INTERDEPARTMENTAL PROGRAMME OF POSTGRADUATE STUDIES (I.P.P.S.) IN ECONOMICS (MASTERS IN ECONOMICS)

Thesis Title: *"Efficiency Consideration of MBIs in the Greek Banking Sector"*

Student: Papakonstantinou Nikolaos

Supervisor: Professor Karagiannis Giannis

Department of Economics

University of Macedonia

ACADEMIC YEAR 2010-2011

THESSALONIKI, GREECE

TABLE OF CONTENTS

Abstract

The objective of this paper is to analyze the performance implication of management buy-ins (MBIs) in the Greek banking sector. Two alternative approaches can be used to analyze the performance impact of MBIs. The first approach considers MBIs as "environmental factors", in the sense of Coelli and Perelman (1999), that affects outputs produced directly. The second approach assumes that MBIs affect outputs indirectly through the realization of maximum potential output and thus it is included in the technical inefficiency effect term of, for example, the Battese and Coelli (1995) model. We present and compare the results obtained from these two models and we also propose and estimate a third alternative model which combines the above two. To model the variable related to MBI we employ Amess (2003) formulation with an interval-type dummy which covers the period before and after the MBI. 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 42 banks over the period 1998-2007.

Keywords: MBIs; Efficiency; SFA

1. INTRODUCTION

During the last two or three decades, several forms of ownership change have been taking place in the banking sector by means of takeovers, buyouts and mergers. Moreover, these transactions increased in terms of intensity, size and geographical dispersion over time (Amel et al., 2004). In the literature, ownership changes are usually motivated by perceived opportunities to improve performance, which can be achieved through three channels: *first*, improving managerial efficiency with the transfer of assets to more productive management. *Second*, the achievement of scale economies that aim in reducing average cost by using scale biased technical change or by spreading fixed cost over a larger base; and *third*, the exploitation of economies of scope.

Siegel, Simons and Lindstrom (2009) summarized the empirical findings concerning the impact of ownership changes on firms' performance as follows: most studies report that firms involved in ownership changes experience an improvement in productivity after the change in ownership. The magnitude of increase seems to vary with the type of ownership change (e.g., leveraged buyouts versus management buyouts). Evidence on relative productivity before ownership change is however mixed. Some studies report that firms involved in ownership change are less productive than comparable firms before the change in ownership while others found the opposite. In addition, Amel et al. (2004) in their literature review for the impact of consolidations in the banking sector mentioned that mergers and acquisitions are likely to bring about smaller efficiency improvements in banking systems with higher dispersion of efficiency scores, i.e., with greater differences between the best practice banks and the others.

The objective of this paper is to analyze the impact of a particular form of ownership change, namely management buy-ins (MBIs), on the performance of the Greek banking sector. As MBIs are considered corporate actions in which an outsider manager or management team purchases an ownership stake and replaces the existing management team and/or change the current managerial organization. The size of the purchased ownership stake is such that allows by itself or in collaboration with other stakeholders for management changes. MBIs are thus another form of management takeovers comparable to management buyouts (MBOs) with the difference being that in the latter the inside management team involves. During the period under consideration 1998-2007, nine MBIs involving nineteen banks were undertaken in Greek banking sector; see the following table for the time placement of these transactions.

Table 1. Total number of MBIs.

Year	# of MBIs
1998	0
1999	0
2000	1
2001	0
2002	2
2003	0
2004	0
2005	2
2006	4
2007	0
Total MBIs	9

In general, management takeovers lead to changes in ownership and financial structure which in turn changes firm's incentive and control systems. According to Amess (2002), these organizational/governance changes are expected to have an impact on firm's output and on the technical relationship between outputs and inputs. Thus such changes can manifest themselves within the production frontier function in two ways: *first*, as one of the factors influencing the managerial/organizational characteristics and control systems associated with the particular governance structure and thus affecting potential output through the efficient use of inputs; and *second*, an "environmental" factor causing a neutral shift in the production frontier function. Nevertheless, previous studies have considered either one impact separately but not the combined impact of management takeovers. For example, Lichtenberg and Siegel (1990) and Harris, Siegel and Wright (2005) adopted the former specification and examined the role of management buyouts as a neutral productivity shift while Amess (2003) used the latter specification and considered its impact on technical efficiency.

In contrast, we develop a model capable of analyzing both impacts of MBIs simultaneously. Its specification is similar to Coelli, Perelman and Romano (1999) combined model. In modeling the impact of MBIs we suppose on the one hand that they influence the relationship between inputs and outputs and thus the shape of the technology. Hence, the dummy variable used to capture the impact of MBIs is a variable to be included in the production function. Following previous studies it is reasonable to assume that it enters into the production frontier function in an additive and separable from the other variables way, which implies that their impact on output is independent of input use and technical change over time. We also assume on the other hand that MBIs influence the degree of technical inefficiency as it is possible to affect output indirectly through the realization of maximum potential output. In such a case the MBI dummy variable should be included in the technical inefficiency effects function. This combined model can easily be nested to previous formulations used respectively by Lichtenberg and Siegel (1990) and Harris, Siegel and Wright (2005) and Amess (2003). Thus in the proposed formulation we can formally test whether the MBI governance structure acts as a neutral productivity shift or a factor influencing only the degree of technical efficiency.

We implement the proposed formulation using a variant of the intermediation approach and to prevent the multi-output nature of banking industry we use an input distance function to model production technology. Whenever firm level price data are not reliable or there is not enough variation in them, the input distance function appears as a promising alternative which due to its duality with the cost function enables us to accommodate cost minimization that is usually assumed as a maintained behavioral assumption in the banking sector. In order to account for both potential impacts of MBIs and at the same time to be able to test formally for the aforementioned nested versions, we use a stochastic frontier analysis and Battese and Coelli (1995) technical inefficiency effect model. The empirical model is estimated econometrically using an unbalanced panel data set of forty two banks operating in Greece during the period 1998-2007.

This setup also enables the examination of the impact of MBI governance structure on scale efficiency. For this purpose we use a two-stage approach where we firstly estimate scale efficiency scores based on Ray (1998) and Balk (2001) approach and then in a second stage we attend to examine their behavior against the MBI dummy variable. From this analysis we want to infer on the possible impact of MBI governance structure on the size of the involved banks. The only relevant empirical results is that of Cummins, Tennyson and Weiss (1999) for life insurance industry in U.S., where they found no evidence of scale efficiency gains for insures involving in ownership changes.

