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Evaluating cost and profit efficiency: A comparison of parametric and non-parametric methodologies

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Abstract
This paper's objective is twofold. First it provides an empirical assessment of the cost and profit stochastic frontiers based on a panel dataset of Greek commercial banks over the 1993-2005 period. Second, on the basis of the same sample, it also compares the most widely used parametric and non-parametric techniques to cost efficiency measurement, namely the Stochastic Frontier Approach and Data Envelopment Analysis. The results suggest greater similarities between the predictions of cost and profit efficiency methods than between parametric and non-parametric techniques. Such evidence is new in the literature and calls for a more technically level playing field for estimating bank efficiency.

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1. Introduction

The investigation of bank efficiency has fuelled a large body of literature globally, and is of vital importance from both a microeconomic and a macroeconomic point of view (Berger and Mester, 1997). From the micro perspective this issue is crucial given the enhancement of competition, and the improvements in the institutional, regulatory and supervisory framework. From the macro perspective, the efficiency of the banking industry influences the cost of financial intermediation, and the overall stability of financial markets. Indeed, an improvement in bank performance indicates a better allocation of financial resources, and therefore an increase in investment that favors growth.

While a thorough search of the literature would reveal hundreds of studies quantifying the efficiency of financial institutions, there have been surprisingly few attempts to compare cost and profit efficiency measures, and even fewer to evaluate the alternative techniques of efficiency measurement. Regarding the former issue, and as previous efficiency studies stress out, a bank may pursue many goals. However, profit efficiency is naturally its ultimate goal, while cost efficiency is an important means of reaching long-run profit efficiency. Yet, Berger and Mester (1997) showed that profit efficiency may not be positively correlated with cost efficiency, suggesting that the measure of profit efficiency may include output features that reflect higher quality or greater market power in pricing. Differently phrased, an estimated cost function may incorporate much different information than a respective cost part of the estimated profit equation.

Concerning the latter issue, the efficiency measurement techniques are based on either parametric or non-parametric frontiers. The parametric methods involve the estimation of an economic function (e.g., production, cost or profit) and the derivation of efficiency scores from either the residuals or dummy variables. In contrast, the non-parametric methods involve solving linear programs, in which an objective function envelops the observed data; then efficiency scores are derived by measuring how far an observation is positioned from the "envelope" or frontier.

Given the above, the aim of this study is twofold. First, it evaluates, in terms of a stochastic frontier approach, both the cost and profit efficiency of the banking system of a medium-sized country like Greece, over the period 1993-2005. Naturally, a comparison of the two methods follows. In addition, this paper proposes an examination of the effect of certain inter-industry factors (such as bank size and ownership status) on efficiency that may suggest differences in the predictions provided by the two schemes. The conclusions drawn could *inter alia* prove useful for the comparison of the cost and profit structures of the banking sectors of other medium-sized economies that currently undergo structural changes in the direction of mergers and acquisitions (M&As) and privatizations.

Second, this study adds to the limited literature that compares the cost efficiency results derived from the two most widely used approaches to bank efficiency measurement, namely the stochastic frontier approach (SFA), a parametric method, and data envelopment analysis (DEA), a non-parametric method. The rationale for using two different methods is well described by Berger and Humphrey (1997), who suggest that policy and research issues that rely upon firm-level efficiency estimates may be more convincingly addressed if more than one frontier technique is applied to the same set of data to demonstrate the robustness of the explanatory results obtained. In other words, while each of the two approaches nurtures its own theoretical discourse, they should not be viewed as mutually exclusive but, more eclectically, as complementary methods.

The rest of the study is organized as follows. Section 2 offers a background of the efficiency measurement concepts and Section 3 outlines the methodologies to be used. Section 4 presents some stylized facts about the Greek banking system and describes the dataset. Section 5 presents the empirical results and compares them on the basis of the various methodologies used. Finally, Section 6 concludes.

2. Efficiency measurement concepts

Our focus in this article is on frontier efficiency (also called X-efficiency in the economic literature), in other words on the distance (in terms of production, cost, revenue or profit) of a Decision Making Unit (DMU) from the best-practice equivalent. This is given by a scalar measure ranging between zero (the lowest efficiency measure) and one (corresponding to the optimum DMU). Farrel (1957), suggested that the efficiency of a DMU consists of two components: technical efficiency, which reflects the ability of a

DMU to maximize output given a set of inputs, and allocative efficiency, which reflects the ability of a DMU to use the given set of inputs in optimal proportions, assuming input prices and technology are known. In this context, the product of technical and allocative efficiency provides a measure of overall economic efficiency.[1] The focus of this article is on technical efficiency, hereafter plainly referred to as efficiency.[2, 3] The literature on the measurement of efficiency is divided into two major approaches that use either parametric or non-parametric frontiers. To serve our purpose we refer to the various techniques used to measure efficiency by indicating only the main lines of methodology.

