Econometric analysis on economies of scale: An application to rice and shrimp production in Thailand

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Abstract

Shrimp production in Thailand has historically been undertaken in the saline and brackish waters of coastal mangroves. In recent years rising demand and prices for shrimp and falling productivity of mangrove areas have motivated an expansion of shrimp production into the fresh-water margins of river estuaries that were previously used for rice cultivation.

Generalised additive models, which offer a comprehensive approach to regression analysis, are mainly used for empirical analysis, and model development and specification for rice and shrimp production in this study. This paper presents a brief introduction to generalised additive models, discusses how they are applied to develop cost functions to satisfy the restriction of production theory, and describes a comparative economic analysis of shrimp and rice production. A final result was found that rice production is characterised by constant returns to scale, and shrimp production by increasing returns to scale. On this basis it was concluded that shrimp production will continue to expand in the fresh-water areas, displacing rice production and exacerbating environmental problems.

Key word: rice, shrimp, returns to scale.

1. Introduction

The study of economies of scale concerns analysing industry production cost as a function of output. Economies arising from an increase in the scale of production of any kind of goods may be divided into two classes - those representing the general development of the industry; and those depending on the resources of individual firms engaged in the industry, on organisation and the efficiency of management (Bohm, 1997). This provides the efficiency rationale for government intervention. The strategic interventions of state may include seeking to protect or subsidise new firms until they have reached the critical size and experience that allows them to compete, and the imposition of export subsidies and temporary tariffs to take advantage of increasing returns (Sadiulet and de Janvry, 1995).

However, government intervention and policy reform under the efficiency oriented goal should be firstly performed to solve an economic problem. This economic problem arises when the choice of production technology made by established firms and individuals has negative effects on other firms and individuals, and vice versa, i.e., production and consumption externalities. This problem requires government intervention and policy reform under the efficiency oriented goal. Also, the requirement is to investigate the economies of the established firms.

A conflict between rice and shrimp production in the fresh area and between environmental quality and food production in Thailand was examined in this study. Both parties are very important to the Thai economy since they contribute to nutrition, employment, and export earnings. They are not only becoming competitive because of the requirement of the same natural resources (land and water), but also their best practices produce externalities to each other and to third parties. The concern is shrimp production which has historically been undertaken in the saline and brackish waters of coastal mangroves. In recent years rising demand and prices for shrimp and falling productivity of mangrove areas have motivated an expansion of shrimp production into the fresh-water margins of river estuaries that were previously used for rice cultivation. This has resulted in environmental problems of nutrient pollution of waterways and salinisation of soils.

The purpose of this study was to propose the empirical analysis of production to help construct a model for estimating economies of scale . An empirical investigation of the model, underlying the satisfaction of the properties of production theory and extending the flexible functional forms, is firstly conducted via nonparametric regression methods, followed by parametric analysis to obtain the economies of scale. Generalised additive models, introduced by Hastie and Tibshirani (1986), are used to implement the econometric analysis.

2. Model

The study of economies of scale is theoretically to analyse industry production costs as a function of output. Therefore, a cost function approach was used, relying on explicit functional forms to describe technological parameters. The model was constructed using duality principles to develop a simple and flexible tool for empirical analysis of producer's behaviour. An exposition of the duality principles in microeconomic theory may be seen in Diewert (1982), Jorgenson (1986), Chambers (1988), and Varian (1992).

To establish the general model, let $P = (P_1, \ldots, P_i)$ denote the positive vector of input prices, $X = (X_1, \ldots , X_i)$ denote the transposed vector of the non-negative row vector of inputs, and f be the production function for a single producer, describing the relationship between inputs and maximum output. The maximum output (Y) that can be produced with inputs X is presented by the equation:

(1) $Y = f(X)$.

Strictly speaking, the production function is valid for an industry as a whole only if all production units are characterised by optimising behaviour. With competitive input markets, the producer's optimisation problem may be considered as a cost minimisation problem, whereby variable costs are minimised for a given amount of output and subject to a vector of exogenous input prices. The result is a restricted cost function which is represented as:

(2) $C(P,Y) = \min_X \{P.X \mid f(X) \geq Y\}$.

Duality between production and costs means that if there exists a continuous, quasi-concave, and monotonic production function $f(Y)$, then there will be exist a cost function $C(P, Y)$ with the following properties:

(1) Non-negativity: a strictly positive amount of inputs are required to produce a positive output level. Thus, it is impossible to produce a positive output at zero cost.
(2) Non-decreasing in output and input prices: input prices are all strictly positive and an increase in any input price will not decrease cost; also increasing output cannot decrease costs.
(3) Concavity of input prices: a curve of minimal cost of production must be less than a passive cost function.
(4) Input prices are a first degree homogeneous: only relative prices.

The elasticity of scale ($\varepsilon(P_i, Y)$), which is defined as the ratio of average cost divided by marginal cost, is derived from the cost function:

(4) $\varepsilon(P_i, Y) = \frac{\partial Y}{\partial C}.\frac{C}{Y} = \frac{AC}{MC}$.

Using Shepherd's Lemma (Chambers, 1988), if the cost function is differentiable in *P*, then the cost-minimising conditional demand of the ith input is equal to the gradient of $C(P_i, Y)$ in *P*:

(5) $X_i(P_i, Y) = \dfrac{\partial C(P_I, Y)}{\partial P_i}$.

Generalised Additive Models

The following discussion of generalised additive models is based on the work of Hastie and Tibshirani (1990), and a library of S-plus functions. These models are a synthesis of three different statistical tools, namely scatterplot smoothers, additive models, and generalised linear models. These tools are briefly summarised below.

Scatter smoothing

The generalised additive model focuses mainly on the conditional expectation of a response variable, say *Y*, given a predictor, say *X*. Suppose

(6) $Y = \phi(X) + \varepsilon$,

where ϕ is a smooth function of *X*, and ε is a random variable with $E(\varepsilon|X) = 0$. Then

(7) $E[Y|X] = E[\phi(X) + \varepsilon|X] = E(\phi(X)|X] = \phi(X)$.

Therefore, an arbitrary function $\phi(X)$ can be estimated by estimating the conditional mean of *Y* given *X*.

There are a wide variety of ways to estimate $E[Y|X]$ when *X* is one-dimensional. If there are multiple observations of *Y* for each unique value of *X*, then $E[Y|X]$ can be estimated as the average of the observed *Y* for each unique value of *X*. The best method is to inspect the estimated relationship by plotting the fitted values on the observed *X*'s, and connecting the points. The univariate estimated conditional expectation drawn out by the relationship between *Y* and *X* is perceived in the scatterplot of *Y* on *X*, known as scatterplot smoother. Two-popular and effective smoothing techniques are locally weighted regression, developed by Cleveland (1979, 1993), and Cleveland and Grosse (1991), and regression splines (Smith, 1979).