The rest of this thesis is organized as follows. Section 2 presents data and the specification of production technology, i.e. inputs and outputs. Section 3 displays the specification of the models and the estimation procedure. Section 4 shows the empirical results and Section 5 summarizes the main conclusions.

2. DATA AND SPECIFICATION OF INPUTS AND OUTPUTS

The definition and measurement of bank outputs have been a matter of longstanding debate among researchers. This is more so because many of the services are jointly produced and prices are typically assigned to a bundle of financial services (Das and Kumbhakar, 2010). In the relevant literature, we can identify two main approaches for the definition of inputs and outputs in the banking sector: the production approach and the intermediation approach. Due to an ambiguity in the treatment of some asset categories, three alternative approaches have evolved in the literature that focus on the intermediation activity of banks, namely *asset, user cost* and *value added* approach.

According to Berger and Humphrey (1992), the value added (VA) approach is considered to be the most accurate in estimating changes in bank technology and efficiency over time. The main advantage of the VA is that it considers all liability and asset categories to have some output characteristics rather than distinguishing inputs and outputs in a mutually exclusive way. This study specifies two inputs and three output variables using the VA approach, under which outputs are identified as those balance sheet activities with a substantial share to the bank value added. Consequently, the two inputs are defined as *labor,* which includes salary and fringe benefits for the employees, and *capital,* which is defined as physical capital at book value less accumulated depreciation. The vector of outputs is consisted of *loans to costumers,* including real estate, commercial, mortgages and agricultural loans, *loans to other banks* and *demand deposits,* including checking and savings accounts.

The data used in this study consists of yearly information from the Balance Sheet Accounts of 42 banks that take an active role in the Greek financial market over the period 1998-2007 obtained from ICAP. Data on MBIs were provided by the Hellenic Bank Association (HBA) and by the Consolidated Balance Sheet Accounts of each bank.

The use of the input distance function in modeling the production technology arise a critical issue concerning the dataset. By definition the distance function depends on input and output quantities, but in our case the data are expressed in current values including a price effect. Thus, a deflation must be done so that the variables used are expressed as implicit quantities, i.e. without the price effect. Note that this can be done by deflating and expressing variables in real terms.

Two implications involved with the correct deflation of the data must have serious consideration. First, Lichtenberg and Siegel (1991) stated that the use of a single set of output and input deflators can introduce substantial measurement errors into the estimation of efficiency. Second, a careful examination of the temporal variation of the variables reveals that each variable follows a different change pattern and that all variables except from capital have an increasing tendency throughout the period under consideration (see Table 2). As a result, 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 all outputs were deflated using a price index accrued by the net production of the Greek financial sector. These price indexes are obtained from the National Accounts of the Greek economy, expressed in real terms of 2007.

Table 2. Annual means of the variables in current prices and variables' deflators

Inputs (millions €)	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Labor	62.28	68.44	104.92	93.18	78.16	82.29	70.32	69.89	72.52	109.36
Capital	140.63	149.1	183.79	150.57	133.06	157.95	147.14	107.92	102.03	128.07
Outputs (millions €)										
Loans to Costumers	2,204.07	2,503.65	3,303.21	3,224.18	3,158.26	3,319.18	3,328.93	3,782.53	4,379.11	7,422.67
Loans to Banks	387.02	570.46	818.79	734.21	605.87	774.46	718.62	862.64	945.44	1,663.09
Demand Deposits	4,299.08	4,610.92	5,590.33	5,294.17	4,517.72	4,076.61	3,873.33	4,248.20	4,647.30	7,247.36

Deflators										
Labor Price Index	0.896	0.908	0.951	0.837	0.946	1.018	1.043	0.957	0.966	1
Capital Price Index	1.236	1.268	1.009	0.995	0.999	0.994	1	1.008	1.001	1
Outputs Deflator	0.669	0.694	0.730	0.748	0.876	0.965	0.993	1.022	1.029	1

3. EMPIRICAL MODEL AND ESTIMATION PROCEDURE

In this section we discuss the implications occurred due to the inclusion of MBIs performance impact in the econometric analysis. In modeling the impact of MBIs we suppose on the one hand that they influence the relationship between inputs and outputs and thus the shape of the technology. Hence, the dummy variable used to capture the impact of MBIs is a variable to be included in the production function. We also assume on the other hand that MBIs influence the degree of technical inefficiency as it is possible to affect output indirectly through the realization of maximum potential output. In such a case the MBI dummy variable should be included in the technical inefficiency effects function.

We begin by providing a short description of the construction of the time interval dummy which is used to capture the effect of MBIs on the performance of the banks under consideration. These dummies are presented here as mbi_{ik}, where subscript i denotes the i-th bank and k denotes the year relative to the year of organizational change; negative values of k signify years preceding an MBI, k=0 denotes the year that bank i is involved in an organizational change, and positive values of k indicate years following MBIs, or so-called post-buyin years. The mbi_{ik} are binary variables equal to one in year k relative to the transaction for firm i that adopts the MBI governance structure and zero otherwise. The estimation procedure commences using dummy variables with values of k from -3 to +6; this length is chosen so as to fit exactly in the time span of our dataset.

Aiming to the comparison of pre and post-buyin impacts of organizational change on the production frontier we include in the input distance function the mbi_{ik} dummies as described by the next equality:

$$\Omega_{ik} = \sum_{k=-3}^{6} \theta_{ik} mbi_{ik} \qquad (1)$$

where θ_k are parameters to be estimated capturing the effect of MBIs on the output produced. Positive values of θ_k indicate an outwards shift of the frontier, meaning that the bank needs more inputs to produce a certain level of output, i.e. the distance from the frontier increases. On the other hand, negative values of θ_k are related with a decrease in the distance from the production frontier.

Thus, the underlying input distance function can be defined in terms of a translog form as follows (e.g., Coelli and Perelman 1999; 2000):

$$\begin{aligned}
&\ln D_{it}^{I}(x, y, \Omega; t) = b_0 + \sum_{j=1}^{3} b_j \ln y_{jit} + \sum_{k=1}^{2} \gamma_{\kappa} \ln x_{kit} + \\
&\frac{1}{2}\sum_{j=1}^{3}\sum_{l=1}^{3} b_{jl} \ln y_{jit} \ln y_{lit} + \frac{1}{2}\sum_{k=1}^{2}\sum_{m=1}^{2} \gamma_{km} \ln x_{kit} \ln x_{mit} + \\
&\sum_{k=1}^{2}\sum_{j=1}^{3} \delta_{kj} \ln y_{jit} \ln x_{kit} + \sum_{k=1}^{2} \varepsilon_k \ln x_{kit} t + \sum_{j=1}^{3} \varphi_j \ln y_{jit} t + \\
&\eta_1 t + \eta_2 t^2 + \Omega_{ik} + e_{it}
\end{aligned} \qquad (2)$$

where x denotes inputs, y denotes outputs, t is a time trend and e_{it} is the noise component which varies through time as well as across banks.

