0.4*	*0.22*	*0.218*	*0.408*	
Min	*0.22*	*0.53*	*0.245*	*0.22*	*0.533*	
Max	*1.143*	*2.14*	*1.00*	*1.143*	*2.145*	

Table 4.3: Technical efficiency and Scale efficiency scores of Region 2

DMU	Region 2 - Chau Phu district					
	TE CRS scores	TE VRS Scores and Ranking	Scale efficiency Scores	TE NIRS Scores	TE NDRS Scores	Scale Efficiency
C01	1.09	1.57 (8)	0.69	1.09	1.57	IRS
C02	0.48	1.30 (13)	0.37	0.48	1.30	IRS
C03	0.50	1.19 (15)	0.42	0.50	1.19	IRS
C04	0.68	1.17 (16)	0.58	0.68	1.17	IRS
C05	0.69	0.92 (25)	0.75	0.69	0.92	IRS
C06	0.46	1.19 (15)	0.39	0.46	1.19	IRS
C07	0.43	0.85 (28)	0.50	0.43	0.85	IRS
C08	0.73	0.75 (35)	0.98	0.73	0.75	IRS
C09	0.42	0.74 (36)	0.57	0.42	0.74	IRS
C10	0.37	0.88 (27)	0.42	0.37	0.88	IRS
C11	0.78	1.00 (21)	0.78	0.78	1.00	IRS
C12	0.27	2.09 (3)	0.13	0.27	2.09	IRS
C13	1.26	1.79 (4)	0.70	1.79	1.26	**DRS**
C14	1.71	1.79 (4)	0.96	1.71	1.79	IRS
C15	0.35	0.84 (29)	0.42	0.35	0.84	IRS
C16	1.15	1.39 (12)	0.83	1.15	1.39	IRS
C17	0.30	1.13 (18)	0.27	0.30	1.13	IRS
C18	0.41	0.84 (29)	0.48	0.41	0.84	IRS
C19	0.61	0.94 (24)	0.65	0.61	0.94	IRS
C20	0.31	1.61 (6)	0.19	0.31	1.61	IRS
Mean	*0.65*	*1.2*	*0.554*	*0.676*	*1.17*	
SD	*0.38*	*0.39*	*0.238*	*0.44*	*0.367*	
Min	*0.266*	*0.73*	*0.127*	*0.266*	*0.737*	
Max	*1.707*	*2.086*	*0.975*	*1.79*	*2.09*	

Table 4.4: Technical efficiency and Scale efficiency scores of Region 3

DMU	Region 3 – Long Xuyen city					
	TE CRS scores	TE VRS Scores and Ranking	Scale efficiency Scores	TE NIRS Scores	TE NDRS Scores	Scale Efficiency
L01	0.32	0.90 (26)	0.35	0.32	0.90	IRS
L02	0.25	1.00 (21)	0.25	0.25	1.00	IRS
L03	0.30	1.76 (5)	0.17	0.30	1.76	IRS
L04	0.86	0.94 (24)	0.92	0.86	0.94	IRS
L05	0.31	0.76 (34)	0.41	0.31	0.76	IRS
L06	0.63	1.58 (7)	0.40	0.63	1.58	IRS
L07	0.76	1.06 (19)	0.72	0.76	1.06	IRS
L08	0.31	0.94 (24)	0.33	0.31	0.94	IRS
L09	0.70	0.94 (24)	0.75	0.70	0.94	IRS
L10	0.29	0.35 (46)	0.85	0.29	0.35	IRS
L11	0.75	0.76 (34)	0.99	0.75	0.76	IRS
L12	0.29	0.68 (40)	0.43	0.29	0.68	IRS
L13	1.47	1.49 (9)	0.99	1.49	1.47	**DRS**
L14	2.09	2.67 (1)	0.78	2.67	2.09	**DRS**
L15	0.40	0.85 (28)	0.47	0.40	0.85	IRS
L16	0.29	0.64 (41)	0.44	0.29	0.64	IRS
L17	0.79	0.83 (30)	0.95	0.79	0.83	IRS
L18	0.46	0.63 (42)	0.73	0.46	0.63	IRS
L19	1.16	1.21 (14)	0.96	1.21	1.16	**DRS**
L20	0.56	0.73 (37)	0.76	0.56	0.73	IRS
Mean	*0.65*	*1.036*	*0.632*	*0.682*	*1.003*	
SD	*0.471*	*0.513*	*0.27*	*0.575*	*0.423*	
Min	*0.25*	*0.345*	*0.17*	*0.25*	*0.345*	
Max	*2.09*	*2.667*	*0.991*	*2.667*	*2.09*	