In the parametric frontier analysis the technology of a DMU is specified by a particular functional form for the cost, profit or production relationship that links the DMU's output to input factors. The most widely applied technique is the stochastic frontier approach (SFA). Under the SFA, the error term is split into two components, allowing for both random effects and X-inefficiencies, where the random effects usually follow a normal distribution and the inefficiencies a truncated normal distribution.[4] An important drawback of the parametric approaches is that they impose a particular functional form (and hence all its associated behavioral assumptions), which predetermines the shape of the frontier. If the functional form is misspecified, the estimated efficiency may be confounded with significant bias. Popular functional forms include the Cobb-Douglas and the translog specifications, each having their own advantages and disadvantages (for a discussion see Coelli et al., 2005).

The nonparametric approaches to efficiency measurement include the Data Envelopment Analysis (DEA) and the Free Disposal Hull (FDH). DEA is a programming technique that provides a linear piecewise frontier by enveloping the observed data

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[1] For more technical definitions of these concepts see Kumbhakar and Lovell (2000).

[2] It is certainly erroneous to refer to technical efficiency simply as efficiency. However, we follow the majority of the literature that clearly does so to ease the discussion.

[3] Estimation of allocative efficiency is relatively easy under a non-parametric approach but is notoriously difficult under a parametric approach due to the problem referred in the literature as the 'Greene problem'. A solution to this problem is offered by Kumbhakar and Tsionas (2005) and Brissimis et al. (2006), however such an analysis is beyond the scope of the present study.

[4] The distribution-free approach (DFA) makes no assumptions about the distribution of the x-inefficiency and the idiosyncratic error terms, since it treats DMU-level efficiency as a time constant. The thick-frontier approach (TFA) provides a general level of overall efficiency, not specific to each DMU. It calculates two frontiers, one for the quartile of DMUs with the lowest average performance and one for the quartile of DMUs with the highest average performance. Then, inefficiency is measured as the difference between the upper and the lower frontier. The x-inefficiency and the idiosyncratic error separation remains, yet no other distributional assumptions are made on the error terms (Berger and Humphrey, 1997).

points, yielding a convex production possibilities set. As such, it does not require the explicit specification of the functional form of the underlying production relationship. The Free Disposal Hull approach (FDH) is a special case of DEA, where, instead of convexity, free disposability of inputs and outputs is assumed. Because the FDH frontier is either congruent with or interior to the DEA frontier, FDH will typically generate larger estimates of average efficiency compared to DEA (Tulkens, 1993). Both approaches permit efficiency to vary over time and make no prior assumption regarding the form of the distribution of inefficiencies across observations (except that the best-practice firms are 100% efficient).

Even though they account for the main problem of the stochastic frontier methods, namely the arbitrary imposition of a specific functional form, the non-parametric methods have some pitfalls of their own. Most importantly they do not permit for random error and, as such, noise can cause severe problems in misleadingly shaping and positioning the frontier. Furthermore, tests of hypotheses regarding the existence of inefficiency and also regarding the structure of the production technology cannot be performed with DEA.[5]

A comparison between DEA and SFA in banking has been offered by Ferrier and Lovell (1990), Eisenbeis et al. (1997), Resti (1997), and Huang and Wang (2002). The first three studies reported fairly close average efficiencies generated by the two approaches, while the latter suggests that the congruency between the results of the two methodologies is rather limited.[6] Resti (1997) and Eisenbeis et al. (1997) found very high rank-order correlations between DEA and SFA, whereas Ferrier and Lovell (1990) found rank-order correlation of only 0.02 (not significantly different from zero). Also, in the most recent study, Huang and Wang (2002), using a panel of Taiwanese commercial banks, report that parametric and non-parametric methods are generally contradictory in ranking the sample banks based on their estimated efficiency scores. In contrast, Eisenbeis et al. (1997) found that while the calculated programming inefficiency scores derived from the DEA approach are two to three times larger than those estimated using a

[5] For a detailed discussion of the pros and cons of each methodology see Coelli et al. (2005).

[6] A potential problem is that the level of efficiency under DEA may be sensitive to "self-identifiers" when there are too few observations relative to the number of constraints in DEA. In particular, Ferrier and Lovell (1990) found that the average efficiency level rose from 54% to 83% when constraints on number of branches and firm size were added to the model.

stochastic frontier, the correlation of the rankings of banks based on their efficiencies under the two methods is also relatively high. The inconclusive evidence of these studies clearly calls for additional research on this issue.

Another fundamental decision in measuring efficiency is which concept to use, which, of course, depends on the question being addressed (Berger and Mester, 1997). There are three main economic efficiency concepts, namely cost, standard profit, and alternative profit efficiency, which are based on economic optimization in reaction to market prices and competition.[7] Cost efficiency gives a measure of how close a bank's cost is to what a best practice bank's cost would be for producing the same output bundle under the same conditions. It is derived from a cost function in which variable costs depend on the prices of variable inputs, the quantities of variable outputs and any fixed inputs or outputs. Similarly, standard profit efficiency measures how close a bank is to producing the maximum possible profit given a particular level of input and output prices (and maybe other variables as well). In contrast to the cost function, the standard profit function specifies variable profits in place of variable costs, and takes variable output prices as given, rather than holding all output quantities statistically fixed at their observed, possibly inefficient levels. That is, the profit dependent variable allows for the consideration of revenues that can be earned by varying outputs as well as inputs. Thus, profit efficiency accounts for errors on the output side as well as those on the input side, and as some prior evidence suggests, inefficiencies on the output side may be equally large or larger than those on the input side (e.g. Berger et al., 1993). Hence, standard profit efficiency may take better account of overall technical efficiency than the cost efficiency measure.