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

$$\sum_{\kappa=1}^{2} \gamma_{\kappa} = 1 \quad \text{and} \quad \sum_{k=1}^{2} \gamma_{km} = \sum_{j=1}^{3} b_{jl} = \sum_{k=1}^{2} \varepsilon_k = \sum_{k=1}^{3} \delta_{kj} = 0$$

The homogeneity restrictions may also be imposed by dividing all input quantities on the right-hand side of the translog function by the quantity of that input used as a *numeraire*, in our case labor (estimates of the input distance function are invariant of the choice of the numeraire input).

Given linear homogeneity, (2) may be written as

$$-\ln x_{2it} = \varphi(.) + \Omega_{ik} - \ln D_{it}^{I} \qquad (3)$$

to obtain an estimable form of the input distance function, where $\ln x_{2it}$ is the *numeraire* input and (•) is the right-hand side of (2) after dividing all input quantities with that of the *numeraire* input.

Because there are no observations for $\ln D_{it}^{I}$ and given that $\ln D_{it}^{I} \leq 0$, it can be assumed that $\ln D_{it}^{I} = -u_{it}$ (Coelli and Perelman 1999, 2000), where u_{it} is a one-sided, nonnegative error term representing the stochastic shortfall of the ith bank output from its production frontier due to the existence of technical inefficiency. Then, the stochastic input distance function model may be written as:

$$-\ln x_{2it} = \varphi(.) + \Omega_{ik} + u_{it} + v_{it} \qquad (4)$$

where v_{it} depicts a symmetric and normally distributed error term (i.e., statistical noise), representing a combination of those factors that cannot be controlled by banks, omitted explanatory variables, and measurement errors in the dependent variable. It is also assumed that v_{it} and u_{it} are distributed independently of each other and our model has truncated-normal distribution:

$v_{it} \sim N(0, \sigma_v{}^2)$ and $u_{it} \sim N(\mu, \sigma_u{}^2)$

The mbi_{ik} dummies we used in the production function are also included in the technical inefficiency effects model, following Battese and Coelli (1995) specification:

$$\mu_{it} = \lambda_0 + \Omega_{ik} + \lambda_1 t + w_{it} \qquad (5)$$

where λ_0 is a constant term, t is time trend capturing the impact of time over inefficiency and is common to all firms (Amess, 2003) and w_{it} is an error term with mean zero and variance σ^2. Here, we employ a different parameterization (ζ_k) of mbi_{ik} dummies in order to distinguish between the two performance impacts. Positive values of ζ_k are associated with a decrease in efficiency levels, while negative values of ζ_k mean that the technical efficiency of the corresponding banks has proliferated. Combining equations (4) and (5) we get the nested model we mentioned earlier, where impacts of MBIs on both production and efficiency are analyzed simultaneously. If we assume that $\vartheta_k = 0, \forall k$, i.e. no effects in the distance function, then our model reduces in the specification of Amess (2003), and if we assume $\zeta_q = 0, \forall q$, i.e. no effects in the inefficiency model, then we get a specification similar to Lichtenberg and Siegel (1991).

The analysis of scale efficiency in the banking literature is not such a widespread task. Thus, objective of this article is to provide a framework under which we can determine whether a bank is operating at the optimal scale. Our effort is based on the combination of Ray's work (1999), where he provided a method of calculating the levels of output and input-oriented scale efficiency at any observed input bundle directly from an econometrically translog production frontier, i.e. within the parametric approach, and the work of Balk (2001), which is an extension of Ray's paper in a more general measure of scale efficiency, using an output distance function in the case of multiple-inputs and multiple-outputs firms.

Therefore, in this paper we establish an input-oriented framework for the computation of scale efficiency from the estimated parameters of the input distance function. An input- oriented measure of scale efficiency evaluates the productivity of an observed input-output bundle *(x_t,y_t)* relative to that of the technically optimal scale. This is equivalent with the ratio of a distance function associated with variable returns to scale (VRS) to a distance function associated with cone technology[1]. Using this definition and after a few manipulations we can specify a measure of scale efficiency in terms of the estimated parameters of the input distance function as follows:

$$\ln ISE_t = \frac{1}{2\beta}\left(\frac{1-E(x_t,y_t)}{E(x_t,y_t)}\right)^2 \qquad (7)$$

where $\beta = \sum_{j=1}^{3}\sum_{i=1}^{3} b_{ij}$ and $E(x_t,y_t) = -\left(\sum_{j=1}^{3}\frac{\partial \ln D_t^I(x_t,y_t)}{\partial \ln y_j}\right)^{-1}$ is the scale elasticity. Input-oriented scale efficiency measures the distance to optimal scale after moving a bank to the frontier by diminishing the use of inputs.

Since by definition $\ln ISE_t \le 0$ ($ISE_t \le 1$) it follows that *β<0*. Relationship (7) implies that scale efficiency of a particular input-output bundle can be computed from the value of the local scale elasticity pertaining to this bundle. The latter can be evaluated at any data point from the estimated parameters of the input distance function.

Another objective of this study is the examination of the impact of MBI governance structure on scale efficiency. In this view, we utilize the two-stage approach following an alternative methodology proposed by Reinhard et al. (2002), where they have argued that it can consistently be applied to explain scale efficiency

[1] Associated with constant returns to scale.

differentials. Within this framework, we estimate a stochastic frontier regression model of the following formation using maximum likelihood techniques:

$$\ln ISE_{it} = \psi_0 + \Omega_{ik} + \psi_1 t + \varepsilon_{it} \qquad (8)$$

where ψ_0 and ψ_1 are parameters to be estimated, $\varepsilon_{it} = v_{it}^* - u_{it}^*$ and the following distributional assumptions:

$v_{it}^* \sim i.i.d.N(0, \sigma_{v*}^2)$ and

$u_{it}^* \sim i.i.d.N^+(\psi_0 + \sum \xi_h mbi_{ih} + \psi_1 t, \sigma_{u*}^2)$

It should be noted that we utilize the same time interval dummy Ω_{ik} and time trend as in technical inefficiency effects model in order to examine whether these variables affect scale and technical efficiency with a similar pattern.