Additive models

An additive model provides the conditional expectation by expressing a sum of low dimensions. The conditional expectation is expressed as a sum of low dimensional functions, instead of a general, multivariate function. The simplest additive model is the sum of univariate functions displayed as follows:

(8) $E[Y|X_1, X_2, \ldots, X_n] = \sum_{i=1}^{n} \psi_i(X_i)$.

This type of model can be estimated with scatterplot smoothers, via the *backfitting algorithm*: given estimates $\hat{\psi}_i$ of (n-1) of the functions, the remaining function $\hat{\psi}_j$ can be estimated by smoothing the *partial residuals*

(9) $\vec{r}_j = \vec{y} - \sum_{i \neq j} \hat{\psi}_i(X_i)$

on X_j.

(10) $\hat{\psi}_j(X_j) = \varsigma(\vec{r}_j | X_j)$,

where $\varsigma(\vec{r}_j | X_j)$ denotes a univariate smoothing operation. Given the estimates of ψ_j, any one of the other estimated transformations can be updated by smoothing the corresponding partial residuals on the predictor.

The generalised linear model

The generalised linear model of Nelder and Wedderburn (1972) extends the classical linear models where the distribution of the response variable is within the exponential family - that is, normal or gamma distributed responses, binary and binomial responses (logit and probit models), and others. One of the most useful innovations of the generalised linear model for the generalised additive models is that it partitions a statistical model into three components: the systematic component, the stochastic component, and the link.

The systematic component isolates the role of independent or predictor variables, expressing their total effects as a linear combination of the given predictors: $\eta = \sum \beta_i X_i$. By specifying the systematic component as an additive function of the predictors, a generalised additive model is estimated by exploiting the estimation of generalised linear models via iteratively re-weighted least-squares. That is, regression of the adjusted response on the predictors in each iteration is replaced with the backfitting algorithm, so that instead of a linear regression, the adjusted response is smoothed for each predictor; the response and weights are then updated for the next iteration, and the backfitting algorithm is applied again. Therefore, estimation consists of two different types of iterative algorithms, collectively called local scoring: the backfitting algorithms nested within each iteration of the iteratively re-weighted least-squares algorithms (Hastie and Tibshirani, 1990).

The stochastic component focuses on the probability distribution of the response, irrespective of the effect of any predictors. For example, if the response was continuous with constant variance, the stochastic component could be specified as $N[\mu, \sigma^2]$; if instead the variance was proportional to μ^2, the stochastic component could be specified as $\Gamma[\mu, \nu]$, where ν is the constant of proportionality in the variance. The variance function is the key to specifying the stochastic component. Without prior information, the best way to specify the variance function is via inspection of the residuals from an ordinary least-squares regression.

The link specifies the relationship between the systematic and stochastic components, expressed as a function of the mean μ: $l(\mu) = \eta = \Sigma\beta_i X_i$. That is, the link function l transforms the mean onto a scale that is linear in the predictors. Note that the classical linear model results when $l(\mu) = \mu$ and the stochastic component is normal; a form of nonlinear regression model results when l is non-linear. Also, note that the link function in a generalised additive model is a given parametric function.

Specifying a generalised additive cost function for econometric analysis

A cost function must be a linearly homogenous and concave function of the input prices, and monotonic in the transformation of output. Expression (2) can be modified to allow for the effect of output and an increasing and quasi-concave composition of input prices as:

(11) $C = u\{\varphi_Y(Y) + \sum \beta\varphi_i^{\gamma}(P_i / u)\}^{1/\gamma}$.

This non-homothetic cost function has a viable elasticity of scale, the form of u determines the range of the elasticity of substitution and the nature of separability. The flexibility in specifying separability can be increased using different forms of u in the price ratios, at the expense of complicating the estimation of the price transformation. However, the transformation of output need only be monotonic in order to satisfy the conditions of a cost function. Expression (11) can be made homothetic by writing $\varphi_Y(Y)$ as a factor outside the brackets, but this makes it more difficult to estimate $\varphi_Y(Y)$. A more convenient form for a homothetic cost function is:

(12) $C = u.\exp\{\beta_0 + \varphi_Y(Y) + \sum \gamma_i \log \varphi_i(P_i / u)\}$, or

$$C = u.\exp\{\beta_0 + \varphi_Y(Y) + \sum \psi_i(P_i / u)\}.$$

The γ_i's must be positive and sum to one. This cost function has variable elasticity of scale, unless $\varphi_Y(Y) = \beta_i logY$.

The model above encompasses a variety of parametric cost functions. Their closest relatives are the strongly separable non-parametric cost function of Chambers (1988, p.114). The CES cost function results by taking $u = P_1$ (or any other input price) and $\varphi_Z(Z) = \beta_i Z$ for all i, (Z refers to the terms (P_i/u). A model similar to a translog results when $\gamma = 1$, when u is the geometric mean the P_i's, and when:

(13) $\varphi_i(Z) = \beta_i\{1 + \log(Z/\alpha_i)\}^2$

for all i.

This function is also similar to the "two-stage" cost function of Pollak and Wales (1987). They note the difficulty of estimating the *CES-CES* cost function, and recommend taking $\gamma = 1$ (the Leontief/*CES*) or $\gamma = 0$ (Cobb-Douglas/*CES*).

Since the elasticity of scale was the main focus of this study, the most important thing was to transform the output, and the transformation of prices was secondary. Thus, the econometric analysis began using a Cobb-Douglas model for the input prices, and a smooth transformation for the corrected output. Transformation of cost by the natural-log was used to help stabilise the variance of this variable. Three transformations of output were chosen, namely locally weighted regression; smooth spline; and natural-log. After that, bivariate interaction and analysis of variance was used to transform input prices. Finally, based on criteria of the classical linear model the cost function was chosen.

3. Estimating economies of scale via a generalised additive model: an application to rice and shrimp production in Thailand.

The previous section focused on the modeling of producer's behaviour and the specification of functions that satisfied the properties usually required in production analysis. This section illustrates the econometric methods applied to data on the production of rice and shrimp in central Thailand. These two industries are considered essential to the Thai agricultural economy in terms of their contribution to export earnings, employment, nutrition, and natural resource use and allocation. However, they are in competition with each other, as they require the same source of natural resources, and produce externalities. Thus, urgent policy reform is required.

Data

The data in this study was collected in a survey of 112 rice firms and 100 shrimp farmers in central Thailand. The survey was conducted in 1998 by the author with assistance from the Office of Agricultural Economics, Ministry of Agriculture and Cooperatives, Thailand. The survey collected data on total yield, different types of inputs used and their prices, and general growing conditions and growing period within the year. Summing dry and wet season data together yielded 224 and 146 data samples for rice and shrimp production, respectively (Table 1).

