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Thesis Title: *"A NON-NEUTRAL, NON-MONOTONIC INEFFICIENCY EFFECT MODEL APPLIED TO GREEK BANKING SECTOR"*

Student: Vrachioli Maria

Supervisor: Professor Karagiannis Giannis
Department of Economics
University of Macedonia

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Abstract

The objective of this work is to propose and estimate a non-neutral, non-monotonic inefficiency effect model which combines Huang and Liu (1994) non neutral production frontier model with Wang (2002) non monotonic efficiency effect model and in addition incorporates the environmental variables in the deterministic kernel of the frontier in the way suggested by Coelli, Perelman and Romano (1999). This generalized stochastic frontier model contains also a special case, the monotonic inefficiency effect model of Battese and Coelli (1995) and Good et all (1993) model. In the empirical model, we use detailed input and output data to estimate an input distance function using stochastic frontier approach (SFA). The data set consists of yearly observations for 32 banks over the period 1998-2008.

Keywords: Non-neutral, Non-monotonic, Technical Efficiency, SFA, Banking Sector

CHAPTER ONE

Introduction

1.1 Stochastic Frontier Analysis

Stochastic frontier (SF) analysis has been widely used to study technical inefficiency in various settings since its production by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The main approach has two components: a stochastic frontier serving as a benchmark against which firm inefficiency is measured, and a one-sided error term which captures technical inefficiency. In early applications the one-sided error term was assumed to be identically and independently distributed across firms, but more recent studies have allowed its contribution to be heterogeneous and depend on various firm characteristics (see Battese and Coelli, 1995; Caudill et al., 1995; Wang, 2002).

Kumbhakar and Lovell (2000), in Chapter 7, discuss in detail how exogenous or environmental factors influence the one-sided error term. As we mentioned before (and according to Kumbhakar and Lovell) the analysis of efficiency has, or at least should have, two components. The first is the estimation of a stochastic frontier that serves as a benchmark against which to estimate technical efficiency. The objective of the first component is to estimate the efficiency with which for example producers allocate their inputs and their outputs, under some maintained hypothesis concerning behavioral objectives. The second component is equally important, although much less frequently explored. It concerns the incorporation of exogenous variables which are neither inputs to the production process nor outputs of it, but have an influence on producer performance. The objective of the second component is to associate variation in producer performance with variation in the exogenous variables characterizing the environment in which production occurs.

1.2 Problem Setting

Since the pioneered works of Aigner et al. (1977), stochastic frontier analysis has been widely used in efficiency studies to describe and estimate models of the frontier. The standard linear parametric SF model has the form $y_{it} = x_{it}\beta + v_{it} + u_{it}$, where v_{it} is the two-sided noise component and u_{it} represents the non-negative inefficiency component. Moreover, v_{it} and u_{it} are assumed to be independent to each other. In order to estimate the SF model by the maximum likelihood (ML) approach, one often assumes that v_{it} follows a normal distribution and u_{it} may have an exponential, a half normal or a truncated distribution. The truncated distribution is the most common distribution in empirical studies.

Extensions of the standard SF model are mostly concentrated on modifications of the distribution of the one-sided error term u_{it}, especially the consideration of possible effects of some exogenous variables on a firm's efficiency. Such extensions have to do with either one or both of the mean and the variance of the truncated-normal distribution to depend on exogenous or environmental variables. So, on the one hand there is the group of scientists that parameterize the mean of the truncated distribution as a way to study the exogenous influence on efficiency (Huang and Liu, 1994; Battese and Coelli, 1995 etc), and on the other hand there are those that seek to address the non-monotonic impact of exogenous variables by parameterizing the variance of the truncated distribution (Caudill et al., 1995 and Hadri, 1999).

Moreover, there is another way to distinguish the models in which we have parameterization of the mean with constant variance. In the case that there are interactions between environmental variables and input variables in the mean of the truncated distribution, we talk about non-neutral stochastic frontier model (Huang-Liu, 1994). In the other case, where only the set of the environmental variables influence the mean of the truncated distribution, we talk about neutral stochastic frontier model (Battese and Coelli, 1995).

The major objective of this work is to present and estimate a non-neutral, non-monotonic inefficiency effect model applied to Greek banking sector during the period 1998-2008 for 32 Greek banks. This work mainly considers six particular parametric models for the technical inefficiency effects in the stochastic frontier function. In addition, one functional form for the stochastic frontier will be used, the translogarithmic cost function.

The majority of economists would be familiar with the use of cost function as alternative method of describing a production technology. The additional alternative of input-distance function has also been available since its development by Shephard (1953, 1970). The most of the recent distance function studies have been motivated by a desire to calculate technical efficiencies. The principle advantage of the distance function representation is that allows the possibility of specifying a multiple-input, multiple-output technology when price information is not available.

1.3 Thesis Structure

This study is divided into 5 chapters. The second presents a review of the standard stochastic frontier model and then extend to present the six different stochastic frontier models with a brief review of the literature. The third chapter summarizes the data used in this work, the functional forms of the frontiers and the variables involved in the empirical study. The empirical results are presented and discussed in chapter 4 and some concluding remarks are drawn in chapter 5.

CHAPTER TWO

General Specification of Stochastic Frontier Models

2.1 Introduction

Stochastic frontier analysis incorporates the notion of an efficient frontier, with the frontier being determined parametrically. The parametric specification allows the inclusion of a stochastic error term. The error term in SFA consists of two parts: traditional random noise with a zero mean and a non-negative inefficiency measure with nonzero mean that captures the distance from the frontier.

The six stochastic frontier models which are considered in this work are those proposed by Good et al. (1993), Battese and Coelli (1995), Coelli et al. (1999), Huang and Liu (1994), Wang (2002) and the last one is the one that this work proposes. All six models are discussed assuming that data are available for a sample of N firms over T time periods. The panel data is not required to be balanced. [1]

The general stochastic frontier cost function which is considered is defined by

$$\ln \mathrm{y}_{\mathrm{it}} = x_{it} * b + u_{it} + v_{it}$$

where y_{it} denotes the output for the i-th firm and the t-th time period

x_{it} represents a (1XK) vector whose values are function of inputs and other explanatory (environmental) variables for the i-th firm in the t-th period

b is a (KX1) vector of unknown parameters to be estimated

v_{it} is assumed to be independently and identically distributed random errors which have normal distribution with mean zero and constant variance σ_v^2, $v_{it} \sim N(0,\sigma_v^2)$

u_{it} is assumed to be non-negative unobservable random variables associated with the technical inefficiency. The model is usually implemented by assuming u_{it} is distributed as $u_{it} \sim N(\mu_{it},\sigma_u^2)$ with various specifications (discussed below) used to model μ_{it} : $\mu_{it} = \sum_{i=1}^{n} \delta_i z_{it} + \sum_{j=1}^{m} \gamma_j \ln x_{jt} + w_{it}$

$$\sigma_u^2 : \sigma_u^2 = \exp(\sum_{i=1}^{n} \alpha_i z_i t + \sum_{j=1}^{m} \beta_j \ln x_{jt})$$

where $w_{it} \sim N(0,\sigma_w^2)$

The six different frontier models which are considered have different specifications for the u_{it}, which is called technical inefficiency effects term, and different specifications of the cost function $f(x_{it}, z_{it})$. [see table 1]

2.2 Model 1: Technical Inefficiency Effect Model

A stochastic frontier cost function is defined for panel data on firms, in which the non-negative technical inefficiency effects are assumed to be a function of firm-specific variables and time. The inefficiency effects are assumed to be independently distributed as transactions of normal distributions with constant variance, but with means that are linear functions of environmental variables.

