

**Evaluating Banking Productivity Results
Using Neural Networks:
The case of Italian Institutions**

by

Dimitrios Angelidis, PhD Candidate*‡

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and

Katerina Lyroudi, Ph.D.*

*University of Macedonia,
Department of Accounting and Finance,
156 Egnatia Str, P.O Box 1591,
Thessaloniki, Greece,
Email: daggel@uom.gr,
Tel/Fax: +30 (2) 310 891674

‡ Corresponding author

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Abstract

This paper examines the productivity of the 100 larger Italian banks for the period 2001-2002. Inputs and outputs are used as nominal values (millions of euros) and as the natural logarithms of these values. The mean error between the actual total factor productivity and the estimated one is calculated according to both approaches. Moreover, the weighted arithmetic mean of the Malmquist productivity index is calculated in addition to the geometric mean. Also, the correlation coefficient and the ranking correlation coefficient are computed to shed more light on the relationship between bank size and its performance. The empirical results revealed that the use of natural logarithms and neural networks regression results in lower error. Finally, there is rather an inverse relationship between size and productivity growth. However, this relationship is not statistically significant.

Key words: Malmquist indices, Italian banking industry, Data Envelopment Analysis, Neural Networks Regression

JEL Classification: C45, G21, O40

1. Introduction

This paper exams whether the use of the natural logarithms instead of the nominal values of the variables is a more appropriate approach to evaluate the level of banking productivity. Moreover, the relationship between size and productivity is under consideration. Our sample consists of the 100 Italian banks with the highest total assets (2002). The Italian banks in most studies that examine several European banking systems have not shown high efficiency relative to the efficiency of the other European banks except in a later study of Casu, Girardone and Molyneux (2004), for the period 1994-2000.

The objective of the present paper is to investigate the productivity of the Italian banking system for the period 2001-2002. We apply DEA analysis and for the first time, we apply neural networks regression analysis for some tests in addition to the OLS traditional approach. We also examine the hypothesis whether the bank size affects its overall performance. In order to achieve our purpose, the paper is structured as follows: The second section contains a relative review of literature. The third section presents the methodology and the data. The fourth section analyses the results and the last section has a summary and concluding remarks.

2. Literature Review

Berg, Forsund and Jansen (1992) introduced the Malmquist index as a measurement of the productivity change in the banking industry. They focused on the Norwegian banking system during the deregulation period 1980-1989. Their results indicated that deregulation lead into a more competitive environment. The increase of productivity was faster for larger banks, due to the increased antagonism they faced.

Favero and Papi (1995) used the non-parametric Data Envelopment Analysis on a cross section of 174 Italian banks in 1991 to measure the technical and the scale efficiencies of the Italian banking industry. In implementing both the intermediation and the asset approach the traditional specification of inputs was modified to allow for an explicit role of financial capital. In addition, regression analysis was used on a bank specific measure of inefficiency to investigate determinants of banks' efficiency. According to the empirical results, efficiency was best explained by productivity specialization by bank size and to a lesser extent by location (north-Italian banks were more efficient than south-Italian banks).

Allen and Rai (1996) estimated a global cost function using an international database of financial institutions for fifteen countries. Their sample was divided into two groups according to the country's regulatory environment. Universal banking countries (Australia, Austria, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, Italy, United Kingdom and Sweden) permitted the functional integration of commercial and investment

banking, while separated banking countries (Belgium, Japan and US) did not. Large banks in separated banking countries exhibited the largest measure of input inefficiency and had anti-economies of scale. All other banks had significantly lower inefficiency measures. Moreover, small banks in all countries showed significant levels of economies of scale. Italian banks, along with French, UK and US ones were found less efficient from Japanese, Austrian, German, Danish, Swedish and Canadians ones.

