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Risk, Regulation and Performance in Banking: Theory and Estimates for Italian Banks

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“The financial system ... may be simultaneously growth-induced and growth-inducing, but what really matter are the character of its services and the efficiency with which it provides them (Cameron et al. (1967), p. 2)”.

In the literature, many studies have analyzed the impact of the financial sector on growth and economic development. This literature often lacks, however, an accurate assessment of the feed-back of growth on the financial sector. Indeed, empirical evidence suggests that environment is important in determining the efficiency of banks. Potential differences in the environmental, risk and regulation conditions of financial institutions have led many researchers to examine the impact of environment on financial development. Seldom this has been reflected upon the studies considering the finance-growth nexus

The present work is addressed to this void of literature, investigating the impact of variables related to local growth and riskiness upon the development of financial sector, as captured by the qualitative proxy of bank efficiency. The latter concept, and its measurement, provides the thread of this thesis.

In Chapter 1 we provide a survey of the main models used in literature to estimate productive efficiency, with some emphasis on the analysis of banking. We analyze the parametric and non-parametric frontier models, their estimation problems and main differences, also considering some recent contributions in this context. Devoting particular care to the analysis of productive processes within banking, we highlight the importance in this field of the multi-input multi-output nature of this production, the relevance of risk aversion, credit risk, and of environmental factors.

In Chapter 2, we test the nexus between financial development and economic growth relying upon territorially disaggregated data (NUTS3 and SLL) from Italy. We use cost and profit efficiency measures, computed through a parametric approach (SFA), as qualitative measures of financial development, and credit volume divided by gross domestic product as its quantitative measure. A key element of novelty of this chapter's analysis is the interaction between banking and national accounting at a territorially very disaggregated level. The banking data, taken from the BilBank 2000 database distributed by ABI (Associazione Bancaria Italiana) over the 1998-2005 and 1998-2008 period, include many cooperative banks that operate at a purely local level. A growth model, similar to Hasan et al (2009), is specified and tested in a panel data context. Our estimates suggest that financial development has a positive significant impact on GDP per capita.

In Chapter 3 we analyze the determination of cost efficiency in a sample of Italian small banks located in different geographical areas and including two great institutional categories: cooperative banks (CB's) and other banks. We highlight the effect of environmental factors (asset quality, local GDP per capita) on banks' performance, and provide novel evidence in favour of the "bad luck" hypothesis suggested by Berger and De Young (1997). Local GDP per capita strongly affects the territorial differentials for technical efficiency, especially for CB's. This can be easily rationalized, as current regulations hamper CB's vis-à-vis other banks in their capability to diversify territorially. Our estimates provide us with a tentative quantitative measure of the costs of missing diversification, ranging between 2 and 7 percentage points. Correspondingly, our evidence suggests that there is potentially strong endogeneity in some currently available bank performance indicators.

CHAPTER 1

THE ESTIMATION OF EFFICIENCY: A REVIEW OF THE LITERATURE

Abstract

In this chapter we provide a survey concerning the main models used in literature to estimate productive efficiency, with some emphasis on the analysis of banking. We analyze the parametric and non-parametric frontier models, their estimation problems and main differences, also considering some recent contributions in this context. Devoting particular care to the analysis of productive processes within banking, we highlight the importance in this field of the multi-input multi-output nature of this production, the relevance of risk aversion, credit risk, and of environmental factors.

1.1 Introduction

In this chapter we present a survey concerning the main models used in the literature to estimate productive efficiency, with some emphasis on the analysis of banking.

From the recent Maietta's overview (2007), we can infer the best-known approaches for estimating the efficiency in the literature. Essentially, these approaches assess a production frontier (or cost) that lies above (or below) the observed points.

In the literature there are four ways to calculate efficiency levels: (i) least-squares econometric production models; (ii) total factor productivity (TFP) indexes; (iii) non -parametric methods, and (iv) stochastic frontiers. Often, the first two methods apply to aggregate time series data. They provide measures of technical change, assuming that all units are technically efficient.

The remaining methods provide for efficiency measures and generally apply to data where there is a sample of firms, or, anyway, of productive units. In particular, non-parametric methods, such as the DEA (Data Envelopment Analysis) and FDH (Free Disposable Hull), stem from Farrell's (1957) original contribution. Their first modern formulations were proposed by Charnes et al. (1978), Banker et al. (1984), Deprins et al. (1984). On the other hand, the parametric approaches, such as the Stochastic Frontier Approach (SFA), Distribution-Free Approach (DFA) and Thick-Frontier Approach (TFA), were initiated by the seminal contributions of Afriat (1972) and Aigner et al. (1977). These two approaches have not only different features, but also relative advantages and disadvantages (Lewin and Lovell, 1990).

Actually, there is no consensus about which method, parametric or non - parametric, to adopt to measure efficiency scores. For instance, in the field of banking, Ferrier and Lovell (1990) and Resti (1997) find that the efficiency scores obtained using either method are reasonably consistent. More recently, a comparison between deterministic and stochastic frontier models was also performed by Weill (2004). He checked the robustness of SFA, DFA and DEA estimates of cost efficiency on a sample of 688 banks in 5 European countries (France, Italy, Germany, Spain and Switzerland) in the period 1992-1998. He too found that SFA, DFA and DEA efficiency scores, although different and positively correlated. between. It is also true, however, that Bauer et al. (1998) obtained completely different results from different approaches[1]. In this chapter, we shall subsequently illustrate the two approaches in order to see whether any of them may be particularly suitable to the measurement of efficiency within given analytical set-ups.

The rest of this chapter is organized as follows. Section 1.2 reviews some basic concepts of efficiency. Section 1.3 analyzes the parametric frontier models, their estimation problems and

[1] Other studies comparing, in the field of banking, parametric and non-parametric methods with no definite outcome are Bauer et al., (1993), Allen and Rai (1996), Hasan and Hunter (1996), Berger and Mester (1997), Berger and Hannan (1998).

main differences. In particular, we compare deterministic and stochastic frontier models. Section 1.4 examines the non - parametric frontier models and their differences in terms of estimation. Section 1.5 compares parametric and non – parametric methods and considers some recent contributions in this context. Section 1.6 concludes and devotes some particular care to the analysis of productive processes within banking.

1.2 Concepts of Efficiency

We mean by efficiency the fit of the observed production process to a given standard of optimality. With reference to a decision-making unit that transforms a set of inputs (productive resources) into a set of outputs (services or products), it is usually possible to define four different concepts of efficiency.

Technical efficiency: the capacity of the decision-making unit, given the technology used, to produce the maximum output level from a given combination of inputs, or alternatively, to use the least possible amount of inputs to obtain a given output set.

Allocative efficiency: the capacity of the decision-making unit to choose the least costly combination of inputs available in relation to their marginal products and their prices, or the more profitable input and output mix in relation to their prices, marginal products and marginal revenues.

Scale efficiency: the capacity of the decision-making unit to choose the input and output vectors consistent with the optimal scale.

Scope efficiency: the capacity of the decision-making unit to choose the input and output vectors with the least costly composition.

To measure the efficiency of a decision-making unit, one must then have a term of reference. As far as **technical efficiency** is concerned, this is represented by the whole production possibility frontier, defined as the efficient frontier. Define the vector of inputs x, the vector of outputs y, and the set of production possibilities, P. This set collects all possible combinations of x that make y, ie all possible technical options for the outputs starting from the inputs. Take for simplicity a one-input one-output production process. This example allows to see graphically both the set of production possibilities and the efficient frontier (Fig. 1.1).

As can be seen the set P coincides with the gray area, while the efficient frontier is determined by the red line OE.

Figure 1.1 - The set of production possibilities and the efficient frontier

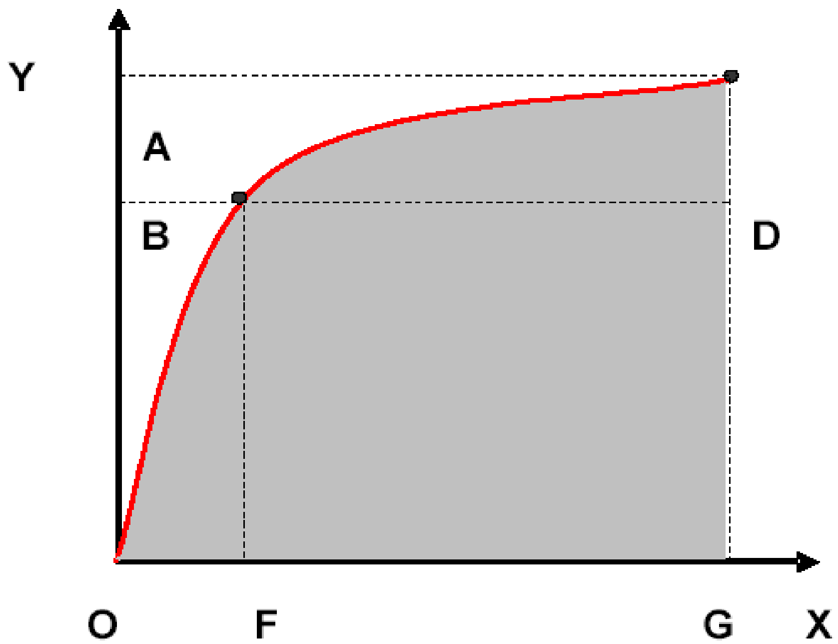


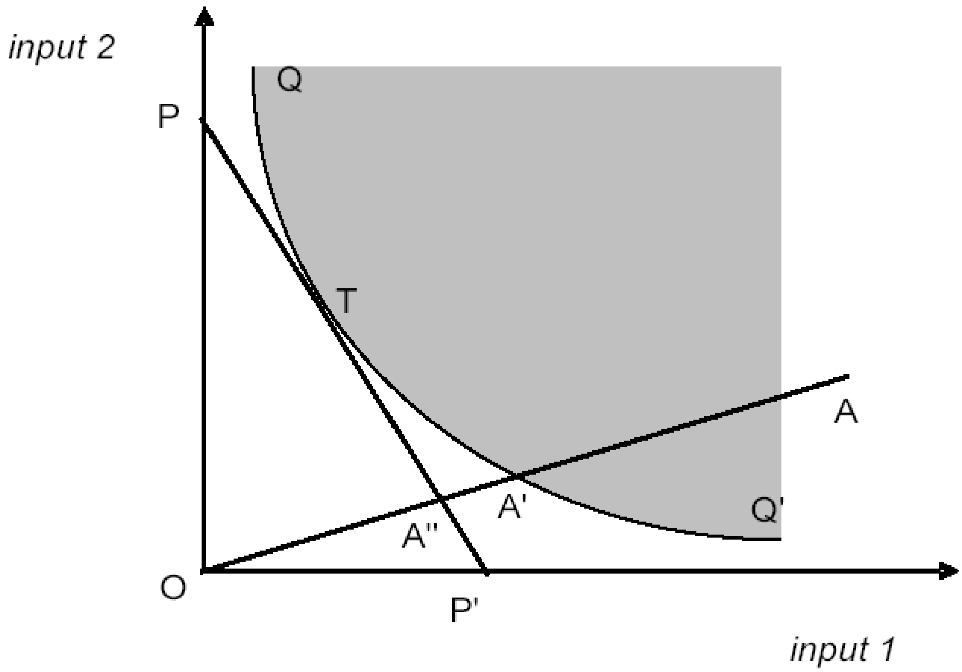
Fig. 1.1 also helps understanding that technical efficiency can be either input- or output-oriented. The decision-making unit situated in point D is inefficient either because, with input OG, can push its output to OA, or because, with a given OB output, can shrink its input to OF. More precisely:

> (*input-oriented technical efficiency*): **OF/OG**. For a given output quantity (OB), input-oriented technical efficiency is the ratio between the optimal and the actual input quantity.
>
> (*output-oriented technical efficiency*): **OA/OB.** For a given input quantity (OG), output-oriented technical efficiency is the ratio between the actual and the optimal output quantity.

The two measures coincide only in the presence of constant returns to scale.

In order to understand the concept of (cost or profit) **allocative efficiency**, let us consider first, in Fig. 1.2, the mechanism of cost minimization. Given the PP' isocost line, a productive process is cost-efficient only if lying on point T. Otherwise, the allocative inefficiency of A is given by the A"O/A'O ratio, where A" represents a minimum cost production process, for given input prices and technology. Point A', is technically, but not allocatively, efficient.

Figure 1.2 – Allocative efficiency

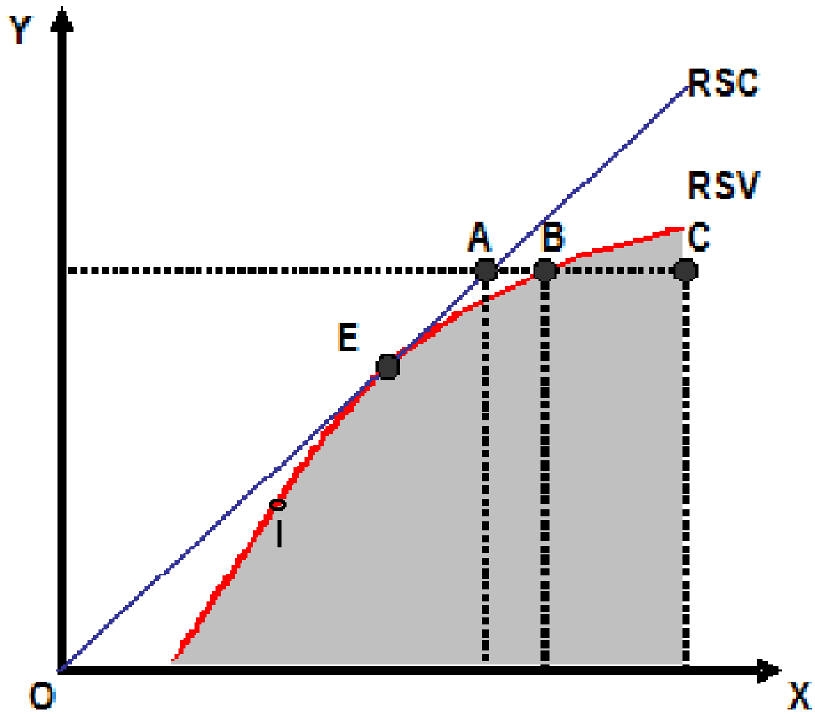


The A''O/A'O ratio is the cost excess bestowed on unit A by its non-optimal input mix. It follows that the A''O/AO ratio is the (total) cost inefficiency of unit A, arising from the joint consideration of its technical and allocative inefficiency.

Similarly to cost efficiency, **profit efficiency** relates the actual to the maximum profit. Traditionally, it is assumed that, given vectors **r** of output prices and **w** of input prices, the decision-making unit determines the profit-maximizing values of output **y** and input **x**. The literature (Berger and Mester, 1997; Rogers, 1998) also presents an alternative hypothesis of profit-maximization: the decision-making unit takes as given vectors **y** (output) and **w** (input prices), determines the profit-maximizing values of output prices **r** and input **x**. This alternative hypothesis is usually associated to the absence of perfect competition.

To explore the concept of **scale efficiency**. it is necessary to construct, always considering a decision-making unit using a one-input one-output technology (Fig. 1.3), a constant returns to scale (RSC in Figure 1.3) and a variable returns to scale (RSV in Fig 1.3) production frontier.

Figure 1.3 – Pure and scale technical efficiency



Point E is optimal both from the standpoint of pure technical efficiency and of scale of production. On the other hands, units B or I are efficient from a purely technical standpoint but are either over- (B) or under-sized (I) experiencing either congestion or unexploited scale economies. Finally, unit C is obviously inefficient on all accounts.

Finally, the concept of **scope efficiency** requires the consideration of a multiproduct technology, where production costs depend both on input prices, w_j, and on output quantities, y_i:

$$C\,(y) = f(w_1, w_2, \ldots, w_m; y_1, \ldots, y_n)$$

Also suppose that the technology is decomposable, allowing to measure the cost associated to producing a single output:

$C\ (y_1)\ ,\ C\ (y_2)\ ,\ \ldots\ ,\ C\ (y_n)$

In this case, there are scale economies if:

$$\text{ec. var.} = [\sum_{i=1}^{n} C(y_i) - C(y)]/C(y)$$

that is if the sum of costs associated to separately produced outputs is higher than the costs associated to jointly produced outputs. Scope efficiency is then identified by the maximum cost saving attainable by changing the output mix.

1.3 Efficiency Estimation in Parametric Frontier Models

Generally, the assumption underlying all parametric approaches (DFA, TFA and SFA alike) is the ability to identify, starting from the set of observed data, Z°, the frontier Eff $Z(Z^{\circ})$ with a function, which surrounds more closely the data. This function is defined by unknown parameters and constants, $f(x, \beta)+\varepsilon$, where x is the vector of parameters, β and ε is the algebraic sum of stochastic error and technical inefficiency.

The error component is expressed as (v+u) or (v-u). In order to lie under the stochastic frontier u, the first case imposes a negative asymmetric distribution, while the second case a positive asymmetric distribution. The two expressions are completely equivalent. This chapter adopts the second specification.

The advantages of this approach are, first of all, that it can allow for the presence of statistical noise in the data. Moreover, the estimated parameters have a readily defined economic interpretation. For example, they can represent the “partial elasticity” of factor substitution, and so on. In addition, the estimator of the technology has known statistical properties and the efficiency is captured by the residuals. The main disadvantage, resulting from the imposition of a predetermined functional form for production technology and predetermined distribution of inefficiency, is due to the risk that errors in technology specification and structure of the error reflect on the measurement of inefficiency. However, this risk is reduced by choosing a flexible functional form. Another limitation is represented by the “approximation error” introduced by the “continuity assumption” of data. Finally, non-spherical residuals may bring about problems of correct inference (under some conditions, however, Bera and Sharma (1999) provide the formulas to get confidence intervals for these estimators).

Depending on assumptions about the process generating the data, it is possible to divide the parametric frontiers in deterministic or stochastic frontier analysis.

1.3.1 Deterministic Frontier Models

The deterministic frontier model assumes no stochastic error, i.e. v = 0. According to this assumption, each observed point is on or below the feasible production frontier (without any undue loss of generality, we consider a *production* frontier; extensions to cost or profit frontiers are straightforward). Analytically:

$$y_i \leq f(x_i, \beta) \quad i=1,\ldots,N$$

In a deterministic frontier, in order to parameterize this inequality, all residuals, $\exp\{-u_i\}$, between the production, y_i, and the production theory, $f(x_i, \beta)$, are considered as measures of technical efficiency ET_i, as follows:

$$y_i = f(x_i, \beta)\exp\{-u_i\} \text{ with } u_i \geq 0$$

$$ET_i = y_i/f(x_i, \beta) = \exp\{-u_i\} \leq 1$$

The statistical analysis of deterministic frontiers, DFA, can be found in Afriat (1972) and Richmond (1974). Computation of the efficiency scores is carried out with different techniques (C_{OLS}, M_{OLS} and maximum likelihood; see Lovell, 1993).