Table 1 Summary statistics for rice and shrimp data collected from 112 rice and 100 shrimp farms in Central Thailand, 1998.

1.1 Rice Data

Description	Units	Minimum	Median	Mean	Maximum
Total cost (TC_{ri})	$US	388	1280	1530	4020
Output (Y_{ri})	kg	4200	15300	17700	45000
Land price (P_a)	$US/ha	39.1	43	44.8	58.6
Seed price (P_s)	$US/kg	0.13	0.139	0.14	0.148
Fertiliser price (P_f)	$US/kg	0.16	0.165	0.166	0.175
Chemical price (P_c)	$US/litre	8	8.82	9	10.4
Fuel price (P_{fl})	$US/litre	0.275	0.28	0.281	0.296
Soil preparation price (P_p)	$US/hr	2.5	3.06	3.04	3.42
Labour price (P_{lb})	$US/hr	0.504	0.513	0.513	0.522
Harvesting price (P_h)	$US/hr	20.8	30	29.1	33.6
Type	R :116	RS: 50	SR: 58		
Location (LOC)	cha :170	chai: 54			
Time	T-01:112	T-02:112			

Note: R = rice, RS = rice-shrimp, SR = shrimp-rice
cha = Chachoengsao province, chai = Chainat province
T-01 = wet season, T-02 = dry season

1.2 Shrimp Data

Description	Units	Minimum	Median	Mean	Maximum
Total cost (TC_{sh})	$US	1780	7430	7090	15500
Output (Y_{sh})	kg	572	3100	2970	6000
Land price (P_a)	$US/ha	312	391	361	469
Soil preparation price (P_{im})	$US/hr	15.0	17.0	17.1	20.0
Fry price (P_{fy})	$US/head	0.0018	0.0038	0.0036	0.0055
Feed price (P_{fd})	$US/kg	0.9300	0.9450	0.9450	0.9640
Lime price (P_{lm})	$US/kg	0.0458	0.0704	0.0717	1.0000
Labour price (P_{lb})	$US/day	3.87	4.070	4.080	4.220
Fuel price (P_{fl})	$US/litre	0.284	0.304	0.308	0.390
Saline water price (P_{sa})	$US/litre	0.0021	0.0048	0.0044	0.0072
Chemical price (P_c)	$US/litre	21.00	33.00	33.00	42.00
Time	T-01:72	T-02:74			
Location (LOC)	A1:111	A2: 35			

Note: T-01 = wet season, T-02 = dry season
A1 = Chachoengsao province, A2 = Chainat province

Model Construction

The generalised additive models and accompanying S-plus library, were used to estimate cost functions of rice and shrimp production. The procedure was: firstly to search for transformation of predictors and systematic component. Then, the stochastic component, specified as $N[\mu,\sigma^2]$, was graphically investigated. Finally, the link between the generalised additive models and the linear model gave the parametric coefficients of estimation from the non-parametric regression.

The estimate began with the exploration of the functional form which satisfied the general properties of the cost function. Without any restrictions, the cost function was estimated using a Cobb-Douglas model for the input prices, and a smooth transformation for the yield. Three models were specified as a function of the generalised additive models as:

(Eq. 1) gam(log(TC) ~ s(Y, df=)+log(P_1)+log(P_2) + … +log(P_n)+Time+Type+LOC+ε,

(Eq. 2) gam(log(TC) ~ lo(Y,df=2)+log(P_1)+log(P_2) + … + log(P_n)+Time+Type+LOC+ε, and

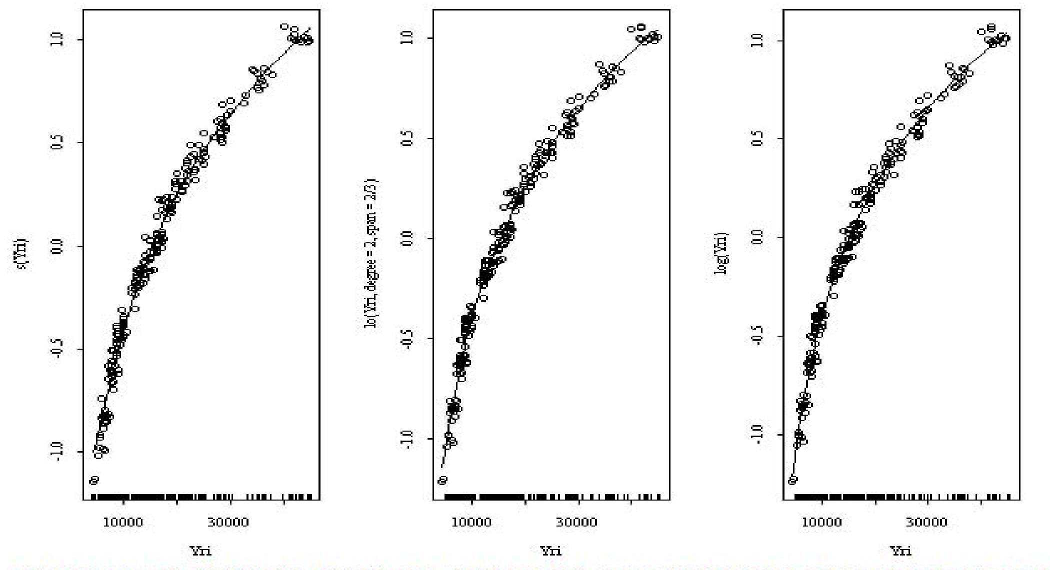
(Eq. 3) gam(log(TC) ~ log(Y)+log(P_1)+log(P_2) + … + log(P_n)+Time+Type+LOC+ε.

Where TC was the total cost of production, coming from the sum of the factor inputs multiplied by their prices, Y was the yield, P_i were input prices, Time, Type and LOC were factor variables, and ε was an error term .

The notation *log* is natural-log, it is used to transform the response variable TC to stabilise its variance. The s(.) function indicates that yield will be smoothed using a smooth spline as the smoother with the default amount of smoothing. The argument df = determines how much smoothing is done. Conversely, the lo(.) function represents a local regression model which provides much greater flexibility as the model is fitted as a single smooth function. The argument degree = determines the order of the local smooth of transformation, for example, degree=2 specifies that the regression is to be locally quadratic.

Rice data

The results of the systematic component of yield transformation of the three models for rice production data were shown graphically (Figure 1).



(a) (b) (c)

Figure 1 Three different estimates of the transformation of yield from rice data, (a) smooth spline (Eq. 1); (b) local weighted regression (Eq. 2); and (c) natural-log transformation (Eq. 3).

The plots showed that the three fitted functions looked alike and monotonic. Thus for this study the three transformations were equivalent.

The price predictors for each model (Eq. 1, 2 and 3) were equivalent and the plots from each function transformed by logarithms were presented in Figure 5. The plots showed that the smooth curves drawn for most functions were fairly linear and increasing. This means that most logarithmic transformed predictors had a strong relationship with the response.