Pastor, Perez and Quesada (1997) analyzed the productivity, efficiency and differences in technology in the banking systems of United States, Spain, Germany, Italy, Austria, United Kingdom, France and Belgium for the year 1992. Using the non-parametric approach DEA together with the Malmquist index, they compared the efficiency and differences in technology of several banking systems. Their study used the added value approach. Deposits, productivity assets and loans nominal values were selected as measurements of banking output, under the assumption that these are proportional to the number of transactions and the flow of services to customers on both sides of the balance sheet. Similarly, personnel expenses no-interest expenses, other than personnel expenses were employed as a measurement of banking input. According to the results France had the banking system with the highest efficiency level followed by Spain, while UK presented the lowest level of efficiency.

Altunbas and Molyneux (1996) examined the banking systems of France, Germany, Italy and Spain for economies of scale and scope. They found differences among the four markets regarding economies of scale. However, the latter were significant only for the Italian banks, which gained as they succeeded in lowering costs.

Bikker (2001) examined the banking productivity of a sample of European banks in various countries, among with was Italy also, for the period 1989-1997. His results indicated that the least inefficient banks were first the Spanish ones, followed by the French and the Italian banks. The most productivity banks were these in Luxemburg followed by Belgian and the Swiss banks.

Dietsch and Lozano-Vivas (2000) focused on comparison of banking efficiency in two countries, France and Spain, for the period 1988-1992. As these two countries used to have different currencies in that period, inputs and outputs variables were converted into US dollars. The authors preferred the value added method and concluded that when the common frontier was defined without environmental variables, the cost-efficiency scores of Spanish banks were quite low compared to French banks. However, when environmental variables were included in the common frontier the differences in efficiency were significantly reduced.

Hasan, Lozano-Vivas and Pastor (2000) analyzed the banking industries of Belgium, Denmark, France, Germany, Italy, Luxemburg, Netherlands, Portugal, Spain and United Kingdom. First, the authors attempted to evaluate the efficiency scores of banking industries operating in their own respective countries. Later, they used a common frontier to control for the environmental conditions of each country. The results based on cross-country efficiency scores suggested that the banks in Denmark, Spain and Portugal were relatively the most technically efficient and successful. Especially, when the banks of these countries tried to enter into any other European country of the sample. Antithetically, the banks in France and Italy were found to be the least efficient institutions among the ones in the sample.

Fernandez, Gascon and Gonzalez (2002) studied economic efficiency in 142 financial intermediaries from eighteen countries over the period 1989-1998 and the relationship between efficiency, productivity change and shareholders' wealth maximization. The authors applied DEA to estimate the relative efficiency of commercial banks of different geographical areas (North America, Japan and Europe). The European banks were from Austria, Belgium, Denmark, Finland, Germany, Ireland, Italy, Luxemburg, Norway, Portugal, Spain, Sweden, Switzerland and UK. The three preferred outputs were total investments, total loans, and non-interest income plus other operating income. In parallel, the four input variables were property, salaries, other operating expenses and total deposits. All these values were expressed in billions of US dollars. Their results showed that commercial banks productivity across the world had grown significantly, 19,6% from 1989 to 1998. This effect had been principally due to relative efficiency improvement, with technological progress having a vary moderate effect.

Maudos et. al. (2002) analyzed the cost and profit efficiency of European banks in ten countries, including Italy, for the period 1993-1996. They used multiple regression analysis along with DEA and they split their sample in large, medium and small banks. Their results indicated that medium sized banks had profit efficiency.

Lozano-Vivas, Pastor and Pastor (2002) examined banking efficiency in ten European countries among which was Italy, for 1993. The authors adopted the value-added approach and analyzed also the macroeconomic environment where the banks operated. Their results showed that banking efficiency was low in Europe during that time period. Furthermore, the most efficient banks in each country were able to operate in a unified European banking system with the exception of the banks in Italy and Netherlands.

Altunbas, Carbo, Gardener and Molyneux (2003) analyzed the relationship between capital, risk and efficiency for a sample of European banks between 1992 and 2000 for the

fifteen countries of the European Union before the enlargement. They did not find any strong relationship between inefficiency and bank risk-taking. They found evidence that the financial strength of the corporate sector had a positive influence in reducing bank risk-taking and capital levels. There were no major differences in the relationships between capital, risk and efficiency for commercial and savings banks although there were such differences for co-operative banks, for which capital levels were inversely related to risks.