Finally, the proposed nested model, the model specification of Lichtenberg and Siegel (1991) – Model 1 and the model specification of Amess (2003) – Model 2 are all estimated through a computer program named Frontier 4.1 developed by Coelli (1992). This program has been written to provide maximum likelihood estimates of the parameters of stochastic frontier production and cost functions. The assumption of asymmetric effect of MBIs is tested using LR-statistic for all three models, i.e. the range of the dummies used is defined by comparing the log-likelihood function value of each regression, and then choosing the specification that fits better in the data in terms of the log-likelihood and the statistical significance of the regressors utilized. The second stage model estimation makes use of scale efficiency scores calculated from the three different models using maximum likelihood and random effects (GLS) techniques for comparison[2].

[2] The two-stage approach is usually carried out using either OLS or Tobit techniques.

4. EMPIRICAL RESULTS

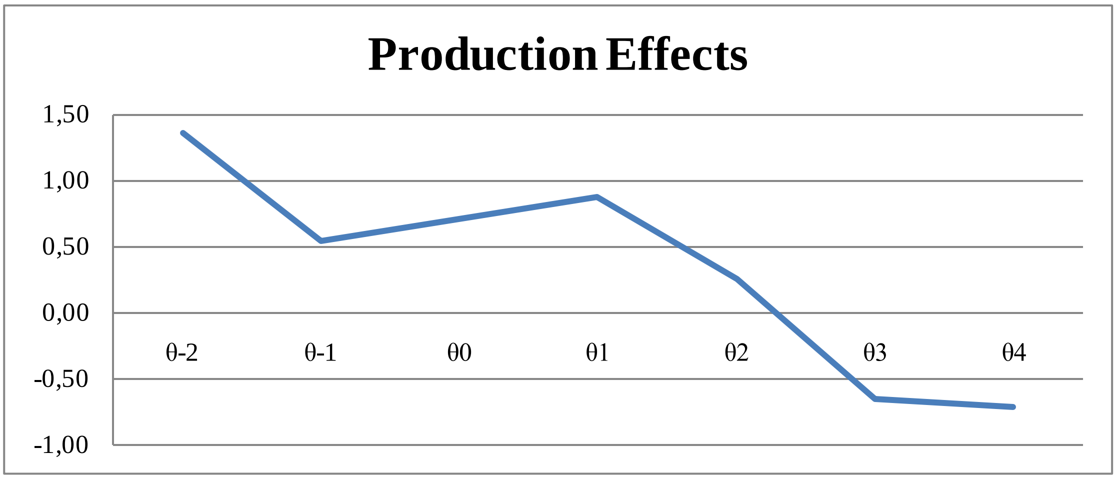
The maximum likelihood parameter estimates of the translog input distance function are presented in Table 3. At the point of approximation, all three models appear to be nonincreasing in outputs and nondecreasing in inputs, implying that our models fit good in the data as far as monotonicity of the distance function is concerned. In order to test which model fits better in the data we use LR-statistic that under the null hypothesis is distributed as a chi-square distribution. The results are presented in table 4. The null hypothesis of the restricted model 1, with the MBI dummies included only in the production function, against the alternative nested model is rejected at 5% level of significance, and the same result stands for the comparison of model 2, where the MBI dummies are included only in the technical inefficiency effects model, with the nested model. Thus, we can conclude that the nested model we propose seems to operate better than the other two models which already exist in the literature. Also, the Hessian matrix of the first and second-order partial derivatives of the nested model with respect to inputs is found to be negative definite and the corresponding Hessian matrix with respect to outputs to be positive definite. These indicate respectively the concavity and convexity of the underlying input distance function with respect to inputs and outputs. Furthermore, most of θ parameters appear to be statistically significant (nested model) leading us to conclude that the MBIs affect output directly. In figure 1, the first graph presents the coefficients of mbi_{ik} dummies that affect production. We observe that for a period starting two years pre-MBI until two years after the MBI we have positive effect on the distance function, but this effect is gradually decreasing and eventually becomes negative three years after the transaction. This result indicates that the banks produce closer to the frontier after a five year transition period.

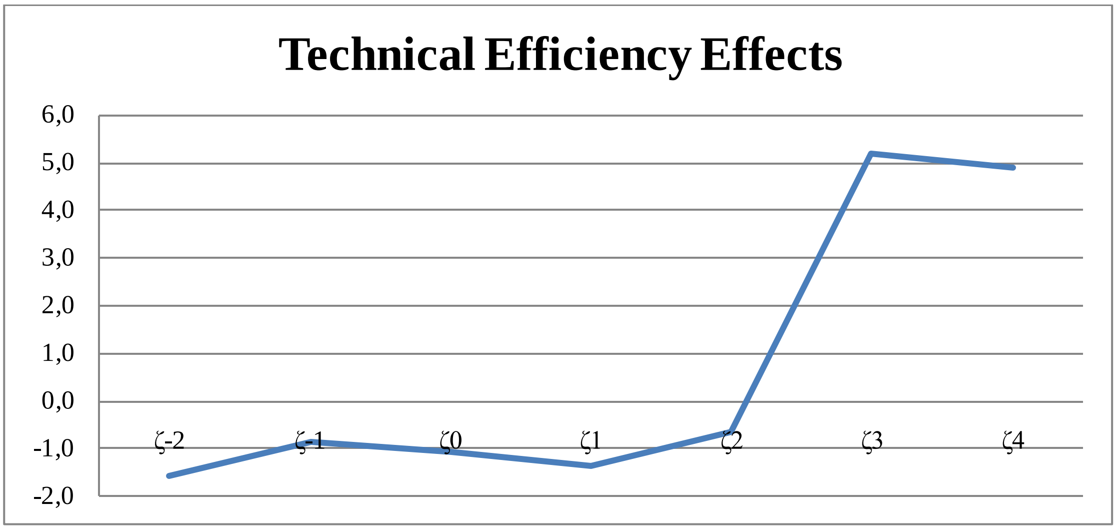
Table 3. Parameter Estimates of the Translog Input Distance Function and Inefficiency Effects Model