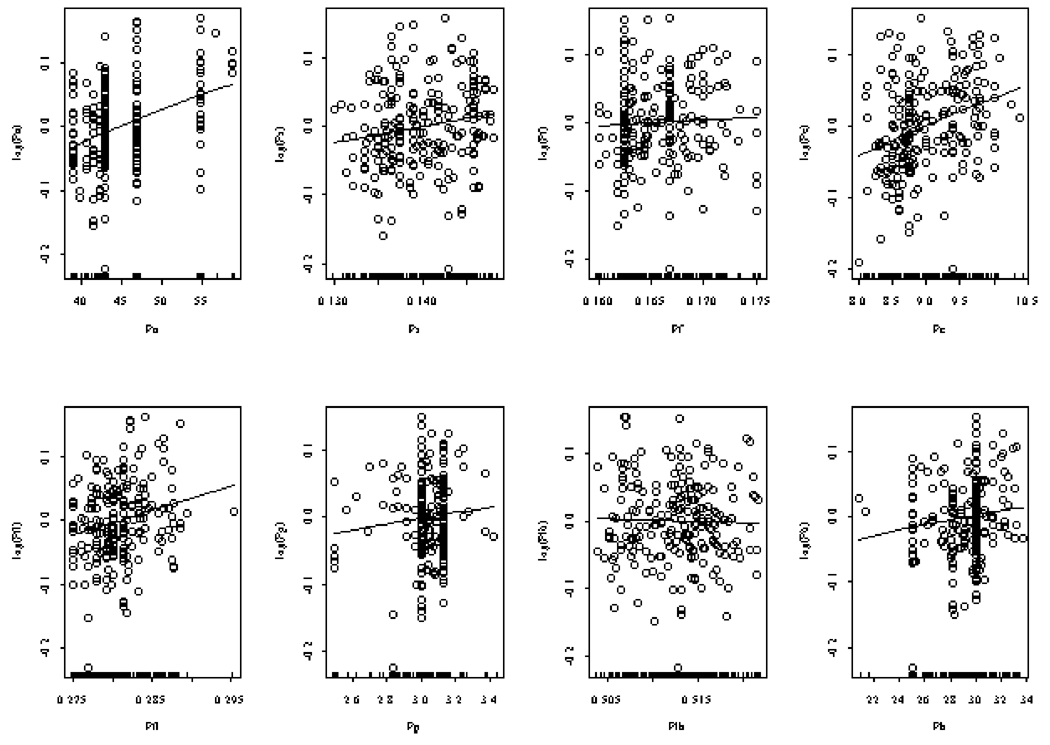


Figure 2 The generalised additive model fit for response log(TC) with eight predictors log(P_i) from rice data.

The stochastic component of the three models was visually examined by graphical plots, using the function of plot.glm from the S+ library. The results from three model were not different, and an example from the Eq.3 model (Cobb-Douglas model) was presented in Figure 3.

Figure 3 had four plots. The first on the top left side was a plot of deviance residuals versus the fitted values. The second on the top right was a plot of the square root of the absolute deviance residuals versus the linear predictor values. The two plots visually showed no obvious pattern, although some observations appear to be outliers. The plot on the lower left side was a plot of the response versus the fitted value. This plot strongly showed that regression line appears to model the trend of the data well. The last plot was a normal quantile plot of the Pearson residuals. The normal plot showed that the residuals were normally distributed.

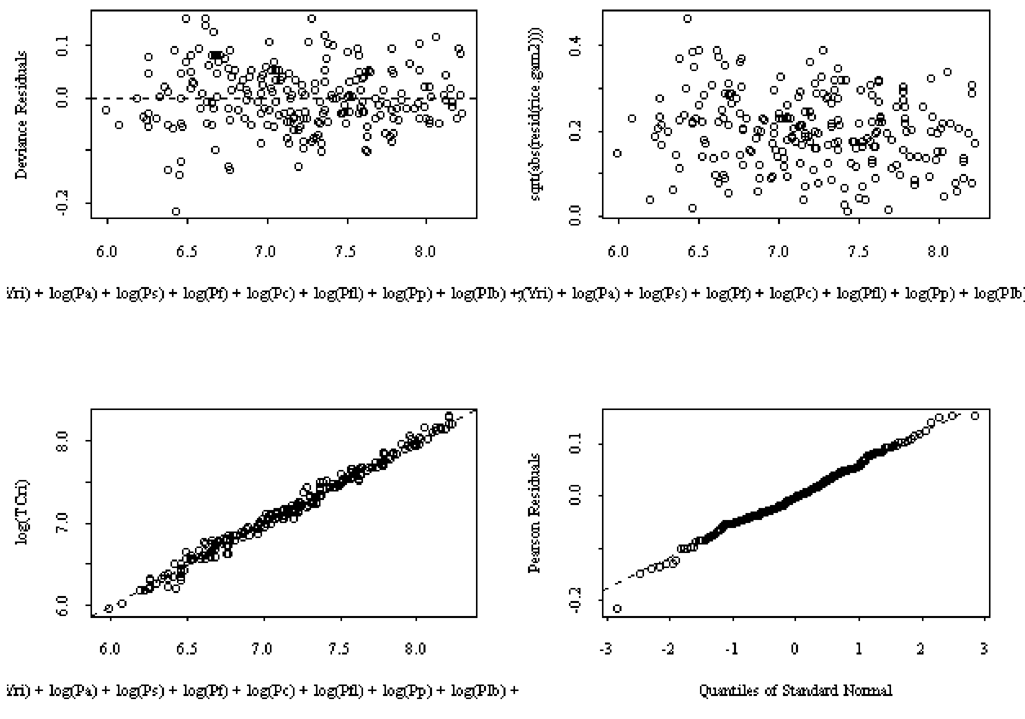


Figure 3 Residual plots of the Cobb-Douglas model of rice data.

The link function between the generalised additive model and the linear model estimated the coefficients to transform the non-parametric regression to a parametric one. This was achieved by executing the summary command to be a linear model. The results from the log-transformed model were summarised in Table 2.

Table 2 Parametric estimates of the non-parametric functional form of rice data with response $\log(TC_{ri})$ and predictors $\log(Y_{ri})$, $\log(P_i)$, and some factors.