Analysis of SE scores by regions indicates that mean SE scores varied from 0.55 to 0.632, with average standard deviation varying from 0.22 in Region 1 to 0.27 in Region 2. Among the regions, Region 3 had the highest mean score with 4 farms had SE scores higher than 0.95 while Region 1 had only 1 farm which is scale efficient. These results indicate that most farms in each region operate at an inefficient scale and, therefore, significant improvements in scale efficiency can be accomplished by most farms in the sample by changing the scale of their operation.

In order to examine differences in the estimated efficiency between the regions, "ANOVA Test" for homogeneity of mean scores of TECRS, TEVRS, and SE scores between the regions were performed in Excel.

The results of the F-tests show that the equality of means for all three regions for TECRS, TEVRS, and SE could not be rejected at the 5% significance level. These results indicate that average TECRS, TEVRS and SE scores are statistically similar among all of the regions.

Table 4.5 reported the results of the tests of comparison the mean of technical efficiency scores between regions. The same letter by the regions indicates that the mean efficiency scores of those regions are not significantly different.

Table 4.5: Mean of technical efficiency scores between regions

Region	TECRS		TEVRS		SE	
An Phu (1)	0.49	A	0.9447	A	0.5562	A
Chau Phu (2)	0.65	A	1.199	B	0.554	A
Long Xuyen (3)	0.6495	A	1.036	B	0.6325	A

The results for each region indicate that under the assumption of VRS, Region 1 has lower average TE scores than Region 2 and Region 3. There is no evidence to reject the hypothesis at the 5% significance level of difference in mean TE scores under CRS and SE scores between all three regions.

4.1.2. Efficiency – Pond size relationship

In order to examine how efficiency scores vary with pond size, Pangasius ponds were classified into 3 size groups as can be seen in Table 4.6, 4.7 and 4.8.

As can be seen in tables 4.6 to 4.8, under consumption of CRS, the most efficient farms were the largest farms, while under VRS, the most efficient farms were the smallest ones. Turning to the scale efficiency, the smallest farms were in average the least efficient and the largest farms were the most efficient.

ANOVA analysis for each farm size group was conducted and showed that pond size had a statistically significant impact on efficiency. The results of the F-tests show that the equality of means for all three pond sizes for TESCRS is rejected at the 1% significance level. For TESVRS, the equality of the means is rejected at the 5% significance level. Equality of the means is also rejected for SE. This result indicates that average SE scores are statistically different among all of the pond sizes.

Table 4.6: Efficiency scores of Pangasius farmers according to Pond size less than 4000m^2

DMU	Area (m^2)	TECRS scores	TEVRS Scores	Scale efficiency Scores	TE NIRS Scores	TE NDRS Scores	Scale Efficiency
A01	1000	0.46	0.99	0.47	0.46	0.99	IRS
A06	1000	0.36	1.13	0.32	0.36	1.13	IRS
L03	1000	0.3	1.76	0.17	0.3	1.76	IRS
C02	1200	0.48	1.3	0.37	0.48	1.3	IRS
C12	1800	0.27	2.09	0.13	0.27	2.09	IRS
A02	2000	0.25	0.82	0.3	0.25	0.82	IRS
A03	2000	0.7	2.14	0.33	0.7	2.14	IRS
A10	2000	0.56	1.16	0.48	0.56	1.16	IRS
A16	2000	0.22	0.61	0.36	0.22	0.61	IRS
C06	2000	0.46	1.19	0.39	0.46	1.19	IRS
C20	2000	0.31	1.61	0.19	0.31	1.61	IRS
A13	2200	0.24	0.71	0.34	0.24	0.71	IRS
A05	2500	0.36	1.48	0.25	0.36	1.48	IRS
A18	2500	0.29	0.62	0.47	0.29	0.62	IRS
A20	2500	0.47	0.79	0.59	0.47	0.79	IRS
C03	2500	0.5	1.19	0.42	0.5	1.19	IRS
L06	2500	0.63	1.58	0.4	0.63	1.58	IRS
C18	3000	0.41	0.84	0.48	0.41	0.84	IRS
L02	3000	0.25	1	0.25	0.25	1	IRS
A12	3500	0.52	1.41	0.37	0.52	1.41	IRS
A21	3500	0.48	0.78	0.61	0.48	0.78	IRS
C01	3500	1.09	1.57	0.69	1.09	1.57	IRS
Mean	2236.3	0.4368	1.2168	0.3809	0.4368	1.2168	
SD	771.24	0.1973	0.4471	0.1418	0.1973	0.61	
Min	1000	0.22	0.61	0.13	0.22	2.14	
Max	3500	1.09	2.14	0.69	1.09		