The first model is that proposed by Battese and Coelli (1995), in which technical inefficiency effects have the below form

$$u_{it} = \alpha_o + \sum_{i=1}^{n} \alpha_i z_{it} + w_{it}$$

where z_{it} is a (1XM) vector of environmental variables associated with the technical inefficiency effects

α_i is an (MX1) vector of unknown parameters to be estimated

w_{it} is unobservable random variable, which is assumed to be independently distributed and follows normal distribution with zero mean and constant variance in a way u_{it} be non-negative [2]

So, the means may be different for different firms and different periods but the variances are assumed to be the same. Finally, as we can see the environmental variables directly influence the degree of technical inefficiency.

2.3 Model 2: Environmental Variables in the Cost Function

This model is that proposed by Good, D., Nadiri, I., Roller, L.H. and Sickles, R. (1993) and according to them, the set of the environmental variables influences the position of the technology and hence these factors should be included directly into the cost function as regressors. In this model each firm faces a different frontier and the general form of the stochastic frontier will be given by

$$\ln y_{it} = \ln x_{it} * \beta + d_o + \sum_{i=1}^{n} d_i z_{it} + w_{it} + v_{it}$$
$$v_{it} \sim N(0, \sigma_v^2)$$
$$w_{it} \sim N(0, \sigma_w^2)$$

where v_{it} and w_{it} are assumed to be identically and independently (i.i.d.) with zero mean and constant variance. Moreover, they are uncorrelated to each other.

2.4 Model 3: Combination of Model 1 & Model 2

One of the main assumptions that underlies frontier analysis and technical efficiency measurement is that all the firms in a sector share the same production technology and face the same environmental conditions. However, this is not generally the case. Two conflicting views exist in the efficient measurement literature regarding the way that the issue of environment should be addressed.

The first approach assumes that the environmental factors influence the technology and for this reason these factors should be included directly into the cost function as regressors (Good et al. 1993). The second approach assumes the environmental factors influence the degree of technical inefficiency and hence that these factors should be directly included in the inefficiency term (Battese and Coelli 1995).

Coelli, T., Perelman. S. and Romano, E. (1999) in order to account the influence of the environmental variables in the stochastic frontier created a pioneered model which combines the two models above. The general form of the combined stochastic model is given by

$$\ln y_{it} = \ln x_{it} * \beta + d_o + \sum_{i=1}^{n} d_i z_{it} + u_{it} + v_{it}$$
$$v_{it} \sim N(0, \sigma_v^2)$$
$$u_{it} \sim N^+(m_{it,} \sigma_u^2)$$

where $u_{it} = \alpha_o + \sum_{i=1}^{n} \alpha_i z_{it} + w_{it}$

with w_{it} i.i.d. with zero mean and constant variance

2.5 Model 4: Non-neutral Stochastic Frontier Model

The model combines a stochastic frontier regression and a truncated regression to estimate the frontier with non-neutral shifting of the average cost function. The truncated regression identifies the sources of efficiency. In the fourth model that was proposed by Huang and Liu (1994), there are interactions between environmental variables and the logarithmic form of the input variables in the stochastic frontier. This model can be defined by:

$$u_{it} = a_0 + \sum_{i=1}^{n} \alpha_i z_{it} + \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} z_{it} \ln x_{jt} + w_{it}$$

where α_{ij} is a vector of unknown parameters

The interaction between a firm's characteristics and inputs has as a result the non-neutrality in efficiency. Model 4 is called non-neutral stochastic frontier because the inefficiency effects are functions of the values of the input variables, which results in the stochastic frontier not being a neutral shift of the intercept for the different firms and time periods.

2.6 Model 5: Non-monotonic Efficiency Effects Model

Wang, who presented this model in his paper in 2002, supported that this model provides flexible parameterizations of the exogenous influences on inefficiency. The main contribution of this model is in demonstrating the non-monotonic efficiency effects, which can be very important and useful in understanding the relationships between the inefficiency and its exogenous determinants.

The general presentation of this model is given by

$$\begin{aligned} \ln y_{it} &= \ln x_{it} * \beta + v_{it} + u_{it} \\ v_{it} &\sim N(0, \sigma_v^2) \\ u_{it} &\sim N^+(m_{it,} \sigma_{it}^2) \end{aligned} \qquad \text{with } u_{it} = \alpha_o + \sum_{i=1}^{n} \alpha_i Z_{it} + \exp(\gamma_0 + \sum_{i=1}^{n} \gamma_i Z_{it}) + w_{it}$$

In the non-monotonic efficiency effect model, the technical inefficiency component u_{it} follows a truncated normal distribution with mean m_{it} and the variance σ_{it}^2 of the pretruncated distribution given by

$$m_{it} = \alpha_o + \sum_{i=1}^{n} \alpha_i Z_{it} + w_{it}$$

$$\sigma_{it}^2 = \exp(\gamma_0 + \sum_{i=1}^{n} \gamma_i Z_{it})$$

$$w_{it} \sim N(0, \sigma_w^2)$$

While the mean measures the expected value of technical inefficiency, the variance measures uncertainty (Bera and Sharma, 1999). As we can see this model allows environmental variables to affect inefficiency in two different channels, and the result of this flexibility is the model's ability to accommodate non-monotonic efficiency effects. [3]