The parametric deterministic frontier, although still widely used and useful from a pedagogical point of view, are considered the worst. In fact, the technical efficiency estimates are sensitive to the functional form f(x) and to the assumptions for the distribution of u_i. Yet, the main failing of the deterministic models is that they do not allow for statistical noise. The strong assumption is made that all deviation from the estimated frontier stand for inefficiency: there is no decomposition of the error in an inefficiency and a random component.

1.3.2 Stochastic Frontier Models

The stochastic frontier model, also called "composite error model", proposed by Aigner et al. (1977), Meeusen and van den Broeck (1977) and Battese and Corra (1977), follows this canonical form:

$$y= f(\beta; x)\exp\{v-u\} \text{ with } u \geq 0$$

where x represents the vector of independent variables, β is the vector of parameters to be estimated, v and u are the error and inefficiency components[2], respectively. In other words, $\beta'x + v$ constitutes a conventional regression model, where $v \sim_{iid} N(0,\sigma^2_v)$. Loosely speaking, a stochastic frontier production function provides random fluctuations of the theoretical values, ŷ, v being a stochastic variable of which there are no known deterministic values. The theoretical values, ŷ, may lie around, above or below the corresponding deterministic production function, depending on the sign of the error component, v, as follows:

[2] In the stochastic model, the parameter γ is approximated to 0. Then, the inefficiency component does not affect the variability of banks' performance, because all deviations from the efficient frontier are due to the stochastic error.

$\hat{y} = f(\beta; x)\exp\{v\}$

Basically, the problems to be solved are: (i) to estimate the unknown parameters β; (ii) to distinguish the inefficiency and error components[3], i.e. u and v and (iii) to assess the efficiency scores. In the literature, there are models differ in order to solve these problems.

In a *cross-section* framework, the problem of decomposing the composite error in the stochastic frontier model has been solved by Jondrow et al. (1982), which suggest deriving the inefficiency estimates drawing the conditional mean of the regression residuals, i.e. $\varepsilon_i = y_i - f(x_i, \beta)$. In other words, they derive a conditional distribution of $u_i|\varepsilon_i$ through the distribution of (u_i, ε_i) to assess the efficiency. However, the maximum likelihood estimates (MLE) are still the best stochastic frontier model in the presence of cross - section observations, even if they are sensitive, especially, to the independence assumption between efficiency, error component and regressor distributions.

There is also a strong debate on the distribution of inefficiency component, u. Over time, researchers have proposed many variants of the stochastic frontier model in order to generalize the distribution of the inefficiency component, f(u), initially distributed either normal-half normal or normal-exponential. In this regard, Greene (1990), Beckers and Hammond (1987) and Stevenson (1990) have proposed the normal-gamma stochastic frontier as an extension of the normal-exponential due by Aigner et al. (1977). This new approach provides a more rich and flexible parameterization of the inefficiency distribution in the stochastic frontier model than either the normal-half normal or the normal-exponential.

Berger and Humphrey (1991) proposed the *Thick Frontier Approach* (TFA) also relying on a

[3] Frequently, u and v are assumed to be independent and distributed as: $u \sim_{iid} N^+(0,\sigma_u^2)$ (or other distribution) and $v \sim_{iid} N(0,\sigma_v^2)$.

functional form for the frontier, but assuming no given distribution for the random or the inefficiency components of the error term. Inefficiency is measured by the difference in performance between the highest and the lowest quartile, the random error terms only existing within quartiles. Whilst arguably more robust, this approach does not produce efficiency scores for the single productive units, but only an estimate of the general level of efficiency in a given sample.

In a *panel data* context, the data can be treated as a pool of NxT observations. We have more information for the same unit in order to perform the decomposition of the error into two components. Indeed, access to panel data enables one to avoid either strong distributional assumptions or the equally strong independence assumption. Some latest developments (Greene, 2005) have also tried to disentangle pure inefficiency from what is to be considered unobserved heterogeneity.

Similarly to the TFA, the *Distribution Free Approach* (DFA), developed by Berger (1993), also assumes a functional form for the frontier, but separates inefficiencies and random term using the information contained in a panel of decision-making units. The basic hypothesis is that inefficiency is stable across time periods, while random terms are on average equal to zero. The estimate of inefficiency for each unit is then determined as the difference between its mean residual and the mean residual of the unit on the frontier (i.e, the minimum cross-unit average residual available in the sample). Within this approach, inefficiencies can follow almost any kind of distribution.

Nowadays the most widely applied SFA technique is the model proposed by Battese and Coelli (1995) to measure technical efficiency across production units, and to relate its determination to some characteristics of the economic environment. This model shall be adopted and presented in greater detail in Chapter 2 (as well as in Appendix A).

1.4 Efficiency Estimation in Non–Parametric Frontier Models

Non-parametric methods, such as the FDH (Free Disposable Hull) and DEA (Data Envelopment Analysis), are based on Farrell's (1957) original formulation of a deterministic frontier model.

These methods do not require the building of a theoretical production frontier, but the imposition of certain, a priori, hypotheses about the technology (free-disposability, convexity, constant or variable returns to scale). However, if these assumptions are too weak, the levels of inefficiency could be systematically underestimated in small samples, generating inconsistent estimates. Furthermore, these methods are very sensitive to the presence of outliers and make it more cumbersome to conduct a specification test on the effect of environment on efficiency. Some of these problems can be solved using a bootstrap technique proposed by Hall and Simar (2002). On the other hand, non-parametric methods do not require any input prices to specify the frontier.

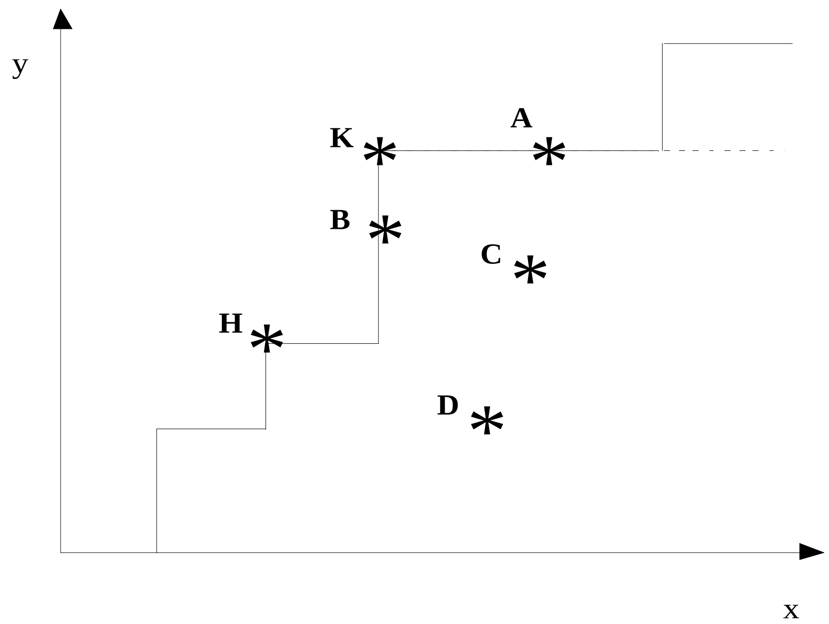
Historically, the main non - parametric methods are the FDH (Free Disposable Hull) and the DEA (Data Envelopment Analysis).

1.4.1 The FDH Model

The FDH approach was developed by Deprins et al. (1984). An excellent introduction to this method is Tulkens (1993). Let $Z^{\circ} = \{(x_i, y_i) \mid i = 1,\dots,N\}$ to be the set of N observations available on the amounts of K inputs (x_i is a K-dimension vector with all non-negative components) and M output (y_i is a M-dimension vector with all non-negative components). The only assumption needed to identify $Z_{FDH}(Z^{\circ})$, $X_{FDH}(y, x^{\circ}(y))$ and $Y_{FDH}(x, y^{\circ}(x))$, is the free-disposability of input and output.

To illustrate the main features of the FDH approach, let us consider Fig. 1.4, where is considered a technology based on an input and an output, and each observation corresponds to a production unit. On the hand, starting from the observation K, we define each observation to the right and below it (i.e, more input and same output, as in A; or less output and same input, as in B; or even more input and less output, as in C) as dominated by K. On the other hand, H is not dominated by K, since it produces less output, but also uses less input. In fact, K and H cannot be compared.

Figure 1.4 - ***The FDH method***



It is important to emphasize that an inefficient producer is necessarily dominated by at least another efficient manufacturer (actually existing). This feature differentiates FDH from the DEA, in which the boundary is largely made up of virtual observations constructed as linear combinations of some efficient producers. The opportunity to highlight some actually existing production units, and to make direct comparisons between them and the units that they dominate, can be considered as one of the major merits of this approach. Moreover, the absence of any assumptions about the convexity of the production technology means that the boundaries obtained by FDH are more likely to “closer” to the data than those obtained by the DEA, when the reference set is characterized, at least locally, the existence of non-convexity.

In order to measure the technical inefficiency of production units dominated is used the radial measure of Debreu-Farrell from the output or input side. In the first case, the technical inefficiency (or, as is commonly said, the efficiency score) is equal to the complement to 1 of a maximum expansion of output consistent with the use of a given input. A producer is technically efficient (and therefore is on the frontier of reference) will not implement such an expansion of output, obtaining an efficiency score of 1. In the second case, input efficiency is given by the complement of a maximum reduction of inputs that allow people to maintain the production of a given output.

When a production unit is simultaneously dominated by two or more units on the frontier of reference (as is the case for D with respect to K and H) is assigned to the unit dominated the efficiency score for efficient observation from which is mostly dominated (K output side and H input side).

1.4.2 The DEA Models

The now classic DEA-VRS approach was first proposed in Banker et al. (1984). The main assumptions that must be made to construct the "production possibility set", are:

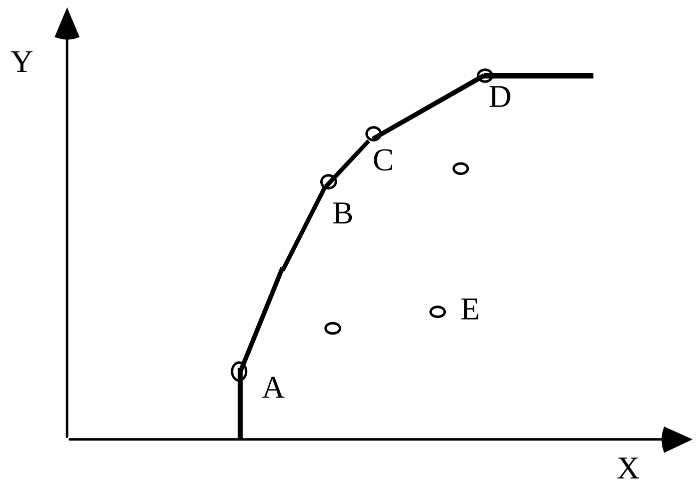
- free disposability (from input and output sides) and, crucially,
- convexity, i.e.:

$\forall (x_i, y_i)$ and $(x_j, y_j) \in Z_{BCC}(Z^{\circ})$ and

$\forall\ 0 \leq \alpha \leq 1, \binom{x}{y} = \alpha \binom{x_i}{y_i} + (1-\alpha) \binom{x_j}{y_j} \in Z_{BCC}(Z^{\circ})$.

The efficient pseudo (or virtual) decision making unit (DMU) is obtained as a convex combination of points over the frontier.

Figure 1.5 - ***The Frontier in the Dea-Vrs model***



The shape of the frontier reflects the possibility to have within this approach variable returns to scale along it. They may be first increasing, then constant, and finally decreasing (repecting the convexity hypothesis).

On the other hand, in the DEA-CRS (constant return to scale), suggested by Charnes et al. (1978), the production possibilities set, Z_{CCR}, is represented by a cone enveloping as close as the data and it is a convex set for the proportionality and additivity assumptions.[4] DEA-CRS is unable to capture the variability of returns to scale along the production possibility set.

The CCR (acronym of Charnes, Cooper and Rhodes's seminar contribution, 1978) or CRS (Constant Returns to Scale) model is obtained by extending of Farrell's work (1957). CRS model consists of a surface envelope of hyperplanes that form the sides of a conical envelope. The

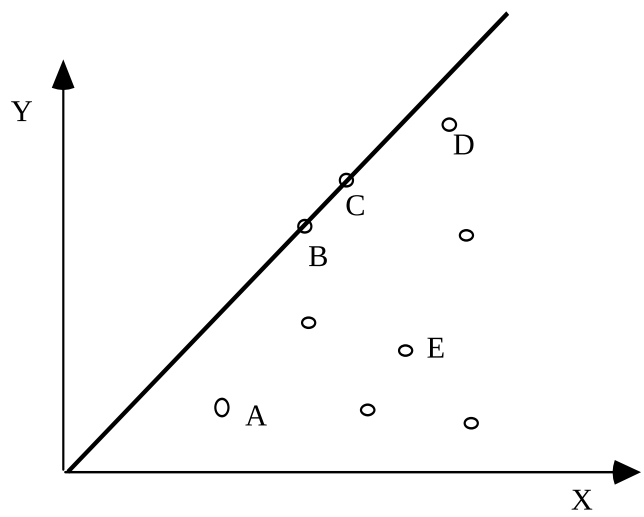
[4] The proportionality assumption says that $\forall(x_i, y_i) \in Z_{CCR}(Z^{\circ}), \lambda \geq 0, (\lambda x_i, \lambda y_i) \in Z_{CCR}(Z^{\circ})$, whilst the additivity ones asserts that $\forall(x_i, y_i)$ and $(x_j, y_j) \in Z_{CCR}(Z^{\circ})$, $\binom{x}{y} = \binom{x_i}{y_i} + \binom{x_j}{y_j} \in Z_{CCR}(Z^{\circ})$, where $\lambda = 1$.

assumptions used to construct the set of production possibilities $Z_{CCR}(Z^{\circ})$ are:

- free disposability (input or output side);
- proportionality;
- additivity;

Postulates 1 and 2 are sufficient to identify $Z_{CCR}(Z^{\circ})$ in the case of a single input and single output, whilst postulate 3 is useful to find $X_{CCR}(y, x^{\circ}(y))$ and $Y_{CCR}(y, y^{\circ}(x))$. The set of production possibilities shown in Figure 1.6 is a cone enveloping the data as closely as possible and is a convex set, for the postulates of proportionality and additivity.

Figure 1.6 - *The Frontier in the Dea-Crs model*



The frontier Eff Z_{CCR} shows constant returns to scale for the proportionality assumption. This implies that the efficiency scores, calculated from the input side, will have the same value than those calculated from the output side.

The comparison between the scores of technical efficiency obtained with the DEA-VRS and the DEA-CRS is useful to measure scale efficiencies (Førsund, 1996). When the scores are the same, the units have efficient production scales, conversely, whether DEA-VRS scores are lower than DEA-CRS scores, the units are too small (if they have increasing returns to scale) or too large (if they have decreasing returns to scale).

1.4.3 The Non – Parametric Methods: A Comparison

By comparing each non-parametric techniques, the advantages of FDH vis-à-vis the DEA are the following: (i) an inefficient producer is necessarily dominated by at least one more efficient producer, it really exists, and not by a (virtual) convex combination of efficient decision making units (DMU_s); (ii) the frontier is closer data if the technology of reference is, at least locally, not convex and, finally, (iii) FDH approach is less sensitive to the presence of outliers or wrongly measured as less extensive stretch of border is influenced by the outlier than DEA method (Tulkens, 1993).

However, just because it makes comparisons between units similar between them, the FDH approach limits the possibility of comparison. One unit as A (see Figure 1.4 about the FDH approach) can be efficient simply because it is not possible make comparisons with adjacent units. In addition, using FDH, given the absence of the hypothesis of convexity, we can obtain a dual formulation of the optimization program only in specific cases of non-linear pricing.

1.5 Parametric and Non–Parametric Method: A Précis

In this chapter, we reviewed the main techniques for measuring the efficiency and we discussed the problems with it. Is almost never easy to choose between the various approaches, as each approach has advantages and disadvantages. Bravo-Ureta and Pinheiro (1993) highlight the paucity of comparative studies and argue that, by the various approaches on the same sample data, the estimates of technical efficiency average are higher by stochastic models than deterministic models, probably because the deterministic models incorporate the stochastic error in the estimates.

More specifically, a comparison of performance on the same set of data between non-parametric approaches (DEA) and stochastic frontier (Diewert and Mendoza, 1995) shows that:

- the same number of observations, the increased decomposition of input or output leads to a spurious increase in efficiency measures in non-parametric approaches, as it narrows the region of feasible solutions. By contrast, the increased disaggregation of input or output produces an uncertain outcome with the econometric methods;

- the relative efficiency of each individual observation decreases, enlarging the sample in both approaches;

- both non-parametric and econometric efficiency measures decreased in the presence of stronger assumptions on the technology of reference (CRS and so on) or on the optimizing behavior of producers;

- the computational difficulty is relatively low in the case of non-parametric techniques, but can grow considerably for the econometric techniques, for a number of input and output more than ten;

- outliers distort substantially non-parametric measures, while the econometric techniques can address this problem through the process of decomposition of the error;

- when only data on quantities are available, non-parametric techniques are preferred than econometric methods because to estimation to the parameters of a single function (e.g. production) can be affected by problems of multicollinearity for the reduced number of degrees of freedom.

Regarding the last point, some recent studies (Kneip et al., 1998, Park et al. 1998; Gijbels et al., 1999) show that there is a significant problem of distortion in small samples for non-parametric methods. This “small-sample bias” reduces, thus, the advantages of non-parametric techniques in the presence of a small number of degrees of freedom.

However, a more fundamental consideration is that the methodological assumption behind each measurement of efficiency is the comparability of the units observed. The efficiency is relative to a benchmark which is defined by comparing the performance of the unit examined to those of other units in the sample. In the case of production units, the assumption of comparability is found in the hypothesis of homogeneity of the units’ technology. Indeed efficiency is derived from a regression residual or from the distance vis-à-vis a non-parametric frontier, selection of the characteristics of the units and eventually of some variables that measure heterogeneity (to include in the frontier specification) is particularly important. These variables define the peer group that determines best-practice performance against which a particular unit’s performance is judged. If something extraneous to the production process is included in the specification, this might lead to too narrow a peer group and an overstatement of efficiency. Moreover, the variables included determine which type of inefficiency gets penalized. If unit age, e.g., young vs. old, is included in the frontier, then an old unit’s performance would be judged against other old units but not against young units, and conversely.

An alternative to including heterogeneity measures in the frontier specification is to measure efficiency based on a frontier in which they are omitted and then to see how they correlate with efficiency. This is easier to do also because, in the case of non-parametric frontiers, in order to include a variable in the production set, one must know a priori whether it is an input or an output. The two-stage approach is subsequently often used in the literature, but has some serious problems of its own: both in the parametric and the non-parametric set-up, it basically assumes that variables included in the second stage are statistically independent from inputs and outputs (Kumbhakar and Lovell, 2000; Simar and Wilson, 2007, 2011). This is certainly a pretty tall assumption.