Table 4.7: Efficiency scores of Pangasius farmers according to Pond size less than 7000m^2

DMU	Area (m^2)	TECRS scores	TEVRS Scores	Scale efficiency Scores	TE NIRS Scores	TE NDRS Scores	Scale Efficiency
A07	4000	0.41	0.7	0.59	0.41	0.7	IRS
A15	4000	0.42	0.64	0.65	0.42	0.64	IRS
C04	4000	0.68	1.17	0.58	0.68	1.17	IRS
C15	4000	0.35	0.84	0.42	0.35	0.84	IRS
C17	4000	0.3	1.13	0.27	0.3	1.13	IRS
L05	4000	0.31	0.76	0.41	0.31	0.76	IRS
L08	4000	0.31	0.94	0.33	0.31	0.94	IRS
L18	4000	0.46	0.63	0.73	0.46	0.63	IRS
A14	4800	0.51	1.03	0.5	0.51	1.03	IRS
C05	5000	0.69	0.92	0.75	0.69	0.92	IRS
C07	5000	0.43	0.85	0.5	0.43	0.85	IRS
C10	5000	0.37	0.88	0.42	0.37	0.88	IRS
C16	5000	1.15	1.39	0.83	1.15	1.39	IRS
A08	5500	0.47	0.63	0.74	0.47	0.63	IRS
L16	5500	0.29	0.64	0.44	0.29	0.64	IRS
L01	6000	0.32	0.9	0.35	0.32	0.9	IRS
L09	6000	0.7	0.94	0.75	0.7	0.94	IRS
L12	6000	0.29	0.68	0.43	0.29	0.68	IRS
L20	6000	0.56	0.73	0.76	0.56	0.73	IRS
A11	6080	0.81	0.97	0.83	0.81	0.97	IRS
Mean	4894	0.4915	0.8685	0.564	0.4915	0.8685	
SD	842.35	0.2204	0.2046	0.1791	0.2204	0.2046	
Min	4000	0.29	0.63	0.27	0.29	0.63	
Max	6080	1.15	1.39	0.83	1.15	1.39	

Table 4.8: Efficiency scores of Pangasius farmers according to Pond size larger than 7000m^2

DMU	Area (m^2)	TECRS scores	TEVRS Scores	Scale efficiency Scores	TE NIRS Scores	TE NDRS Scores	Scale Efficiency
A09	7000	0.61	0.61	1	0.61	0.61	CRS
A19	7000	0.39	0.53	0.74	0.39	0.53	IRS
C19	7000	0.61	0.94	0.65	0.61	0.94	IRS
L07	7000	0.76	1.06	0.72	0.76	1.06	IRS
L15	7000	0.4	0.85	0.47	0.4	0.85	IRS
A04	9000	1.14	1.41	0.81	1.14	1.41	IRS
A17	9000	0.63	0.68	0.93	0.63	0.68	IRS
C09	10000	0.42	0.74	0.57	0.42	0.74	IRS
C11	10000	0.78	1	0.78	0.78	1	IRS
L10	15000	0.29	0.35	0.85	0.29	0.35	IRS
L14	15000	2.09	2.67	0.78	2.67	2.09	DRS
C08	16000	0.73	0.75	0.98	0.73	0.75	IRS
L13	18000	1.47	1.49	0.99	1.49	1.47	DRS
L17	18000	0.79	0.83	0.95	0.79	0.83	IRS
L04	20000	0.86	0.94	0.92	0.86	0.94	IRS
C13	30000	1.26	1.79	0.7	1.79	1.26	DRS
C14	30000	1.71	1.79	0.96	1.71	1.79	IRS
L11	30000	0.75	0.76	0.99	0.75	0.76	IRS
L19	30000	1.16	1.21	0.96	1.21	1.16	DRS
Mean	15526.3	0.8868	1.0736	0.8289	0.9489	1.0115	
SD	8758.28	0.4773	0.5544	0.1566	0.6004	0.4371	
Min	7000	0.29	0.35	0.47	0.29	0.35	
Max	30000	2.09	2.67	1	2.67	2.09	