2.7 Model 6: Non-neutral, Non-monotonic Inefficiency Effect Model

The major purpose of this work is to present and estimate the non-neutral, non-monotonic inefficiency effect model which is the combination of the three models of Huang and Liu (1994), Wang (2002) and Coelli et al. (1999) and derives the following SFA model

$$\ln y_{it} = \ln x_{it} * \beta + d_o + \sum_{i=1}^{n} d_i z_{it} + u_{it} + v_{it}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

with $u_{it} = a_0 + \sum_{i=1}^{n} \alpha_i z_{it} + \ln \frac{x_r}{x_t} + \sum_{j=1}^{m} \ln y_j + \exp(\gamma_0 + \sum_{i=1}^{n} \gamma_i Z_{it} + \ln \frac{x_r}{x_t} + \sum_{j=1}^{m} \ln y_j) + w_{it}$

$$w_{it} \sim N(0, \sigma_w^2)$$

In the non-neutral, non-monotonic inefficiency effect model, the technical inefficiency component u_{it} follows a truncated normal distribution with the following mean m_{it} and variance σ_{it}^2

$$m_{it} = a_0 + \sum_{i=1}^{n} \alpha_i z_{it} + \ln\frac{x_r}{x_t} + \sum_{j=1}^{m} \ln y_j + w_{it}$$
$$\sigma_{it}^2 = \exp(\gamma_0 + \sum_{i=1}^{n} \gamma_i Z_{it} + \ln\frac{x_r}{x_t} + \sum_{j=1}^{m} \ln y_j)$$

The main feature of the model is to explain in which way environmental variables affect the efficiency of each firm. On the one hand, the ability to accommodate non-monotonic inefficiency effects is important for seeking to understand the relationships between (in)efficiency and the environmental variables. The reason is obvious: many of the relationships between economic variables are indeed non-monotonic. On the other hand, non-neutrality in efficiency allows the interactions between environmental variables and input variables in the stochastic frontier.

We can consider various specific interesting restrictions each of these corresponds to a simplified version of the general model. This general model nests several simpler models, many of which have been presented previously. (see Table 3)

CHAPTER THREE

Variables, Data and Empirical Model

3.1 Introduction

In this chapter, we argue the specification of multiple inputs and multiple outputs with respect to banking technology and the data used for estimating the models. The specification of inputs and outputs for the banking sector is very complicated. Economists are divided over the conceptual issue of the correct definitions of inputs and outputs in the banking industry. According to the literature there are two main approaches: the production approach and the intermediation approach. Both of them apply the microeconomic theory of the firm to banking and differ only in the specification of banking activities.

Under the production approach, banks are defined as producers of deposit accounts and loan services and are viewed as providers of services to customers. The inputs in this case include mainly physical variables (e.g. labour, material, information systems) or their associated costs. Under the intermediation approach, financial institutions are viewed as intermediating funds between savers and investors. This approach includes both operating and interest expenses as inputs, whereas loans and other main assets are appeared as outputs.

The literature on the identification of banking output led to the establishment of three variants of the intermediation approach: asset, user cost and value-added approach. The asset approach focuses on the role of banks as financial intermediaries between depositors and final users of bank assets. The user cost approach determines whether a financial product is an input or an output on the basis of its contribution to bank revenue. If the financial returns on an asset are greater than the opportunity cost of the funds, they are considered as outputs; respectively in the case of inputs. Finally, the value-added approach identifies those balance sheet categories (assets or liabilities) as outputs that contribute to the bank value added. In general, under this last approach, the main categories of produced deposits and loans are viewed as outputs because they are responsible for the significant proportion of value added.

The appropriateness of each approach varies according to the issues and the problems that are addressed each time. It is obvious that banks perform many activities within the framework of both main approaches. Consideration of a particular approach limits several quality aspects of banking services. According to Berger and Humphrey (1992), the value-added (VA) approach is considered to be the most adequate method in estimating changes in bank technology and efficiency over time. The major advantage of the VA approach is that it considers all liability and asset categories to have some output characteristics rather than distinguishing inputs and outputs in an exclusive way. (see table 2)

3.2 Specification of the variables

In the banking literature, as we mentioned before, there has been considerable disagreement about the "proper" definition of inputs and outputs. So, the first problem faced by all studies that analyze efficiency in banking firms is the identification and measurement of outputs and inputs. In this work we adopt the value-added approach to identify banking inputs and outputs. According to the selected approach, we specify two outputs: y_1=demand deposits and y_2=loans to customers; and two inputs:

x_1=labor, which includes salary and fringe benefits for the employees, and x_2=capital, which is defined as physical capital at book value. We consider labor input in terms of personnel cost instead of the number of employees due to the lack of data.

Moreover, it is very important to point out that a deflation should be done so that the variables, which we are going to use in this work, are expressed as implicit quantities, without the price effect. This can be done by deflating and expressing variables in real terms. Finally, the previous procedure is necessary to be done because, as we will mention below, we are going to use the distance function in order to estimate the models, and according to the theory, distance function depends on input and output quantities, but in our case the data are expressed in current values including a price effect.

Consequently, labor is deflated with a labor price index of financial services, capital with the deflator of gross fixed capital formation of the banking sector and the two outputs are deflated by using a price index accrued by the net production of the Greek banking sector. These price indexes are obtained from the National Accounts of the Greek economy, expressed in real terms of 2008 (see table 4).

Additionally, in order to explain efficiency, three environmental variables for banks are chosen. These are: z_1= the number of branches per bank, z_2= dummy variable if the bank is of Greek or foreign interest and z_3= dummy variable if a particular bank institute has branches not only in the two bigger cities of Greece (Athens and Thessaloniki) but also in the rest of Greece. In the case of the dummy which is used to capture if the bank is of Greek or of foreign interest, we use the value 0 if we have a Greek-owned bank and the value 1 if we have a bank of foreign interest. As far as the second dummy is concerned, we use the value 1 if a bank has branches only in Athens and Thessaloniki; otherwise, we use the value 0 if a bank has branches not only in the two main cities of Greece, but also and in the rest of the country.

3.3 Data Description

In our empirical study we use data which consists of yearly information from the Balance Sheet Accounts of 32 bank industries that take an active role in the Greek financial market over the period 1998-2008 obtained from ICAP and the National Printing Office. The data for the definition of the environmental variables were gathered from the Hellenic Bank Association (HBA) and the Balance Sheet Accounts of each bank. All variables are presented in terms of Euro currency and have been deflated as we mentioned above.

3.4 Empirical Model

We want to estimate a stochastic cost frontier using data from N=32 banks for T=11 years (1998-2008) with 2 outputs, 2 inputs and 3 environmental variables (that parameterize the inefficient component). We also include a linear and a quadratic time trend in the specification, and an intercept. Thus, we use multiple inputs – outputs distance function to investigate technical inefficiency. The input distance function can be defined in terms of a translog form (see Grosskopf et al.; Coelli and Perelman, 1999; 2000):

$$\ln D_{it}^{I}\left(y,x;t\right)=a_0+\sum_{m=1}^{2}a_m \ln x_{mit}+\frac{1}{2}\sum_{m=1}^{2}\sum_{j=1}^{2}c_{mj}\ln x_{mit}\ln x_{jit}+\sum_{k=1}^{2}\beta_k \ln y_{kit}+$$
$$\frac{1}{2}\sum_{k=1}^{2}\sum_{l=1}^{2}\beta_{kl}\ln y_{kit}\ln y_{lit}+\sum_{m=1}^{2}\sum_{k=1}^{2}p_{mk}\ln x_{mit}\ln y_{kit}+\sum_{m=1}^{2}\theta_m \ln x_{mit}t+\sum_{k=1}^{2}n_k \ln y_{kit}t \quad (1)$$
$$+\varphi_1 t+\varphi_2 t^2+\varepsilon_{it}$$

where x denotes inputs, y denotes outputs, t is a time trend and ε_{it} is the noise component which varies through time as well as across banks and follows i.i.d with $N(0,\sigma_{\varepsilon}^{2})$.