Alternative profit efficiency may be helpful when some of the assumptions underlying cost and standard profit efficiency are not met. Within this framework, efficiency is measured by how close a bank comes to earning maximum profits given its output level rather than its output prices. The alternative profit function employs the same dependent variable as the standard profit function and the same exogenous variables as the cost function. Thus, instead of counting deviations from optimal output as

[7] Here and up to the end of this section reference is made to the parametric methods of efficiency estimation. For a thorough review of these concepts and a much more detailed discussion see Berger and Humphrey (1997).

inefficiency, variable output is held constant (as in the cost function) while output prices are free to vary and affect profits. Also, the alternative profit function provides a way of controlling for unmeasured differences in output quality, since it considers the additional revenue that higher quality output can generate. Still, the alternative profit efficiency concept may be apt in situations in which the firms exercise some market power in setting output prices. Under conditions of market power, it may be appropriate to consider output levels as relatively fixed in the short run and allow for efficiency differences in the setting of prices and service quality. Finally, the measurement of alternative profit efficiency may also be motivated by inaccuracies in the output price data. If prices were inaccurately measured, the predicted part of the standard profit function would explain less of the variance of profits and yield more error.

To the best of our knowledge, only four studies analyze both profit and cost efficiency (Berger and Mester, 1997; Lozano, 1997; Rogers, 1998; Maudos et al., 2002) and not always to serve the purpose of result comparison. Consequently, the above discussion regarding the various efficiency concepts strongly motivates a comparison of the results obtained by the corresponding methodologies.

3. Methodology

To the extent that efficiency scores from various techniques contain different information, multiple sets of efficiency scores might be used as the basis for decision-making. The efficiency scores derived from different methods could be assigned different weights based on how much information they convey to the decision maker. This possibility is the central notion of the information principle. Bauer et al. (1998) suggest that it is not necessary to have a consensus on which is the single best frontier approach for measuring efficiency, for the estimated efficiencies to be useful for regulatory analysis. Instead, they propose a set of consistency conditions that the efficiency measures derived from the various approaches should meet, so as to be more useful for regulators and other decision makers. Thus, the efficiency estimates should be consistent (1) in their efficiency levels, (2) rankings, and (3) identification of best and worst firms. They should also be consistent (4) over time and (5) with competitive conditions in the market, and finally (6) consistent with standard non-frontier measures of performance. It could be argued that efficiency scores that satisfy these consistency conditions are more "informative" than those that do not. To examine these conditions we estimate the X-efficiencies of a sample of 28 Greek banks over the period 1993 to 2005, using two very different (but widely applied in banking) methodologies. The stochastic frontier approach (SFA) with a composed error term (Aigner et al., 1977) and a linear programming cost frontier (DEA based on Färe et al., 1985). The stochastic frontier technique is also extended to account for the cost and profit efficiency concepts, as discussed in the previous section. Note that the models' choice rests on the intention to compare the most widely applied techniques of efficiency measurement in banking, rather than identifying the more robust or the most up-to-date methodologies.

3.1 The Stochastic Frontier Approach (SFA)

In the banking sector, econometric measurement of inefficiency has been undertaken mainly through estimating a cost function. The implementation of the profit function approach is rather difficult (even though probably more appropriate as discussed above) due to chronic data problems, as the profit function requires price data for outputs, which is hard to construct in banking.

The SFA, as developed by Aigner et al. (1977) and applied to banking by Ferrier and Lovell (1990),[8] specifies a particular form for the cost (profit) function, usually a translog form, and allows for random error. It assumes that these errors consist of inefficiencies, which follow an asymmetric distribution (usually a truncated or half normal distribution), and random errors that follow a symmetric distribution (usually the standard normal distribution).[9] The reason for this particular structure of the composite error term is that, by definition, inefficiencies cannot be negative. Both the inefficiencies and random errors are assumed to be orthogonal to input prices, outputs and country-level or bank-specific variables specified in the estimating equation.

According to the SFA, total cost assumes the following specification:

$$TC_{it} = f(P_{it}, Y_{it}, Z_{it}) + v_{it} + u_{it} \tag{1}$$

[8] Recent econometric developments are summarized in Kumbhakar and Lovell (2000); Berger and Mester (1997) discuss applications to banking.
[9] The rationale for this is that inefficiency cannot lower cost and thus must have an asymmetric distribution, whereas random error can add or subtract cost and thus it can follow a symmetric distribution.

where *TC* denotes observed operating and financial cost for bank *i* at year *t*, *P* is a vector of input prices, *Y* is a vector of outputs of the bank, and *Z* stands for a set of control variables (fixed netputs). This approach disentangles the error term in two components. The first (v), corresponds to the random fluctuations, and is assumed to follow a symmetric normal distribution around the frontier, capturing all phenomena beyond the control of management. The second (u), accounts for bank's inefficiency and is assumed here to follow a truncated normal distribution.