Terms	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.99	0.90	-2.21	0.03
$\log(Y_{ri})$	0.95	0.01	93.31	0.00
$\log(P_a)$	0.25	0.07	3.62	0.00
$\log(P_s)$	0.33	0.16	2.11	0.04
$\log(P_f)$	0.15	0.21	0.70	0.48
$\log(P_c)$	0.37	0.12	2.96	0.00
$\log(P_{fl})$	1.10	0.38	2.90	0.00
$\log(P_p)$	0.13	0.12	1.07	0.29
$\log(P_{lb})$	-0.19	0.61	-0.31	0.76
$\log(P_h)$	0.11	0.07	1.51	0.13
Type1	0.04	0.01	4.53	0.00
Type2	-0.01	0.00	-3.31	0.00
LOC	0.00	0.01	-0.23	0.82
Time	0.01	0.01	1.25	0.21

Residual standard error: 0.0624 on 210 degrees of freedom
Multiple R-Squared: 0.987
F-statistic: 1250 on 13 and 210 degrees of freedom, the p-value is 0

Note: TC_{ri} = total cost, Y_{ri} = output, P_a = land price, P_s = seed price, P_f = fertiliser price, P_c = chemical price, P_{fl} = fuel price, P_p = price of soil preparation, P_h = price of harvesting, P_{lb} = price of general labour, Type = dummy variable for type of technology (3 types), LOC = location (2 provinces), Time = seasons (2, dry and wet).

This model had a goodness of fit (R-squared) equal to 98.7%, the highest of the three models. The t-values indicated that the estimated coefficients for the natural-log transformation of yield and most of the input prices were significantly different from zero. The only exception was the coefficient for $\log(P_{lb})$. Thus, the Cobb-Douglas model was appropriate for the econometric analysis for the cost function of rice data.

Bivariate Interaction

The analysis of the cost function was continued by searching for bivariate interactions between the input prices. The Transcendental Logarithmic functional form (translog, for short), originally proposed by Christensen, Jorgenson and Lau (1971) was used for this purpose and for constructing the model. After regressing log(TC) on the linear terms of log(Y), log(P), some factors (Type, LOC and Time) and the bivariate, multiplicative interactions of $\log(P_i)$ and $\log(P_j)$, it was determined all of the estimated coefficients of interaction terms were not significantly different from zero (not present), except $\log(P_a):\log(P_s)$. Thus, it can be concluded that the translog model is not appropriate for rice data.

Model Selection for deriving information

As the cost function requires homogeneity in input prices to satisfy expression (12), the Cobb-Douglas model (Table 2) was imposed by P_{lb}, which was the least important variable in the model. The selected model for deriving information was displayed in Table 3.

Table 3 Parametric double-log estimates of cost function of rice data, with response $\log(TC_{ri}/P_{lb})$ and homogeneity imposed.

Terms	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	-2.883	0.70	-4.14	0.00
$\log(Y_{ri})$	0.952	0.01	93.68	0.00
$\log(P_a/P_{lb})$	0.237	0.07	3.51	0.00
$\log(P_s/P_{lb})$	0.307	0.16	1.97	0.05
$\log(P_f/P_{lb})$	0.065	0.20	0.32	0.75
$\log(P_c/P_{lb})$	0.328	0.12	2.69	0.01
$\log(P_{fl}/P_{lb})$	0.796	0.33	2.43	0.02
$\log(P_p/P_{lb})$	0.080	0.12	0.70	0.49
$\log(P_h/P_{lb})$	0.101	0.07	1.45	0.15
Type1	0.037	0.01	4.36	0.00
Type2	-0.014	0.00	-3.27	0.00
LOC	-0.001	0.01	-0.11	0.91
Time	0.015	0.01	1.88	0.06

Residual standard error: 0.0626 on 211 degrees of freedom
Multiple R-Squared: 0.987
F-statistic: 1340 on 12 and 211 degrees of freedom, the p-value is 0

This model had a goodness of fit of 98.7%, the same as the model without imposed homogeneity in Table 2, the F-statistic (= 1340) indicated the model was statistically significant and the estimated coefficients were significantly different from zero in most cases. The exceptions were the coefficients for $\log(P_f/P_{lb})$, $\log(P_p/P_{lb})$, $\log(P_h/P_{lb})$, and LOC.

In order for the model to satisfy the properties of a linear regression model, residuals must be normally distributed, with constant variance and independence from the fitted values. These properties were examined by visual inspection of the plots shown in Figure 4.

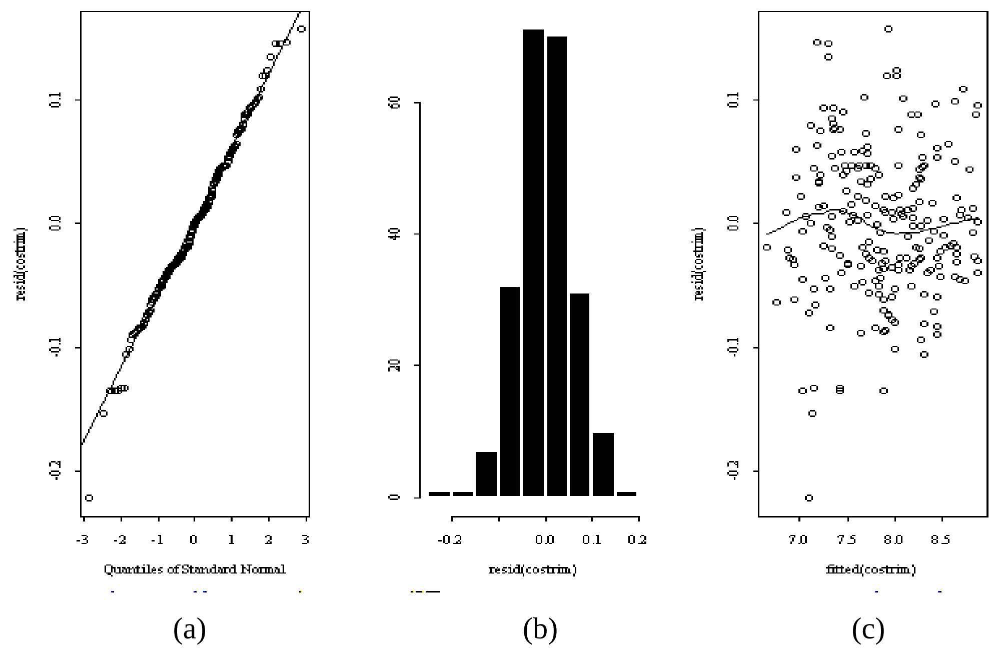
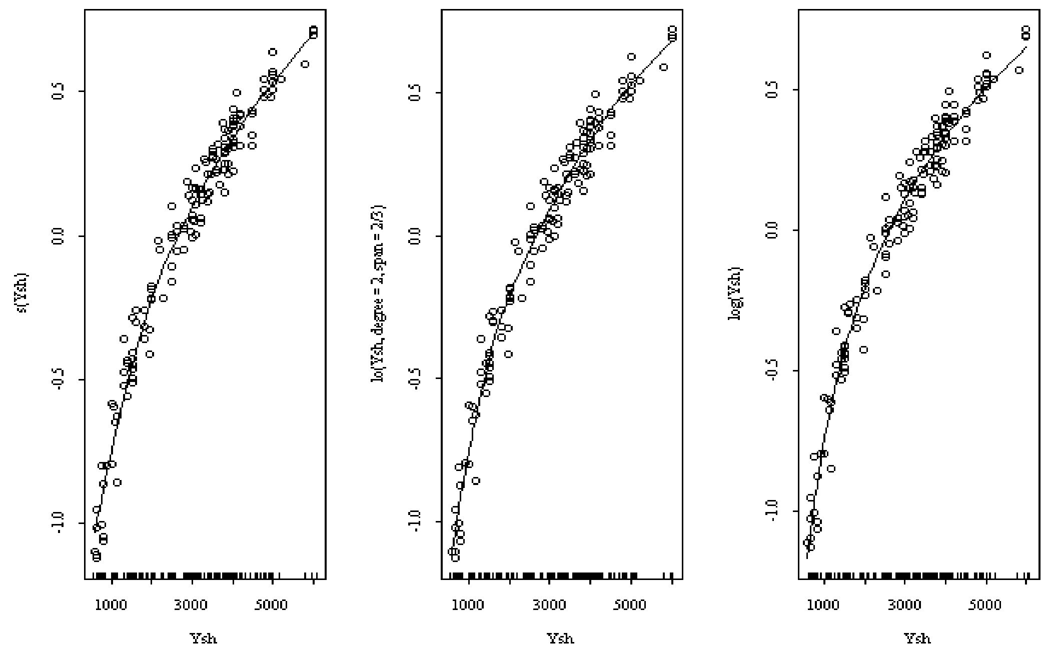