1.6 The Analysis of Efficiency within Banking. Some General Considerations

As can be gathered from some classic accounts (European Union, 1977; Niehans, 1978; Fama, 1980), banks are a typical example of multi-output activities. These activities include: (i) asset management, (ii) foreign currency management (iii) provision of export credit, (iv) issue of various securities (checks, payment cards, etc.), (v) asset safekeeping, (vi) support for various kinds of financial transactions (buying and selling government securities, bonds, shares, mutual investment funds). This multi-faceted nature finds a counterpart in the variety of approaches utilized to describe the production process of banks (Van Hoose, 2010).

In the “asset” approach (Sealey and Lindley, 1997), akin to the “intermediation” approach, the bank is mainly a financial intermediary, which uses deposits to fund loans and other types of financial assets in order to encourage customers to invest. For this reason, deposits are included in the vector of inputs, thus differing from the "value added", also called "production", approach (Goldschmidt, 1981). According to the latter, the primary task of lending institutions is to provide services related to both loans and deposits using labour and capital as inputs. The superiority of one approach over the other is still the matter of some discussion. Combining the "asset" and "value added" approaches, we obtain the "modified production" or "profit/revenue" approach (Berger and Humphrey, 1991). This approach captures the dual role of banking operations, considering the price of deposits to be an input, whilst the volume of deposits is an output. In this specification, banks are assumed provided intermediation and loan services as well as payment, liquidity, and safekeeping services at the same time. The three approaches are compared in Table 1.1.

The "asset" approach has maintained some ascendancy within the literature, especially when focusing on the role of banking efficiency for economic development (Lucchetti et al., 2001; Hasan et al., 2009), and it will be the approach chosen in the following empirical analysis. At any rate, the awareness has grown that in order to measure accurately bank efficiency, allowance must be made for environmental factors beyond the control of bank managers, as well as for the role of risk aversion. The correct measurement of bank efficiency hence requires the analysis to include not only the inputs and outputs enumerated in Table 1.1, but also indicators of environment and risk-aversion.

Table 1.1 - *Value Added, Asset and Modified Production Approaches: The Production Set.*

Approaches	Outputs	Inputs
Value Added Approach (Goldschmidt, 1981)	Customer Deposits Customer Loans Securities (bank loans, Treasury bills and similar securities, bonds and other debt minus bonds and debt securities held by banks and other financial institutions) Other Services (Fees and other operating incomes)	Physical Capital Labour
Asset Approach (Sealey and Lindley, 1997)	Customer Loans Securities (bank loans, Treasury bills and similar securities, bonds and other debt minus bonds and debt securities held by banks and other financial institutions) Other Services (Fees and other operating incomes)	Physical Capital Labour Funds (customer deposits, bank debts, bonds, certificates of deposit and other securities)[5]
Modified Production Approach (Berger and Humphrey, 1991)	Customer Loans Customer Deposits Securities (bank loans, Treasury bills and similar securities, bonds and other debt minus bonds and debt securities held by banks and other financial institutions) Other Services (Fees and other operating incomes)	Physical Capital Labour Funds (customer deposits, bank debts, bonds, certificates of deposit and other securities)

Source: Own elaboration.

It is well known that efficiency measurement involving banks from different territories ought to make allowance for differences in the socio-economic and institutional environment beyond the control of bank managers. There are various studies of bank efficiency across US states (see Lozano-Vivas et al., 2002). Dietsch and Lozano-Vivas (2000) analyze the impact of other environmental factors beyond the control of bank managers, notably the degree of concentration (measured by the Herfindahl-Hirschman index), population density, GDP per capita, in a European cross-country set-up. It can be easily argued that similar indicators are needed in order to take into account territorial differences in the socio-economic environment even within a given European country, if the latter is characterized by marked heterogeneity. However, more seldom, if at all (a recent *partial* exception is Hasan et al., 2009), these factors have been utilized

[5] Sometimes free capital, the difference between equity and fixed assets, is also included in the input vector because it constitutes an additional source of resources, over and above the collection of funds (see Destefanis, 2001).

in works dealing with within-country comparisons for European countries.

A key indicator varying along with the socio-economic environment is risk. Banks can be mainly hit by credit risk, which relates to the management of subjective uncertainty and, in many cases, depends on the discretion of managers, who may not behave in the bank's interest. According to Berger and De Young (1997), the existence of risky assets entails additional “monitoring” and “screening” costs that banks must meet in order to assess them. Hence, changes in economic environment may bring about deteriorations in the banks’ performances (the “bad luck” hypothesis), but also poor risk management may bring about a higher insolvency risk (the “bad management” hypothesis).

A popular indicator of credit risk is the ratio between bad and total loans. This indicator is related to the probability of bank failure. If banks do not bear any credit risk it is close to zero, and it approaches unity if financial intermediaries incur in a higher percentage of outstanding claims. Clearly, however, this indicator is linked to both the “bad luck” and “bad management” mechanisms. Indeed, Berger and De Young (1997) resort to a time-series analyses in order to disentangle the two different links between it and banks’ efficiency. A related point, made by Berger and De Young themselves, is that it could be interesting to examine the “bad luck” hypothesis relying on indicators of credit risk that are exogenous for a given bank. To the best of our knowledge, this attempt has never been carried out in the literature.

In any case, if bank managers are not risk-neutral, their degree of risk-aversion is likely to be reflected in their choices about the production set. The bank’s behavioral response to risk is measured by an index of capitalization, very often the relationship between equity and total assets (Hughes and Mester, 1993; Mester, 1996). This index approximates to one if banks are highly capitalized. In this case, the banks can cope with possible risks without incurring danger of default. A similar situation arises when banks are subject to more intense merger and acquisition processes.

Another fundamental point concerning risk management is risk diversification. Broadly speaking, diversification can occur across income sources, industries or geographical areas (Rossi et al., 2009). Focusing on territorial diversification, Hughes et al. (1996, 1999) find that territorial diversification is positively correlated with bank efficiency in the US. In particular, interstate bank diversification has improved bank efficiency in the US after the passage of the Riegle-Neal Interstate Banking and Banking Efficiency Act in 1994. Also for the US, Deng et al. (2007), measuring territorial diversification through various indexes of deposit dispersion, find that diversification has a favorable impact upon the risk-return profile of bank holding companies.[6]

Last but not least, it should be noted that ignoring non-traditional activities, i. e. those activities producing non-interest or fee incomes, leads to a misspecification of bank output. Several studies (DeYoung, 1994; Rogers, 1998; Stiroh, 2000; Tortosa-Ausina, 2003; Casu and Girardone, 2005) have shown that average performance is improved when these types of activities are taken into account. A possible explanation for this is that the resources that are used to produce non-traditional products are somehow included by default in the input vector but not in the output vector. According to another explanation, banks are better producers of non-traditional rather than traditional items (Rogers, 1998). In either way, the finding that bank performance is underestimated in case non-traditional activities are ignored corroborates the growing importance of this kind of activities in the operation of banks.

[6] These findings are related to the huge block of literature relating to the impact of M&A on bank efficiency, a point also made in Bos and Kolari (2005), who, considering the potential gains from geographic expansion for large European and US banks, concluded that profit efficiency gains were obtainable from cross-Atlantic bank mergers.

Summing up, we believe that this section highlights the intrinsically multi-input multi-output nature of the productive process within banking. This is all the more true, if we consider the need for taking important factors, such as credit risk or credit diversification, into account. In this sense, non-parametric efficiency analysis, with its easy treatment of many inputs and outputs, seems to the lend itself naturally to the analysis of the banks' productive processes. Non-parametric analysis has however a great problem: the components of the production set should be defined a priori as inputs or outputs. This may be rather difficult for some indicators of credit risk and risk aversion, and is certainly very difficult for the proxies of various environmental factors. In empirical work, this has led to a widespread application of parametric methods, especially if the use of cost or profit frontiers helped to circumvent the multi-output nature of the productive process. Indeed, within cost or profit frontiers, a single cost (or profit) term can be conditioned on various output quantities, input and output prices, *and other variables as well*, without any need to forejudge the impact of the latter (see Kumbhakar and Lovell, 2000, for the analytical details, or Giordano and Lopes, 2006, for a recent application on Italian data). We shall keep in mind these considerations in carrying out the empirical analyses of the following chapters.

CHAPTER 2

LOCAL FINANCIAL DEVELOPMENT AND ECONOMIC GROWTH: THE OULOOK FROM ITALIAN TERRITORIAL DATA

Abstract

In this chapter, we test the nexus between financial development and economic growth relying upon territorially disaggregated data (NUTS3 and SLL) from Italy. We use cost and profit efficiency scores, computed through a parametric approach (SFA), as qualitative measures of financial development, and credit volume divided by gross domestic product as its quantitative measure. A key element of novelty of this chapter's analysis is the interaction between banking and national accounting at a territorially very disaggregated level. The banking data, taken from the BilBank 2000 database distributed by ABI (Associazione Bancaria Italiana) over the 1998-2005 and 1998-2008 period, include many cooperative banks that operate at a purely local level. A growth model, similar to Hasan et al (2009), is specified and tested in a panel data context. Our estimates suggest that financial development has a positive significant impact on GDP per capita.

2.1 Introduction

"Economic development" is one of the most important concepts in economics. Often "growth" and "economic development" are used interchangeably, even if they are relatively different concepts. "Growth" relates to quantitative wealth indicators such as time variations in gross domestic product (GDP) per capita. On the other hand, “economic development” refers to the complex structural transformation process, changing the production structure that marks the transition from a predominantly agricultural economy to a greater role in goods and services.

Although the demand for goods and services is the primary factor driving the economy of a country, it alone cannot explain why countries with the same have so markedly different propensities for development or growth. It is obvious that there are a number of obstacles which slow the growth phases. In principle, the obstacles may include: (i) differences in social capital (Guiso et al., 2004a); (ii) failures to implement political intervention by the public authority focused on development (Bencivenga and Smith, 1991; Greenwood and Jovanovic, 1990) and (iii) differences between political, legal and cultural rights (La Porta et al., 1997, 1999) which encourage inequality; (iv) difference in financial development (Guiso et al., 2004b; Levine, 2005).

Indeed, in the past, many studies have deal with the finance-growth nexus empirically (Cameron, 1967; Sylla, 1969, 1972, 2002; Levine, 2005). In this context, many works have neglected the potential problem of endogeneity (Guiso et al., 2004b; Levine, 2005): does causality run from finance to growth, or is it the other way around? The present work attempts to deal with this problem, by considering the impact on growth of variables related to local credit and bank efficiency, allowing for the impact that environment may have on the latter.

It is well known that differences in the environment, risk and regulation conditions have an important impact upon the banking industry. As was noted in Chapter 1, various studies have tested the relevance of these factors (Ferrier and Lovell, 1990; Kaparakis et al., 1994; Berger and Mester, 1997). With respect in particular, to the role of environment on banking efficiency, the study of Dietsch and Lozano-Vivas (2000) has been particularly influential: they investigate the factors that could explain cross-country differences in measured efficiency scores, isolating three groups of environmental variables and taking into account the French and Spain market. Similarly, Fries and Taci (2005) employ two categories of variables: country-level factors and other correlates with bank inefficiencies. Bonin et al. (2005) focus on ownership characteristics affecting efficiency score variability and also control for some environmental variables.

In this chapter, we build upon those contributions, employing similar techniques to allow for the impact of environment on banking efficiency, and then assessing the impact of the efficiency scores obtained in this manner on local development. We build upon the growth model tested in Hasan et al. (2009), but unlike in that work, *we use data disaggregated at the same territorial level both for the environmental controls in the efficiency analysis and the variables of the growth model*. We thus trust to reduce to a minimum the impact of endogeneity on our estimates. Indeed, we seek to contribute to the literature that examines the nexus between financial development and economic growth relying upon territorially disaggregated data (SLL, *Sistemi Locali del Lavoro*, and NUTS3) from Italy, also considering how the behaviour of cooperative banks influences growth. On the hand, we use cost and profit efficiency scores, computed through a parametric approach (SFA), as qualitative measures of financial development, and credit volume divided by gross domestic product as a quantitative measure of financial development. In this context, a key element of novelty is the interaction between banking and national accounting at a territorially very disaggregated level (SLL and NUTS3). Furthermore, we believe that the importance of cooperative banks has not yet received appropriate attention in the empirical literature in term of their implications upon economic growth. Yet, there is a widespread consensus (see e.g. Fonteyne, 2007) to the effect that these banking institutions are geared to support local economic development, financing the local economy and contributing to sustain local employment, rather than merely pursuing a proper financial return. In other words, we must expect to see in the data a strong contribution from cooperative banks to local development, competitiveness and employment.

The rest of the chapter is organized as follows. Section 2.2 analyzes the main works concerning finance-growth nexus and banking efficiency. Section 2.3 describes the methodology used to assess the nexus between financial development and economic growth. The description of our data sources is detailed in Section 2.4. The key findings are set out in Section 2.5, while Section 2.6 concludes.

2.2 Financial Development and Economic Growth. A Literature Review

The relationship between “financial development” and “economic growth” has attracted many researchers over time. In literature, there is an important and extensive line of research that examines this connection (for a survey on recent empirical research see Levine, 1997, 2005), a key point of which is the direction of causality: does causality run from finance to growth, or is it the other way around? Failing an answer to this question, empirical results are quite ambiguous.

At any rate there are two strands of research that, analyzing the finance-growth nexus, find significantly different results. The first strand of research shows that financial development predicts, optimally, growth (McKinnon, 1973; King and Levine 1993a, 1993b; Demirgüç-Kunt and Maksimovic, 1998; Neusser and Kugler, 1998; Rousseau and Wachtel, 1998; Rajan and

Zingales, 1998; Christopoulos and Tsionas, 2004), also with a differential impact in various phases of growth (Levine and Zervos, 1998; Bekaert et al., 2001). However, evidence that finance *predicts* growth cannot be used to conclude that it *determines* growth because of: (i) the role of expectations and (ii) the possibility of important and necessary omitted factors.

Generally speaking, growth determines finance but precedes it if the expectations of future economic development induce current financial development. In fact, if firms anticipate future economic growth, increasing demand for financial services, they may invest in the creation of additional financial intermediaries today in anticipation of future profits. Instead, the causality between growth and finance is unknown when there is the possibility of missing factors.[7]

The second strand of research attempts some more structural kind of estimation, and often concludes that economic growth determines financial development (Gurley and Shaw, 1967; Goldsmith, 1969; Jung, 1986), while others show that the causal direction is two-way (e.g. Demetriades and Hussein, 1996; Blackburn and Huang, 1998; Khan, 2001; Shan et al., 2001).

The general consensus stemming from this literature is in any case that there is a positive correlation between financial development and economic growth especially for developing countries, but not for those countries with a high income (see e.g. Hassan et al., 2011). It should be noted that the effect of financial development on growth is investigated by most researchers in a cross-country set-up (often in periods of very low capital mobility), which obviously heighten the risk of omitting potentially relevant factors (legal institutions, etc.). Only a few works

[7] Omitting a variable such as the “saving rates” might determine both current financial development and future economic growth. For instance, a younger population will tend to save more relative to GDP than older population. On the hand, the economy of the younger population will be more financially developed because the financial system is able to allocate more resources. On the other hand, if these funds will be invested in productive projects that promote growth, there will be a higher growth rate for this economy. So, finance does not cause growth at all, but both are driven by demography structure, also if finance precedes growth.

analyze this phenomenon within the same country (Jayaratne and Strahan, 1996; Dehejia and Lleras - Muney, 2003; Guiso et al., 2004b).

These studies use different proxies associated with the financial sector development in order to investigate the finance-growth nexus. Nevertheless, the indicators commonly used can be distinguished in two groupings. The first group focuses mainly on the role that banks can have in stimulating the accumulation and distribution of capital (e.g. see Goldsmith, 1969; McKinnon, 1973; Gertler and Rose, 1994; King and Levine, 1993a, 1993b, 1993c; and Guiso et al., 2004b). This body of literature uses proxies linked to credit volume to measure the state of financial development: they do not seem wholly suitable to explain the relationship between financial development and growth, because the role of financial intermediaries is not simply to mediate the savings, but also to identify the quality of borrowers, so as to prevent the spread of harmful risks for the entire banking system. It is in this sense interesting to consider the approach adopted by Hasan et al. (2009) in order to test the direction between financial sector and economic growth in 11 European countries. They use the banking (cost or profit) efficiency and the bank credit volume relative to GDP as qualitative and quantitative proxies, respectively, associated to financial development. The second group of indicators measures the amount of financing intermediated by banks (e.g. Rajan and Zingales, 1998; and Levine et al., 2000), as is traditional in this literature. However, according to Hasan et al. (2009), banks can encourage and promote the growth of a country not only by placing more credit in the system; but also by greater efficiency of banks and by the interaction between credit availability and the efficiency of banks. Indeed, already Cameron et al. (1967) had forcefully stressed the key role of bank efficiency in the finance-growth nexus. Hasan et al. (2009) find that efficiency has a strong effect upon local development, while the interaction term has no strong effect on regional growth.

All these analyses attempt to capture the role of banks in economic development. However, as has already been recalled, it is well known that a potential endogeneity problem affects the finance-growth nexus. Hasan et al. (2009) are acutely aware of this problem. Accordingly, they base their growth estimates on the GMM procedure, which should in principle account for the presence of endogeneity. There is however a basic problem with their empirical analysis.

Hasan et al., building upon Dietsch and Lozano-Vivas (2000) use various factors (macroeconomic, bank structure and regulation variables) in order to model the impact of the economic environment on efficiency (and thus on the qualitative side of financial development). In particular, they calculate the (cost or profit) efficiency of banks belonging to several countries, by controlling for the impact of environment on banking efficiency through proxies *computed at the country level* (bank branches per capita, deposits per branch, deposit density, and so on). Then they proceed to assess the impact of the efficiency scores obtained in this manner on local development measured at the NUTS2 level. They do this because of data availability problems within their European sample. Arguably, however, this procedure leaves a lot of unobserved heterogeneity in the measures of bank efficiency, especially for small, local, banks.

Accordingly, in this chapter we build upon the growth model tested in Hasan et al. (2009), but unlike in that work, and relying on some data-sets hitherto virtually not utilized in empirical work, we adopt data disaggregated at the same territorial level both for the environmental controls in the efficiency analysis and the variables of the growth model. We thus trust to reduce to a minimum the impact of unobserved heterogeneity, and, thus, endogeneity, on our estimates.