The SFA to calculate cost efficiency is based on the following standard translog cost function[10]:

$$\begin{aligned}\ln TC = {} & \alpha_{i0} + \sum_i \alpha_i \ln P_i + \sum_i \beta_i \ln Y_i + \frac{1}{2}\sum_i \sum_j \alpha_{ij} \ln P_i \ln P_j + \frac{1}{2}\sum_i \sum_j \beta_{ij} \ln Y_i \ln Y_j \\ & + \frac{1}{2}\sum_i \sum_j \delta_{ij} \ln P_i \ln Y_j + \sum_i \phi_i \ln Z_i + \frac{1}{2}\sum_i \sum_j \phi_{ij} \ln Z_i \ln Z_j + \frac{1}{2}\sum_i \sum_j \eta_{ij} \ln Z_i \ln Y_j \qquad (2) \\ & + \frac{1}{2}\sum_i \lambda_{ij} \ln Z_i \ln P_j + \tau T + v_{it} + u_{it}\end{aligned}$$

where *T* is a time trend, included in the equation to control for the effects of technical progress on bank costs.[11] To ensure that the estimated cost frontier is well behaved, standard homogeneity and symmetry restrictions are imposed (see Kumbhakar and Lovell, 2000).

We also use an alternative profit function specification, where the dependent variable is given by $\ln(\pi+k+1)$, and k indicates the absolute value of the minimum value of profit (π) over all banks in the sample, and is added to every firm's dependent variable in the profit function. This transformation allows us to take the natural log of profits, given that profits can obtain negative values. Also, the composite error term is now defined as v_{it} - u_{it}.

The general procedure for estimating cost inefficiency from Equation (2) is to estimate equation coefficients and the error term $\varepsilon_{it} = u_{it} + v_{it}$ first, and then calculate

[10] We prefer the translog specification compared with the alternative Fourier-flexible functional form, since (*i*) most of the literature applies the translog and the purpose of this study is to compare widely used methods, and (*ii*) the Fourier requires additional truncations of data (Hasan and Marton, 2003). Moreover, Berger and Mester (1997) report that differences between the mean efficiency estimates of two procedures is very small.

[11] Because of sample size limitations, the time trend indicator *T* is not specified to interact with the outputs *Yi* and input prices *Pj* variables. Accordingly, only the impact of the neutral technical change on the cost function is considered in this paper, whereas the relevant impact, if any, of the non-neutral technical change is not identified.

efficiency for each observation in the sample. The cost frontier can be approximated by maximum likelihood, and efficiency levels are estimated using the regression errors. Jondrow et al. (1982), show that the variability, σ, can be used to measure a firm's mean efficiency, where $\sigma^2 = \sigma_u^2 + \sigma_v^2$. Bank-specific estimates of inefficiency terms can then be calculated by using the distribution of the inefficiency term conditional to the estimate of the composite error term.

3.2 Data Envelopment Analysis (DEA)

In their original paper, Charnes et al. (1978) proposed a model that had an input orientation and assumed constant returns to scale (CRS). The CRS assumption is only appropriate when all DMUs are operating at an optimal scale. However, factors like imperfect competition and constraints on finance may cause a DMU not to be operating at optimal scale. As a result, the use of the CRS specification may provide measures of technical efficiency, which are confounded by scale efficiencies. Therefore, the VRS specification (introduced by Banker et al., 1984) has been the most commonly used specification.[12]

In the input-orientated models, the DEA method seeks to identify technical inefficiency as a proportional reduction in input usage. It is also possible to measure technical inefficiency as a proportional increase in output production. These two measures provide the same value under CRS, but do not equate when VRS is assumed. The choice of orientation has both practical and theoretical implications. Many studies have tended to select input-orientated measures because the input quantities appear to be the primary decision variables, although this argument may not be valid in all industries. Other studies have pointed out that restricting attention to a particular orientation may neglect major sources of technical efficiency in the other direction (Berger et al., 1993). To date, the theoretical literature is inconclusive as to the best choice among the alternative orientations of measurement. In the present study, we evaluate cost inefficiency as a proportional reduction in input usage (input-orientation) following, once more, the majority of the literature.

[12] In applying DEA, we followed the standard procedures outlined in Fare et al. (1994). Variable returns to scale were permitted through use of a side summation restriction in the linear programming.

To this end, we use the following input-oriented DEA model:

$$\theta^* = \min \theta, \text{ subject to}$$

$$\begin{aligned}
&\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{ij} \qquad i = 1, 2, ..., m; \\
&\sum_{j=1}^{n} \lambda_i y_{rj} \ge y_{r0} \qquad r = 1, 2, ..., s; \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0 \qquad\qquad j = 1, 2, ..., n;
\end{aligned} \tag{3}$$

where DMU_0 represents one of the n DMUs under evaluation, and x_{io} and y_{ro} are the ith input and rth output for DMU_0, respectively. Since $\theta = 1$ is a feasible solution to (3), the optimal value to (3) is $\theta^* \le 1$. If $\theta^* = 1$, then the current input levels cannot be reduced (proportionally), indicating that DMU_0 is on the frontier. Otherwise, if $\theta^* < 1$, then DMU_0 is dominated by the frontier. Thus, θ^* represents the (input-oriented) efficiency score of DMU_0.