Comparison of the mean scores of three pond sizes groups under assumption of CRS suggests that farms of the smallest size group are 50.56% and farms of 4000 to under 7000 m^2 are 45% less than farms above 7000 m^2, which are in average the most efficient. However, farms under 4000 m^2 are the best farms under consumption of VRS. They are 28.7% more efficient than farms of 4000- under 7000 m^2, and by 12.3% more efficient than farms above 7000 m^2. The highest scale efficiency score was achieved by farms of the largest size group. Farms under 4000 m^2 are 54.2% and farms of 4000- under 7000 m^2 are 32.5% less efficient than farms above 7000 m^2.

Further, to examine differences in the estimated efficiency between the pond size groups, mean scores of TECRS, TEVRS, and SE scores between the different groups were analyzed by ANOVA in Excel.

Table 4.9: Mean of technical efficiency scores between different group of pond size

Pond size groups	TECRS		TEVRS		SE	
< 4000 m^2	0.4368	A	1.2168	A	0.3809	A
4000 – 7000 m^2	0.4915	A	0.8685	BA	0.564	B
≥7000 m^2	0.8868	B	1.0736	A	0.8289	C

Test results show that under CRS, there are significant differences between technical efficiency of farms above 7000 m^2 and other size groups at 1% level, and inability to reject the hypothesis of difference in mean TE scores between the smallest and middle size groups. For TEVRS, the test shows different results where there is significant differences between technical efficiency of the smallest size group and the middle one at 1% level, while there was no statistically significant difference in TE scores between other groups. Under assumption of VRS, the farms of 4000-7000 m^2 had the lowest average statistically significant TE scores as compared to other size groups.

Equality of the means for SE is also rejected at 1% significant level as comparison the SE mean scores of each size group. These results indicate that average SE scores are statistically different among each of the pond sizes. The largest size group achieves the highest scale efficiency score while the smallest size group get the lowest score.

4.2. Technical Efficiency and Farm-Specific Factors

In this section, the results of the regression analysis of technical efficiency under the assumption of VRS of Pangasius farming are presented. Table 4.9 reports the results of ordinary least square (OLS) estimation. The econometric package Shazam was used (SHAZAM, 2001) to estimate the relationship between technical efficiency and selected farm specific characteristics.

The translog production function is tested for significance. First, the null hypothesis that the interactive terms have significant effects is tested. The F-test statistic, 0.55 with 21 and 25 degrees of freedom, suggests that the interactive terms should be removed from the model. Then, the F-test is also used to test whether the second order terms have significant effects. The test statistic, 1.07 with 7 and 46 degrees of freedom, are in favor of the absence of the second order terms in the model.

4.2.1. Test for the heteroscedasticity of the errors by the Goldfeld-Quandt test:

Regression disturbances whose variances are not constant across observation are heteroscedastic. Hereroscedasticity arises in numerous applications, in both cross-section and times-series data. Hereroscedasticity poses potentially severe problems for inferences based on least squares. It is useful to be able to test for homoscedasticity and if necessary, modify our estimation procedures accordingly.

Several types of tests have been suggested. The Goldfeld-Quandt test is used to detect the presence of hereroscedasticity in this research.

For the Goldfeld-Quandt test, we assume that the observations can be divided into two groups that under the hypothesis of homoscedasticity, the disturbance variances would be the same in the two groups, whereas under the alternative, the disturbance variances would differ systematically.

The test is applied by dividing the sample into two subsets with n_1 and n_2 observations. Denote the variance in the first subset by σ_1^2 and the variance in the second subset by σ_2^2. The null hypothesis is H_0: $\sigma_1^2 = \sigma_2^2$ and the alternative hypothesis is H_1: $\sigma_1^2 > \sigma_2^2$.

To obtain statistically independent variance estimators, the regression is then estimated separately with the two sets of observations. The test statistics is calculated as:

$$F\,[n_1 - K, n_2 - K] = \frac{RSSE1 / (n_1 - K)}{RSSE2 / (n_2 - K)}$$

Where RSSE1 and RSSE2 are the sum of squared errors from the first N_1 and the last N_2 observations respectively. Under the null hypothesis of homoscedasticity, this statistic has an F distribution with $n_1 - K$ and $n_2 - K$ degrees of freedom.