The regularity conditions associated with the input distance function require homogeneity of degree one in input quantities and symmetry, which implies the following restrictions on the parameters of the translog function:

Symmetry restrictions: $c_{mj}=c_{jm}$
$\beta_{kl}=\beta_{lk}$

Homogeneity restrictions: $\sum_{m=1}^{2}a_m=1$
$\sum_{m=1}^{2}c_{mj}=\sum_{m=1}^{2}p_{mk}=\sum_{m=1}^{2}\theta_m=0$

Given linear homogeneity the initial input distance function (1) may be written as:

$$-\ln x_{2_{it}} = W(.)-\ln D_{it}^{I} \quad (2)$$

to obtain an estimable form of the input distance function, where j=2 is the numeraire input and Ω(.) is the right hand side of (1). Because there are no observations for $\ln D_{it}^{I}$ and given that $\ln D_{it}^{I}$<0, it can be assumed that $\ln D_{it}^{I}=-u_{it}$ (see Grosskopf et al.; Coelli and Perelman, 1999; 2000), where u_{it} is one-sided, nonnegative observable random variables associated with the technical inefficiency. Then, the general form of the stochastic input distance function model will be:

$$-\ln x_{2it} = \Omega(.) + u_{it} + v_{it} \tag{3}$$

where v_{it} is assumed to be independent and identically distributed random errors which have normal distribution with mean zero and unknown variance, representing a combination of those factors that cannot be controlled by the financial institutes. It is also important that v_{it} and u_{it} are distributed independently to each other.

As discussed in chapter 2, six alternative models will be estimated in order to take into account the environmental factors. For model 1, we have the translog frontier (3) with $m_{it} = \delta_1 z_1 + \delta_2 z_2 + \delta_3 z_3 + w_{it}$, in which the environmental variables influence the degree of technical inefficiency. For model 2, we assume that these factors influence directly the shape of the translog frontier and for this reason equation (3) becomes: $-\ln x_{2it} = \Omega(.) + \delta_1 z_1 + \delta_2 z_2 + \delta_3 z_3 + u_{it} + v_{it}$. As a result the model 3, which is a combination of model 1 & 2, will appear the environmental variables not only in the technical inefficiency term but also in the stochastic input distance function.

However, for model 4, we estimate the stochastic frontier (3) with $m_{it} = \delta_1 z_1 + \delta_2 z_2 + \delta_3 z_3 + \delta_{11} z_1 \ln x_1 + \delta_{12} z_1 \ln x_2 + \delta_{21} z_2 \ln x_1 + \delta_{22} z_2 \ln x_2 + \delta_{31} z_3 \ln x_1 + \delta_{32} z_3 \ln x_2 + w_{it}$, where there are interactions between environmental and input variables in the stochastic frontier. In all the previous models, the variance of the technical inefficiency effect term remains constant, in contrast with the model 5 in which the technical inefficiency component follows a truncated normal distribution with mean

$m_{it} = \delta_1 z_1 + \delta_2 z_2 + \delta_3 z_3 + w_{it}$ and variance $\sigma_{it}^2 = \exp(\gamma_1 z_1 + \gamma_2 z_2 + \gamma_3 z_3)$. Lastly, for model 6, specification of the mean and the variance is the following: $m_{it} = \delta_1 z_1 + \delta_2 z_2 + \delta_3 z_3 + \delta_4 \ln \frac{x_1}{x_2} + \delta_5 \ln y_1 + \delta_6 \ln y_2 + w_{it}$ and $\sigma_{it}^2 = \exp(\gamma_1 z_1 + \gamma_2 z_2 + \gamma_3 z_3 + \gamma_4 \ln \frac{x_1}{x_2} + \gamma_5 \ln y_1 + \gamma_6 \ln y_2)$. The main feature of the last two models is that both the mean and the variance of the inefficiency effects u_{it} can influence the technical efficiency.

CHAPTER FOUR

Empirical Remarks

4.1 Introduction

The empirical results concerning the parameters of the translog input distance function and the (TE) technical efficiency level of the banks participated in the Greek banking sector during the period 1998-2008 are presented to this chapter. Six different models are estimated. Except from model 2, all the other models parameterize m_{it} and they differ on whether σ_{it}^2 is also parameterized.

Model 1, 2, 3 and 4 are all estimated through a computer program named Frontier 4.1 developed by Coelli (1992, 1994). This program has been written to provide maximum likelihood estimates of the parameters of stochastic production and cost functions. Model 5 and 6 are characterized by non-monotonic relationships between the inefficiency and its determinants, which means parameterization of m_{it} and σ_{it}^2 by the same vector of exogenous variables. For this reason, Model 5 and 6 are estimated using the maximum likelihood code written by Wang (2002) in STATA. Wang STATA program is available in his cite http://homepage.ntu.edu.tw/~wangh/ .

In the rest of this chapter, we present all the estimated coefficients of α, c, β, p, θ, n and φ. Moreover, we examine if the properties of input distance function are valid or not, around the point of approximation and we conclude with the frequency distribution of technical efficiency. [4]

4.2 Results

In this section, we report the estimation results under alternative model specifications for the inefficiency component. We use a flexible translog functional form. The maximum likelihood parameter estimates of the translog input distance function are presented in table 5. The translog input distance is given by

$$-\ln X_2 = a_0 + \underline{a_1 \ln\left(\frac{X_1}{X_2}\right)} - \underline{\frac{1}{2} c_{12}\left[\ln\left(\frac{X_1}{X_2}\right)\right]^2} + \underline{\beta_1 \ln Y_1} + \underline{\beta_2 \ln Y_2} + \frac{1}{2}\beta_{11}\left(\ln Y_1\right)^2 + \underline{\beta_{12} \ln Y_1 \ln Y_2} + \frac{1}{2}\beta_{22}\left(\ln Y_2\right)^2$$
$$+ p_{21} \ln Y_1 \ln\left(\frac{X_2}{X_1}\right) + p_{12} \ln Y_2 \ln\left(\frac{X_1}{X_2}\right) + \varphi_1 t + \varphi_2 t^2 + \theta_1 t \ln\left(\frac{X_1}{X_2}\right) + n_1 \ln Y_1 t + n_2 \ln Y_2 t + u_{it} + v_{it}$$

As far as the properties of input distance function are concerned, the models should appear to be non-increasing (β_1, β_2 <0) and convex (β_{12} >0) in outputs; and non-decreasing (α_1 >0) and concave (c_{12} <0) in inputs.