2.3 The Empirical Methodology

In order to test the nexus between financial development and economic growth (local GDP per capita from SLL-level) relying upon territorially disaggregated data (NUTS3 and SLL) from Italy, a growth model, similar to Hasan et al (2009), is specified in a dynamic unbalanced panel context as follows:

$$Y_{i,t} = a_1 Y_{i,t-1} + a_2 Y_{i,t-2} + b_1 \ln FV_{i,t} + b_2 \ln FQ_{i,t} + b_3 \ln FV_{i,t} \times \ln FQ_{i,t} + b_4 N_{i,t} + \eta_i + \tau_t + e_{i,t}$$

where Y represents the rate of growth in GDP per worker explained by its lagged values, and by FV (finance volume), aggregate credit relative to GDP, by FQ (finance quantity), i.e. cost or profit efficiency obtained through SFA, by the interaction between FV and FQ, by N, the rate of growth in employment (controlling for various local influences), by η, unobserved area-specific effects, and finally by τ, year dummies controlling for time-specific effects; ε are the disturbance terms. Subscripts i and t respectively refer to areas (either “SLL” or “NUTS3") and time periods (years). The dynamic panel specification suggests the use of the two-step system Generalized Method Moment (sys-GMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). Moreover, given the well-known endogeneity problems between financial development and economic growth, we include lagged levels and differences as instruments for FV and FQ (see also Levine et al., 2000). As usual, the correctness of the model is checked with the Sargan-Hansen test of overidentifying restrictions for validity of instruments, while the Arellano-Bond test is used for testing autocorrelation between error terms over time.

We stress that a distinctive feature of our analysis, taken from Hasan et al. (2009), is that we rely on both qualitative and quantitative proxies of financial development, as measured by banking efficiency and the bank credit volume relative to GDP. It is thus of paramount importance to understand how the measurement of efficiency is carried out in the present study.

As already seen in Chapter 1, the main approaches used in the literature to calculate efficiency scores are non-parametric and parametric models. As already said, there is no general consensus about which method (parametric or non-parametric) to adopt to measure banking efficiency. However, as already noted in Chapter 1, the great advantage that non-parametric methods have in dealing with multi-input multi-output production sets fails if the measurement of cost or profit efficiency allows the use of specifications conditioned on a single dependent variable. In our set-up, these are exactly the kind of efficiency measures that we need. Furthermore, employing a stochastic frontier enables us to estimate the impact of environmental and risk factors on banks in a more flexible manner than would be feasible with non-parametric methods. Hence, we shall rely on SFA, whose additional advantage consists in taking into account possible noise in the data, in order to calculate the efficiency scores in the present chapter.

The SFA specification has been widely used over the past two decades. Over the years, this specification has undergone many changes and extensions, especially on the distributional assumptions for the inefficiency component and the consideration of panel data and time-varying technical efficiencies (for survey papers on frontier functions see Førsund et al., 1980; Schmidt, 1986; Bauer, 1990; Greene, 1993). Here we shall adopt the very widely estimation procedure proposed in Battese and Coelli (1995), which is explained in greater detail in Appendix A.

Over time, many studies estimating either cost (e.g. Kwan and Eisenbeis, 1996; Berger and DeYoung, 1997; Kumbhakar and Sarkar, 2003; Williams et al., 2004; Altunbas et al., 2007) or profit (Berger and Bonaccorsi di Patti, 2006) efficiency, or both (Giordano and Lopes, 2006; Pasiouras et al., 2009; Battaglia et al., 2010; Fiordelisi et al., 2011) in banking have used a SFA. In this chapter, we contribute to this literature, by carefully allowing for environmental and risk factors in the productive process of banks. In particular, as has already been mentioned, we shall use proxies of the economic environment computed at a very disaggregated territorial level.

Cost and profit efficiency are measured using the Battese and Coelli's (1995) stochastic frontier model as follows:

$$y_{it} = f(\mathbf{x}_{it}, \boldsymbol{\beta}) \exp\{v_{it} \pm u_{it}\}$$

where y_{it} is the (natural log of) total cost or profit of bank i at time t; $\mathbf{x}_{it}$ is a k×1 vector of explanatory variables (output quantities, input and output prices; also taken in natural logs) of bank i at time t; $\boldsymbol{\beta}$ is an vector of unknown parameters; v_{it} are random variables assumed to be i.i.d. N $(0, \sigma_v^2)$ and independent of the u_{it}, while u_{it} are non-negative random variables measuring inefficiency. They are assumed to be independently but not identically distributed: they obtain from the truncation to zero of the distribution N (m_{it}, σ_u^2) where $m_{it} = \mathbf{z}_{it} \boldsymbol{\delta}$, $\mathbf{z}_{it}$ being a vector of determinants of (profit or cost) efficiency of bank i at time t, and $\boldsymbol{\delta}$ a vector of unknown coefficients. Parameters $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are estimated simultaneously and the (profit or cost) efficiency of bank i at time t is respectively defined by:

$$PE_{it} = \exp\{-u_{it}\} = \exp\{-\mathbf{z}_{it} \boldsymbol{\delta} - w_{it}\}$$

$$CE_{it} = \exp\{u_{it}\} = \exp\{\mathbf{z}_{it} \boldsymbol{\delta} + w_{it}\}$$

where w_{it} is a random variable defined by the truncation of a normal distribution with $- \mathbf{z}_{it} \boldsymbol{\delta}$ as the truncation point.

Recall that the asset model asserts that a bank is a financial intermediary, which uses deposits to fund loans and other types of financial assets in order to encourage customers to invest (Van Hoose, 2010). So, deposits are included in the vector of inputs, thus differing from the value added or production (Goldschmidt, 1981) model. According to the latest approach, the primary task of credit institutions is to provide services related to both loan and deposit using as inputs labor and capital. Both approaches can be used to model the banking production set, as it was still demonstrated the supremacy of one method over another. According to Berger and Humphrey (1997), the "asset" or "intermediation" approach would be more appropriate to evaluate the activities carried out by financial intermediaries, and this is the approach that we shall follow here.

We rely for our estimation on a translog functional form (see Appendix A for further details).

2.4 Data and Variables

Following the asset model (Sealey and Lindley, 1997), the output vector (**y**) is composed by: customer loans (y_1), services (administrative) or non – traditional activities (y_2), i.e. commission income and other operating income, and securities (y_3), i.e. bank loans, Treasury bills and similar securities, bonds and other debt less bonds and debt securities held by banks and other financial institutions. Non-traditional activities play an important role in the banking output. In this work, we include a proxy for capture the effect of these activities, as the commission income and other operating income, on bank performance (e.g. Casu et al., 2004; Tortosa - Ausina et al., 2008). Instead, the inputs vector (**x**) consists of the following items: number of branches (x_1), number of workers (x_2) and fundraising (x_3), i.e. total liabilities to customers, amounts owed to banks and debt securities (bonds, certificates of deposit and other securities).

Output prices are calculated as follows: customer loan price – ratio of interest income of customer loans a customer loans (p_1); services price – normalized to 1 (p_2); debt securities price – ratio of interest income on debt securities and debt securities (p_3).

The cost vector (**w**) incurred by the credit institutions is composed by: labour cost (w_1) obtained as the ratio of personnel expenses (wages and salaries, social charges, indemnities working, treatment pensions and similar) and number of employees; cost of physical capital (w_2), i.e. ratio of other administrative expenses, value adjustments to tangible and intangible assets and other operating expenses to number of branches and cost of financial capital (w_3), consisting of interest expenses and similar charges and commission expenses over total liabilities.

Following Lozano-Vivas et al. (2002) and Hasan et al. (2009), we include some environmental variables in one stage stochastic frontier capturing the institutional and risk characteristics of cooperative and other banks and the geographical location of branches, deposits and loans (their specific value), taken either at SLL and NUTS3 level such as: deposits density (DD), intermediation ratio (IR), branch density (BD) and deposits per branch (DB). Moreover, we also adding capitalization (ETA) and credit risk (NPLL). All these variables are included in the so-called z-vector of the Battese-Coelli (1995) method, explaining the mode of the inefficiency term distribution.

Yet, compared to other works, we have a better spatial stratification than enables us to better capture the differences between geographical areas and to obtain more accurate estimates. Our analysis is then fully conducted on a local and provincial basis to accurately capture the contribution of local credit institutions. DD, IR, BD and DB shall be measured not at the national level 8as in previous studies), but at the local level. A very important analytical category for territorial economic analysis in Italy is the *Sistema locale del lavoro* (SLL). This is a group of municipalities (akin to the UK's Travel-to-Work-Areas) adjacent to each other geographically and statistically comparable, characterized by common commuting flows of the working population. They are an analytical tool appropriate to the investigation of socio-economic structure at a fairly disaggregated territorial level. The identification of 686 SLL's made by ISTAT (the Italian Statistical Office) in some recent research (ISTAT, 2005) has highlighted remarkable differences in economic performance across the Italian territory. For purposes of comparison note that there are nowadays in Italy 110 *province* (the NUTS3 category). In our analysis, we shall be able to rely on data at both NUTS3 and SLL level for the variables relating to local growth, *as well as to the environmental proxies for banking efficiency*.

A potential anomaly with the use of SFA concerns the presence of negative values that correspond to the losses incurred by banks. Since the log of negative numbers associated to profit of banks is not defined, this leaves us with a potential problem. The main approaches used in the literature to deal with it are: (i) truncation, by eliminating observations with negative profits; (ii) rescaling, by adding the sample minimum plus one to the negative value of profits and (iii) censoring, by assigning negative profits to 1 and specify an addition dummy variable that takes value 1 if profits are positive and value 0 if profits are zero or negative, before taking logs. Bos and Koetter (2011), who propose it, stressed that the latter method improves the precision of profit efficiency scores, making them less likely to be biased. Accordingly, censoring shall be the method employed in our analysis to deal with negative profits.

In order to investigate the nexus between financial development and economic growth we take a large sample of Italian banks classified by the Bank of Italy as small (commercial (COB's) and popular (PB's) banks - average funds intermediated between 1.3 and 9 billion euro) and minor (cooperative banks (CB's) - average funds intermediated less than 1.3 billion euro), We exclude larger banks both because they their technology is likely to be very different from that of smaller banks, and because their nexus with local development is likely to be much flimsier. On the other hand, it should be stressed that our estimates include both cooperative and commercial banks or reasons that shall be better explained in Chapter 3, cooperative can be more or less considered along with other banks as far as cost minimization is concerned, but they differ widely in their profit maximization process. The "*principle of mutuality*", in particular, includes many other objectives along with profits in the cooperative banks' utility function[8]. All this means that we shall keep all banks together when measuring cost efficiency, but separate them in order to measure profit efficiency[9].

The sample of banks we consider is an unbalanced panel for the 1998-2008 period. We focus chiefly on the 1998-2005 period since data prior to 1998, especially environmental variables at the SLL and NUTS3 level, are not available, and after 2005 the implementation of Basel II might complicate the interpretation about the impact of environmental and risk factor on banking performance. In fact, we include the capitalization degree in order to capture the risk aversion of bank. For purposes of robustness check, anyway, we shall also consider the 1998-2008 period as a whole.

The data were taken from BilBank 2000 database distributed by ABI (Associazione Bancaria Italiana) because it has a large time extension and wealth of information on bank balance sheets, where the total of banks is about 400 units for each year concerned. The sample of banks consists

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8 Based on data provided by Fonteyne (2007), there is evidence that Italian CB's have reached on average a 6.7% return on equity over 2002-2004 period (see Table 3.1 in Chapter 3 that lists bank performance indicators in Italy).

9 We have also relied on an alternative approach, where the explanatory model of *cost* inefficiency includes a dummy variable having a value of 1 when the banks are CB's and the interactions between this dummy and the environmental factors, as well as a time trend that captures the banks ability to converge toward the efficient frontier (see Giordano and Lopes, 2006, p. 20). The results, available upon request, are not noticeably different from those reported in the text.

for the majority by CB's, a less than other branches of banks located abroad. The GDP per capita for SLL is constructed by updating the SLL value added data from ISTAT through the 2006-2008 period with data from the Bureau Van Dijck's AIDA dataset. Population and employment are from the ISTAT SLL data-set. All NUTS3 data are from ISTAT's territorial accounting. All monetary aggregates are in thousands of deflated 2002 Euros. All the regression analysis (GMM and SFA alike) is carried out with STATA 11.

2.5 The Empirical Evidence

We present our results in Appendix A, along with some descriptive evidence, and a detailed description of the translog function associated to the measurement of cost and profit efficiency. The actual translog estimated specifications are available on request.

In order to test the nexus between financial development (FV and FQ) and economic growth (local GDP per capita from SLL-level) relying upon territorially disaggregated data (SLL and NUTS3) from Italy, a growth model similar to Hasan et al (2009), is specified in a panel data context. The efficiency scores are calculated using a stochastic frontier analysis (SFA) and including some environmental variables (see Table 2.4 in Appendix A) in order to capture the institutional and risk characteristics of cooperative and other banks and to obtain accurate estimates. Including these controls improves banking performance.

Perusal of Table 2.5 in Appendix A shows that cooperative banks generally have lower cost efficiency than other banks only for the whole sample. Therefore, the principle of mutuality seems to penalize these banks in the process of cost minimization, only if allowance is made for the great financial crisis starting in 2007, given perhaps the relatively lower share of loans held.

Accordingly, we also find that cooperative banks achieve lower profit efficiency if the sample includes the financial crisis. This result confirms that, in the wake of the crisis, cooperative banks have been strongly penalized by the “principle of mutuality”, because they have to maximize the utility of the members and customers and promote economic development, rather than to maximize their profits. These issues, as well as the relevance of the so-called principle of territorial competence, are further pursued in Chapter 3.

Turning now to the GMM estimates of the growth model, we first notice that it was always necessary to specify an autoregressive process of order 2, lest incurring in very high residual autocorrelation. Hence, only results with this kind of specification are shown in Appendix A (Tables 2.6-2.9). Our estimates, that, as already said, allow for a finer degree of territorial disaggregation than usually adopted in the literature, suggest that financial development has indeed some (positive) significant impact on GDP per capita. The quantitative (finance volume) proxy turns up almost invariably with a positive and significant coefficient. This is also true, by and large, of the qualitative efficiency proxies. Yet, it should be noticed that the performance of the model deteriorates if we take into account the full 1998-2008 period. The instruments included in the model are found less often to be valid (see the Sargan tests), while we reject more often the hypothesis of zero order-3 autocorrelation among the error terms. Thus it seems that the current financial crisis and the occurrence of Basel II have indeed some detrimental impact on our specification. A puzzling feature of our estimates, not easily explained, and to be left for future research, is also that the interaction between qualitative and quantitative proxies of financial development (suggested by Hasan et al, 2009) has very often a negative sign, which is quite difficult to rationalize.

2.6 Concluding Remarks

The potential differences on the environmental, risk and regulation conditions have led many researchers to examine the impact of environment on financial development. To our knowledge, this study is the first to explore the finance-growth nexus considering the role of local institutions at a very territorially disaggregated level. Our estimates, that allow for the potentially two-way nature of the finance-growth nexus in various ways, suggest that both qualitative and quantitative proxies of financial development has a positive significant impact on GDP per capita, although further research seems to be in order, especially with a view to model the recent economic evolution appropriately.

CHAPTER 3

RISK AND REGULATION: THE EFFICIENCY OF ITALIAN COOPERATIVE BANKS

Abstract

In this chapter we analyze the determination of cost efficiency in a sample of Italian small banks located in different geographical areas and including two great institutional categories: cooperative banks (CB's) and other banks. We highlight the effect of environmental factors (asset quality, local GDP per capita) on banks' performance, and provide novel evidence in favour of the "bad luck" hypothesis suggested by Berger and De Young (1997). Local GDP per capita strongly affects the territorial differentials for technical efficiency, especially for CB's. This can be easily rationalized, as current regulations hamper CB's vis-à-vis other banks in their capability to diversify territorially. Our estimates provide us with a tentative quantitative measure of the costs of missing diversification, ranging between 2 and 7 percentage points. Correspondingly, our evidence suggests that there is potentially strong endogeneity in some currently available bank performance indicators.

3.1 Introduction

In the literature concerned with the determination of bank efficiency the themes of regulation and proprietary forms have always enjoyed a prominent status (Berger and Humphrey, 1997; Berger and Mester, 1997). These themes have almost invariably been taken in account without explicit allowance for changes in the socio-economic environment of banks. The latter are, on the other hand, intimately connected with the theme of risk management within the productive process of banks (Hughes and Mester, 1993; Berger and De Young, 1997). In this chapter we bring together these two strands of the banking literature, within a frontier efficiency analysis of Italian small banks. As a matter of fact, we focus on Italian cooperative banks (CB's), whose regulatory structure is particularly suited to the analysis of the interaction between regulation and risk. Other Italian small banks will mainly be considered for purposes of comparison. We believe that our analysis may be of relevance, not only because European cooperative banks have recently spurred considerable policy interest (see, for instance, Fonteyne, 2007, who also highlights the important role of Italian CB's), but also because we produce some quantitative estimates of the impact of (territorial) risk diversification upon bank efficiency. Estimates of this kind are not yet widely available (see however Hughes et al., 1996, 1999; and Deng et al., 2007), and are to the best of our knowledge wholly missing for European banks. This suggests that providing novel evidence about territorial bank efficiency differentials in a country characterized by strong economic heterogeneity as Italy could be of some general interest.

Our analysis consists of the following steps. Section 3.2 examines the production process of banks, considering some traditional ways to incorporate risk and socio-economic environment in it. In Section 3.3 we introduce the reader to some features of Italian CB's and, more generally, of the Italian economy, which provide the backbone of our empirical set-up. Section 3.4 describes the latter. We argue that the regulatory structure of Italian CB's, as well as the utilization of relatively novel, territorially very disaggregated, information about economic activity, makes it possible to obtain some innovative evidence about the impact of risk and diversification upon bank efficiency. We also briefly describe our data sources and empirical methods. Our key findings are set out in Section 3.5. Some concluding remarks close the chapter, taking stock of our evidence and proposing avenues for future research.

3.2 The Production Process of Banks: Background and Recent Extensions

As already seen in Chapter 1. the "asset" approach has maintained some ascendancy within the literature, especially when focusing on the role of banking efficiency for economic development (Lucchetti et al., 2001; Hasan et al., 2009), and it will be the approach chosen in the following empirical analysis. At any rate, the awareness has grown that in order to measure accurately bank efficiency, allowance must be made for environmental factors beyond the control of bank managers, as well as for the role of risk aversion. The correct measurement of bank efficiency hence requires the analysis to include not only the usual inputs and outputs enumerated, but also indicators of environment and risk-aversion.

Since the seminal contribution of Berger and Mester (1997), the role of credit risk and financial capital (as a proxy of risk aversion) in the production process of banks have been at the fore of the measurement of their productive efficiency.

Banks can be mainly hit by credit risk, which relates to the management of subjective uncertainty and, in many cases, depends on the discretion of managers, who may not behave in the bank's interest. According to Berger and De Young (1997), the existence of risky assets entails additional "monitoring" and "screening" costs that banks must meet in order to assess them. Hence, changes in economic environment may bring about deteriorations in the banks' performances (the "bad luck" hypothesis), but also poor risk management may bring about a higher insolvency risk (the "bad management" hypothesis).