Figure 4 Plots of residuals for the Cobb-Douglas cost function estimates on rice data: (a) the normal quantile-quantile plot; (b) the histogram plot; and (c) the scatter plot of residuals against fitted values, with a smooth curve added.

The quantile plot showed that residuals from this model closely follow a normal distribution. Also, the histogram plot closely displays a bell shape, with zero mean, with few outliers. The scatter plot indicates that the residual variance is fairly constant. A smooth curve is added to confirm that there is only a weak relationship between the residuals and the fitted values of cost. Thus, the data meet the assumptions of the classical linear regression model.

Shrimp Data

The procedures for estimating a cost function of shrimp data are the same as those previously described for the rice data. The results of the systematic component of yield transformation of the three models (Eq. 1, 2, and 3) were visually displayed in Figure 5.



(a) (b) (c)

Figure 5 Three different estimates of the transformations of yield from shrimp data, (a) smooth spline (Eq. 1); (b) local weighted regression (Eq. 2); and (c) = natural-log transformation (Eq. 3).

The plots showed that the three fitted functions from three different transformations (Eq. 1, 2, and 3) looked alike and monotonic. Thus, for this study they were considered equivalent.

For the price predictors, each function used natural-log transformation thus the plots were the same (Figure 6).

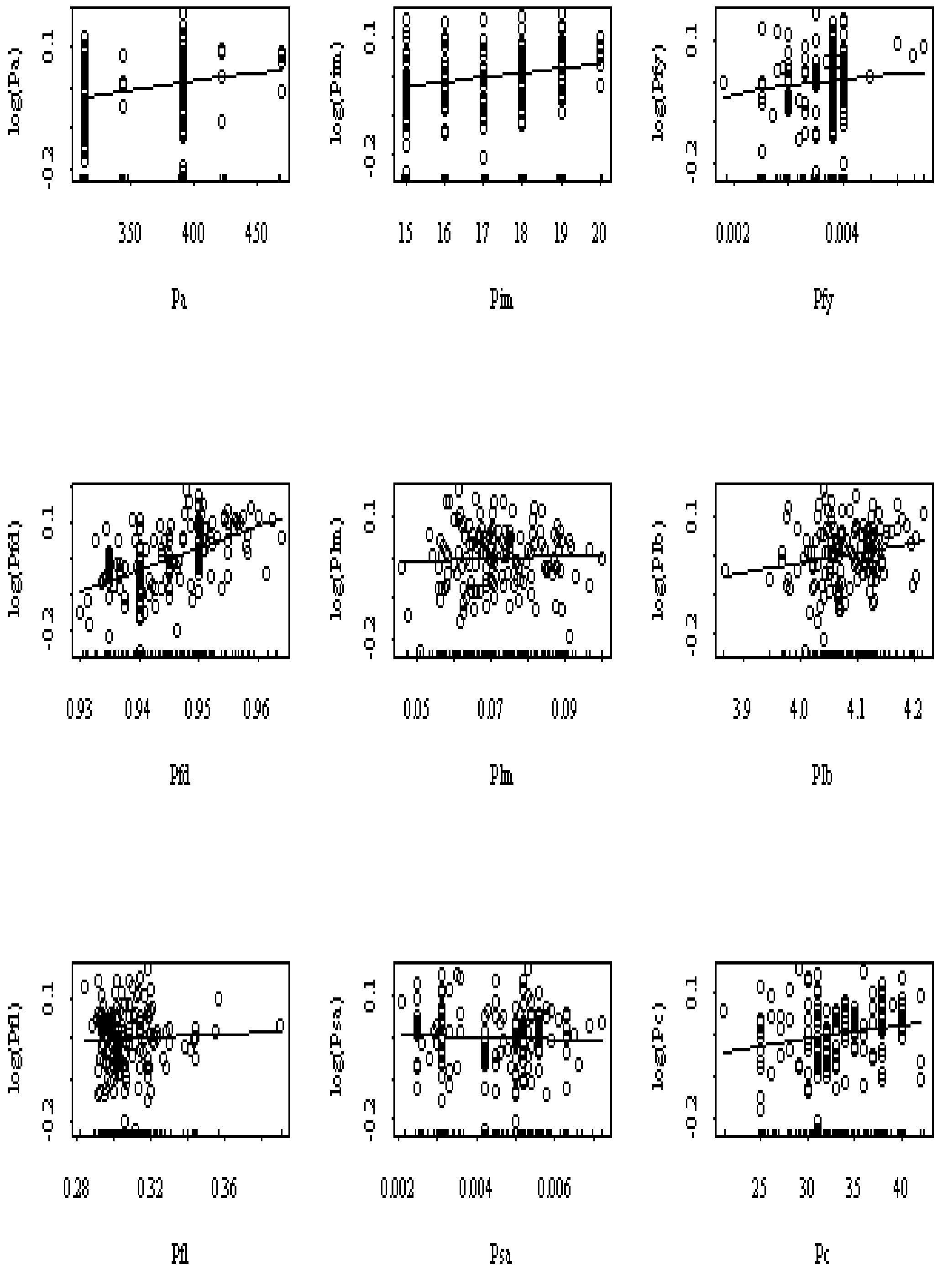


Figure 6 The generalised additive model fit for response log(TC) with nine predictors log(P_i) from shrimp data.