4. Greek commercial banks: Data and variables

The dataset comprises financial statements of all commercial banks operating in Greece during the 1993–2005 period. As new banks entered the market and a number of mergers and acquisitions took place, our sample has an uneven number of banks each year. After reviewing the data for reporting errors and other inconsistencies, we obtain an unbalanced panel consisting of 244 bank-level observations. Overall, our sample accounts for a significant proportion of total banking assets (around 80 per cent). [13]

The beginning of the examination period coincides with the acceleration of liberalization and deregulation of the Greek financial system, with the adoption of the Second Banking Directive, in view of the country joining the European Monetary Union (EMU). Indeed, the macroeconomic stabilization program, the liberalization of interest rate determination, the annulment of various credit rules, the release of capital

[13] According to the Greek law governing the operation of corporations, foreign banks' branches in Greece are not required to publish full-blown annual financial statements and thus are excluded from our sample. Moreover, specialized credit institutions are excluded from the analysis, as their operations differ substantially from those of commercial banks, while cooperative institutions are also excluded due to their small size and different legal form.

movements, the application in advanced information technologies, the internationalization of banking activities, the Euro circulation, and the phenomenon of disintermediation have triggered major structural changes in the Greek banking environment during the examined period, enhancing competition in both price and quality levels. Also, the examined period captures the new conditions that appeared in the banking industry in terms of organization, with banks moving towards the model of universal banking, with specialized subsidiaries providing the entire spectrum of financial services efficiently and flexibly, also taking advantage of the various synergies (Bank of Greece, 1999).

The environment that emerged since 1993 led to the establishment of new credit institutions, either domestic or branches of foreign banks[14]. In addition, in order to adjust to new conditions and cope with the intensified competition, both domestically and cross-border, several Greek banks involved into mergers and acquisitions since the mid 1990s, so as to become more efficient and obtain a size that would enable them to increase their market shares, facilitate their access to international financial markets and exploit any possible economies of scale (Kamberoglou et al., 2004). The observed wave of mergers and acquisitions, mostly between smaller banks (and also banks with non-banks), apart from the possible cost and efficiency gains was also motivated by the privatization process initiated by the government, in line with EU developments. Indeed, in the early 1990's, the state commercial banks controlled around 85 per cent of total commercial banking operations, while in the period 1995-2000, state-ownership fell by almost 20 percentage points, from 72.3% in 1995 to 52.9% in 2000 (Kamberoglou et al., 2004).

Mergers and acquisitions have resulted in higher concentration in the banking industry, as it is indicated by the rise in the market share of the top-5 banks, as a percentage of total assets, from 57% in 1995 to 65.6% in 2005. Although concentration in the Greek banking industry is much higher than the EU average, which stands at about 40.5 % (ECB, 2005), this does not necessarily imply low competition. As evidenced by the reduction in interest rate spreads, especially in the segments of consumer and housing loans, in the past few years, which can only partly be attributed to convergence to the

[14] Foreign presence was mainly concentrated in niche markets, specialized in areas such as shipping and corporate finance, private and personal banking, asset management, and capital market activities.

rates prevailing in the eurozone, competition has increased in the Greek banking system (Hondroyiannis et al. 1999).

The aforementioned developments of the Greek banking system have obviously affected the structure of banks' balance sheets and loss and profit accounts. Regarding banks' income structure, interest revenues constitute banks' main source of income, amounting to 75.3 % of total revenues in 2005, while, on the other hand, non-interest income is less that 16% of the total earnings (Bank of Greece, 2005). The efficiency levels of Greek banks, measured by simple accounting indicators, do not look fully adequate to international standards. In particular, the ratio of operating expenses to total assets stands at 2.1 percent in 2005, which is much higher than the average European figure. However, one can observe a clear downward trend in this ratio over the examined period, verifying the increasing efforts of Greek banks towards improving their efficiency by installing modern information technology systems, cutting their operating costs and improving their organizational structure, while they have extended their scope of business by offering new products and services.

(Please insert table 1 about here)

Table 1 describes the variables included in our models. For the definition of inputs and outputs, we adopt the intermediation approach proposed by Sealey and Lindley (1977).[15] Total cost is defined as the sum of overheads (personnel and administrative expenses), interest, fee, and commission expenses. In the case of the profit function, we employ profit before tax. We specify two outputs, loans and other earning assets. Labor and borrowed funds are the input variables, whereas costs associated with these inputs are personnel expenses and interest expenses on funds, respectively. The price of funds is computed by dividing total interest expenses by total interest bearing borrowed funds, while the price of labor is defined as the ratio of personnel expenses to total assets. We specify physical capital and equity as fixed netputs. The treatment of physical capital as a fixed input is relatively standard in efficiency estimation (Berger and Mester, 1997),

[15]A variety of approaches have been proposed in the literature, i.e. the production, the intermediation, the asset, the value-added and the user-cost approach. Yet, there is little agreement among economists on the explicit definition of banking outputs and inputs, mainly as a result of the nature and functions of financial intermediaries (Berger and Humphrey, 1991).

while the level of equity captures capitalization, insolvency risk and different risk preferences across banks.