A popular indicator of credit risk is the ratio between bad and total loans. This indicator is related to the probability of bank failure. If banks do not bear any credit risk it is close to zero, and it approaches unity if financial intermediaries incur in a higher percentage of outstanding claims. Clearly, however, this indicator is linked to both the "bad luck" and "bad management" mechanisms. Indeed, Berger and De Young (1997) resort to a time-series analyses in order to disentangle the two different links between it and banks' efficiency. A related point, made by Berger and De Young themselves, is that it could be interesting to analyse the "bad luck" hypothesis relying on indicators of credit risk that are exogenous for a given bank. To the best of our knowledge, this attempt has never been carried out in the literature.

In any case, if bank managers are not risk-neutral, their degree of risk-aversion is likely to be reflected in their choices about the production set. The bank's behavioural response to risk is measured by an index of capitalization, very often the relationship between equity and total assets (Hughes and Mester, 1993; Mester, 1996). This index approximates to one if banks are highly capitalized. In this case, the banks can cope with possible risks without incurring danger of default. A similar situation arises when banks are subject to more intense merger and acquisition processes.

Another fundamental point concerning risk management is risk diversification. Broadly speaking, diversification can occur across income sources, industries or geographical areas (Rossi et al., 2009). Focusing on territorial diversification, Hughes et al. (1996, 1999) find that territorial diversification is positively correlated with bank efficiency in the US. In particular, interstate bank diversification has improved bank efficiency in the US after the passage of the Riegle-Neal Interstate Banking and Banking Efficiency Act in 1994. Also for the US, Deng et al. (2007), measuring territorial diversification through various indexes of deposit dispersion, find that diversification has a favorable impact upon the risk-return profile of bank holding companies.[10] There certainly seems to be room in literature for further evidence on this point,

[10] These findings are related to the huge block of literature relating to the impact of M&A on bank efficiency, a point also made in Bos and Kolari (2005), who, considering the potential gains from geographic expansion for large European and US banks, concluded that profit efficiency gains were obtainable from cross-Atlantic bank mergers.

especially if coming from small European banks.

Furthermore, it has long been known that efficiency measurement involving banks with different structural characteristics ought to make allowance for differences in the socio-economic and institutional environment beyond the control of bank managers. Perhaps the first study to bring this point forcefully to the fore was Berger and Mester (1997). In a two-stage frontier analysis these authors highlight the relevance for efficiency measurement of some potential efficiency correlates (which, in principle, ought to be uncorrelated with the banks' inputs and outputs): there are first some banks' idiosyncratic characteristics, such as size, age, property rights (ownership, forms of governance), the occurrence of mergers and acquisitions. Then there are market characteristics, related to the location of banks: concentration, buoyancy or slack in the economic environment,...). Finally there are legal or institutional features, usually associated with the concept of regulation. More recent studies of the modeling of heterogeneity in banking frontiers have been carried out by Carbó Valverde et al. (2003), Hughes and Mester (2008), Fethi and Pasiouras (2010).

In a set-up similar to the present one, there are various analyses of bank efficiency across US states (see Lozano-Vivas et al., 2002). Dietsch and Lozano-Vivas (2000) and Lozano-Vivas et al. (2002) analyse the impact of other environmental factors beyond the control of bank managers, notably the degree of concentration (measured by the Herfindahl-Hirschman index), population density, GDP per capita, in a European cross-country set-up. It can be easily argued that similar indicators are needed in order to take into account territorial differences in the socio-economic environment even within a given European country, if the latter is characterized by marked heterogeneity. However, more seldom, if at all, these factors have been utilized in works dealing with within-country comparisons for European countries.

Summing up, we believe this short survey highlights the need for novel European-based evidence on the impact of territorial diversification on bank efficiency and risk-return profile. This evidence should rely on disaggregated indicators of socio-economic environment, likely to capture hitherto neglected heterogeneity and to allow a sharper test of the “bad luck” hypothesis (being exogenous for a given bank). This is our endeavour in the present study. We analyse efficiency for a sample of small Italian banks, modeling differences in risk-preferences through an index of capitalization and allowing for differences in the socio-economic environment through GDP per capita indicators computed at a finer level of territorial disaggregation than hitherto utilized in the literature (this level approximately entails a population close to a local bank customers’ pool). In order to shed light on the impact of territorial diversification on bank efficiency and risk-return profile, we chiefly compare the performance of cooperative and traditional small banks across Italian regions. As will be presently clarified, we exploit here the fact that CB’s follow different rules from other banks as far as diversification is concerned.

3.3 Italian Cooperative Banks: Main Features and Environment

In Italy there are nowadays approximately 430 CB’s with 3600’s branches (11% of the total of all branches) and shares from 6.6% and 8.3% over, respectively, total loans and deposits. Italian CB’s have an important role in the financing of households, artisans and small businesses, and are characterized by small size, self-governance, a very local attitude, and the principle of mutuality (internal: the activity is mainly biased in favour of associates; external: there important activities aimed at supporting the moral, cultural and economic development of the local community).

The strengths of CB’s are the deep understanding of local economies (which reduces the typical problems of asymmetric information existing in the credit market) and the network externalities associated with their mutual aid system (see Angelini et al., 1998). However, recently, deregulation and technological progress have increased the contestability of local credit markets, requiring CB's to improve their performance. As is also shown by Table 3.1, CB’s face relatively low profit margins, high costs, and restricted income sources.

It must be said that there exists for Italian CB's a so-called *principle of prevalence*, requiring that more than 50% of assets are either detained by members or in risk-free assets, according to the criteria established by the Financial Regulator. Furthermore, as far as profit distribution is concerned, the Testo Unico Bancario, 1993, requires that CB's must:

- devote at least 70% of annual net profits to legal reserve;
- pay a share of annual net profits to mutual funds for the promotion and development of cooperation in an amount equal to 3%;
- devote to purposes of charity or mutual aid, the remaining share of profits.

Table 3.1 - *Selected Bank Performance Indicators (in %, 2002-04 average).*

	Banking system	***Banche popolari***	**CB's**
Non-performing loans/total loans	6.6	5.5	6.5
Bad debts/total loans	4.6	3.7	3.0
Net interest income / total assets	2.2	2.5	3.2
Gross income / total assets	3.5	3.8	4.1
Share of non-interest income in total income	38.2	35.8	21.8
Operating expenses / Gross income	59.4	59.4	67.8
Loan losses / total assets	0.48	0.44	0.25
Return on equity	7.9	7.6	6.7
Solvency ratio	11.4	10.1	17.8

Source: Fonteyne (2007).

Because of these regulations, the possibility to compare CB’s with other banks profit-efficiency wise must be seriously doubted. On the other hand, comparing their cost, and especially their technical, efficiency with that of other banks seems much more appropriate. Although generally the banking objective function is to maximize profits by choosing an optimal combination of inputs for maximum output, the same is not true for CB's (Fonteyne, 2007). However, also the latter are likely to aim for cost minimization by choosing the mix of inputs corresponding to the lowest cost, because they need to meet a survival requirement (Pestieau and Tulkens, 1993).

There is a further point, crucial for present purposes. CB's can provide loans only within a given area, the so-called area of territorial competence, (*area di competenza territoriale)*. The territorial competence (jurisdiction) of the CB's is determined by the Supervisory Instructions of the Bank of Italy and must be specified in their statute. It includes the municipalities in which the bank has its head office, branches and the surrounding areas, so that there must be territorial contiguity between these areas. Only in very special cases can CB's open branches in non-contiguous municipalities.

In Table 3.2 we highlight some consequences of this state of affairs. CB's have less branches than other small banks (as defined by the Bank of Italy), and the mean distance between their head office and a given branch is smaller.

Table 3.2 - *Number of branches and head office-branches mean distance, various bank types, years 2006-2008.*

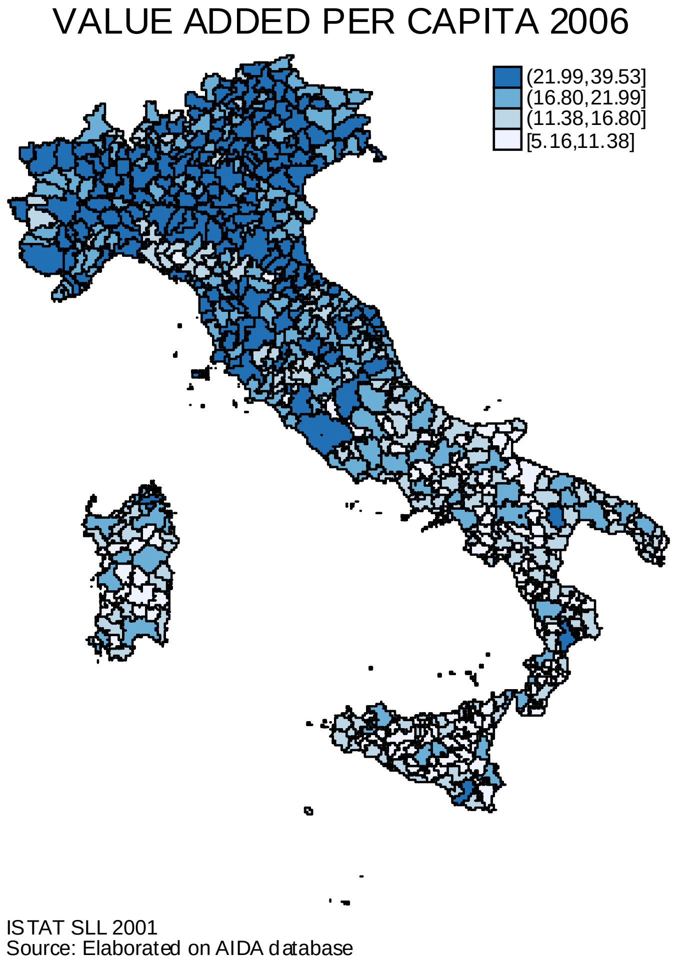
Percentiles	CB's Number of branches	Other Small Banks Number of branches	CB's Head office-branches Mean distance	Other Small Banks Head office-branches Mean distance
5%	1	1	0	0
25%	2	7	3.81	16.44
50%	4	29	7.40	34.51
75%	8	63	12.50	110.34
95%	18	144	26.26	317.95

Source: own calculations on BilBank 2000 data.

Sticking to the area of territorial competence greatly hampers any move to territorial diversification on the part of CB's and is likely to make them very sensitive to local shocks. In this chapter we rely on this institutional difference between CB's and other banks in order to provide some measures of the cost of missing diversification. To do so, however, we must have some quantitative indicators of local shocks at an appropriate territorial level.

A very important analytical category for territorial economic analysis in Italy is the *Sistema locale del lavoro*, SLL). This is a group of municipalities (akin to the UK's Travel-to-Work-Areas) adjacent to each other geographically and statistically comparable, characterized by common commuting flows of the working population. They are an analytical tool appropriate to the investigation of socio-economic structure at a fairly disaggregated territorial level. The identification of 686 SLL's made by ISTAT (the Italian Statistical Office) in some recent research (ISTAT, 2005) has highlighted remarkable differences in economic performance across the Italian territory.

Fig. 3.1 - *The Italian SLL's (sistemi locali del lavoro). Economic performance – Year 2006.*



Source: GDP is constructed by updating the SLL value added data from ISTAT through the 2006 data from the Bureau Van Dijck's AIDA dataset. Population is from the ISTAT SLL data-set.

For purposes of comparison note that there are nowadays in Italy 110 *province* (the NUTS3-type classification) and 20 *regioni* (the NUTS2-type classification).

Figure 3.1 below depicts the economic performance of the SLL's in 2006. We believe that Fig. 3.1, relying on GDP per capita, very aptly describes the strong economic differences across Italy. Roughly speaking, the darker the area, the better the performance.

Interestingly, not only the well-known North-South divide, but also some finer territorial differences, show up. This suggests that SLL-level indicators provide a much more accurate representation of the socio-economic environment than the usually adopted provincial (NUTS3) or regional (NUTS2) indicators.

It could be rightfully asked what is the precise relevance of SLL-level statistical information for local banks. We immediately stress that there is no precise correspondence between a SLL and the area of territorial competence of a CB. However, especially for the smaller CB's, there is a close correspondence between the SLL's population and the bank customers' pool (calculated as the sum of populations from municipalities where the bank has a branch). This correspondence is shown in Table 3.3, that also highlights how the population of the closest territorial divide (the *provincia*) is usually much larger than the CB customers' pool. Also note that the customers' pool of other small banks, unhampered by territorial regulations about loan provision, is even larger.

Table 3.3 - *Population and customers' pools for various territorial divides and bank types, years 2006*-2008

Percentiles	SLL Population	*Provincia* (NUTS3) population	CB's customers'pool	Other Small Banks customers'pool
5%	6,978	141,195	4,485	54,147
25%	13,718	231,330	19,129	694,700
50%	34,276	369,427	74,373	2547,677
75%	79,595	580,676	250,342	7109,032
95%	268,503	1239,808	1225,440	28417,586

Source: own calculations on ISTAT and BilBank 2000 data

We conclude that SLL-level data are likely to provide useful information on the local shocks relevant for CB's, potentially yielding novel evidence about the "bad luck" hypothesis and the importance of territorial diversification. Note also that, since the impact of local environment on cost efficiency should be exerted regardless of input cost considerations, we shall expect here a much stronger impact upon technical (vis-à-vis allocative) efficiency.

3.4 The Empirical Set-Up

We believe the asset approach has maintained some ascendancy within the literature, especially when focusing on the role of banking efficiency for economic development (Lucchetti et al., 2001; Hasan et al., 2009). We subsequently adopt it in the following empirical analysis, and define our output and input vectors accordingly.

The vector of outputs is composed as follows: *customer loans*, *securities* (loans to banks, Treasury bills and similar securities, bonds and other debt less bonds and debt securities held by banks and other financial institutions), *other services* (commission income and other operating income). The vector of inputs consists of the following items: *number of branches*, *number of workers*, and *fundraising*: total liabilities to customers, amounts owed to banks and debt securities (bonds, certificates of deposit and other securities). In order to measure cost efficiency, we also need a cost vector, which is composed as follows: (i) *labour cost*, the ratio between personnel costs (wages and salaries, social charges, pensions and the like) and the number of employees, (ii) *cost of physical capital*, the ratio of other administrative expenses, value adjustments to tangible and intangible assets and other operating expenses to the number of branches and (iii) *cost of financial capital*, the ratio of interest expense and similar charges and commission expenses on total debt.

A key aspect of our analysis is the treatment of heterogeneity, linked to risk-aversion, credit risk, and other environmental factors. Coelli et al. (2005) discuss four approaches that can be used to incorporate environmental variables in non-parametric frontiers. The first method, by

Banker and Morey (1986), requires the environmental variables to be ordered from the least to the most harmful ones for efficiency. Then, the efficiency of a given unit is compared with those units in the sample that have a value of the environmental variable which is less than or equal to the given unit. This ensures that banks are not compared with peers operating in a more favorable environment.

The second method, by Charnes et al. (1981), requires the investigator to: (i) divide the sample into sub-samples and solve L.P. problems for each sub-sample, (ii) project all observed data points into their prospective frontiers, and (iii) solve a single L.P. problem using the projected points and assess any difference in the mean efficiency of the two sub-samples. According to Coelli et al. (2005) the following two problems are common in both methods: (i) by splitting up the sample they reduce the comparison set, and (ii) only one environmental variable can be considered in each case thereby limiting the scope of the analysis.

Under the third method, the environmental variables are included directly in the non-parametric frontier as non-discretionary inputs (if it is believed to have a positive effect on efficiency) or outputs (if they have a negative effect on efficiency). The disadvantage of this approach is that one must know a priori the direction of the influence, a shortcoming that is also applicable in the case of the first method. Alternatively, the environmental variables can be included as non-discretionary neutral variables using an equality form. The shortcoming of this approach is that it can reduce the reference set for each unit.

The fourth method that is discussed in Coelli et al. (2005) is the two-stage approach. This involves a non-parametric frontier with traditional inputs and outputs in the first stage. In the second stage, the efficiency scores obtained are regressed on the environmental variables. While this approach has been frequently used in the banking literature with numerous applications, it but has some serious problems: it basically assumes that variables included in the second stage are statistically independent from inputs and outputs (Simar and Wilson, 2007, 2011). This is certainly a pretty tall assumption, very unlikely to be be fulfilled by risk-aversion and credit risk measures in particular.

A seldom noted drawback of the modeling of heterogeneities within a non-parametric framework is that the more potentially heterogeneities are dealt with, the lower will be the measured inefficiency. Importantly, this occurs whether or not the specified variables really are related to inefficiency. Each additional influence (constraint) in non-parametric approaches reduces the set of units being compared with the result that measured average inefficiency necessarily declines. In parametric approaches, if a specified influence is truly unimportant, measured inefficiency is unchanged.

According to the above considerations, in our analysis we shall adopt the third method. Risk-aversion, and credit risk proxies, as well as other environmental variables are included directly in the non-parametric frontier as non-discretionary inputs (if it is believed to have a positive effect on efficiency) or outputs (if they have a negative effect on efficiency). In other to make this choice we shall rely on economic theory considerations (which, we should add, are apparently supported by the SFA analysis from Chapter 2). We shall also attempt to be as parsimonious as possible in the modeling of these factors.

Traditionally enough, we model differences in risk-preferences through an index of capitalization (equity, equal to capital plus reserves – without adding profits or losses -, over total assets). As an indicator of socio-economic differences we take the SLL-level GDP per capita. As previously argued, this indicator is likely to capture hitherto neglected heterogeneity. Yet it can be reasonably supposed to be exogenous for small banks, allowing an appropriate test of the “bad luck” hypothesis. For each bank, we include in the production set the GDP per capita of the SLL where the bank’s head office is located. As also been said above, the impact of diversification is chiefly assessed by comparing the performance of cooperative and traditional small banks across Italian regions. The impact of SLL-level shocks, the “bad luck effect”, is expected to be stronger for CB’s, because they have less scope for territorial diversification out of this area. We can also readily provide a robustness check for this expected nexus: we include in the production set, along with the SLL-level GDP per capita, the mean distance between a bank’s head office and its branches (a measure akin to the diversification indicators constructed by Deng et al., 2007). Taking this structural indicator into account should reduce the differential “bad luck effect” across bank types, as a fundamental aspect of diversification should then be controlled for.

Finally, in order to provide evidence about the impact of territorial diversification on the risk-return profile, we also estimate a production set including a measure of asset quality, which is inversely related with credit risk. A popular indicator of asset quality is constructed as one minus the ratio between bad and total loans (more precisely, as the ratio between “adjustments and recoveries of loans and provisions for guarantees and commitments” and total loans). The ratio between bad and total loans has been used in many works (Berger and De Young, 1997; Fiordelisi et al., 2011). We do not include non-performing loans in it because they represent a milder form of risk, possibly biasing the measurement of credit risk.[11]

Our key a priori expectation is that local GDP per capita affect CB’s efficiency (and risk-return profile) much more than the other banks’ outcomes, due to CB’s stricter localization rules. In principle local shocks ought to affect the relationship between bank inputs and outputs for given input prices, so that the differential “bad luck effect” should be stronger for technical than

[11] See Fiordelisi et al. (2011) for further details on credit risk indicators.

for allocative efficiency. Given this interest in decomposing efficiency in a multi-output production set, we estimate efficiency using the DEA (variable-returns to scale) nonparametric method (Farrell, 1957; Banker et al., 1984). DEA, like other non-parametric approaches, is very apt to the modeling of multi-input multi-output production processes, but is also very sensitive to the presence of outliers, which may bias estimates. To circumvent these problems, we applied the bootstrapping method suggested in Hall and Simar (2002). Also, we searched and eliminated all the outliers in the dataset using the super-efficiency and rho - Tørgensen's concepts (Tørgensen et al, 1996).