The plots showed that the smooth curves drawn of most functions were fairly linear and increasing. This implied that most logarithmic transformed predictors had a strong relationship with the response.

As the results from the three models were the same, the stochastic component of one of the three models was visually examined by graphical plots. Using the Cobb-Douglas model (Eq. 3) as an example, the residuals and the fitted values are plotted in Figure 7.

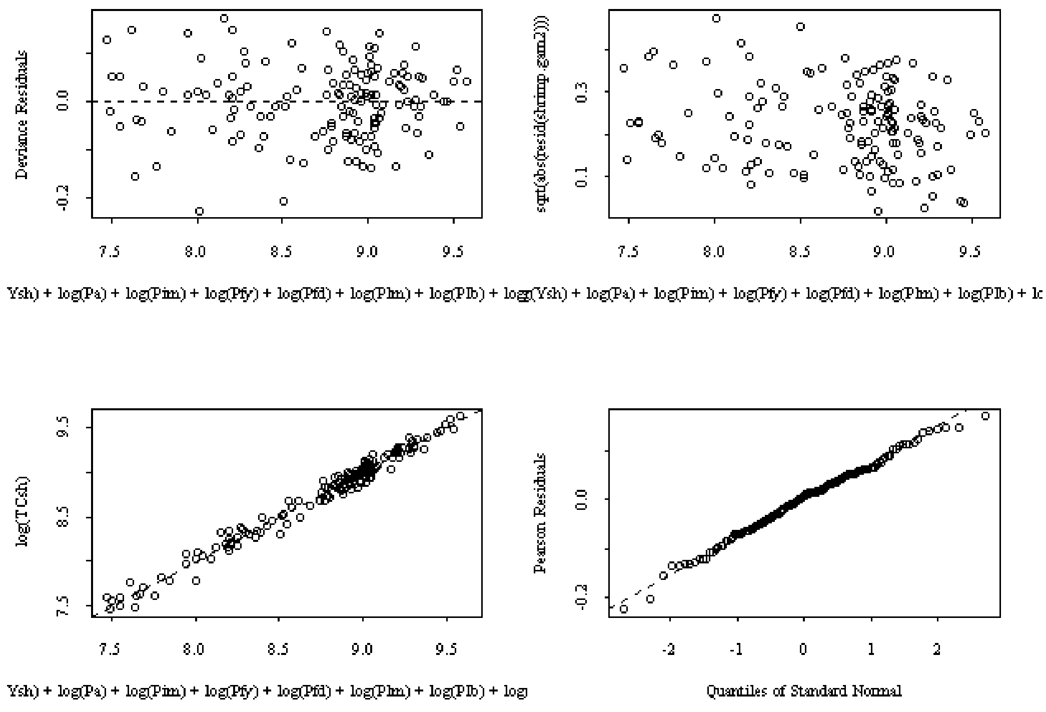


Figure 7 Residual plots of the Cobb-Douglas model of shrimp data.

In Figure 7, the two plots of deviance residuals did not show an obvious pattern. Moreover, a plot of the response versus the fitted value showed that the regression line appears to model the trend of the data well. Also, the last plot was normal and gives no reason to doubt that the residuals are normally distributed.

The link function transformed the results from the generalised additive model to produce a linear model and provided statistical tools for model and coefficient testing for the linear model. The results from the Cobb-Douglas model were summarised in Table 4.

Table 4 Parametric estimates of the non-parametric functional form of shrimp data with response $\log(TC_{sh})$ and predictors $\log(Y_{sh})$, $\log(P_i)$, and other factors

Terms	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	0.45	0.98	0.46	0.65
$\log(Y_{sh})$	0.77	0.02	40.49	0.00
$\log(P_a)$	0.16	0.07	2.38	0.02
$\log(P_{im})$	0.18	0.09	2.07	0.04
$\log(P_{fy})$	0.05	0.05	1.03	0.30
$\log(P_{fd})$	5.67	1.44	3.94	0.00
$\log(P_{lm})$	0.02	0.05	0.50	0.62
$\log(P_{lb})$	1.02	0.57	1.78	0.08
$\log(P_{fl})$	0.08	0.15	0.55	0.59
$\log(P_{sa})$	-0.01	0.04	-0.28	0.78
$\log(P_c)$	0.10	0.05	1.98	0.05
LOC	0.04	0.01	4.11	0.00
Time	0.00	0.01	-0.08	0.94

Residual standard error: 0.0775 on 133 degrees of freedom
Multiple R-Squared: 0.979
F-statistic: 518 on 12 and 133 degrees of freedom, the p-value is 0

Note: TC_{sh} = total cost, Y_{sh} = output, P_a = land price, P_{im} = soil improvement price, P_{fy} = fry price, P_{fd} = feed price, P_{lm} = lime price, P_{lb} = price of general labour, P_{fl} = price of fuel, P_c = price of chemical, P_{sa} = price of saline water, LOC = location (2 provinces), Time = seasons (2, dry and wet).

This model had a goodness of fit (R-squared) equal to 97.9%, the highest of the three models. The t-values indicated that the individual estimated coefficients of the logarithmic transformations of yield and four of the input prices were significantly different from zero (Table 4). The weakness is in the estimated coefficient of $\log(P_{sa})$ which the sign was negative. Thus, the Cobb-Douglas was specified as the appropriate model for a cost function of the shrimp data.

Bivariate Interaction

The Transcendental Logarithmic functional was used to search for bivariate interactions among the input prices. Regressing $\log(TC_{sh})$ on the linear terms of $\log(Y_{sh})$, $\log(P_i)$, some factors (LOC and Time) and the bivariate, multiplicative interactions of $\log(P_i)$ and $\log(P_j)$, showed that estimated coefficients of interaction terms were not significantly different from zero. Thus, the translog model was not appropriate for shrimp data, as it did not meet the criteria of a linear model.

Model selection for deriving information

The Cobb-Douglas cost model (Table 4) was imposed by P_{sa} in order to meet the requirement of homogeneity in input prices underlining the properties of cost function and a model in expression (12). The selected model for deriving information is presented in Table 5.

Table 5 Parametric double-log estimates of cost function of shrimp data, with response $\log(TC_{sh}/P_{sa})$ and homogeneity imposed.