	Model 1		**Model 2**		**Nested Model**	
	parameter estimates	t-statistics	parameter estimates	t-statistics	parameter estimates	t-statistics
b_0	0.413*	5.03	0.435*	5.39	0.731*	5.61
γ_1	0.471*	5.47	0.444*	5.08	0.401*	4.39
b_1	-0.295*	-3.56	-0.308*	-3.83	-0.336*	-4.06
b_2	-0.040	-0.73	-0.035	-0.63	-0.072	-1.28
b_3	-0.760*	-12.65	-0.749*	-11.83	-0.694*	-11.97
γ_{11}	-0.023	-1.07	-0.017	-0.80	-0.013	-0.61
b_{11}	0.009	1.23	0.008	1.08	0.005	0.63
b_{22}	0.064*	4.98	0.061*	4.74	0.063*	4.81
b_{33}	-0.018*	-3.66	-0.018*	-3.58	-0.013*	-2.73
b_{12}	-0.031*	-2.49	-0.028*	-2.33	-0.030*	-2.49
b_{13}	-0.007	-0.98	-0.008	-1.17	-0.003	-0.45
b_{23}	-0.051*	-3.85	-0.048*	-3.58	-0.056*	-4.08
δ_{11}	0.059*	2.46	0.057*	2.33	0.062*	2.60
δ_{12}	-0.011	-0.52	-0.005	-0.22	0.003	0.14
δ_{13}	0.006	0.27	-0.001	-0.03	-0.016	-0.69
ε_1	0.002	0.16	0.006	0.62	0.001	0.14
φ_1	0.006	0.70	0.004	0.49	0.003	0.38
φ_2	-0.010	-1.10	-0.011	-1.19	-0.023*	-2.44
φ_3	0.006	0.81	0.007	0.97	0.011	1.59
η_1	0.044**	2.26	0.037**	1.91	-0.030	-1.13
η_2	0.016*	3.39	0.015*	3.27	0.017*	3.76
θ_{-3}	0.219	1.34				
θ_{-2}	0.228	1.44			1.359*	2.79
θ_{-1}	0.136	0.97			0.548***	1.79
θ_0	0.138	1.00			0.712*	2.70
θ_1	0.037	0.25			0.883*	2.55
θ_2	-0.097	-0.46			0.252	0.76
θ_3	-0.114	-0.40			-0.652*	-2.64
θ_4					-0.718*	-2.87
δ_0	-24.032	-0.94	-5.291	-1.58	1.030*	3.03
λ_1	0.224	1.60	-0.009	-0.17	-0.125*	-2.46
ζ_{-3}			-6.456***	-1.67		
ζ_{-2}			0.070	0.09	1.556*	2.66
ζ_{-1}			0.987	1.14	0.861	1.55
ζ_0			0.405	0.43	1.077**	2.06
ζ_1			0.164	0.27	1.347*	2.61
ζ_2			-1.920	-1.15	0.627	0.73
ζ_3			-6.154**	-1.99	-5.206**	-2.25
ζ_4					-4.901**	-2.23
σ^2	8.589	1.00	2.217**	2.06	0.443*	5.44
γ	0.984*	56.94	0.930*	25.71	0.893*	11.63
LL		-225.55		-227.45		-218.32

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

Figure 1. Graph of the Coefficients on the MBIs Dymmies in the Production Function and Technical Efficiency Equation





Aiming at the validation of the empirical results we examine several statistical hypotheses, concerning only the nested model, to specify the appropriate representation. The first test is based on the idea of whether the nested model can be reduced to Aigner et al. (1977) formulation. The null hypothesis is rejected at 5%, implying that the technical inefficiency effects do not follow a half normal distribution. Second, the null hypothesis is Stevenson's (1980) specification where the technical inefficiency effects have the same truncated normal distribution with mean equal to λ_0. This null is rejected at 5% meaning that we cannot use Stevenson's formulation. The third test presented in table 4 examines whether the distance function is characterized by constant returns to scale. In that case, scale inefficiency could not be a source of deviation from the technically maximum level of output. The null hypothesis of CRS is rejected at 5% level of significance, implying that there exists scale inefficiency. Finally, the last hypothesis of time-invariant technical efficiency (i.e. $\lambda_1=0$) is also rejected at 5% level of significance indicating that significant differences in the degree of technical efficiency occurred during the period 1998-2007.

Table 4. Hypotheses testing for model representation

		LR	Degrees of Freedom	Critical Value a=0.05
Model 1 vs Nested Model		14.46	7	14.07
Model 2 vs Nested Model		18.26	7	14.07
No technical efficiency	H_0:$\gamma=\lambda_0=\zeta_{-2}=\ldots=\zeta_4=0$	29.15	10	17.67*
Aigner et al. formulation	H_0: $\lambda_0=\zeta_{-2}=\ldots=\zeta_4=0$	21.44	9	16.92
Stevenson's specification	H_0: $\zeta_{-2}=\ldots=\zeta_4=0$	15.63	8	15.51
CRS		195.31	7	14.07
Time invariant technical efficiency		4.48	1	3.84

Note: an aterisk * indicates critical values obtained from Kodde and Palm (1986).

The estimated variance of the one-sided error term is $\sigma_u^2=0.396$ and that of the statistical noise is $\sigma_v^2=0.047$. The statistical significance of σ_u^2 is a signal of the presence of technical inefficiency. Thus, output variability is partly due to differences in technical efficiency. The likelihood-ratio test of the one-sided error has a value of 29.15 which is bigger than the upper five per cent value of 17.67 of the truncated-normal distribution (under the null the LR-test is asymptotically distributed as a mixture of chi-square distributions, Kodde and Palm, 1986). The null hypothesis that there are no technical inefficiency effects in the model is rejected (table 4) at 5%, implying that banks in our sample are operating below the frontier due to technical inefficiency.

Technical inefficiency estimates are also included in table 3 and the estimated coefficients are presented graphically[3]. A crucial outcome is that the impact of the buyin on technical efficiency is identical with the effect on the production frontier.

[3] The coefficients in the graph have the opposite of the estimated signs, and thus they show the impact on efficiency.

Our results indicate that for a period of five years, which spans between two years prior to the year the MBI occurred and two post-MBI years, there have been negative effects on efficiency. The result concerning the pre-MBI period confirm previous findings by Harris, Siegel and Wright (2005) which also found that firms involved in MBIs were less productive than others before experiencing a buyin but they do not cope with Amess (2003) findings. Concerning now the post-MBI we find out that there was lead period before the positive performance effect of MBIs has been realized. This period was estimated on average to be two years. During this period, MBIs banks exhibited lower efficiency than non-MBI banks.

On the other hand, post-buyout technical efficiency is higher for MBI firms 3 years after the transaction. According to Lichtenberg and Siegel (1990), after an MBI, resources that were used for intangible investment are shifted to the production of current output. This results in a short-run improvement in efficiency with however a subsequent decline some years later due to a gradual decline in intangible capital stock. In addition, an MBI and its organizational changes create a shock-therapy initially leading to efficiency improvements that tend to disappear in later years as managers and workers become accustomed to the new structure.