Efficiency scores are measured in three different models, summarized in Table 3.4: a baseline asset-approach model (also including capitalization), the baseline model plus GDP per capita, and the baseline model plus GDP per capita and the distance measure. Evidence about the risk-return profile is obtained going through these three models again with the asset quality indicator in the production set. Capitalization and asset quality (one minus the ratio between bad and total loans) are included in the production set as outputs, because they can be both thought as good outcomes whose realization uses up bank resources[12]. On the other hand GDP per capita is included in the production set as a fixed (non-discretionary) input, and distance, being to some extent a choice variable and a feature of the bank branches, is modeled as an ordinary input. In estimating our DEA models, we relied on two packages based on the freeware R (FEAR 1.13, Benchmarking 0.18).

Given our interest in CB's and local shocks, and the eminently comparative nature of frontier analysis, our sample relates to essentially local banks. It is made up by Italian banks classified by the Bank of Italy as a small (funds below 9 billion euro). We use data compiled from the

[12] Indeed, in the SFA model adopted in Chapter 2, both these variables turn out to increase cost efficiency (results are available upon request). This is consistent with their above proposed modeling as outputs.

database "BilBank 2000 - Analysis of bank balance sheets" distributed by ABI (Italian Banking Association) for the 1994-2008 period. Yet, our chief interest is in the 2006-2008 period, because only for it we have a measure of the mean distance between a bank head office and a given branch. The larger 1994-2008 sample shall be used mainly for purposes of robustness check.

Table 3.4 - *The Empirical Models: The Production Set*

Models	**# 1**	**# 2**	**# 3**
INPUTS	Physical Capital Labour Funds	"# 1" + SLL- level GDP per capita, (non-discretionary input)	"# 1" + SLL- level GDP per capita, (non-discretionary input) + Mean Distance (discretionary input)
OUTPUTS	Customer Loans Securities Other Services Capitalization	"# 1"	"# 1"

Source: Own elaboration.
Note: When assessing the risk-return profile, asset quality is included in all the three models as an output.

This sample includes all CB's and most of the former savings and *popular* (*popolari*) banks. Table 3.5 (in Appendix B) provides some background information about the sample by geographical location and bank type. The balance-sheet information in this database allows calculation of measures for our inputs and outputs, as well as for asset quality and capitalization. The GDP per capita of the head-office's SLL is constructed by updating the SLL value added data from ISTAT through the 2006-2008 period with data from the Bureau Van Dijck's AIDA dataset. Population is from the ISTAT SLL data-set. The mean distance between a bank head office and a given branch is taken from the Bank of Italy's database of branches. It is the availability for this variable that fundamentally drives our main sample choice. Descriptive statistics about all these variables are provided in Tables 3.6 and 3.7 (also in Appendix B).

3.5 The Empirical Evidence

We applied DEA to the three versions of the asset approach, without and with the asset quality indicator, year by year, considering two different groupings of banks. The first grouping is simply given by all the banks in our sample, and it will be referred to as One Sample. Then, because of the important regulatory differences between CB’s and other banks, it could be thought that a sharp distinction should be drawn between these two bank types. Estimates are then carried out for the two subsets separately, and we refer to these estimates as to those belonging to Two Samples. Our main a priori expectation is that CB's are much more affected by the “bad luck effect” than the other banks, due to their strict localization rules. This impact should also be stronger when considering technical efficiency, as local shocks ought to affect the relationship between bank inputs and outputs for given input prices. The estimates reported in Table 3.8 (in Appendix B) support this expectation to a large extent. In order to make results more understandable, we only report mean efficiency scores from Italy's four territorial partitions (North-West, North-East, Centre, South). When comparing efficiency scores from Models #1, #2 and #3, it clearly appears that local shocks, such as proxied by SLL-level GDP per capita, affect technical efficiency differentials, especially for CB’s. No great difference exists on the other hand between Models #2 and #3. If we control for the mean distance between a bank head office and a given branch, the “bad luck effect” greatly diminishes.

All in all, the “bad luck effect” comes out most clearly comparing Models #1 and #2, and considering banks located in the South, for One Sample. This can be easily rationalized. If we consider Two Samples, banks are not differentiated by their capability to absorb local shocks through territorial diversification. Hence, the impact of local shocks ought to be relatively weaker than in One Sample. In the latter, the technical efficiency of CB’s gains between 2 and 7 percentage points in Model # 3, providing a quantitative measure of the costs of missing diversification. No large gain of this kind appears to exist for the other banks. Also, no clear pattern emerges across Models #1, #2 and #3 for allocative efficiency. The pattern of cost efficiency across models is decisively driven by technical efficiency, as was also expected. Note finally that the inclusion of the asset quality proxy makes no sizable difference to the estimates. Provided we believe that risk is adequately measured by our proxy, the above illustrated evidence then implies that territorial diversification has a significant impact on the risk-return profile of Italian small banks.

In Table 3.9 of Appendix B, we give to our analysis a more formal twist. We consider the efficiency scores year by year, and apply to them the test for the equality of means suggested in Kittelsen (1999). Should this test be significant (we give in Table 3.9 its p-values), the differences between respectively Models #1 and #2, and Models #2 and #3, would be statistically significant. The results from Table 3.9 are overwhelmingly aligned with the previous considerations. In One Sample, the technical and cost efficiency scores are significantly higher in Model # 2 than in Model #1 for the CB's only. The difference between CB's and Other Banks partially fades away in Two Samples, but the significance tests always show lower p-values for the CB's. Once again no strongly consistent pattern shows up for allocative efficiency. This also explains why Models #2 and #3 are almost never significantly different. All in all, there is rather convincing evidence that a larger territorial spread among a bank's branches reduces significantly the impact of local GDP per capita on cost efficiency.

For purposes of robustness check, we replicated the above analysis for the longer 1994-2008 period (see Tables 3.10-3.11 in Appendix B). As said above, we do not have for that sample as a whole a measure of the mean distance between a bank head office and a given branch. Yet, the previously obtained results carry through without much change, which is rather comforting.

As we will discuss below, this evidence can be refined in various ways. However, we believe that these results show that modeling “environmental” variables at the SLL-level reduces to a great deal differences in technical and cost efficiency among Northern and Southern Italian banks. Analytically, this could point to a potentially strong endogeneity of previously available bank performance indicators. From a more practical standpoint, there appears to be some reasons to ease the localization constraints for CB’s.

3.6 Concluding Remarks

In this chapter we have analyzed the cost efficiency differentials among Italian small banks located in different geographical locations and belonging to two great institutional categories: CB’s and other banks. We have applied DEA throughout the 1994-2008 period, highlighting the effect of some environmental and institutional factors on banks' performance. The evidence shows that local shocks, proxied by SLL-level GDP per capita, affect technical efficiency differentials, especially for CB’s. This can be easily rationalized, as current regulations hamper CB’s vis-à-vis other banks in their capability to diversify territorially. Our estimates provide us with a tentative quantitative measure of the costs of missing diversification, ranging between 2 and 7 percentage points. On the other hand our evidence suggests that there is potentially strong endogeneity in some currently available bank performance indicators.

We are fully aware that there are various ways in which our evidence could be made much more robust. Perhaps most prominently, the return-risk profile of banks should be evaluated in the light of more sophisticated proxies than our simple measure relying on the ratio between bad and total loans In future work we plan to include our measure of local shocks in a panel analysis of bank efficiency, risk, and capitalization, also allowing for lagged relationships, as in Fiordelisi et al. (2011) or in Rossi et al. (2009).

Appendix A

The Stochastic Frontier Analysis

In order to assess the cost and profit efficiency for Italian banks, we specify the stochastic frontier for panel data using the "Technical Inefficiency Effects" model[13] as benchmark proposed by Battese and Coelli (1995) as follows:

$$Y_{it} = exp(x_{it}\beta + \varepsilon_{it})$$

$$\varepsilon_{it} = v_{it} \pm u_{it}$$

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

$$u_i \sim_{iid} N^+(\mu + z_{it}\delta, \sigma_u^2) \text{ i} = 1, \dots, \text{N}; \text{ t} = 1, \dots, \text{T}$$

where Y_{it} denotes the cost or profit of the ith banks, x_{it} represents *1xk* vector of explanatory variables, β is *kx1* vector of unknown parameters to be estimated, v_{it} are random variables assumed to be *i.i.d* distributed as a $N(0, \sigma_v^2)$ and independent of u_i, and u_i are non negative random variables, which are assumed to be independently but not identically distributed by each unit as truncation at zero of the $N^+(\mu + z_{it}\delta, \sigma_u^2)$, where z is a (1 x m) vector of environmental factors associated with technical inefficiency of production of units and δ is a (m x 1) vector of unknown coefficients.

This model permits us to estimate both technical change in the stochastic frontier and time – varying technical inefficiencies as well as to overcome the problem of heterogeneity that could

[13] This model is based on the underlying assumption that all the units in the sample have a common technology and environmental variables influence only the distance from the best practice (i.e. the inefficiency).

bias the efficiency scores and to avoid the limitations of the "two-step" approach.

We specify a translog cost functional frontier[14] following an approach similar to Altunbas et al. (2000), with some exceptions: (i) in the translog frontier is not included total equity capital and specific interaction terms with both output quantities and input prices; (ii) the model follows a single stage[15] in which environmental and risk factors are incorporated directly into the inefficiency error component and (iii) the definition of bank inputs and outputs following the asset approach (Sealey and Lindley, 1997), including deposits as ordinary input. Formally, the translog specification[16] is described as follows:

$$
\begin{aligned}
lnY = \alpha_0 + \sum_{i=1}^{3} \alpha_i lny_i \\
&+ \sum_{i=1}^{3} \beta_i lnw_i + \tau_1 T + \frac{1}{2}\left[\sum_{i=1}^{3}\sum_{j=1}^{3} \delta_{ij} lny_i lny_j + \sum_{i=1}^{3}\sum_{j=1}^{3} \gamma_{ij} lnw_i lnw_j + \theta_{11} T^2\right] \\
&+ \sum_{i=1}^{3}\sum_{j=1}^{3} \rho_{ij} lny_i lnw_j + \sum_{j=1}^{3} \varphi_i T lny_i + \sum_{i=1}^{3} \vartheta_i T lnw_i + \varepsilon_{it}
\end{aligned}
$$

14 The translog is seen as a "second order logarithm approximation" to an arbitrary continuous transformation surface. The reasons that push us to adopt a translog functional form are: (i) to impose no restrictions on first and second order effects; (ii) to overcome the problem of multicollinearity inherent to the direct approach proposed by Schmidt (1986) and (iii) to reduce the problem related with heterogeneous data sets with respect to use Fourier functional form (see Altunbas and Chakravarty, 2001), even if the difference in the efficiency scores not greater than 1% (Berger and Mester, 1997).

15 This approach is specified in many works (e.g. see also Kumbhakar et al., 1991; Reifschneider and Stevenson, 1991; Huang and Liu, 1994; Battese and Coelli, 1995), where either mean or variance of inefficiency error component is assumed to be a function of the explanatory variables. We use this methodology because the "two-stage" estimation procedure, where the inefficiencies are estimated in the first stage, and estimated inefficiencies are regressed against a vector of explanatory variables in a second stage (e.g. Pitt and Lee, 1981), could lead to inconsistent estimation about the independence assumption between inefficiency and stochastic component.

16 The translog equation is assessed using the "alternative profit efficiency" (Berger and Mester, 1997). This approach is a closer representation of reality whenever the assumption of perfect competition in the setting of prices is questionable or when there are differences of quality/specialization among the individual of the sample. Alternatively, there is the "standard profit efficiency" assumes perfect competition in the markets for inputs and outputs. So, the banking firms try to maximize the profits by adjusting the vector of outputs and inputs, given the vector of output and input prices.

where lnY is the natural logarithm of total cost and profit[17], y_i $(i = 1,2,3)$ are output quantities, w_j $(j = 1,2,3)$ are input prices, T denotes the time trend that captures the influence of technical change leading to shifts in the cost function over time and ε_{it} represents the error composite term. Finally, $\alpha, \beta, \tau, \delta, \gamma, \theta, \rho, \varphi, \vartheta$ are the coefficients of parameters to be estimated. The formulation used to measure the cost efficiency of banks (see Maudos et al., 2001) is the following:

$$CE_{it} = \frac{C^{min}}{C}$$

where C^{min} and C are the minimum costs necessary for producing the output vector Y if the bank were efficient $(i.e.\ u = 0)$ and the observed costs, respectively. Indeed, we measure the profit efficiency as follows:

$$PE_{it} = \frac{\Pi}{\Pi^{max}}$$

in which Π and Π^{max} describe the profit obtain by a bank and the maximum that it could achieve if it were efficient. As usual, in order to guarantee the linear homogeneity in factor prices is necessary (and sufficient) to apply linear restriction of the translog function specified in equations (1.1), $\sum_{j=1}^{3} \beta_i = 1, \sum_{i=1}^{3} \gamma_{ij} = 0$ and $\sum_{j=1}^{3} \rho_{ij} = 0,$ and to impose symmetry

[17] The total cost is composed by: personnel expenses, other administrative expenses, value adjustments to tangible and intangible assets and other operating expenses and interest expenses and similar charges and commission expenses, while the total profit is the difference between revenue and cost, where revenue is composed by: interest and similar income on loans to costumers, interest and similar income on debt securities and services (administrative) or non – traditional activities, i.e. commission income and other operating income, and services.

conditions, i.e. $\delta_{ij} = \delta_{ji}$ and $\gamma_{ij} = \gamma_{ji}$. The linear restriction conditions allow ensuring “constant returns to scale”.

Table 2.1 - *The Sample Size and Macro Areas for Cooperative (CB's) and Other (COB's & PB's) Banks.*

Year\Geo.Loc	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**Total**
CB's	523	491	478	465	447	436	436	423	3699
Other	231	206	191	208	219	187	203	173	1618
All	754	697	669	673	666	623	639	596	5317
CB's									
North East	199	185	179	173	167	162	160	157	1382
North West	102	97	90	89	84	83	83	84	712
Centre	92	87	95	94	94	91	92	85	730
South	130	122	114	109	102	100	101	97	875
Other									
Nord East	67	57	56	70	73	63	70	56	512
Nord West	53	53	44	46	49	43	46	42	376
Centre	60	56	55	60	61	54	57	48	451
South	51	39	35	32	33	26	30	27	273

Source: Own calculations on BilBank 2000 data.

Table 2.2 - *Descriptive Statistics for "CB's" and "Other" Banks.*

Var.	**Loans**	**OtherLoans**	**Services**	**Funds**	**Workers**	**Branches**	**Fin, Cap.**	**Labour**	**Phys, Cap.**
CB's									
Mean	117106	63678	2289914	161041,3	5419919	7079827	0,02553	5658545	4395152
S.D.	156579	88980	3182763	212041,0	1602704	2101828	0,00951	7205346	3101379
Min	778,620	48,950	6837735	1754872	2126425	0,92584	0,00224	5866004	1594326
Max	2446221	1825043	53886,6	4068634	376,265	1091121	0,08671	1509494	5765562
Other									
Mean	887294	564715	48560,8	1361699	4763286	4226845	0,03375	5878215	4590962
S.D.	1032966	790647	121361,3	1415727	5583222	4702508	0,03421	1529494	18840
Min	1095109	9293527	1032614	3283713	4724451	0,92584	0,00213	0,49901	0,17014
Max	6239236	6111304	1848584	7958950	9505213	3061444	0,54384	1982269	420158

Source: Own calculations on BilBank 2000 data (values on average).
Note: All variables averaged between 1998 and 2005. All monetary aggregates in thousands of deflated 2002 Euros.
S.D.: Standard Deviation.

Table 2.3 - *Efficiency Estimation and Environmental Factors. A Legend.*

Variables	**Symbol**	**Description**
Cost and profit efficiency.	CE, PE	Efficiency SFA estimates
Credit Risk.	NPLL	Bad and total loans ratio.[a]
Banking Capitalization.	ETA	Equity and total assets ratio.[a]
Local GDP per capita.	GDPC	Local GDP and workers ratio.[b]
Branch density.	BD	Number of branches per square kilometer.[b]
Deposits per branch.	DB	Aggregate deposits and number of branches ratio.[b]
Deposit density.	DD	Aggregate deposits per square kilometer.[b]
Intermediation ratio.	IR	Aggregate deposits and loans ratio.[b]

[a]*Source: ABI (Associazione Bancaria Italiana).*
[b]*Source: ISTAT (2005).*

Table 2.4 - *Environmental variables and risk factors included in the stochastic frontier, SLL and NUTS3 level*

	Var.	DD	NPLL	ETA	IR	BD	DB	FV	GDPC
NUTS3									
South	**Mean**	1,43	0,13	0,14	1,14	0,07	17,42	12524,8	0,0134
	SD	3,04	0,10	0,06	0,28	0,11	39,91	29266,8	0,0055
Centre	**Mean**	2,01	0,07	0,13	0,75	0,10	16,90	75561,9	0,0182
	SD	2,48	0,07	0,04	0,20	0,08	5,07	208282,0	0,0051
N-W	**Mean**	3,06	0,04	0,14	0,67	0,18	15,52	8117,9	0,0223
	SD	3,17	0,03	0,08	0,19	0,13	3,56	18414,2	0,0045
N-E	**Mean**	4,28	0,05	0,13	0,72	0,19	17,52	30900,2	0,0234
	SD	9,60	0,04	0,07	0,23	0,24	6,35	110299,1	0,0069
Total	**Mean**	2,63	0,08	0,14	0,81	0,13	16,78	32296,9	0,0198
	SD	5,53	0,07	0,06	0,30	0,15	5,04	122145,2	0,0070
SLL									
South	**Mean**	2,49	0,12	0,15	1,25	0,12	16,17	628,3	0,0148
	SD	4,81	0,10	0,07	0,64	0,18	6,15	1403,9	0,0053
Centre	**Mean**	2,01	0,07	0,13	0,78	0,12	13,59	127458,5	0,0175
	SD	2,68	0,05	0,04	0,28	0,10	5,72	309668,9	0,0045
N-W	**Mean**	3,40	0,04	0,14	0,66	0,21	14,16	1439,3	0,0228
	SD	3,17	0,03	0,08	0,19	0,13	4,16	3607,7	0,0045
N-E	**Mean**	3,64	0,04	0,13	0,67	0,17	11,87	25964,5	0,0248
	SD	10,58	0,03	0,05	0,27	0,24	7,71	145053,7	0,0080
Total	**Mean**	2,90	0,07	0,14	0,80	0,16	14,26	45840,2	0,0204
	SD	6,28	0,06	0,06	0,42	0,18	6,51	193577,7	0,0070

Source: Own calculations on BilBank 2000 data (values on average). All variables are averaged over 1998-2005. All monetary aggregates in thousands of deflated 2002 Euros.