Terms	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	0.073	1.08	0.07	0.95
$\log(Y_{sh})$	0.795	0.02	41.50	0.00
$\log(P_a/P_{sa})$	0.215	0.07	3.08	0.00
$\log(P_{im}/P_{sa})$	0.253	0.09	2.80	0.01
$\log(P_{fy}/P_{sa})$	0.030	0.05	0.55	0.58
$\log(P_{fd}/P_{sa})$	0.087	0.62	0.14	0.89
$\log(P_{lm}/P_{sa})$	0.029	0.05	0.60	0.55
$\log(P_{lb}/P_{sa})$	0.347	0.58	0.60	0.55
$\log(P_{fl}/P_{sa})$	-0.084	0.16	-0.54	0.59
$\log(P_c/P_{sa})$	0.091	0.05	1.68	0.10
LOC	0.051	0.01	5.16	0.00
Time	0.015	0.01	1.33	0.19

Residual standard error: 0.0817 on 134 degrees of freedom
Multiple R-Squared: 0.974
F-statistic: 461 on 11 and 134 degrees of freedom, the p-value is 0

This model had a goodness of fit of 97.4%, and the F-statistic (= 461) indicated that the model was statistically significant. The estimated coefficients for $\log(Y_{sh})$, $\log(P_a/P_{sa})$, $\log(P_{im}/P_{sa})$ and LOC were significantly different from zero, while the others were not.

In order for the model to satisfy the properties of a linear regression, residuals must be normally distributed, with constant variance and independent from the fitted values. These properties are examined by visual inspection of the plots displayed in Figure 8.

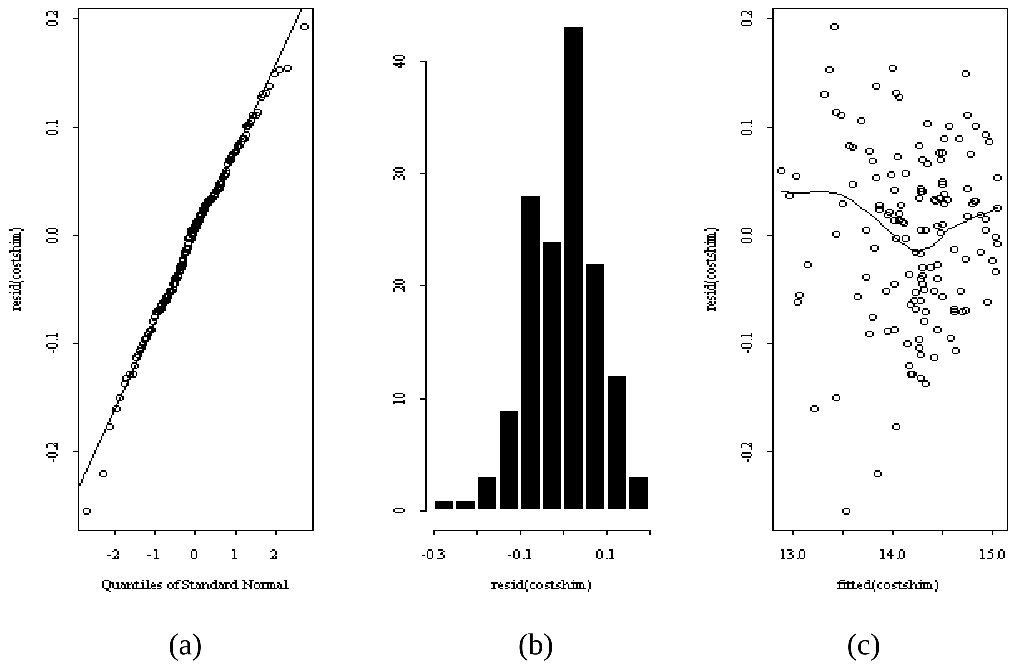


Figure 8 Plots of residuals for the Cobb-Douglas cost function estimates on shrimp data: (a) the normal quantile-quantile plot; (b) the histogram plot; and (c) the scatter plot of residuals against fitted values, with a smooth curve added.

The quantile plots shows that residuals from this model closely follow a normal distribution. However, the histogram plot does not conform to a bell shape, but it is not different, with zero mean. The scatter plot indicates that the residual variance is constant. A smooth curve is added to confirm that there is only a weak relationship between the residuals and the fitted values of cost. Therefore, the data was considered to have met the assumptions of the classical linear regression model.

Estimating economies of scale

The economies of scale are theoretically measured by examining the effects on the cost structure of an increase in the production level. Differentiating the cost function with respect to the production level yields the cost flexibility ($\theta_{cy} \equiv \dfrac{\partial \ln C}{\partial \ln Y}$). The duality principles of microeconomic theory implies that the effect of a production increase on the cost level is closely tied to the scale properties of the production function. When a general increase in the production level causes a less than proportional increases in cost, there must be increasing returns to scale. On the other hand, if the increase in the production level causes a more than proportional increase in costs, there must be decreasing returns to scale. Defining the economies of scale as Ω_y, and following Diewert (1982) the scale elasticity of production may be written as: $\Omega_y = (\theta_{cy})^{-1}$. Decreasing returns to scale means that $\Omega_y < 1$ ($\theta_{cy} > 1$), constant returns implies $\Omega_y = 1$ ($\theta_{cy} = 1$), while increasing returns has the effect that $\Omega_y > 1$ ($\theta_{cy} < 1$).

The results of econometric analysis in Table 3 and 5 are used for estimating economies of scale from rice and shrimp production. The point estimates suggest that the economies of scale of rice production is close to 1, and shrimp production is less than 1. This means that constant returns to scale are exhibited in rice production, but shrimp production exhibits increasing returns to scale. This implies that for an increase in all inputs will result in a more than proportionate increase in output for shrimp production. Thus, it will be expected that new firms will be induced to enter the market and planted areas for shrimp will be expanded, and existing firms will increase in size to take advantage of increasing returns to scale.

4. Conclusion

Generalised additive models provide a flexible and comprehensive approach to empirical production analysis. One of the best uses of these models is in exploratory data analysis, especially to specify functions consistent with the properties of the cost function. This problem is simplified by decomposing the model specification problem into two stages. The first stage of model construction is to compose the transformations to satisfy the desired economic properties. This leads to determining the general form of the systematic component and the link. The second stage is purely technical, focusing on how to best approximate the transformations.

When applying the generalised additive models to the rice and shrimp data from central Thailand, the methods took two different directions of empirical analysis. The first was to develop richer compositions of functions and to explore their economic properties. The second was to link the non-parametric results with the parametric coefficients for local approximation to derive further information.

The results from a comparative economic analysis of shrimp and rice production are very important for policy makers in Thailand. It was found that rice production is characterised by constant returns to scale, and shrimp production by increasing returns to scale. On this basis it was concluded that shrimp production will continue to expand in the fresh-water areas, displacing rice production and exacerbating environmental problems. Shrimp production in Thailand has historically been undertaken in the saline and brackish waters of coastal mangroves. However, in recent years increasing demand and prices for shrimp and falling productivity of mangrove areas have motivated an expansion of shrimp production into the fresh-water margins of river estuaries that were previously used for rice cultivation. This has resulted in nutrient pollution of waterways and salinisation of soils. Further investigation will examine trade-offs between the returns from shrimp production and the costs of environmental degradation. This will have implications for optimal regulatory policies.

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