5. Empirical results

5.1 Cost and profit efficiency based on the Stochastic Frontier Approach

Cost and alternative profit inefficiency scores are obtained from the estimation of cost and profit frontiers as described above. Note that we truncated the extreme values from the estimated inefficiencies, in order to avoid biases attributable to estimation errors (see Maudos et al., 2002). Overall, the results (Table 2) suggest modest levels of cost inefficiency in the Greek banking industry, with the average throughout the period being 0.164. However, Greek banks seem to be more efficient in controlling costs than in generating profits, as average profit inefficiency is much higher and stands at 0.553. This result could be partly justified by the existence of a fairly low level of intermediation depth compared with other EU countries. In addition, given the potential reward of expanding market shares, banks have little incentive to maximize profits by means of full utilization of their discretionary pricing power. Banks' efforts to expand their activities led to restraining many resources, a strategy that only partly paid off, which in turn left profit efficiency trailing behind cost efficiency. Moreover, as interest margins have been kept at relatively high levels, banks may have faced less pressure to further increase profitability shifting their attention to control costs. The bank ranking under the profit efficiency approach differs from the respective cost efficiency ranking, which may imply a quality effect in the provision of intermediation services (banks with relatively high cost inefficiency offer better service quality and, thus, are able to generate higher profits).

(Please insert table 2 about here)

To identify additional, inter-industry sources of inefficiency we look into the effect of bank size and ownership (private vs. public). As regards the effect of bank size, we divide banks into two different categories on the basis of the size of their balance sheet aggregates. In particular, we distinguish between the five larger and the remaining banks of our sample (a bank is classified as 'large' if it holds total assets above €20 million in 2005). The results (reported in Table 3) suggest that large-sized banks are slightly more cost efficient, obtaining an average inefficiency score of 0.153, compared to an average inefficiency score of 0.173 for the rest. However, this picture is reversed under the profit efficiency approach, since small and medium-sized banks appear to be slightly more profit efficient. An explanation for this finding (even though the overall effect is not particularly significant) is that small banks may find it easier to engage in relationship lending than large banks. Furthermore, small banks may undertake risky loans (with higher returns during certain periods such as the one examined), in contrast to large banks, which usually avoid undertaking this type of loans regardless of the economic coincidence.

(Please insert table 3 about here)

Table 3 also reports average cost and profit inefficiency scores for banks with different ownership status.[16] The results indicate that private banks are associated with slightly lower cost but higher profit efficiency. The relatively low cost efficiency of private banks certainly raises questions about the effectiveness of the initial liberalization policies. However, in the last few years, private banks' operating costs have been declining and are now at almost the same level as those of the state-owned banks. The significantly higher profit efficiency of private banks highlights the importance of the revenue side, and thus the possible superiority of profit efficiency techniques in line with the discussion in Section 2. This finding also suggests that the ownership status is less important for cost efficiency than for profit efficiency.

5.2 Cost efficiency based on parametric and non-parametric methods

Following the consistency conditions of Bauer et al. (1998), in this subsection we use the same efficiency concept (cost inefficiency-technical inefficiency), the same sample of banks, the same time interval and the same specification of inputs and outputs. The sample period is characterized by many regulatory changes and many changes in market conditions, making it an almost ideal period to examine how the different frontier approaches measure bank inefficiency over a variety of extreme conditions. At this point we choose cost minimization over profit maximization because it is more commonly

[16] Eichengreen and Gibson (2001) point out that public banks are different from private banks in a number of ways. They face softer budget constraints and their management is protected from hostile takeovers. Their loan portfolios and human resources management also differ, while they tend to manage their assets more inefficiently.

specified in the literature, and because of the notorious difficulties in measuring output prices in banking (an alternative profit efficiency scheme is not defined under non-parametric techniques).[17]

Given the above, we rerun the stochastic frontier model of Section 5.1, this time on two outputs and three inputs (instead of two outputs, two inputs and two netputs). Table 4 presents the cost inefficiency estimates and the results suggest somewhat higher levels of inefficiency than the previous approach. Next we apply VRS DEA on the same panel dataset, using Program (3). The results of the exercise turned out to be robust to slight changes in the sample.[18] A number of distributional characteristics of the inefficiency scores generated by the two efficiency techniques, SFA and DEA, are reported in Table 4. The mean inefficiency from the SFA method is 19.5%, while the mean inefficiency from the DEA method is 36.1%. Hence, calculated programming inefficiency scores are almost double those derived from the SFA. The average standard deviation of parametric inefficiency estimates (0.193) is also lower than that of the non-parametric model (0.254). These results are consistent with the studies that compare bank inefficiency between parametric and non-parametric approaches. For example, Eisenbeis et al. (1999) found that calculated programming inefficiency scores of U.S. bank holding companies are two or three times larger than those estimated using a stochastic frontier.