Table 2.5.a - *CE and PE stochastic frontier scores, NUTS3 and SLL level, 1998-2005*

	NUTS3				SLL			
	Mean	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**
	North				**North**			
All								
CE	0,95	0,06	0,34	0,99	0,94	0,06	0,32	0,99
PE	0,51	0,14	0,10	0,96	0,5	0,14	0,10	0,96
Others								
CE	0,96	0,04	0,62	0,98	0,88	0,04	0,6	0,98
PE	0,45	0,21	0,09	0,95	0,45	0,21	0,09	0,95
CB's								
CE	0,97	0,07	0,43	0,99	0,95	0,07	0,41	0,99
PE	0,52	0,18	0,11	0,97	0,48	0,18	0,11	0,97
	Centre				**Centre**			
All								
CE	0,95	0,07	0,29	0,98	0,94	0,07	0,59	0,98
PE	0,52	0,19	0,11	0,94	0,5	0,19	0,11	0,94
Others								
CE	0,93	0,04	0,62	0,98	0,92	0,05	0,4	0,98
PE	0,49	0,18	0,12	0,92	0,47	0,18	0,12	0,92
CB's								
CE	0,96	0,08	0,4	0,98	0,95	0,08	0,37	0,98
PE	0,51	0,19	0,12	0,96	0,49	0,19	0,12	0,96
	South				**South**			
All								
CE	0,94	0,06	0,3	0,98	0,92	0,07	0,28	0,98
PE	0,54	0,19	0,1	0,94	0,51	0,19	0,1	0,94
Others								
CE	0,94	0,07	0,46	0,98	0,93	0,09	0,41	0,98
PE	0,51	0,18	0,1	0,93	0,5	0,18	0,1	0,93
CB's								
CE	0,95	0,08	0,41	0,99	0,94	0,05	0,38	0,99
PE	0,57	0,19	0,1	0,95	0,56	0,19	0,1	0,95
	Italy				**Italy**			
All								
CE	0,95	0,06	0,31	0,98	0,93	0,07	0,40	0,98
PE	0,51	0,17	0,10	0,95	0,50	0,17	0,10	0,95
Others								
CE	0,94	0,05	0,57	0,98	0,91	0,06	0,48	0,98
PE	0,48	0,19	0,10	0,93	0,47	0,19	0,10	0,93
CB's								
CE	0,96	0,08	0,41	0,99	0,95	0,07	0,39	0,99
PE	0,53	0,19	0,11	0,96	0,51	0,19	0,11	0,96

Table 2.5.b - *CE and PE stochastic frontier scores, NUTS3 and SLL level, 1998-2008*

	NUTS3				SLL			
	Mean	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**
	North				**North**			
All								
CE	0,94	0,07	0,33	0,99	0,93	0,08	0,25	0,99
PE	0,53	0,16	0,10	0,99	0,52	0,16	0,10	0,99
Others								
CE	0,96	0,02	0,72	0,99	0,95	0,02	0,79	0,98
PE	0,57	0,13	0,09	0,91	0,58	0,13	0,12	0,92
CB's								
CE	0,91	0,10	0,33	0,99	0,90	0,11	0,25	0,99
PE	0,44	0,18	0,11	0,99	0,43	0,19	0,09	0,99
	Centre				**Centre**			
All								
CE	0,93	0,08	0,21	0,98	0,93	0,06	0,54	0,98
PE	0,47	0,19	0,12	0,99	0,48	0,18	0,18	0,98
Others								
CE	0,95	0,04	0,61	0,98	0,94	0,05	0,54	0,98
PE	0,48	0,17	0,11	0,91	0,49	0,17	0,18	0,91
CB's								
CE	0,89	0,11	0,21	0,98	0,90	0,06	0,55	0,98
PE	0,44	0,22	0,14	0,99	0,46	0,18	0,18	0,98
	South				**South**			
All								
CE	0,92	0,06	0,30	0,99	0,90	0,08	0,28	0,99
PE	0,46	0,22	0,14	0,99	0,43	0,23	0,12	0,99
Others								
CE	0,92	0,05	0,43	0,99	0,91	0,07	0,39	0,99
PE	0,48	0,21	0,12	0,94	0,47	0,22	0,14	0,95
CB's								
CE	0,90	0,08	0,30	0,99	0,89	0,09	0,28	0,98
PE	0,38	0,24	0,13	0,99	0,36	0,24	0,12	0,99
	Italy				**Italy**			
All								
CE	0,93	0,08	0,26	0,99	0,92	0,09	0,38	0,99
PE	0,46	0,21	0,11	0,99	0,46	0,22	0,13	0,99
Others								
CE	0,95	0,04	0,31	0,99	0,94	0,05	0,42	0,99
PE	0,49	0,11	0,12	0,97	0,50	0,18	0,15	0,95
CB's								
CE	0,89	0,13	0,31	0,99	0,88	0,13	0,32	0,99
PE	0,40	0,23	0,12	0,99	0,39	0,22	0,13	0,99

Table 2.6 - GMM, 1998-2005, NUTS3

MODELS regressor	A1	A2	A3	A4	A5	A6	A7
$Y_{i,t-1}$	1,00***	1,10***	0,96***	1,00***	0,96***	0,68***	0,76***
$Y_{i,t-2}$	-0,18**	-0,18**	-0,05	-0,13**	-0,13**	0,12***	0,13***
ln FV	0.03**			0.03***	0,04***	0,02***	0,01***
ln CE		0,03**		0,11**		0,13***	
ln PE			0.06**		0.05***		0,04***
ln FV × ln CE						-0,10**	
ln FV × ln PE							-0,06***
$N_{i,t}$	-0,16	-0,1	-0,13	-0,13**	-0,05*	0,12	0,13
n	1889	1889	1889	1889	1889	1889	1889
Sargan	0,03	0,62	0,6	0,02	0,22	0,02	0,06
AR (3)	0,01	0,18	0,34	0	0,33	0,09	0,13

*NB: time dummies always included; n is the sample size. The statistics for the Sargan and Arellano-Bond tests are p-values. *, **, *** Significant at 10%, 5% and 1%, respectively.*

Table 2.7 - GMM, 1998-2005, SLL

MODELS regressor	B1	B2	B3	B4	B5	B6	B7
$Y_{i,t-1}$	0,48***	0,89***	0,91***	0,68***	0,84***	0,82***	0,81***
$Y_{i,t-2}$	0,47***	0,03	0,02	0,23***	0,11	0,11*	0,14**
ln FV	0.05**			0.09***	0,02**	0,03**	0,10**
ln CE		0,02**		0,02**		0,13***	
ln PE			0.03**		0.06**		0,08***
ln FV $\times$ ln CE						0,02*	
ln FV $\times$ ln PE							0,07***
$N_{i,t}$	-0,06	-0,11	-0,09	-0,11*	-0,05*	0,08	0,11
n	2945	2945	2945	2945	2945	2945	2945
Sargan	0,05	0,92	0,92	0,20	0,13	0,01	0,07
AR (3)	0,01	0,47	0,47	0,20	0,13	0,08	0,07

*NB: time dummies always included; n is the sample size. The statistics for the Sargan and Arellano-Bond tests are p-values. *, **, *** Significant at 10%, 5% and 1%, respectively.*

Table 2.8 - GMM, 1998-2008, NUTS3

MODELS regressor	C1	C2	C3	C4	C5	C6	C7
$Y_{i,t-1}$	0,91***	0,92***	0,67***	1,00***	0,76***	1,09***	0,81***
$Y_{i,t-2}$	0,06	-0,07	0,15**	-0,08**	0,13**	-0,12***	0,12***
ln FV	0.03*			0,01*	0,02*	0,02*	0,01
ln CE		0,09**		0,02		0,07*	
ln PE			0.07**		0.05**		0,04**
ln FV × ln CE						0,02	
ln FV × ln PE							-0,03***
$N_{i,t}$	0,05	-0,04	-0,01	0,03	-0,03*	0,10**	0,03*
n	2012	2012	2012	2012	2012	2012	2012
Sargan	0,02	0,35	0,86	0,02	0,11	0,03	0,08
AR (3)	0,03	0,32	0	0,28	0,32	0,01	0

*NB: time dummies always included; n is the sample size. The statistics for the Sargan and Arellano-Bond tests are p-values. *, **, *** Significant at 10%, 5% and 1%, respectively.*

Table 2.9 - GMM, 1998-2008, SLL

MODELS regressor	D1	D2	D3	D4	D5	D6	D7
$Y_{i,t-1}$	0,52***	0,83***	0,88***	0,74***	0,67***	0,66***	0,83***
$Y_{i,t-2}$	0,43***	0,10	0,06	0,19**	0,28**	0,28***	0,13***
ln FV	0.05**			0.01*	0,02**	-0,02*	0,02*
ln CE		0,02*		0,03		-0,03*	
ln PE			-0,01		-0.01*		-0,02**
ln FV × ln CE						0,01*	
ln FV × ln PE							0,01*
$N_{i,t}$	-0,16	-0,11	-0,13	-0,04	-0,05*	0,01	-0,01
n	3396	3396	3396	3396	3396	3396	3396
Sargan	0,08	0,73	0,73	0,01	0,30	0,03	0,08
AR (3)	0,73	0,84	0,26	0,90	0,03	0,90	0,01

*NB: time dummies always included; n is the sample size. The statistics for the Sargan and Arellano-Bond tests are p-values. *, **, *** Significant at 10%, 5% and 1%, respectively.*

Appendix B

Table 3.5 - *Sample by bank types and areas.*

Year	**2006**	**2007**	**2007**
CB's	429	437	422
Other Banks	179	204	216
ALL	608	641	638
Geogr. location			
North – West CB's	82	83	80
North – East CB's	158	160	158
Centre CB's	90	91	86
South CB's	99	103	98
North – West Other Banks	43	45	48
North – East Other Banks	61	68	71
Centre Other Banks	47	57	62
South Other Banks	28	34	35

Source: Own calculations on BilBank 2000 data

Table 3.6 - *Production and Costs: Some Descriptive Statistics, years 2006-2008.*

ALL SAMPLE	Loans	Securities	Other Services	Funds	Workers	Branches	Phys. Cap. Cost	Fin. Cap. Cost	Labour Cost
Mean	660,202	291279	18789	831699	196	23	0.029842	900.589	68.60
st. dev.	1198322	737977	49892	1460213	334	42	0.017417	6,070.122	16.14
Min	22	2810	5	1594	3	1	0.004378	8	9.73
Max	8808730	8767580	608546	9157992	2471	727	0.313573	176910	213.75
CB's (mean values)									
North-West	183,537.5	73459.22	3336.985	220969.2	74	10	0.0366172	364.5561	56.3551
North-East	134,558.3	60986.43	2095.631	166734	51	7	0.037272	390.7106	57.24301
Centre	116,429.3	72112.01	2234.488	170309.1	56	6	0.0358567	451.15	55.29879
South	38,795.43	43718.11	824.2861	73897.55	25	4	0.0351298	367.4843	56.56504
Total	117,433	61370.09	2055.504	155504.3	50	7	0.0363564	391.6745	56.53395
Other Banks (mean values)									
North-West	1070078	476200.2	33274.49	7,488,347	499	47	0.036865	1223.601	57.38187
North-East	1025914	835781.4	61077.01	9,964,507	515	43	0.0471912	6279.818	65.91323
Centre	929979.1	577952	40867.89	8,891,967	488	46	0.0391703	2742.779	59.28032
South	684018.9	479397	19783.29	2,571,438	432	40	0.0382668	862.296	52.88012
Total	946197.7	615112.1	41383.01	7,885,528	488	44	0.0409286	3125.571	59.68412

Source: Own calculations on BilBank 2000 data, Money values in thousands of euros.

Table 3.7 - *Environmental factors, mean values by area and bank type, years 2006-2008*

	Equity/ Asset Ratio		Asset Quality		GDP per capita		Head office-branches Mean distance	
AREA	**CB's**	**Other Banks**	**CB's**	**Other Banks**	**CB's**	**Other Banks**	**CB's**	**Other Banks**
North-West	0.1307	0.1445	0.9742	0.9752	25.15	26.73	14.53	63.74
North-East	0.1510	0.1443	0.9639	0.9785	25.04	30.84	7.92	99.92
Centre	0.1252	0.1383	0.9526	0.9593	21.32	19.99	9.13	66.87
South	0.1396	0.1458	0.9241	0.9441	15.49	17.39	17.01	75.16
Total	0.1394	0.1430	0.9541	0.9661	22.08	24.76	11.55	78.539

Source: own calculations on BilBank 2000 data.

Table 3.8 - *The Mean Efficiency Scores, 2006-2008*

CB's, One sample, model without Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,7196	0,8565	0,6158	0,7339	0,8588	0,6298	0,7517	0,8406	0,6317
North-East	0,7649	0,8897	0,6800	0,7824	0,8917	0,6973	0,8037	0,8695	0,6986
Centre	0,6694	0,8739	0,5844	0,6993	0,8682	0,6068	0,7115	0,8547	0,6080
South	0,6452	0,8155	0,5263	0,7268	0,8164	0,5933	0,7342	0,8078	0,5931

CB's, One sample, model with Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,7336	0,8497	0,6229	0,7477	0,8521	0,6367	0,7637	0,8358	0,6382
North-East	0,7790	0,8870	0,6906	0,7957	0,8909	0,7086	0,8178	0,8683	0,7101
Centre	0,6710	0,8731	0,5853	0,7016	0,8683	0,6088	0,7141	0,8545	0,6101
South	0,6452	0,8160	0,5266	0,7310	0,8198	0,5992	0,7390	0,8106	0,5991

Other banks, One sample, model without Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8108	0,8242	0,6688	0,8171	0,8252	0,6749	0,8427	0,8018	0,6762
North-East	0,8611	0,8192	0,7057	0,8694	0,8248	0,7174	0,8809	0,8138	0,7173
Centre	0,7645	0,7695	0,5885	0,7919	0,7674	0,6084	0,8065	0,7531	0,6081
South	0,7605	0,7585	0,5767	0,8081	0,7569	0,6117	0,8140	0,7519	0,6122

Other Banks, One sample, model with Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8176	0,8224	0,6729	0,8242	0,8251	0,6805	0,8509	0,8006	0,6818
North-East	0,8864	0,8407	0,7458	0,8929	0,8466	0,7565	0,9037	0,8367	0,7566
Centre	0,7794	0,7680	0,5992	0,8054	0,7695	0,6204	0,8193	0,7564	0,6206
South	0,7687	0,7558	0,5809	0,8140	0,7586	0,6176	0,8196	0,7538	0,6180

(continue)

CB's, Two samples, model without Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8235	0,9450	0,7782	0,8266	0,9462	0,7822	0,8339	0,9378	0,7821
North-East	0,8480	0,9482	0,8041	0,8548	0,9518	0,8136	0,8702	0,9356	0,8142
Centre	0,8135	0,9463	0,7698	0,8210	0,9482	0,7785	0,8263	0,9421	0,7784
South	0,8333	0,9084	0,7571	0,8701	0,9167	0,7977	0,8718	0,9134	0,7964

CB's, Two samples, model with Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8384	0,9452	0,7925	0,8418	0,9469	0,7971	0,8479	0,9398	0,7969
North-East	0,8612	0,9504	0,8185	0,8684	0,9545	0,8290	0,8820	0,9404	0,8294
Centre	0,8168	0,9483	0,7746	0,8255	0,9506	0,7847	0,8307	0,9446	0,7847
South	0,8346	0,9118	0,7612	0,8743	0,9218	0,8060	0,8765	0,9181	0,8047

Other banks, Two samples, model without Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8443	0,7950	0,6713	0,8536	0,7945	0,6784	0,8815	0,7711	0,6800
North-East	0,8813	0,8023	0,7071	0,8899	0,8081	0,7193	0,9013	0,7982	0,7197
Centre	0,8078	0,7309	0,5902	0,8373	0,7391	0,6191	0,8506	0,7274	0,6190
South	0,7888	0,7388	0,5826	0,8426	0,7595	0,6398	0,8468	0,7557	0,6399

Other Banks, Two samples, model with Asset Quality Indicator, 2006-2008 Averages

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8494	0,7979	0,6777	0,8643	0,8031	0,6945	0,8881	0,7899	0,6933
North-East	0,9050	0,8266	0,7485	0,9147	0,8406	0,7697	0,9194	0,8317	0,7651
Centre	0,8197	0,7333	0,6013	0,8494	0,7547	0,6415	0,8534	0,7428	0,6340
South	0,7941	0,7398	0,5873	0,8470	0,7710	0,6531	0,8498	0,7619	0,6474

Source: Own elaboration.