Casu and Molyneux (2003) employed DEA approach to investigate whether the productivity efficiency of European banking systems had improved and converged towards a common European frontier between 1993 and 1997. The geographical coverage of the study was France, Germany, Italy, Spain and the United Kingdom. All data were reported in ECU as the reference currency. Their results showed relatively low average efficiency levels. Nevertheless, it was possible to detect a slight improvement in the average efficiency scores over the period of analysis for almost all banking systems in the sample, with the exception of Italy.

Schure, Wagenvoort and O'Brien (2004) estimated the productivity of the European banking sector for the period 1993-1997. They found that larger banks were more productive on average than smaller banks, for the commercial banks only, and not for the saving banks. The Italian and the Spanish banks were found to be the least efficient.

On the other hand, Casu, Girardone and Molyneux (2004) for the period 1994-2000, in an efficiency analysis of the European banking system found that Italian banks had 8,9% productivity increase, Spanish banks had 9,5% increase, while German, French and English banks had 1,8%, 0,6% and 0,1% productivity increase, respectively. The main reason for such improvement in efficiency for the Italian and Spanish banks was the lower cost that these institutions managed to achieve.

3. Methodology and Data

Methodology

This section describes the methodology employed in the present study. In order to decide whether raw data should be preferred for consideration as nominal values (NV) or as the natural logarithm (ln) of their nominal values it is necessary to estimate first the productivity change. There is a plethora of different methodologies for the measuring of productivity change in the literature but none of them can be distinguished as the best. In this study the Data Envelopment Analysis (DEA) technique is preferred to calculate the Malmquist indices of Total Factor Productivity (TFP) change. DEA is a non-parametric approach of frontier estimation. The term DEA was invented by the paper of Charnes, Cooper

and Rhodes (1978). These authors proposed a model, which had an input orientation and assumed constant returns to scale. The present paper follows the above model. Since then, a large number of papers used and extended the DEA methodology. Tavares (2002) stated that until January of 2002 the DEA bibliography database consisted of 3,203 publications written by 2,152 distinct authors.

Malmquist TFP index measures changes in total output relative to inputs. The idea was developed by the Swedish statistician Malmquist (1953). The Malmquist TFP index is one of the most frequently used method to evaluate productivity change. To capture the productivity changes in the banking sector, the TFP index was initially introduced by the pioneer study of Berg, Forsund and Jansen (1992). That study was focused on productivity during the deregulation period of the Norwegian banking. Since then, a great number of studies employed the Malmquist TFP index to assess productivity of financial institutions.

The Malmquist TFP index calculates the change in productivity between two points by estimating the ratio of the distances of each point relative to a common technology. The Malmquist input oriented TFP change index between the base period t and the following period $t+1$ is defined as:

$$M(y_t, x_t, y_{t+1}, x_{t+1}) = \left[\frac{d_{t+1}(Y_{t+1}, X_{t+1})}{d_t(Y_t, X_t)} \times \frac{d_t(Y_{t+1}, X_{t+1})}{d_{t+1}(Y_{t+1}, X_{t+1})} \right]^{1/2} \quad (1)$$

As long as M is greater than unity a positive TFP growth from the period t to period $t+1$ has taken place. Otherwise, a value of M less than one indicates TFP decline. Equation (1) is the geometric mean of two TFP indices. The first index is calculated with respect to period t technology, while the second index is evaluated with respect to period $t+1$ technology.

The productivity change (M) can be decomposed into technical efficiency change (TEC) and technological change (TC). The first ratio in Equation (1) represents the TEC and the second ratio represents the TC. The technological change captures the improvement or the worsening in the performance of best practice decision making unions (DMUs), as financial firms tend to be called in the DEA literature. DMU is a more appropriate term than firm when, for example, a bank is studying the performance of its branches. In parallel, technical efficiency change reflects the convergence towards, or divergence from the best practice by the remaining DMUs.