The statistic can be compared with an $F_{(n1 - K,\, n2 - K)}$ to the standard F table to carry out the test, with a large value leading to rejection of the null hypothesis.

The computed G – Q test statistic in Shazam at 22 and 23 degrees of freedom is 0.55 then the p-value 0.082 at a 5 percent level of confidence. Since the computed G – Q test statistic is less than 1 then the p-value is more than 0.05, the null hypothesis of homoscedasticity is not rejected by this test and we conclude that there is no the existence of hereroscedasticity in the sample.

4.2.2. Test for omitted regressors and/or wrong functional form

The Ramsey (1969) RESET tests (REgression Specification Error Test) are computed by introducing test variables constructed as powers of the predicted value $\hat{Y}$ as additional regressors. The RESET test is an F tests whether the coefficients on the new regressors are zero.

The test statistics for the various mis-specification tests are calculated from auxiliary regressions that include m additional regressors as given in the table below.

Test	M	Test Variables
RESET (2)	1	$\hat{Y}_t^2$
RESET (3)	2	$\hat{Y}_t^2$, $\hat{Y}_t^3$
RESET (4)	3	$\hat{Y}_t^2$, $\hat{Y}_t^3$, $\hat{Y}_t^4$

Denote the multiple coefficient of determination from the initial regression by R_0^2 and the multiple coefficient of determination from the auxiliary regression by R^2. The F statistic that can compared with an F-distribution with (m, N – K – m) degrees of freedom is:

$$F\,[m, N - K - m] = \frac{(R^2 - R_0^2)\,/\,m}{(1 - R^2)\,/\,(N - K - m)}$$

The computed Ramsey – RESET test statistics then p-values in Shazam are:

RESET(2)= 2.4253 - F WITH DF1= 1 AND DF2= 52 P-VALUE= 0.125
RESET(3)= 1.9689 - F WITH DF1= 2 AND DF2= 51 P-VALUE= 0.150
RESET(4)= 1.3108 - F WITH DF1= 3 AND DF2= 50 P-VALUE= 0.281

Since the computed p-values are more than 0.05, the null hypothesis of the coefficients on the new regressors are zero is not rejected by this test and we conclude that the estimated model is well specified.

4.2.3. Ordinary least squares estimation:

Ordinary least squares (OLS) estimates of the parameters of the model are presented in Table 4.9. With the R^2 value of 0.54, the independent variables used in the model were able to explain 54% of the variation in the technical efficiency scores under VRS for the study area.

Table 4.10: Parameter estimate and test statistics of Ordinary least squares model

Variables	Parameters	Estimated coefficients	t-value
Constant	α_0	- 0.59064	- 0.7926
Investment	α_I	0.13953	2.083**
Age of household head	α_A	- 0.15084	- 0.8799
Education of household head	α_{ED}	0.080951	0.6801
Experience in Pangasius farming	α_{EX}	0.19583	2.241**
Debt to assets ratio	α_{DA}	0.34494	1.895***
Bank debt to asset ratio	α_{BDA}	0.000002	1.496
Debt to equity ratio	α_{DE}	0.36064	3.550*

* *Statistically significant at the level of 1%*
** *Statistically significant at the level of 5%*
*** *Statistically significant at the level of 10%*

t- statistics are calculated, with the null hypothesis that a parameter is zero, which means that the estimated variable has no effect on the dependent variable given that the other variables are in the model.

Result indicates that the effect of investment for Pangasius farming is significant at the 5% level. Increased investment for applying modern machines to mix the feed for fish and equipment in operating such as the pumps to change water in fish ponds in the last month of cultivating, warehouses and improvement of ponds before starting the new crop, lead to better performance of technical efficiency.

Variables Age, Education, which measured by schooling years, and Experience, which measured in number of years of the head of the household were included in the model to estimate the effects of socio-economic factors on the level of technical efficiency. It is believed that increased age and farming experience go together with higher level of educational achievement may lead to a better assessment in using inputs efficiently and making complex and important decisions in farm investment or farm operating. Results in Table 4.9, however, show that only variable of Experience has an expected sign and statistically significant at the level 5% confidence. This result indicates that farming experience has an effect on a farmers' ability to allocate resources or decision to invest their farms more efficiently. Variable Education level has an expected sign, but it is not statistically significant. Variable Age of the head of household has a negative influence on technical efficiency, but it is also not significant in statistic. These contradictory results might be explain due to the fact that although older farmers might have more experience than younger farmers, they may be more careful and conservative in adopting new technology, therefore, lead to less efficiency.