According to the estimated parameters, the translog input distance function is found, at the point of approximation and in the most cases, to be non-increasing in outputs and non-decreasing in inputs. Also, at the point of approximation, the Hessian matrix of the second order partial derivatives with respect to inputs is found to be negative definite, in the most of the models, and the corresponding Hessian matrix with respect to outputs to be positive definite. These indicate respectively the concavity and convexity of the input distance function with respect to inputs and outputs.

In the cases, where the parameter estimates don't follow the theory about the properties of input distance function, there is no statistical significance and for this reason we can imply that our models fit good in the data as far as monotonicity and curvature are concerned. Moreover, the statistical significance of σ^2 of the one-sided error term in all the models is a sign of the presence of technical inefficiency.

The parameter signs of the inefficiency effects model (see the parameters δ_{ij}) show the average impacts of exogenous variables on the technical inefficiency. As far as the model 6 is concerned, the first exogenous variable is the number of branches (z_1), which has negative impacts on technical efficiency, indicating the larger the bank size, the lower the technical efficiency. The two dummies (z_2 and z_3) have positive impacts on technical efficiency, implying that technical efficiency is higher when the banks are of Greek interest and have branches only in Athens and Thessaloniki. Also, $\ln y_1$ and $\ln(x_1/x_2)$ have positive impacts in technical efficiency, but y_2 , loans to customers, has negative impacts in technical efficiency, which means that the larger the loans to customers , the lower the technical efficiency.

Frequency distributions of technical efficiency scores as well as their mean values are presented in table 6 for all the models that we examine. The estimated mean technical efficiency was found to be 21.5%, 14.3%, 30.3%, 33.9%, 34.3% and 57.3% for models 1-6 respectively during the period 1998-2008 (11 years). Thus, for example in the model 6 that we propose, on average, a 42,7% decrease in total cost could have been achieved during this period, without altering the total volume of outputs, production technology and inputs usage. The vast majority of the banks in this model have consistently achieved scores of technical efficiency greater than 50%. In addition, mean technical efficiency decreased from 64.4% in 1998 to 50% in 2008 implying that the contribution of technical efficiency to output growth would be negative.

CHAPTER FIVE

Conclusions

This paper combines the work of Battese and Coelli (1995), Good et al. (1993), Coelli et al. (1999), Huang and Liu (1994) and Wang (2002) in order to propose a non-neutral, non-monotonic inefficiency effect model to investigate the impact of the environmental variables on technical efficiency of 32 banks in the Greek banking sector during the period 1998-2008. The combined model allows exogenous variables to affect inefficiency through two different channels.

This work highlights the possible differences which may arise when different model formulations for functional form of the frontier function and specifications for the technical inefficiency effects are made in empirical applications. We employ a parametric method in estimating a specific translog input distance stochastic frontier function and a truncated efficiency regression. The development of the distance function approach provides a more realistic framework for parametric analysis of inefficiency effect term appropriate to the multi-input, multi-output context of the banking sector.

It is important to include in these conclusions that the three environmental variables we have used is unlikely to fully capture all environmental influences. Further theoretical and applied work is obviously required to obtain better and more general models from stochastic frontiers and the technical inefficiency effects associated with the analysis of panel data in the Greek banking sector.

Table 1: List of Models

Model		$N^{+}(m_{it,}\sigma^2_{it})$	
	Cost Function	Mean	Variance
Model 1: Technical Inefficiency Effect Model (Battese and Coelli, 1995)	$\ln y_{it} = \ln x_{it} * \beta$	$m_{it} = \alpha_o + \sum_{i=1}^{n} \alpha_i z_{it}$	$\sigma^2_{it} = \sigma^2_u$
Model 2: Environmental Variables in the Cost Function (Good et al., 1993)	$\ln y_{it} = \ln x_{it} * \beta + d_o + \sum_{i=1}^{n} d_i z_{it}$	$m_{it} = a_0$	$\sigma^2_{it} = \sigma^2_u$
Model 3: Combination of Model 1 & Model 2 (Coelli et al., 1999)	$\ln y_{it} = \ln x_{it} * \beta + d_o + \sum_{i=1}^{n} d_i z_{it}$	$m_{it} = \alpha_o + \sum_{i=1}^{n} \alpha_i z_{it}$	$\sigma^2_{it} = \sigma^2_u$
Model 4: Non-neutral Stochastic Frontier Model (Huang and Liu, 1994)	$\ln y_{it} = \ln x_{it} * \beta$	$m_{it} = a_0 + \sum_{i=1}^{n} \alpha_i z_{it} + \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} z_{it} \ln x_{jt}$	$\sigma^2_{it} = \sigma^2_u$
Model 5: Non-monotonic Efficiency Effects Model (Wang, 2002)	$\ln y_{it} = \ln x_{it} * \beta$	$m_{it} = \alpha_o + \sum_{i=1}^{n} \alpha_i Z_{it}$	$\sigma^2_{it} = \exp(\gamma_0 + \sum_{i=1}^{n} \gamma_i Z_{it})$
Model 6: Non-neutral, Non-monotonic Inefficiency Effect Model (proposed model)	$\ln y_{it} = \ln x_{it} * \beta + d_o + \sum_{i=1}^{n} d_i z_{it}$	$m_{it} = a_0 + \sum_{i=1}^{n} \alpha_i z_{it} + \ln \frac{x_r}{x_t} + \sum_{j=1}^{m} \ln y_j$	$\sigma^2_{it} = \exp(a_0 + \sum_{i=1}^{n} \alpha_i z_{it} + \ln \frac{x_r}{x_t} + \sum_{j=1}^{m} \ln y_j)$

Table 2: A Summary of Various Inputs and Outputs Definitions in Some Studies with VAA (Value Added Approach)

Authors	Outputs	Inputs
Berger and Humphrey (1992)	Demand deposits Loans	Capital Labour (employees)
Olivei (1992)	Loans Deposits Non-interest income	Labour (employees) Non-interest expenses Fixed assets and premises Interest expenses
Berg et al. (1993)	Loans Deposits Number of branches	Labour (hour per year) Capital
Resti (1993)	Loans Deposits Net loans to other banks	Capital (number of branches) Labour (employees) Purchased funds
Dietsch and Lozano (2000)	Loans Deposits Other earning assets	Price of labor Price of physical capital Price of financial factor
Lozano, Lozano and Pastor (2002)	Loans Deposits Other earning assets	Personnel Expenses Operating expenses
Pastor (2002)	Loans Deposits Other earning assets	Price of deposits Price of physical capital Price of labour