TFP change indices will be estimated twice. First, raw data will be used as nominal numbers in millions of euro and second the ln of their nominal numbers will be used. To test

which case provides better results, the classical ordinary least square (OLS) method, and a more modern neural network approach will be employed. In parallel, a comparison between OLS and neural networks will be possible at two levels; one for the nominal values and one for the natural logarithms to distinguish which approach is more appropriate.

The neural network system, which is used in this study, is called 'Pathfinder'. Neural networks use a set of processing nodes. These processing nodes are interconnected in a network that can then identify patterns in data as it is exposed to the data. Using back propagation a neural network learns through an iterative procedure. The network is repeatedly shown examples of the data to learn and make adjustments to the weights so that it fit the model better. This process is repeated thousands of time. In order to perform a neural network analysis the data set has to be split into three parts. These are the training set, the test set and the validation set. The neural network learns the problem by using the training set. Then, the test set is used during training to monitor the learning performance. The validation set is used after training as a final check to determine how well the model performs.

As the sample of the present study is comprised by 100 DMUs, 60 observations will be employed for the first set, 20 for the second set and 20 for the third set. Afterwards, the predicted values that have been extracted by the latter set will be compared with the actual values that have been obtained by the DEA program. Hence, the mean absolute percent error (MAPE) of the predicted values will be computed using the following formula:

$$\text{MAPE} = \frac{\sum_{i=1}^n \left| \frac{R_i - P_i}{R_i} \right|}{N} * 100, \quad R_i \neq 0 \quad (2)$$

Where R_i is the real value, P_i is the predicted value and N is the number of observations. In order to compare the MAPE of neural networks to the MAPE of OLS, 80 observations (60 from the training set and 20 from the test set) are used to create a multi-regression model. The endogenous variable of this model will be the productivity index change and the exogenous variables will be the inputs and outputs that are employed for the estimation of the productivity index change. Afterwards, the MAPE will be computed in the same way. Last, the MAPE calculated by OLS and the MAPE calculated by the neural networks will be compared to each other. The lower (higher) value of MAPE indicates the better (worse) fit of the model.

Finally, this study tests the hypothesis whether there is a connection between the size of a DMU and its overall performance. For this reason the weighted arithmetic mean of TFP change indices based on the total assets of DMUs will be computed. Total assets are

employed as a measure of size. The weighted arithmetic mean might give a more comprehensive measure than the geometric mean that DEA provides. This is because in the case of the geometric mean all the observations have equal importance, but in the case of the weighted arithmetic mean DMUs with greater (lower) total assets have a more (less) important role in the final TFP. This is more consistent to the economic theory and to the real life situations. As long as the weighted arithmetic mean is greater (less) than the geometric mean, it implies that larger DMUs have better (worse) performance than their smaller counterparts. However, we have to keep in mind that by definition the geometric mean tends to be lower than the weighted arithmetic mean.

In addition, the Pearson coefficient correlation between size and productivity and the Spearman coefficient correlation (or rank coefficient correlation) is also used to catch the size effect. The weighted arithmetic mean is too vulnerable to extreme values. Sorting observations by ranking them, allows for the determination of whether there is a connection.

Data

The data has been collected from the Bankscope database. The pertinent information is obtained from the banks' balance sheets for the years 2001 and 2002. The final sample is comprised of 100 DMUs from Italy with the highest total assets. To avoid the double calculation of a DMU the selected consolidation codes of Bankscope are: 1) Consolidated statements with an unconsolidated companion, 2) consolidated statements with no unconsolidated companion and 3) unconsolidated statements with no consolidated companion.

The definition of a bank's inputs and outputs is an issue related directly to its function description. As a result, a variety of definitions about input and output variables exist in the relatively literature. Roughly, the various definitions can be divided into three categories based on the preferred approach: *the value added approach*, *the intermediation approach* and *the user cost approach*. The value added approach considers deposits as outputs. The idea is that funds are collected from depositors and there is competition among DMUs to attract customers. Berger and Humphrey (1992) modified this approach and considered deposits as both outputs and inputs. According to the intermediation approach, only banks' assets are thought as outputs (uses of funds), while deposits are regarded as inputs (sources of funds). The notion of this approach is that DMUs buy and sell funds acting as intermediaries between borrowers and receivers of funds. Finally, the user cost approach defines a variable as output or input oriented according to its contribution to the bank revenues. That means that if the

financial return of the assets exceeds the opportunity cost of funds, DMU's assets are considered as outputs.