Leverage variables DA (current debt-to-asset ratios in this research) was statistically significant at the 10% level, while no significant influence of variable BDA (current bank debt-to asset ratio) is found in the sample. These results indicate that although total debt to asset ratios has certain effects on technical efficiency, the level of bank debt in comparison to the total debt has no effects on technical efficiency. As mentioned in chapter 3, informal financing is still common in Vietnam, especially in agriculture sector. Besides, the difficulties in approaching the credit from the bank and constraints of collateral assets are also the important reasons to explain why farmers do not base their farming in only the formal financing. However, of course, without or less collateral assets, farmers need to pay more for the interest rate for the moneylenders.

Variable DA has a positive influence on technical efficiency. The result supports the free cash flow concept and, contradicts the agency cost concept in finance. The farmers are indebted face to the pressure of their repayment obligations and therefore, they are motivated to improve their efficiency. In practical, this result suggests that benefits of debt motivate managers to become more efficient because farmers who are indebted can generate enough financial resources to cover their operating expenses. It is appropriate in the case of Pangasius farming which need the high cost for operating.

As expected, the debt to equity ratio (DE) variable has a positive impact on technical efficiency and is significant at the 1% level. As mentioned before, variable DE has more potential effect to the technical efficiency in comparison to variable DA. Equity is mainly kept in cash which is using to buy and pay for inputs serves for farming, while Assets include the fixed properties (i.e land, houses, equipment) that are not easy to transform to cash in a short time. Therefore, it is easier to see the effects of DE on technical efficiency than DA.

In short, the results indicate that financial exposure (as measured by DA and DE) is a source of efficiency for all pangasius farms in the sample, the increase in indebtedness is positively related to the technical efficiency scores for those farms.

CHAPTER 5: SUMMARY AND CONCLUSIONS

Thesis Summary

This research uses the DEA method to estimate the technical efficiency and scale efficiency of selected Pangasius farms of the An Giang province, the leading region of Pangasius farming in the Mekong Delta of Vietnam. Cross-sectional data of directly interviews from 61 farms from three geographic regions were used in the study. To estimate the technical efficiency, the data for each farm in the sample were aggregated into six inputs (Labor, Fuel and oil, Electricity, Chemicals, Seed and Feed) and one output (Pangasius production).

Farm individual technical efficiency scores were used in a regression model to reveal the relationship between the technical efficiency under assumption of variable returns to scale and different farm-specific characteristics that including farm's financial variables. Variables hypothesized to influence technical efficiency included farm investment, age, education, experience of household head, total debt-to-asset ratios, bank-debt-to-asset ratios, total debt-to-equity ratios .

Results and discussions

Findings of the research showed that, on average, Pangasius farms under the analysis were 0.595 technically efficient under the assumption of constant returns-to-scale (CRS) with TECRS ranged from a minimum of 0.22 to a maximum 2.9, 1.058 technically efficient under the assumption of variable returns-to-scale (VRS) with TEVRS ranged between 0.34 and 2.67, and 0.58 scale efficient with SE ranged between 0.13 and 1.00. Minimum and maximum values of efficiency score show considerable variability among farms. Mean technical efficiency under CRS suggests that the inputs used by Pangasius farms can be reduced by 40.5% and produce the same level of output if each farm in the sample was producing on the the efficient frontier at constant returns to scale. When adjusted for farm size, many farms have a higher level of VRS technical efficiency, 1.058 on average. These mean levels of technical efficiency measures are higher in comparison to technical efficiencies of the Catfish farms in Chicot, Arkansas, which were calculated as 0.57 and 0.73, respectively (Kaliba and Engle, 2006). However, techincal efficencis of Pangasius farming are much lower in comparison to the technical efficiencies of aquaculture sector in other countries, which was estimated for trout pond farming in the Black Sea Region, Turkey which was estimated 0.82 (Cinemre (2006), for tilapia pond operations in Philippines which was estimated as 0.83 (Kumar et al, 2004), for milkfish (Chanos chanos) farming in pond in Taiwan (Chiang et al., 2004) which was estimated as 0.84 and for Chinese fish farms polyculture and the prawn-carp farming of Bangladesh, which were estimated 0.83 (Sharma, 1999) and 0.85 (Ferdous Alam, Murshed-e-Jahan, K. (2008), respectively. This indicates that consierable scope to raise Pangasius production using the existing laval of input use and technology. The scale efficiency level of 0.58 indicates that 42% of all farms in the sample is scale inefficient. Mean level of scale efficiency of Pangasius farming is also lower in comparison to that measure for the Catfish farms in Chicot, Arkansas, which were calculated as 0.77 (Kaliba and Engle, 2006) and for the prawn-carp farming of Bangladesh, which were estimated 0.88 (Ferdous Alam, Murshed-e-Jahan, K. (2008). The low scale efficiency in comparison to the VRS technical efficiency suggests that inefficiencies of Pangasius farms are mostly due to scale inefficiency rather than inefficient management pratices. The observed technical inefficiency can be eliminated and improved by eliminating the problem of increasing returns to scale as about 92% of the sample pangasius farms exhibits increasing returns to scale (IRS). Therefore, the Pangasius efficiency could be increased by increasing the scale of the average farms in the sample.