(Please insert table 4 about here)

The year-by-year average efficiency scores derived from the two methods suggest DEA inefficiency estimates with significantly higher variability over time. In the beginning of the sample period DEA inefficiency is much higher than the respective stochastic frontier inefficiency, whilst at the end of the period DEA inefficiency is 8% lower. DEA also suggests a consistently downward trend in inefficiency, while the SFA posits that the downward trend is interrupted in 2002, and inefficiency corrects to higher levels thereafter. The beginning of the examination period coincides with the acceleration of liberalization of interest rates, and the deregulation of the Greek financial system, which started in the mid-1980s, and consequently the decline in cost inefficiency seems

[17] Ideally, both cost and profit specifications would be employed and compared, but examining consistency conditions over the two techniques already seem to strain the very limits of theoretical identification.

[18] DEA is a deterministic technique and therefore is very sensitive to outliers. Hence, it is fundamental to check that solutions are stable, and do not vary dramatically when some units are excluded from the sample.

reasonable. The increase in inefficiency after 2002 also looks reasonable in light of the prolonged correction of the stock prices in the Greek market after the boom in the years 1999-2000. Thus, the inefficiency trend under the parametric approach appears more reasonable. It is also noteworthy that the correlation between the estimates derived by the two methods is positive and quite significant (41%). This correlation is to a certain extend satisfactory, considering the wide differences in the engineering assumptions of the two methods.

The results of the parametric approach are also aligned with what are generally believed to be the competitive conditions in the banking industry. The relatively low inefficiencies for the majority of banks under the SFA seem consistent with a reasonably competitive industry in a market that allowed entry. A potential explanation for this finding is the standard problematic feature of DEA. It does not account for random error. The dispersion from random error would likely result in higher average inefficiency. If a bank is simply very "lucky" and finds itself on the frontier, the rest will have very high measured inefficiency.

The estimates of the levels of cost inefficiencies of the parametric and non-parametric frontier methods are quite different across banks. The relatively high mean inefficiency for the DEA method is manifested in high inefficiencies for the majority of banks. In addition, the data suggests that DEA and the SFA give weakly consistent rankings with each other. Hence, DEA and the SFA cannot be relied upon to consistently rank the banks in the sample, as they may offer conflicting results when evaluating important regulatory questions. Also, this result reinforces the existing evidence, suggesting that the structure of the different models proves crucial for the computed inefficiency scores.

Next, as in Section 5.1, we divide banks into 2 groups based on their size, in order to test whether DEA and the SFA offer similar insights regarding the effect of bank size on efficiency. Table 5 reports the average cost inefficiency results of the stochastic and programming frontier methodologies for banks of different size. The SFA results suggest that the top five banks are more cost efficient than the rest, with an average inefficiency score of 0.145 compared to 0.237 for small banks, indicating a positive relationship between size and cost efficiency.[19] DEA results yield the same conclusions. In particular, large banks obtain an average inefficiency score of 0.285, while small banks obtain an average inefficiency score of 0.392.

(Please insert table 5 about here)

Table 5 also reports the average cost inefficiency of the SFA and DEA when banks are grouped according to their ownership status. The SFA results suggest that state-owned banks are more cost efficient than private banks with average inefficiency scores being 0.166 and 0.206, respectively. In contrast, DEA results are in line with theories suggesting that privately-owned financial institutions are ceteris paribus more efficient than the publicly-owned ones. Under this method, the reported average inefficiency scores are 0.343 and 0.410 for private and state-owned banks, respectively. Therefore, in this case, DEA may outperform the SFA.

6. Concluding remarks

The Greek banking sector provides an interesting context for studying bank efficiency, as it underwent significant changes during the last two decades. Since the mid 1980s it was extensively liberalized through the abolition of administrative interventions and regulations, which seriously hampered its development. The reforms were adopted gradually and supported the further improvement of the institutional framework and the more efficient functioning of banks and financial markets in general. This has created a new, more competitive economic environment, within which the banking sector nowadays operates.

Along the lines of Bauer et al. (1998), we have argued that a comprehensive approach to bank efficiency measurement requires crosschecking between the different available techniques. To perform this task the present study proceeded in two stages. First, it analyzed both cost and alternative profit efficiency of the Greek banking system over the period 1993-2005, using the Stochastic Frontier Approach. Translog cost and profit functions were estimated, following the intermediation approach. Our findings showed lower levels of cost efficiency than profit efficiency, which is an expected result,

[19] Note the strengthened significance of the effect of bank size compared to the effect identified in Section 5.1. This may suggest an important role for the categorization of the inputs as fixed and variable (see Berger et al., 1993).

both measures reflecting an improving trend over the sample period. However, the difference between the levels of cost and profit efficiency is quite significant. Moreover, we analyzed the effect of size and of the ownership status (public vs. private) on the cost and profit measures of efficiency. Large-sized banks were found more cost efficient than their smaller counterparts, while an opposite result was established under profit efficiency. Furthermore, state-owned banks emerged as more cost efficient, while at the same time they were less profit efficient. All these results suggest an important role (at least in the Greek banking sector) for revenue efficiency, output quality and the market structure in determining bank efficiency, thus indicating that the profit efficiency approach provides a methodology more aligned with existing theoretical considerations.