Table 3: The Relationships among Various SF Models

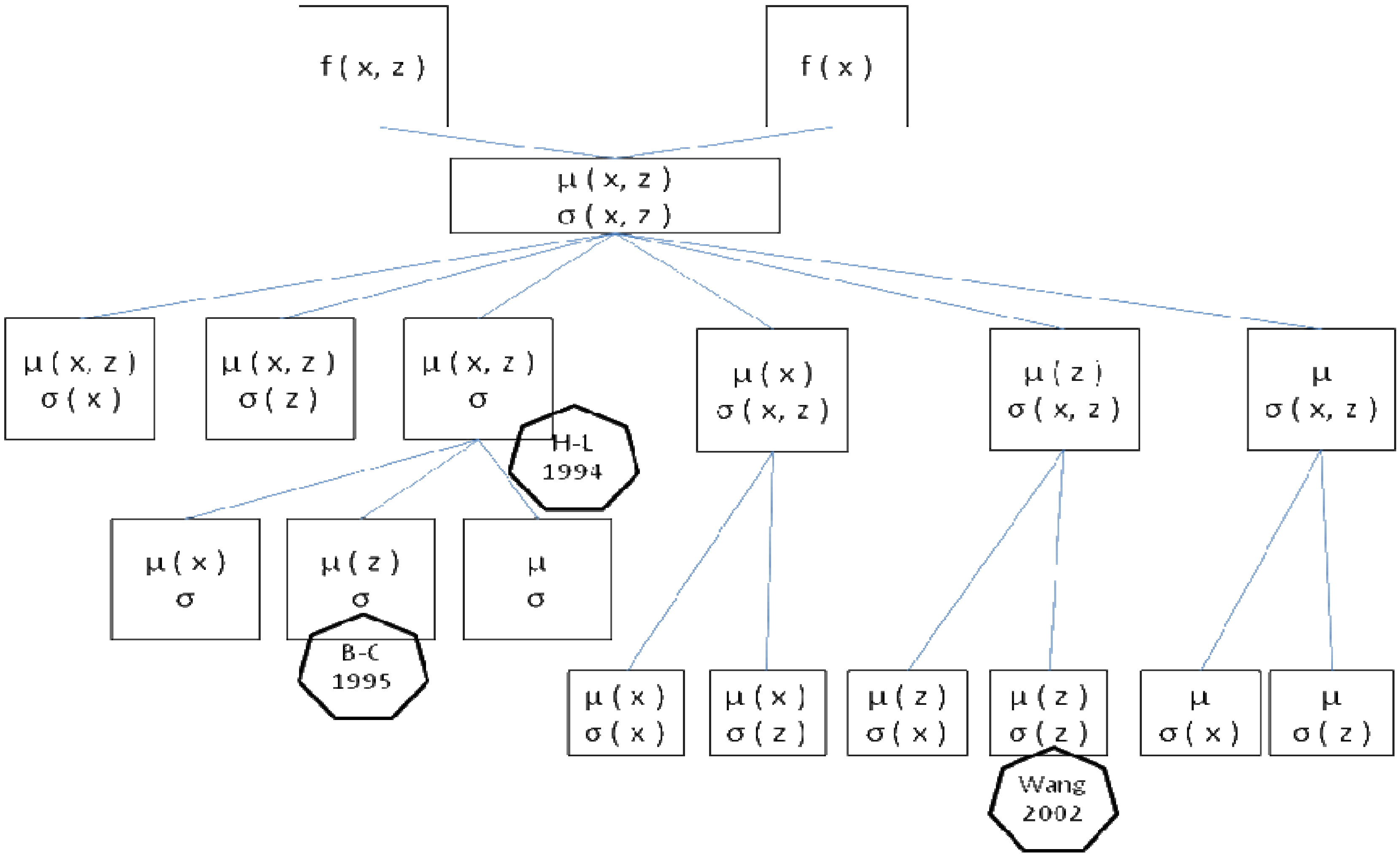

Table 4: Annual Means of the Variables in Current Prices and Variables' Deflators

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Inputs (millions €)											
Labor	67.60	80.97	95.86	101.24	95.67	85.54	96.70	88.78	98.07	107.66	116.97
Capital	119.15	154.23	170.81	165.79	174.28	164.42	136.40	143.85	141.16	132.94	153.13
Outputs (millions €)											
Loans to Costumers	1,075.47	2,235.45	3,043.26	3,571.81	3,801.39	3,762.18	4,139.42	4,752.57	5,592.86	6,833.84	8,709.24
Demand Deposits	3,548.13	4,302.07	5,318.32	6,115.42	5,754.71	4,884.84	5,023.91	5,305.68	5,942.96	6,740.78	7,871.22
Deflators											
Labor Price Index	0.900	0.912	0.954	0.890	1.008	1.043	1.098	0.990	1.002	0.993	1
Capital Price Index	0.956	1.236	1.268	1.009	0.995	0.999	0.994	1.000	1.008	1.001	1
Outputs Deflator	0.686	0.712	0.748	0.767	0.902	0.993	1.022	1.050	1.053	1.022	1