Although no approach can be considered as superior to the others, the value added method has been chosen for the present paper. Consequently, the variables that are defined as outputs are: 1) Total other earning assets, 2) total customer loans and 3) total deposits. On the other hand, as input variables are characterized the followings: 1) Personnel expenses, 2) other operating expenses and 3) total fixed assets.

4. Results and Analysis

Using the data envelopment analysis computer program written by Tim Coelli and the center for efficiency and productivity analysis of Australia, the input oriented Malmquist Total Factor Productivity (TFP) change index has been calculated. A value of the index greater than unity implies a positive growth of total productivity. An index equal to unity underlines no change in productivity level and a value less than one indicates decline in productivity from period t to period $t+1$.

The Malmquist index can be decomposed into two elements. These two components are the technological change (TC) and the technical efficiency change (TEC). The product of the TC and the TEC provides the TFP index. In symbols: $TFP=TC * TEC$. A value of TC greater (less) than one indicates an amelioration (deterioration) in the frontier created by best practices decision making unities (DMUs). At the same time, whether the TEC index is higher (lower) than unity, the remaining DMUs are moving towards to (away from) the best practice frontier.

The productivity change indices are presented in Table 1. Overall, based on the nominal values of the input and output variables, the total productivity of Italian banking institutions increased from 2001 to 2002, at a rate equal to 3.5% ($TFP=1.035$). However, based on the natural logarithm of the data the total productivity decreased by 2.6% ($TFP=0.974$). Moreover, quite interesting conclusions can be extracted by the decomposition of the Malmquist TFP index. It is obvious that the TEC index and the TC index are not moving towards the same direction in both cases. Specifically, the TEC index achieved an increase of 85.3% throughout the period, while the TC index met a considerable decrease equal to 44.1% based on the nominal numbers. On the other hand, the TEC index improved only by 0.5% and the TC index was reduced by 3% based on the natural logarithm.

Table 1. Productivity Change Indices

NV	TEC	TC	Malmquist TFP
Geometric means of the 100 DMUs	1.853	0.559	1.035
Ln	TEC	TC	Malmquist TFP
Geometric means of the 100 DMUs	1.005	0.97	0.974

The economic and financial implementation of the above results is that the best practice DMUs failed to achieve gains. Also, the distance between the latest institutions and the remaining DMUs was shortened, since the not-best practice DMUs moved towards the optimal frontier. This may suggest that only the not best practice DMUs improved their performance. In any case, the results that are derived by the natural logarithm approach are more moderate than those that are extracted by the approach of nominal values. Nevertheless, it must be underlined that the Malmquist TFP index has different signs for the two approaches. So, a reasonable question is whether Italian banks achieved a productivity increase or not during the examined period.

To answer this question it would be very helpful to determine which approach gives better-fitted results. For this purpose the method described in section 3 will be followed, to evaluate MAPE. The prices of MAPE of the 20 DMUs for each case measured by OLS and by a neural networks regression as well, are illustrated in Table 2.

Table 2. Mean Absolute Percent Error

NV	OLS	Neural network
MAPE	96.97%	105.3%
Ln	OLS	Neural network
MAPE	131.27%	8.02%

The results are not quite clear. Based on the OLS approach nominal prices of the variables seem to be more appropriate for the calculation of the TFP as the MAPE in this case is lower. Antithetic, based on the neural networks approach the transformation of the variables into their natural logarithm is by far superior. However, the value of MAPE computed by the predicted values of the TFP based on the neural networks and used the natural logarithm version is clearly lower than any other case. So, a first conclusion is that the

natural logarithm of the variables shall be preferred than the nominal numbers. However, a more enhanced sample is required for more reliable results. Moreover, the neural networks seem to be superior to the traditional OLS for the prediction of TFP change indices. As a consequence, it would be advisable for the managers of the DMUs and for the academic researchers to use neural networks than OLS approaches.