Second, we compared the results of the SFA method with those obtained by a non-parametric approach, namely VRS-DEA. The results of the DEA exercise revealed higher average inefficiency than those of the SFA, which is an expected result given the fact that DEA is not stochastic. In fact, the average programming inefficiency scores almost doubled those of the SFA. Furthermore, inefficiency scores derived from the stochastic and programming frontiers appear to have gradually declined over the sample period, indicating a significant positive correlation between the yearly average scores of the two approaches. Both methods indicated that cost efficiency is positively related to bank size, while the findings regarding the effect of the ownership status were contradictory between the two approaches.

In a nutshell, the results obtained from the various methods are substantially different. This may be attributed to the inner advantages and disadvantages of each approach, and leads to the conclusion that it is important to use more than one methodology to evaluate bank inefficiency. To phrase this differently, a more technically level playing field is required. Hence, the need to improve this study, would involve certain factors that are uncontrollable at this stage. We consider the most important extensions to be related to: (*i*) the effect of other bank-specific, industry-specific and macroeconomic determinants on efficiency; (*ii*) the consideration of the disentanglement of overall efficiency into its technical and allocative component; and (*iii*) the possible merging of parametric and non-parametric methodologies so as to optimize the efficiency results.

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Table 1
Variable definitions and notation

	Variable	Definition	Notation
Dependent Variable (s)	Total Cost	Overheads +Interest expenses +Fee & commission expenses + Other operating expenses	TC
	Profit	Profit before tax	π
Input prices	Price of Labor	Personnel expenses/ Total Assets	P_1
	Price of Funds	Interest expenses/ Total Funds	P_2
Outputs	Loans	Gross Loans	Y_1
	Other Earning Assets	Investment Assets + Securities + Other Earning Assets	Y_2
Fixed Netputs	Equity	Equity Capital	Z_1
	Physical Capital	Fixed Assets	Z_2

Table 2
Basic results for cost and profit inefficiency

		Cost inefficiency	Profit inefficiency
Mean		0.164	0.553
Standard deviation		0.100	0.216
Minimum		0.033	0.206
Maximum		0.746	0.948
No. of obs		244	244
Log likelihood function		75.55	-292.52
Wald $x^2(21)$ (Prob> x^2)		15,634 (0.000)	226.38 (0.000)
Variances:	$\sigma(v)$ =	0.127	0.769
	$\sigma(u)$ =	0.213	0.315
	$\sigma=[(\sigma^2(u)+\sigma^2(v)]$ =	0.061	0.690

Table 3
The effect of size and ownership on parametric cost and profit inefficiency

	Mean	Std. Dev.	Min	Max	Obs
Cost inefficiency					
Bank size					
Large	0.153	0.021	0.053	0.281	65
Small	0.173	0.113	0.033	0.746	179
Ownership structure					
Government (state controlled)	0.152	0.086	0.074	0.564	68
Domestic private	0.173	0.104	0.033	0.746	176
Profit inefficiency					
Bank size					
Large	0.566	0.239	0.285	0.931	65
Small	0.535	0.204	0.206	0.948	179
Ownership structure					
Government (state controlled)	0.674	0.172	0.366	0.931	68
Domestic private	0.478	0.194	0.206	0.948	176

Table 4
Parametric vs. non-parametric inefficiency over time

Methodology	DEA		SFA		
Year	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Obs.**
1993	0.380	0.285	0.276	0.247	22
1994	0.447	0.259	0.275	0.301	23
1995	0.459	0.273	0.195	0.166	22
1996	0.503	0.263	0.163	0.138	23
1997	0.498	0.248	0.175	0.222	22
1998	0.478	0.215	0.223	0.217	20
1999	0.380	0.228	0.186	0.177	18
2000	0.392	0.210	0.173	0.167	14
2001	0.319	0.144	0.172	0.179	14
2002	0.231	0.152	0.145	0.142	17
2003	0.172	0.139	0.151	0.105	17
2004	0.132	0.124	0.164	0.106	16
2005	0.100	0.132	0.179	0.161	16
1993-2005	**0.361**	0.254	**0.195**	0.056	244

Table 5
The effect of size and ownership on parametric and non-parametric cost inefficiency

	Mean	Std. Dev.	Min	Max	Obs
Bank size					
SFA					
Large	0.145	0.037	0.034	0.403	65
Small	0.237	0.202	0.025	0.034	179
DEA					
Large	0.285	0.130	0.000	0.744	65
Small	0.392	0.233	0.000	0.812	179
Ownership structure					
SFA					
Government (state controlled)	0.166	0.180	0.039	0.989	68
Domestic private	0.206	0.197	0.025	1.000	176
DEA					
Government (state controlled)	0.410	0.271	0.000	0.791	68
Domestic private	0.343	0.246	0.000	0.812	176