Table 5: Parameter Estimates of the Translog Input Distance Function

	Model 1		Model 2		Model 3		Model 4	
	parameter estimates	t-statistics	parameter estimates	t-statistics	parameter estimates	t-statistics	parameter estimates	t-statistics
a_0	-0.248*	-3.47	0.564*	2.70	1.454*	8.58	-0.225*	-2.82
a_1	0.774*	11.26	0.786*	9.86	0.842*	15.47	0.869*	12.34
c_{12}	-0.077*	-3.97	-0.014	-0.64	-0.004	-0.23	0.033	1.56
β_1	-0.085	-0.68	0.082	0.62	0.031	0.29	-0.135	-1.13
β_2	-0.679*	-5.95	-0.767*	-5.46	-0.491*	-4.50	-0.618*	-5.94
β_{11}	0.029	1.09	0.007	0.27	0.014	0.56	-0.026	-0.94
β_{12}	-0.046	-0.98	0.017	0.37	-0.006	-0.12	0.025	0.49
β_{22}	0.002	0.10	-0.030	-1.19	0.003	0.14	-0.033	-1.34
p_{21}	-0.047	-1.30	-0.033	-0.88	-0.042	-1.29	0.079***	1.89
p_{12}	-0.096*	-3.01	-0.078**	-2.29	-0.067**	-2.20	-0.044	-1.12
φ_1	-0.019	-0.76	-0.018	-0.57	-	-1.64	-0.025	-0.85
φ_2	-0.001	-0.19	-0.001	-0.01	0.001	0.49	0.003	1.05
θ_1	0.017**	2.22	0.001	0.12	0.003	0.54	0.002	0.36
n_1	0.024***	1.80	0.013	1.06	0.012	1.05	0.001	0.10
n_2	-0.025***	-1.95	-0.012	-1.03	-0.016	-1.37	-0.001*	-5.22
m_1			-0.002*	-3.90	-0.001*	-4.18		
m_2			0.019	0.19	-0.858*	-5.29		
m_3			-0.313*	-3.28	-1.476*	-8.71		
δ_1	-0.009*	-4.35			-0.008*	-17.74	0.002***	1.67
δ_2	0.619*	5.68			0.847*	5.29	-0.212	-0.94
δ_3	0.449*	3.22			1.288*	11.05	-0.606*	-2.85
δ_{11}							-0.001	-1.23
δ_{12}							-0.001***	-1.82
δ_{21}							-0.859*	-7.10
δ_{22}							0.460*	6.13
δ_{31}							-0.302*	-2.83
δ_{32}							-0.243*	-3.07
γ_0								
γ_1								
γ_2								
γ_3								
σ^2	0.437*	10.18	0.253*	3.43	0.195*	7.15	0.120*	8.39
γ	0.937*	48.01	0.602**	2.37	0.931*	48.05	0.698*	10.15
LL		-122.56		-138.82		-81.06		-52.09
monotoniciy								
outputs	*yes*		*no*		*no*		*yes*	
inputs	*yes*		yes		*yes*		*yes*	
curvature								
outputs	*no*		yes		*no*		*yes*	
inputs	*yes*		yes		*yes*		*no*	

Note: *, ** and *** indicate significant coefficients in 1%, 5% and 10% respectively.

	Model 5		Model 6	
	parameter estimates	z	parameter estimates	z
a_0	1.822*	12.90	-0.294*	-4.20
a_1	0.777*	11.19	0.711*	10.33
c_{12}	0.032	1.57	-0.029	-1.12
β_1	-0.220***	-1.79	-0.445*	-3.52
β_2	-0.420*	-3.61	-0.291*	-2.86
β_{11}	-0.068*	-2.62	-0.138*	-4.00
β_{12}	0.122**	2.45	0.393*	6.50
β_{22}	-0.054**	-2.22	-0.272*	-9.02
p_{21}	0.048	1.08	0.019	0.55
p_{12}	0.017	0.39	0.040	1.07
φ_1	-0.037	-1.44	-0.011	-0.43
φ_2	0.003	1.18	-0.001	-0.19
θ_1	0.006	0.78	0.011	1.50
n_1	0.022***	1.79	0.021**	2.40
n_2	-0.019***	-1.69	-0.019**	-2.41
m_1				
m_2				
m_3				
δ_1	0.002*	6.66	-0.004**	-2.55
δ_2	-0.118	-1.24	0.802*	6.50
δ_3	1.304*	10.06	0.252***	1.93
δ_3			0.523*	4.32
δ_4			1.427*	8.70
δ_5			-1.503*	-9.74
γ_1	-0.014*	-3.49	-0.006**	-2.31
γ_2	-0.037***	-1.89	-1.484*	-3.45
γ_3	-0.997*	-3.52	-0.598**	-2.16
γ_4			-0.553*	-3.32
γ_5			-0.811*	-4.25
γ_6			0.894*	4.66
σ^2	-3.487*	-12.50	-3.779*	-12.38
LL		-121.41		-79.11
monotonicity				
outputs	*yes*		*yes*	
inputs	*yes*		*yes*	
curvature				
outputs	*yes*		*yes*	
inputs	*no*		*yes*	

Note: *, ** and *** indicate significant coefficients in 1%, 5% and 10% respectively.

Table 6: Frequency Distribution of Technical Efficiency Scores

Technical efficiency Model 1	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
<0.099	0	0	0	0	0	0	0	0	0	0	0
0.1-0.199	13	15	12	14	15	14	18	18	17	20	19
0.2-0.299	4	4	6	5	4	9	6	9	10	8	7
0.3-0.399	2	1	1	1	3	2	2	2	3	1	2
0.4-0.499	1	1	2	0	1	1	1	0	0	2	1
0.5-0.599	0	0	0	1	0	1	0	0	0	0	0
0.6-0.699	0	0	0	0	0	0	1	1	1	1	1
0.7-0.799	0	0	0	0	0	0	1	0	0	0	0
0.8-0.899	0	0	0	0	0	0	0	0	0	0	0
>0.9	0	0	0	0	0	0	0	0	0	0	0
Mean	0.360	0.181	0.202	0.192	0.197	0.212	0.221	0.187	0.204	0.216	0.198

Technical efficiency Model 2	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
<1.099	0	0	0	0	0	0	0	0	0	0	0
1.1-1.199	3	2	4	3	4	3	3	3	3	5	6
1.2-1.299	6	8	3	7	7	9	9	12	5	5	5
1.3-1.399	3	4	2	3	3	5	6	4	13	9	6
1.4-1.499	4	3	6	2	1	4	3	3	3	6	5
1.5-1.599	0	0	0	2	6	3	2	3	2	2	3
1.6-1.699	0	1	1	1	1	1	3	3	2	2	1
1.7-1.799	2	2	4	1	1	0	0	1	1	1	2
1.8-1.899	2	0	1	2	0	1	1	0	1	1	1
>1.9	0	1	0	0	0	1	2	1	1	1	1
Mean	1.41	1.39	1.46	1.40	1.39	1.44	1.49	1.40	1.44	1.46	1.44

Technical efficiency Model 3	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
<0.099	0	0	0	0	0	0	0	0	0	0	0
0.1-0.199	11	13	13	13	13	14	16	16	13	16	16
0.2-0.299	3	3	1	1	1	3	3	5	9	7	7
0.3-0.399	1	2	3	2	6	6	4	2	2	3	2
0.4-0.499	2	0	1	3	0	0	1	3	4	4	3
0.5-0.599	1	1	1	1	2	1	2	3	1	0	1
0.6-0.699	1	2	1	0	0	2	2	1	2	1	1
0.7-0.799	1	0	1	0	0	1	1	0	0	1	0
0.8-0.899	0	0	0	0	0	0	0	0	0	0	0
>0.9	0	0	0	1	1	0	0	0	0	0	0
Mean	0.276	0.309	0.326	0.274	0.290	0.339	0.360	0.298	0.297	0.299	0.261