Tests for homogeneity of variance between efficiency ratios among the regions indicated that the equality of means for technical efficiency under CRS and VRS and scale efficiency scores for all three regions could not be rejected at the 5% significance level, which indicates that average TECRS, TEVRS and SE scores are statistically similar among all of the regions. The results for each region indicated that The results for each region indicate that under the assumption of VRS, Region 1 has lower average TE scores than Region 2 and Region 3.

The results of the F-tests for whether the existence of the impact of pond size groups on the efficiency show that the equality of means for all three pond sizes for TESCRS is rejected at the 1% significance level and rejected at the 5% significance level for TESVRS. Under CRS, the farms in the largest group (>7000 m^2) are more technical efficiency than other size groups. Under VRS, the farms of 4000-7000 m^2 had the lowest average statistically significant TE scores as compared to other size groups while there is no statistically difference between the farms of the largest and smallest size groups. Equality of the means is also rejected for SE indicating that average SE scores are statistically different among all of the pond sizes. The largest size group (>7000 m^2) achieves the highest scale efficiency score while the smallest size group (< 4000 m^2) get the lowest score.

Farm technical efficiency was found to be influenced by farm indebtedness. The resuls indicate that financial exposure is a source of efficiency for all Pangasius farms in the sample. In other words, the increase in debts positively influences the technical efficiency of those farms. The significant positive relationships were found between technical efficiency and the short-term debt-to-asset ratio, and between technical efficiency and the short-term debt-to-equity ratio while the variable bank debt-to-asset ratio was not statistically significant. This can be explained as the farmers have the constraints in accessing the bank credit and try to borrow money from the other informal financing. The results for the short-term debt-to-asset ratio and the short-term debt-to-equity ratio are consistent with the free cash flow and do not support the agency cost concepts of finance theory.

Technical efficiency is positively influenced by farm investment. Increased cost for applying modern machines and equipment in operating as well as improvement of ponds before starting the new crop, lead to better performance of technical efficiency.

The experience of household head measured by the years of pangasius farming has positive effects on technical efficiency indicates that the more experiences the farmers have had in previous time of farming, the more efficiency those farms will have.

Conclusion remarks:

The main findings of this research are: (1) technical efficiencies of Pangasius farming in Vietnam was estimated under assumption of constant returns to scale and variable returns to scale as 0.595 and 1.058, respectively; (2) estimated scale efficiency is 0.58 which exhitbits increasing returns to scale; (3) financial variables (indebtedness of farms) are among the farm specific factors influenced on technical efficiency and the sign of effects of these financial variables is positive.

Pangasius farming is continuing to be one of the important sectors of the aquaculture industry in Vietnam. Due to the very favourable conditions in the South of Vietnam, especially in the Mekong Delta, i.e., warm weather and water all seasons in the year, Pangasius grows well in this region. Moreover, with its characteristics of adapting well with the environment and high ability to resist most of the diseases, Pangasius is farmed commonly in the Mekong Delta since 1990 and intensively since the reform of Vietnam to enlarge the international trade. However, the Pangasius industry is still young. The results of this research suggest that technical efficiency of Pangasius farms in Vietnam is still not on a par with similar aquacultural operations in other countries and in Asia. More efficient use of inputs, such as feed, seed, and labor as well as increasing the scale of farms may in the future be the key for lifting productivity and hence profitability of Pangasius farming in Vietnam. Moreover, this research suggests the positive role of debt in Pangasius farming in the Mekong Delta of Vietnam. These findings might be informative for policy formation and future researchs.

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