Contrary results between the nominal numbers approach and the natural logarithm approach can be extracted for the size effect as well. Table 3 presents the results of the geometric mean of the TFP indexes provided by the DEA program and the calculated weighted arithmetic mean of the TFP indices based on the total assets of DMUs as a measurement of their size.

Table 3. Geometric and weighted arithmetic means of TFP indices

Nominal	Geometric mean	Weighted arithmetic mean
Values	1.035	1.19
Natural	Geometric mean	Weighted arithmetic mean
Logarithms	0.974	0.956

The weighted arithmetic mean increases the TFP from 3.5% to 19% according to the nominal numbers approach. However, based on the natural logarithm approach the TFP index deteriorates as the decrease of the index gets from -2.6% to -4.4% . The weighted arithmetic mean is greater than the geometric mean for the nominal values approach. This implies that bigger DMUs perform better than smaller ones. On the other hand, based on the natural logarithms approach smaller DMUs perform better than larger ones, since the weighted arithmetic mean is lower than the geometric mean.

To shed more light to this puzzle of the size effect (without forgetting that natural logarithm approach gives less MAPE), the Pearson coefficient correlation and the Spearman correlation coefficient (or rank coefficient correlation) are employed. The results of this test are illustrated in Table 4.

Table 4. Spearman and Pearson correlation between total assets and TFR indices

	Nominal Values	Natural Logarithms
Spearman correlation	0.059	-0.027
Pearson correlation	-0.032	-0.154
P-Value	0.754	0.125

The Spearman correlation coefficient is positive according to the nominal values approach and negative according to the natural logarithm approach. These results are consistent with the figures of the weighted arithmetic mean and the geometric mean for both approaches. The positive Spearman correlation coefficient of the nominal numbers approach and the greater arithmetic mean than the geometric mean implies a better performance of the bigger DMUs. In the same way, the negative Spearman correlation coefficient keeps up with the fact that the geometric mean is greater than the weighted arithmetic mean based on the natural logarithm approach, implying superior performance by smaller DMUs. The Pearson correlation coefficient between total assets (measured either in nominal numbers or natural logarithm) and the TFP change indices is negative. This relationship –as expected– is stronger for the latest approach but in both cases not statistically significant. This is because the P-Value of the correlation coefficient dictates that the null hypothesis of no statistically important relationship between the two variables cannot be rejected. In addition, the null hypothesis cannot be rejected for the Spearman correlation coefficient even at the 10% significance level. As a final conclusion, there is rather an inverse than direct relationship between size and total productivity growth, although this relationship is not statistically significant.

5. Summary and Concluding Remarks

This study examined the productivity of the Italian banking industry for the period 2001-2002. The productivity was measured by the Malmquist index and was found to be equal to 1.035, which means a total productivity increased by 3.5%. Its two components, the technological change index was found equal to 0.559 and the technical efficiency change index was equal to 1.853 (in nominal values).

However, in logarithmic values the results differed. Hence, we applied the OLS and neural networks regression to evaluate the MAPE (mean absolute percent error) for each approach. In nominal values, the MAPE according to the OLS is lower than the MAPE according to the neural networks regression, while in logarithmic values the opposite is true. Since, the error is smallest in the case of logarithmic values evaluated by applying neural networks regression (8.02%) we cannot ignore the results that show increase of the technical efficiency by 0.5% and a decrease of the technological efficiency by 3% and the total factor productivity by 2.6%.

Therefore, our results regarding Italian banks' efficiency are inconclusive. We need a larger sample of banking institutions and we need to examine a broader time period after the

euro era. Based on the pertinent literature, the Italian banks up to the end of the 20th century were not distinguished among their European counterparts for their efficiency and productivity. We expected the situation to change after 2000 and 2001 with the adoption of a single currency. Obviously the time period we had available is not enough to get clear results and more inferences.

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