Frequency distributions of technical and scale efficiency as well as their mean values are presented in table 5 for the nested model. The degree of technical efficiency is quite close to that of scale, but it is obvious that the distribution of the scores is different. Scale scores have bigger variation than the scores of technical efficiency. Specifically, many banks operate below 40% and above 90% (very close to unity) while mean scale efficiency increased by 13% in the period under consideration, with a mean value of 46.4%.

Table 5. Distribution of technical and scale efficiency scores

Technical efficiency	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
0-0.1	1	1	1	1	0	0	2	0	0	0
0.1-0.2	0	0	2	2	1	3	3	3	2	2
0.2-0.3	6	7	2	1	2	2	2	4	6	3
0.3-0.4	4	5	4	5	5	6	6	3	1	3
0.4-0.5	4	3	2	5	3	3	3	2	7	2
0.5-0.6	1	2	6	7	8	9	6	8	3	2
0.6-0.7	2	2	2	2	4	0	3	7	6	4
0.7-0.8	0	0	2	3	5	5	7	4	7	7
0.8-0.9	2	2	2	0	3	4	5	7	8	7
0.9-1.0	0	0	0	1	1	2	2	2	2	0
Mean	0.416	0.416	0.483	0.477	0.564	0.542	0.540	0.583	0.583	0.593

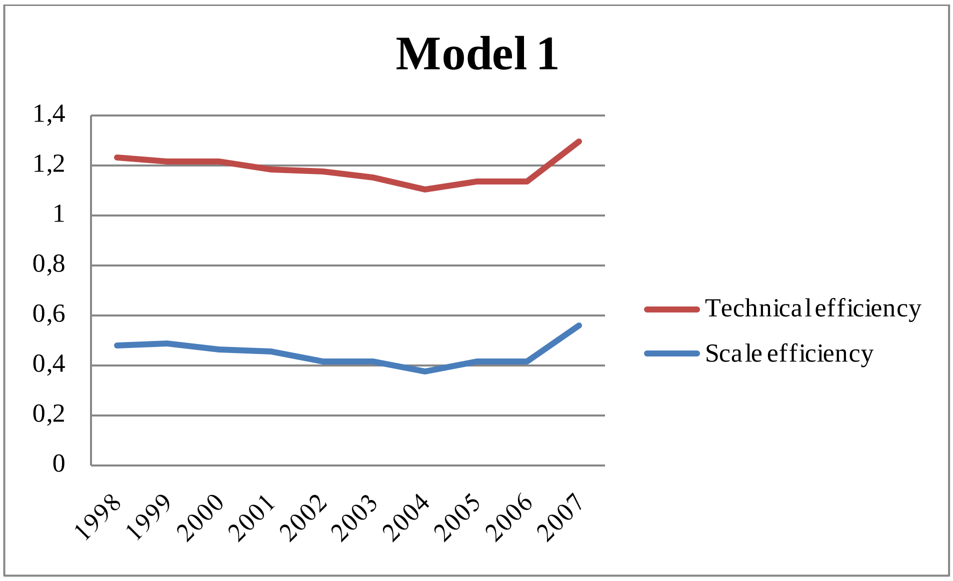
Scale efficiency	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
0-0.1	6	6	7	7	10	11	15	14	12	5
0.1-0.2	0	1	1	1	1	1	2	2	4	2
0.2-0.3	2	0	0	2	3	4	3	2	1	2
0.3-0.4	1	4	4	3	2	3	2	4	5	1
0.4-0.5	2	1	1	1	3	0	2	0	2	1
0.5-0.6	2	0	0	3	2	2	0	2	1	2
0.6-0.7	0	2	1	2	1	2	2	1	1	2
0.7-0.8	2	2	4	1	2	3	2	3	3	2
0.8-0.9	1	0	1	3	3	3	5	6	5	7
0.9-1.0	4	6	4	4	5	5	6	6	8	6
Mean	0.463	0.485	0.469	0.471	0.430	0.432	0.401	0.441	0.454	0.597

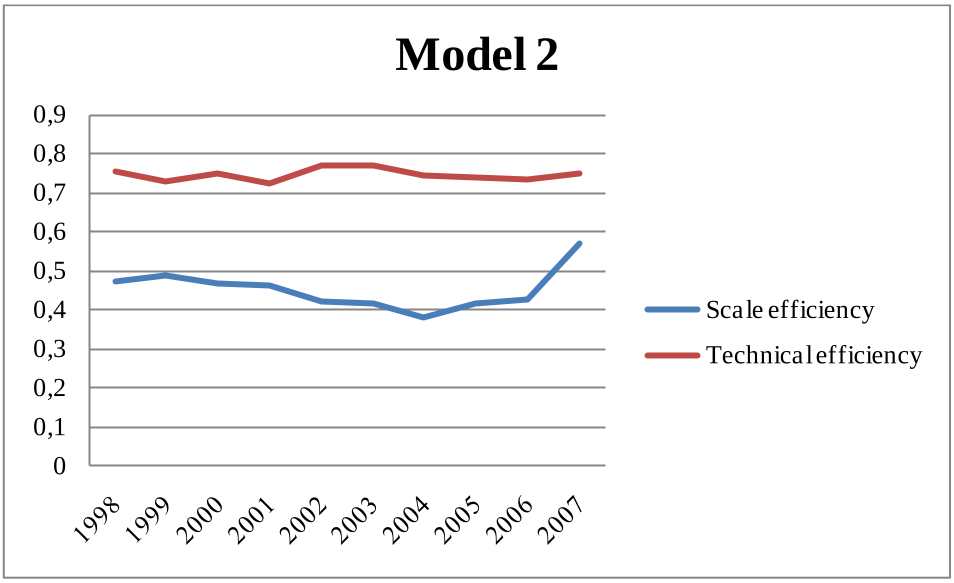
The estimated mean technical efficiency is 52% during the period 1998-2007. Thus, on average, a 48% decrease in total cost could have been achieved during this period, without altering the total volume of outputs, production technology and input usage. Approximately 6 out of 10 banks in the sample have consistently achieved scores of technical efficiency greater than 50% (table 5). This means that the portion of banks facing significant technical inefficiency problems has been decreased. Specifically, mean technical efficiency increased from 41.6% in 1998 to 59.3% in 2007 implying that the contribution of technical efficiency to output growth would be positive.