Technical efficiency Model 4	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
<0.099	0	0	0	0	0	0	0	0	0	0	0
0.1-0.199	11	12	9	9	10	13	15	17	18	20	20
0.2-0.299	1	1	2	5	5	5	4	4	4	5	3
0.3-0.399	3	2	2	1	3	2	2	2	3	2	1
0.4-0.499	1	4	2	1	1	2	2	3	2	0	3
0.5-0.599	0	2	2	2	1	2	1	2	2	1	1
0.6-0.699	1	0	0	2	0	3	2	0	1	1	0
0.7-0.799	0	0	2	0	2	0	1	1	0	1	1
0.8-0.899	2	0	0	1	0	0	0	0	0	1	1
>0.9	1	0	2	0	1	0	2	1	1	1	0
Mean	0.446	0.494	0.392	0.290	0.320	0.341	0.308	0.291	0.292	0.278	0.275

Technical efficiency Model 5	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
<0.099	1	1	1	1	1	1	1	1	2	1	1
0.1-0.199	6	6	6	6	7	7	8	7	7	8	9
0.2-0.299	2	4	3	4	4	4	4	7	6	6	10
0.3-0.399	4	3	2	2	4	7	5	5	3	7	0
0.4-0.499	2	1	4	4	2	2	3	2	2	1	0
0.5-0.599	2	3	1	1	0	2	3	3	6	2	4
0.6-0.699	1	2	0	1	2	1	1	1	2	1	0
0.7-0.799	1	0	1	1	2	1	1	2	2	4	4
0.8-0.899	1	1	3	1	1	2	1	1	0	1	2
>0.9	0	0	0	0	0	0	2	1	1	1	0
Mean	0.365	0.347	0.382	0.337	0.366	0.344	0.328	0.296	0.324	0.358	0.330

Technical efficiency Model 6	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
<0.099	2	2	1	2	2	2	1	1	1	2	2
0.1-0.199	1	1	2	1	1	2	3	3	3	4	4
0.2-0.299	1	1	1	0	1	3	3	4	3	1	1
0.3-0.399	1	0	2	2	2	1	1	1	1	0	0
0.4-0.499	1	1	1	3	4	4	3	4	3	8	7
0.5-0.599	1	0	4	2	1	3	5	2	7	4	2
0.6-0.699	2	5	3	3	1	2	3	5	3	2	4
0.7-0.799	1	1	1	2	3	2	2	2	2	2	1
0.8-0.899	7	7	1	1	3	4	3	3	2	3	3
>0.9	3	3	5	5	5	4	5	5	6	6	6
Mean	0.644	0.644	0.589	0.589	0.575	0.570	0.569	0.576	0.552	0.497	0.500

Notes

1) In this work N=32, as we have 32 banks, and T=11, as the examining period is from 1998 to 2008.

2) In this work M=3, as we are going to use three environmental variables, according to chapter 3 (specification of inputs, outputs and environmental variables)

3) By contrast, in the monotonic inefficiency effect model (Battese and Coelli, 1995), $\gamma_i = 0 \quad \forall i$ and thus the variance of the pretruncated distribution is constant.

4) Input distance function D^I is non-decreasing $\left\{ \frac{\partial D^I}{\partial x} > 0 \right\}$ and concave $\left\{ \frac{\partial^2 D^I}{\partial x^2} < 0 \right\}$ in inputs x, and non-decreasing $\left\{ \frac{\partial D^I}{\partial y} < 0 \right\}$ and convex $\left\{ \frac{\partial^2 D^I}{\partial y^2} > 0 \right\}$ in outputs y.

References

Alvarez, A., Amsler, C., Orea, L. and Schmidt, P. 'Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics', *Journal of Productivity Analysis*, 2006, 25, 201-212.

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

Battese, G.E. and Broca, S.S. "Functional forms of stochastic frontier production functions nad models for technical inefficiency effects: A comparative study for wheat farmers in Pakistan", *Journal of Productivity Analysis*, 1997, 8, 395-414.

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

Berger, A.N. and Humphrey, D.B. "Measurement and efficiency issues in commercial banking." in Griliches, Z. (editor) "Output Measurement in the Service Sectors" *NBER SIW No 56, University of Chicago Press*, 1992, ch.7, 245-300.

Coelli, T.J., Perelman, S. and Romano, E. "Accounting for environmental influences in stochastic frontier models: With application to international airlines." *Journal of Productivity Analysis*, 1999, 11, 251-273.

Coelli, T. and Perelman, S. "Technical Efficiency of European Railways: A Distance Function Approach", *Applied Economics*, 2000, 32, 1967-76.

Das, A. and Kumbhakar, S.C. "Productivity and efficiency dynamics in Indian banking: An input distance function approach incorporating quality of inputs and outputs." *Journal of Applied Econometrics*, 2010

Favero, C.A., and Papi, L. "Technical efficiency and scale efficiency in the Italian banking sector: a non-parametric approach." *Applied Economics*, 1995, 27:4, 385-395.

Good, D., Nadiri, M., Roller, L.H. and Sickles, R.C. "Efficiency and productivity growth comparisons of European and U.S. air carriers: A first look at the data." *Journal of Productivity Analysis*, 1993, 4, 115-125.

Grosskopf, S., Hayes, K., Taylor, L. and Weber, W. "Budget constrained frontier measures of fiscal equality and efficiency in schooling", *Review of Economics and Statistics*, 1997, 79, 116-124.

Huang, C.J. and Liu, J.-T. 'Estimation of a non-neutral stochastic frontier production function', *Journal of Productivity Analysis*, 1994, 5, 171-180.

Karagiannis, K., Midmore, P. and Tzouvelekas, V. 'Parametric decomposition of output growth using a stochastic input distance function', *American Journal of Agricultural Economics*, 2004, 86, 1044-1057.

Lozano-Vivas, A., Pastor, J.T. and Pastor, J.M. 'An efficiency comparison of European banking systems operating under different environmental conditions', *Journal of Productivity Analysis*, 2002, 18, 59-77.

Liu, Y. and Myers, R. 'Model selection in stochastic frontier analysis with an application to maize production in Kenya', *Journal of Productivity Analysis*, 2009, 31, 33-46.

Meeusen, W. and J. van den Broeck. 'Efficiency estimation of Cobb-Douglas production functions with composed error', *International Economic Review*, 1977, 18, 435-444.

Wang, H.-J. 'Heteroskedastcity nad non-monotonic efficiency effects of a stochastic frontier model', *Journal of Productivity Analysis*, 2002, 18, 241-253.

Wang, H.-J. and Schmidt, P. 'One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels', *Journal of Productivity Analysis*, 2002, 18, 129-144.

Zhu, X., Karagiannis, G. and Oude Lansink, A. 'The impact of direct income transfers of CAP in Greek olive farms' performance: Using a non-monotonic inefficiency effects model', *Journal of Agricultural Economics*, 2011