In figure 2, we present graphs of the mean technical (TE) and scale efficiency (SE) for the three estimated models. It is obvious that in the first two models TE is quite higher than SE throughout the period we examine. On the contrary, results for the nested model are completely different. In particular, since 2001 SE is greater than TE, from 2002-2006 TE is higher than SE and for the last year of the analysis the two measures of efficiency coincide. Although the temporal evolution of both performance indicators follows an increasing tendency, this trend has different variability patterns.

As far as the relationship between scale elasticity and scale efficiency is concerned, it can be seen from table 6 that the vast majority of banks exhibit increasing returns to scale (IRS), which means that their output levels were relatively low and should have been expanded to reach the optimal scale. Constant returns to scale are associated with scale efficiency equal to one and decreasing returns to scale with higher values of scale efficiency relative to the scores of IRS banks. Table 6 reveals some features characterizing the performance of Greek banks. First, we observe an increasing tendency of 14% of the scale efficiency scores associated with IRS. Second, banks with CRS have on average lower technical efficiency scores than banks with DRS and IRS. Third, technical efficiency of banks under the cone technology has improved eventually from 44% to 73%.

Figure 2. Mean Technical and Scale Efficiency from the three different models





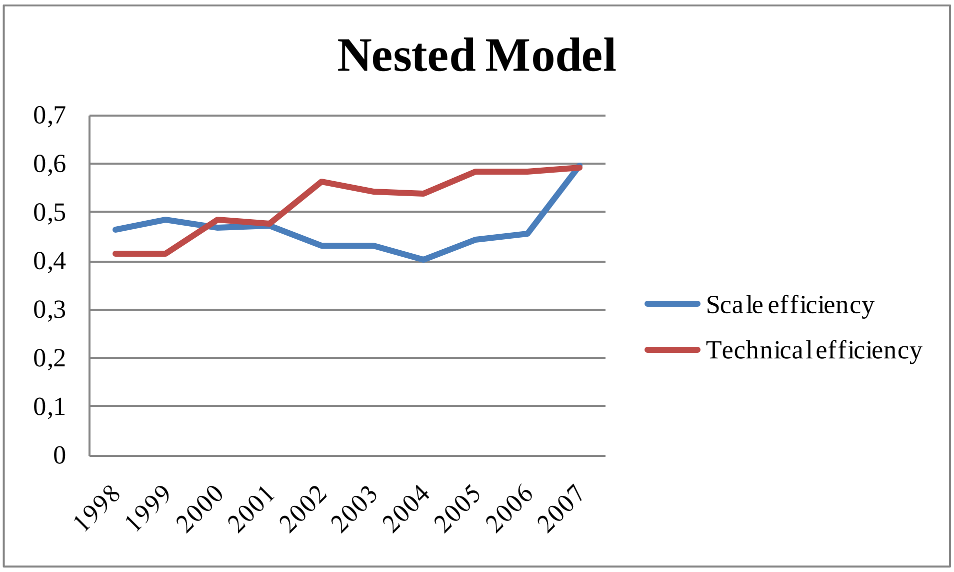


Table 6. Scale and efficiency scores

		Nested Model		
		# of Banks	TE	SE
1998	DRS	5	0.5	0.58
	CRS	1	0.44	0.99
	IRS	14	0.38	0.38
		# of Banks	TE	SE
1999	DRS	6	0.42	0.64
	CRS	2	0.40	0.99
	IRS	14	0.42	0.35
		# of Banks	TE	SE
2000	DRS	6	0.4	0.6
	CRS	2	0.27	0.99
	IRS	15	0.54	0.35
		# of Banks	TE	SE
2001	DRS	8	0.45	0.56
	CRS	1	0.37	0.99
	IRS	18	0.49	0.4
		# of Banks	TE	SE
2002	DRS	7	0.53	0.65
	CRS	1	0.33	0.99
	IRS	24	0.58	0.34
		# of Banks	TE	SE
2003	DRS	11	0.52	0.43
	CRS	1	0.21	0.99
	IRS	22	0.57	0.41
		# of Banks	TE	SE
2004	DRS	13	0.6	0.36
	CRS	1	0.11	0.99
	IRS	25	0.4	0.53
		# of Banks	TE	SE
2005	DRS	15	0.55	0.43
	CRS	1	0.77	0.98
	IRS	24	0.59	0.43
		# of Banks	TE	SE
2006	DRS	13	0.6	0.48
	CRS	2	0.86	0.99
	IRS	27	0.55	0.4
		# of Banks	TE	SE
2007	DRS	10	0.66	0.68
	CRS	1	0.73	0.99
	IRS	19	0.55	0.52

Finally, empirical results concerning the determinants of scale efficiency among banks are reported in table 7. The appropriateness of the frontier specification (8) is tested by computing the skewness of the OLS residuals. The $\sqrt{b_1}$ statistic (Schmidt and Lin, 1984) is -0.141 indicating that the residuals exhibit the expected negative skewness, and that a stochastic frontier model is appropriate. The first two columns of each model give the results of maximum likelihood using Frontier 4.1. In particular, MBIs do not affect scale efficiency (the estimated parameters are not statistically significant) while they influence technical efficiency. The time trend is significant with positive sign, implying that time affects positively scale efficiency; this result is depicted from the increase in mean scale efficiency reported in figure 2. The relatively large estimated value of $\gamma = \sigma_u^2 \big/ (\sigma_v^2 + \sigma_u^2)$ indicates that almost the entire error in the second stage is due to unexplained, by the explanatory variables, scale inefficiency. Thus, the role of statistical noise in explaining scale efficiency scores is very small. The other two columns show the random effects estimated parameters. Again, mbi_{ik} dummies have small t-statistics and thus they are statistically insignificant, and we observe that scale efficiency exhibits significant increasing tendency over time ($\psi_1 > 0$). It is straightforward that the two methods give the same results for all three models, something that do not cope with the results of Reinhard et al. (2002).

Table 7. Determinants of scale efficiency under the two alternative approaches.

	Model 1				Model 2				Nested Model			
	MLE		**Random effects**		**MLE**		**Random effects**		**MLE**		**Random effects**	
	parameter estimates	t-statistics	parameter estimates	t-statistics	parameter estimates	t-statistics	parameter estimates	t-statistics	parameter estimates	t-statistics	parameter estimates	t-statistics
ψ_0	-0.22	-1.27	-2.93*	-7.15	-0.26	-1.59	-2.84*	-7.21	-0.426*	-2.54	-2.862*	-7.57
ξ_{-2}	0.03	0.11	0.05	0.16	0.03	0.12	0.07	0.22	0.084	0.29	0.113	0.37
ξ_{-1}	0.07	0.26	0.09	0.32	0.07	0.25	0.10	0.35	0.120	0.45	0.155	0.54
ξ_0	0.25	0.94	0.28	0.95	0.24	0.93	0.28	1.00	0.253	0.93	0.301	1.07
ξ_1	0.37	1.33	0.40	1.32	0.35	1.35	0.39	1.35	0.352	1.28	0.401	1.37
ξ_2	0.06	0.16	0.06	0.15	0.04	0.11	0.07	0.18	0.032	0.08	0.051	0.12
ξ_3	0.20	0.43	0.16	0.28	0.13	0.25	0.15	0.27	0.108	0.21	0.110	0.20
ξ_4	0.07	0.13	0.05	0.09	0.00	0.01	0.04	0.07	-0.008	-0.02	-0.024	-0.04
ψ_1	0.06*	2.68	0.06*	2.57	0.06*	3.04	0.06*	2.83	0.088*	4.26	0.088*	4.05
σ^2	56.05*	3.48			52.21*	2.75			45.786*	2.53		
γ	0.99*	203.19			0.99*	168.44			0.984*	116.97		
μ	-14.87*	-3.15			-14.35*	-2.47			-13.426*	-2.12		
			F-stat	1.54			F-stat	1.80**			F-stat	3.16*
LL		-476.17	Prob(F-stat)	0.14	*LL*	-463.19	Prob(F-stat)	0.08	*LL*	-460.93	Prob(F-stat)	0.002

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

5. CONCLUDING REMARKS

This paper combines the work of Lichtenberg and Siegel (1990) and Harris, Siegel and Wright (2005) and Amess (2003) in order to establish a methodology to investigate the impact of management buy-ins (MBIs) on production and technical efficiency of 42 banks in the Greek banking sector during the period 1998-2007.

The nested model we propose seems to operate better than the other two models which already exist in the literature. The crucial outcome of our study is that MBI factors affect in the same way both the production function and technical efficiency, while they do not affect scale efficiency. In particular, we find a lead period of five years before the positive effect of MBIs is observed. Furthermore, mean technical efficiency increased from 41.6% to 59.3% and mean scale efficiency increased from 46.3% to 59.7% during the period under consideration. Finally, the vast majority of banks exhibit increasing returns to scale (IRS), which means that their output levels were relatively low and should have been expanded to reach the optimal scale.

References

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.

Amel, D., Barnes, C., Panetta, F. and Saleo C. "Consolidation and efficiency in the financial sector: A review of the international evidence." *Journal of Banking and Finance*, 2004, 28, 2493-2519.

Amess, K. "The effect of management buyouts on firm-level technical inefficiency: Evidence from a panel of UK machinery and equipment manufacturers." *Journal of Industrial Economics,* 2003, 1, 35-44.

Amess, K. "Management buyouts and firm-level productivity: Evidence from a panel of UK manufacturing firms." *Scottish Journal of Political Economy,* 2002, 49, 304-317.

Balk, B.M. "Scale efficiency and productivity change." *Journal of Productivity Analysis*, 2001, 15, 159–183.

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. "A computer program for frontier production function estimation: Frontier version 2.0." *Economics Letters,* 1992, 39, 29-32.

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. "A comparison of parametric and non-parametric distance functions: with application to European railways." *European Journal of Operational Research,* 1999, 117, 326-339.

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.

Hancock, D. “A theory of production for the financial firm: Innovations in Financial Markets and Institutions.” *Massachusetts: Kluwer Academic Publishers,* 1991.

Harris, R., Siegel, D.S., and Wright, M. “Assessing the impact of management buyouts on economic efficiency: Plant-level evidence from the United Kingdom.” *Review of Economics and Statistics,* 2005, 87(1), 148-153.

Jensen, M.C. “Eclipse of the public corporation.” *Harvard Business Review,* 1989, 5, 1-75.

Karagiannis, G. and Sarris, A. “Measuring and explaining scale efficiency with the parametric approach: The case of Greek tobacco growers.” *Agricultural Economics,* 2005, 33, 441-451.

Pantzios, C., Karagiannis, G. and Tzouvelekas, V. “Parametric decomposition of the input-oriented Malmquist productivity index: With an application to Greek aquaculture.” *Working Paper.*

Kodde, D. A., Palm, F. C. “Wald criteria for jointly testing equality and inequality restrictions.” *Econometrica,* 1986, 54, 1243–1248.

Lichtenberg, F.R., and Siegel, D. “The effect of leveraged buyouts on productivity and related aspects of firm behavior.” *Journal of Financial Economics,* 1990, 27, 165-194.

Lichtenberg, F.R., and Siegel, D. “Productivity and changes in ownership of manufacturing plants.” *Brookings Papers on Economic Activity,* 1987, 643-683.

Noulas, A. “Profitability and efficiency of the Greek banks (1993-1998).” *Issue of the Union of Greek Banks,* 1999, 4, 53-60.

Rappaport, A. “The staying power of the public corporation.” *Harvard Business Review,* 1990, 1, 96-104.

Ray, S. C., “Measuring scale efficiency from a translog production function.” *Journal of Productivity Analysis,* 1998, 11, 183–194.

Reinhard, S., Lovell, C. A. K., Thijssen, G. J. "Analysis of environmental efficiency variation." *American Journal of Agricultural Economics,* 2002, 84, 1054–1065.

Rezitis, A.N. "Efficiency and productivity effects of banks mergers: Evidence from the Greek banking industry." *Economic Modelling,* 2008, 25, 236-254.

Schmidt, P., Lin, T. F. "Simple tests of alternative specifications in stochastic frontier models." *Journal of Econometrics,* 1984, 24, 349–361.

Siegel, D.S., Simons, K.L. and Lindstrom, T. "Ownership change, productivity, and human capital: New evidence from matched employer – employee data", in Dunne, T., Jensen, J.B., and M.J. Roberts (eds) "Producer Dynamics: New Evidence from Micro-Data", *NBER SIW No 68, University of Chicago Press*, 2009, ch.11, 397-442.

Staikouras, C., and Steliarou, M. "Determinants of profitability for the Greek banking institutes." *Issue of the Union of Greek Banks*, 1999, 61-66.

Stevenson, R. E. "Likelihood functions for generalised stochastic frontier estimation." *Journal of Econometrics,* 1980, 13, 58–66.