Table 3.9 - *The Mean Efficiency Scores, Annual Values and Some Tests, 2006-2008*

CB's, One sample, model without Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0.7249	0.8140	0.5931	0.7535	0.8226	0.6227	0.7626	0.8145	0.6233
2007	0.6918	0.8878	0.6161	0.7229	0.8914	0.6469	0.7456	0.8664	0.6482
2008	0.7092	0.8866	0.6274	0.7526	0.8750	0.6591	0.7673	0.8588	0.6592
				Model # 2 vs Model # 1			Model # 3 vs Model # 2		
				Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006				0.0006	0.0936	0.0011	0.1535	0.1072	0.4766
2007				0.0003	0.2444	0.0006	0.0064	0.0000	0.4468
2008				0.0000	0.0083	0.0001	0.0426	0.0008	0.4954

CB's, One sample, model with Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,7295	0,8117	0,5950	0,7602	0,8226	0,6283	0,7704	0,8134	0,6289
2007	0,7005	0,8865	0,6230	0,7329	0,8905	0,6554	0,7548	0,8666	0,6565
2008	0,7206	0,8831	0,6351	0,7629	0,8737	0,6673	0,7777	0,8575	0,6673
				Model # 2 vs Model # 1			Model # 3 vs Model # 2		
				Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006				0,0004	0,0496	0,0004	0,1330	0,0832	0,4788
2007				0,0004	0,2169	0,0006	0,0104	0,0000	0,4541
2008				0,0000	0,0246	0,0001	0,0460	0,0009	0,4968

Other Banks, One sample, model without Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,7956	0,7380	0,5959	0,8100	0,7423	0,6099	0,8245	0,7298	0,6103
2007	0,7962	0,8371	0,6700	0,8177	0,8338	0,6864	0,8370	0,8150	0,6872
2008	0,8282	0,8154	0,6782	0,8509	0,8183	0,7006	0,8612	0,8083	0,7007
				Model # 2 vs Model # 1			Model # 3 vs Model # 2		
				Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006				0,1580	0,3798	0,2404	0,1525	0,1924	0,4922
2007				0,0648	0,3794	0,1687	0,0778	0,0472	0,4828
2008				0,0340	0,3961	0,0782	0,1944	0,1887	0,4959

Other Banks, One sample, model with Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,8043	0,7449	0,6095	0,8207	0,7511	0,6269	0,8350	0,7390	0,6273
2007	0,8134	0,8405	0,6885	0,8316	0,8413	0,7056	0,8515	0,8225	0,7063
2008	0,8487	0,8229	0,7022	0,8686	0,8262	0,7226	0,8780	0,8172	0,7224
				Model # 2 vs Model # 1			Model # 3 vs Model # 2		
				Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006				0,1233	0,3391	0,2040	0,1525	0,2155	0,4922
2007				0,0993	0,4713	0,1698	0,0698	0,0538	0,4847
2008				0,0499	0,3936	0,1131	0,2047	0,2327	0,4972

(continue)

CB's, Two samples, model without Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,8259	0,9263	0,7657	0,8421	0,9316	0,7849	0,8494	0,9232	0,7843
2007	0,8293	0,9464	0,7852	0,8401	0,9477	0,7967	0,8495	0,9372	0,7962
2008	0,8430	0,9411	0,7937	0,8557	0,9462	0,8102	0,8647	0,9363	0,8097

	Model # 2 vs Model # 1			Model # 3 vs Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,0186	0,1265	0,0121	0,1706	0,0356	0,4726
2007	0,0779	0,3403	0,0750	0,1120	0,0009	0,4752
2008	0,0457	0,0652	0,0194	0,1159	0,0023	0,4784

CB's, Two samples, model with Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,8318	0,9284	0,7732	0,8497	0,9353	0,7954	0,8564	0,9275	0,7948
2007	0,8386	0,9469	0,7947	0,8507	0,9488	0,8079	0,8589	0,9395	0,8074
2008	0,8540	0,9446	0,8075	0,8671	0,9499	0,8245	0,8754	0,9409	0,8241

	Model # 2 vs Model # 1			Model # 3 vs Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,0122	0,0728	0,0062	0,1975	0,0509	0,4739
2007	0,0602	0,2801	0,0550	0,1436	0,0033	0,4761
2008	0,0417	0,0626	0,0192	0,1369	0,0055	0,4797

Other Banks, Two samples, model without Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,8371	0,7044	0,6003	0,8555	0,7208	0,6279	0,8680	0,7112	0,6282
2007	0,8220	0,8124	0,6743	0,8503	0,8072	0,6940	0,8708	0,7894	0,6951
2008	0,8537	0,7953	0,6841	0,8725	0,8061	0,7091	0,8831	0,7961	0,7089

	Model # 2 vs Model # 1			Model # 3 vs Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,0575	0,1424	0,0896	0,1374	0,2741	0,4936
2007	0,0095	0,3196	0,1250	0,0327	0,0614	0,4768
2008	0,0385	0,1637	0,0559	0,1513	0,1904	0,4948

Other Banks, Two samples, model with Asset Quality Indicator

	Model # 1			Model # 2			Model # 3		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,8431	0,7168	0,6166	0,8635	0,7348	0,6473	0,8756	0,7255	0,6477
2007	0,8362	0,8195	0,6931	0,8596	0,8206	0,7144	0,8680	0,8253	0,7257
2008	0,8733	0,8046	0,7089	0,8994	0,8359	0,7583	0,8979	0,8078	0,7320

	Model # 2 vs Model # 1			Model # 3 vs Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
2006	0,0413	0,1382	0,0813	0,1431	0,2936	0,4926
2007	0,0262	0,4643	0,1191	0,2293	0,3469	0,2698
2008	0,0040	0,0044	0,0014	0,4352	0,0105	0,0565

Source: Own elaboration.

Table 3.10 - *The Mean Efficiency Scores, 1994-2008*

CB's, One sample, model without Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,6933	0,8302	0,5895	0,7076	0,8325	0,6035
North-East	0,7386	0,8634	0,6537	0,7561	0,8654	0,671
Centre	0,6431	0,8476	0,5581	0,673	0,8419	0,5805
South	0,6189	0,7892	0,5	0,7005	0,7901	0,567

CB's, One sample, model with Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,71	0,8261	0,5993	0,7241	0,8285	0,6131
North-East	0,7554	0,8634	0,667	0,7721	0,8673	0,685
Centre	0,6474	0,8495	0,5617	0,678	0,8447	0,5852
South	0,6216	0,7924	0,503	0,7074	0,7962	0,5756

Other banks, One sample, model without Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,7845	0,7979	0,6425	0,7935	0,8016	0,6513
North-East	0,8348	0,7929	0,6794	0,8458	0,8012	0,6938
Centre	0,7382	0,7432	0,5622	0,7683	0,7438	0,5848
South	0,7342	0,7322	0,5504	0,7845	0,7333	0,5881

Other Banks, One sample, model with Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,794	0,7988	0,6493	0,7979	0,7988	0,6542
North-East	0,8628	0,8171	0,7222	0,8666	0,8203	0,7302
Centre	0,7558	0,7444	0,5756	0,7791	0,7432	0,5941
South	0,7451	0,7322	0,5573	0,7877	0,7323	0,5913

(continue)

CB's, Two samples, model without Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8079	0,9294	0,7626	0,8101	0,9297	0,7657
North-East	0,8324	0,9326	0,7885	0,8383	0,9353	0,7971
Centre	0,7979	0,9307	0,7542	0,8045	0,9317	0,762
South	0,8177	0,8928	0,7415	0,8536	0,9002	0,7812

CB's, Two samples, model with Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8248	0,9316	0,7789	0,8258	0,9309	0,7811
North-East	0,8476	0,9368	0,8049	0,8524	0,9385	0,813
Centre	0,8032	0,9347	0,761	0,8095	0,9346	0,7687
South	0,821	0,8982	0,7476	0,8583	0,9058	0,79

Other banks, Two samples, model without Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,828	0,7787	0,655	0,84	0,7809	0,6648
North-East	0,865	0,786	0,6908	0,8763	0,7945	0,7057
Centre	0,7915	0,7146	0,5739	0,8237	0,7255	0,6055
South	0,7725	0,7225	0,5663	0,829	0,7459	0,6262

Other Banks, Two samples, model with Asset Quality Indicator, 1994-2008 Averages

	Model # 1			Model # 2		
	Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
North-West	0,8358	0,7843	0,6641	0,848	0,7868	0,6782
North-East	0,8914	0,813	0,7349	0,8984	0,8243	0,7534
Centre	0,8061	0,7197	0,5877	0,8331	0,7384	0,6252
South	0,7805	0,7262	0,5737	0,8307	0,7547	0,6368

Source: Own elaboration.

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Table 3.11 - *The Mean Efficiency Scores, Mean Values and Some Tests, 1994-2008*

CB's, One sample, model without Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,6944	0,8744	0,6144	0,7335	0,8635	0,6435
			Model # 2 vs Model # 1		
			0,0000	0,0077	0,0001

CB's, One sample, model with Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,707	0,8695	0,6215	0,7469	0,8577	0,6513
			Model # 2 vs Model # 1		
			0,0000	0,0246	0,0001

Other Banks, One sample, model without Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,8119	0,7991	0,6619	0,8373	0,8047	0,687
			Model # 2 vs Model # 1		
			0,0340	0,41	0,0782

Other Banks, One sample, model with Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,8351	0,8093	0,6886	0,8523	0,8099	0,7063
			Model # 2 vs Model # 1		
			0,04	0,42	0,1

CB's, Two samples, model without Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,8274	0,9255	0,7781	0,8392	0,9297	0,7937
			Model # 2 vs Model # 1		
			0,04	0,06	0,01

CB's, Two samples, model with Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,82	0,931	0,77	0,8511	0,9339	0,8085
			Model # 2 vs Model # 1		
			0,02	0,0626	0,02

Other Banks, Two samples, model without Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,8374	0,779	0,6678	0,8589	0,7925	0,6955
			Model # 2 vs Model # 1		
			0,03	0,17	0,06

Other Banks, Two samples, model with Asset Quality Indicator

Model # 1			Model # 2		
Tech.	Alloc.	Cost	Tech.	Alloc.	Cost
0,8597	0,791	0,6953	0,8831	0,8196	0,742
			Model # 2 vs Model # 1		
			0,0040	0,02	0

Source: Own elaboration.

References

Afriat S.N. (1972), "Efficiency estimation of production functions", *International Economic Review*, 13, pp. 568-98.

Aigner D., Lovell C.A.K., Schmidt P. (1977), "Formulation and estimation of stochastic production function models", *Journal of Econometrics,* 6, pp. 21-37.

Allen L., Rai A. (1996), "Operational efficiency in banking: an international comparison", *Journal of Banking and Finance*, 20, pp. 655-72.

Altunbas Y., Carbo S., Gardener E.P.M., Molyneux P. (2007), "Examining the relationships between capital, risk and efficiency in European banking", *European Financial Management*, 13, pp. 49-70.

Altunbas Y. Chakravarty S. P. (2001), "Frontier cost functions and bank efficiency", *Economic Letters*, 72, pp. 233-40.

Altunbas Y., Liu M.H., Molyneux P., Seth R. (2000), "Efficiency and risk in Japanese banking", *Journal of Banking and Finance*, 24, pp. 1605-1628.

Angelini P., Di Salvo R., Ferri G. (1998), "Availability and cost of credit for small businesses: customer relationships and credit cooperatives", *Journal of Banking and Finance*, 22, pp. 925-954.

Arellano M., Bover O. (1995), "Another look at the instrumental variable estimation of error-components models", *Journal of Econometrics*, 68, pp. 29-52.

Banker R. D., Charnes A., Cooper W. W. (1984), "Some models for estimating technical and scale inefficiencies in Data Envelopment Analysis", *Management Sciences*, 30, pp. 1078-

1092.

Battaglia F., Farina V., Fiordelisi F., Ricci O. (2010), “The efficiency of cooperative banks: the impact of environmental economic conditions”, *Applied Financial Economics*, 20, pp. 1363-1376.

Battese G.E., Coelli T.J. (1995), “A model for technical inefficiency effects in a stochastic frontier production function for panel data”, *Empirical Economics*, 20, pp. 325-332.

Battese G.E., Corra G. (1977), “Estimation of a production frontier model: with application to the pastoral zone of Eastern Australia”, *Australian Journal of Agricultural Economics*, 21, pp. 169-179.

Bauer P.W. (1990), “Recent developments in the econometric estimation of frontiers”, *Journal of Econometrics*, 46, pp. 39-56.

Bauer P.W., Berger A.N., Humphrey D.B. (1993), “Efficiency and productivity growth in U.S. banking”, in *Fried H.O., Lovell K.A.L., Schmidt S.S. (Eds.), The Measurement of Productive Efficiency: Techniques and Applications*, Oxford, Oxford University Press, pp. 386-413.

Bauer P.W., Berger A.N., Humphrey D.B., Ferrier G.D. (1998), “Consistency conditions for regulatory analysis of financial institutions: a comparison of frontier efficiency techniques”, *Journal of Economics and Business*, 50, pp. 85-114.

Beckers D., Hammond C. (1987), “A tractable likelihood function for the normal-gamma stochastic frontier model”, *Economics Letters*, 24, pp. 33-38.

Bekaert G., Harvey C.R., Lundblad C. (2001), “Emerging equity markets and economic development”, *Journal of Development Economics*, 66, pp. 465-504.

Bera A.K., Sharma S. (1999), “Estimating production uncertainty in stochastic frontier production function model”, *Journal of Productivity Analysis*, 12, pp. 187-210.

Bencivenga V.R., Smith, B.D. (1991), “Financial intermediation and endogenous growth”, *Review of Economic Studies*, 58, pp. 195-209.

Berger A.N. (1993), “Distribution-free estimates of efficiency in the US banking industry and tests of the standard distributional assumptions”, *Journal of Productivity Analysis*, 4, pp. 261-292.

Berger A.N., Bonaccorsi di Patti E. (2006), “Capital structure and firm performance: a new approach to testing agency theory and an application to the banking industry”, *Journal of Banking and Finance*, 30, pp. 1065-1102

Berger A.N., DeYoung R. (1997), “Problem loans and cost efficiency in commercial banks”, *Journal of Banking and Finance*, 32, pp. 849-870.

Berger A.N., Hannan T.H. (1998), “The efficiency cost of market power in the banking industry: a test of the “quiet life” and related hypotheses”, *Review of Economics and Statistics*, 80, pp. 454-465.

Berger A.N., Humphrey D. (1991), “The dominance of inefficiencies over scale and product mix economies in banking”, *Journal of Monetary Economics*, 28, pp. 117-148.

Berger A.N., Humphrey D. (1997), “Efficiency of financial institutions: international survey and directions for future research”, *European Journal of Operational Research*, 98, pp. 175-212.

Berger A.N., Mester L.J. (1997), “Inside the blackbox: what explains differences in the efficiencies of financial institutions,” *Journal of Banking and Finance*, 21, pp. 895-947.

Blackburn K., Huang V. (1998), “A theory of growth, financial development and trade”, *Economica*, 65, pp. 107-124.

Blundell R., Bond S. (1998), “Initial conditions and moment restrictions in dynamic panel data models”, *Journal of Econometrics*, 87, pp. 115-143.

Bonin J.P., Hasan I., Wachtel P. (2005), "Bank performance, efficiency and ownership in transition countries", *Journal of Banking and Finance*, 29, pp. 31-53.

Bos J.W.B., Koetter M. (2011), "Handling losses in translog profit models", *Applied Economics*, 43, pp. 307-312.

Bos J.W.B., Kolari J.W. (2005), "Large bank efficiency in Europe and the United States: are there economic motivations for geographic expansion in financial services?" *Journal of Business*, 78, pp. 1555-1592.

Bravo-Ureta B.E., Pinheiro A.E. (1993), "Efficiency analysis of developing country agriculture: a review of the frontier function literature", Agric. Res. Econ. Rev., 22, pp. 88-101.

Cameron R., Crisp O., Patrick H.T., Tilly R. (1967), *Banking in the Early Stages of Industrialization: A Study in Comparative Economic History*, New York, Oxford University Press.

Carbó Valverde S., Humphrey D., Fernandez F.R. (2003), "Deregulation, bank competition and regional growth", *Regional Studies*, Taylor and Francis Journals, 37, pp. 227-237.

Casu B., Girardone C., Molyneux P. (2004), "Productivity in European banking - A comparison of parametric and non-parametric approaches", *Journal of Banking and Finance*, 28, pp. 2521-2540.

Casu B., Girardone C. (2005), "An analysis of the relevance of off-balance sheet items in explaining productivity change in European banking", *Applied Financial Economics*, 15, pp. 1053-1061.

Cazals C., Florens J.P., Simar L. (2002), "Nonparametric frontier estimation: a robust approach", *Journal of Econometrics*, 106, pp. 1-25.

Charnes A, Cooper W.W., Rhodes E. (1978), "Measuring the efficiency of Decision Making

Units", *European Journal of Operation Research*, 2, pp. 429- 444.

Charnes A., Cooper W.W., Rhodes E. (1981), "Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through", *Management Science*, 27, pp. 668-697.

Christopoulos D. K., Tsionas E.G. (2004), "Financial development and economic growth: evidence from panel unit root and cointegration tests", *Journal of Development Economics*, 73, pp. 55-74.

Coelli T.J., Rao D.S.P., O'Donnell C.J., Battese G.E. (2005), *An Introduction to Efficiency and Productivity Analysis*, New York, 2nd edition, Springer.

Debreu G. (1951), "The coefficient of resource utilization", *Econometrica*, 19, pp. 273-292.

Dehejia R., Lleras-Muney A. (2003), "Why does financial development matter? The United States from 1900 to 1940", *National Bureau of Economic Research Working Papers*, 9551.

Demetriades P., Hussein K. (1996), "Does financial development cause economic growth? Time series evidence from 16 countries", *Journal of Development Economics*, 5, pp. 387-411.

Demirgüç-Kunt A., Maksimovic V. (1998), "Law, finance and firm growth", *Journal of Finance*, 53, pp. 2107-2137.

Deng E., Elyasiani E. (2007), "Geographic diversification, bank holding company, and risk", *Journal of Money, Credit and Banking*, 40, pp. 1217-1238.

Deprins D., Simar L., Tulkens H. (1984), "Measuring labor-efficiency in post offices", in Marchand M., Pestieau P., Tulkens H. (eds.), *The Performance of Public Enterprises: Concepts and Measurement*, North Holland, Amsterdam.

Destefanis S. (2001), "A non-parametric analysis of the Italian banking system's efficiency", in Baldassarri, M., Bagella, M., Paganetto, L. (Eds.), Financial Markets Imperfect Information and Risk Management. Palgrave, Basingstoke.

DeYoung R. (1994), "Fee-based services and cost efficiency in commercial banks", in *Bank Structure and Competition*, Federal Reserve Bank of Chicago, pp. 501-519.

Diewert, W.E., Mendoza, M.N.F. (1995), "Data Envelopment Analysis: a practical alternative", UBC Departmental Archives 95-30, UBC Department of Economics.

Dietsch M., Lozano - Vivas A. (2000), "How the environment determines banking efficiency: a comparison between French and Spanish banking industry", *Journal of Banking and Finance*, 24, pp. 985-1004.

Fama E.F. (1980), "Agency problems and the theory of the firm", *Journal of Political Economy*, 88 (2), pp. 288-307.

Farrell M.J. (1957), "The measurement of productive efficiency", *Journal of the Royal Statistical Society*, 120, pp. 253-281.

Ferri G., Mattesini F. (1997), "Finance, human capital and infrastructure: an empirical investigation on postwar Italian growth", *Temi di discussione*, Banca d'Italia, 321.

Ferrier G., Lovell C.A.K. (1990), "Measuring cost efficiency in banking: econometric and linear programming evidence", *Journal of Econometrics*, 46, pp. 229-245.

Fethi M.D., Pasiouras F. (2010), "Assessing bank performance with operational research and artificial intelligence techniques: a survey", *European Journal of Operational Research*, 204, pp. 189-198.

Fiordelisi F., Marques-Ibanez D., Molyneux P. (2011), "Efficiency and risk in European banking", *Journal of Banking and Finance*, 35, pp. 1315-1326.

Fonteyne W. (2007), "Cooperative banks in Europe–policy issues", *International Monetary Fund*, WP 07/159.

Førsund F.R. (1996), “On the calculation of the scale elasticity in DEA models”, *The Journal of Productivity Analysis*, 7, pp. 283-302.

Førsund F.R., Lovell C.A.K., Schmidt P. (1980), “A survey of frontier production functions and of their relationship to efficiency measurement”, *Journal of Econometrics*, 13, pp. 5-25.

Fries S., Taci A. (2005), “Cost efficiency of banks in transition: evidence from 289 banks in 15 post-communist countries”, *Journal of Banking and Finance*, 29, pp. 55-81.

Gertler M., Rose, A. (1994), “Finance, public policy and growth”, in *Caprio, G., Atiljas, I. and Hanson, J.A. (eds.), Financial Reform*: *Theory and Experience*, Cambridge University Press, New York, pp. 13-45.

Gijbels I., Mammen, E., Park, B. U., Simar, L. (1999), “On estimation of monotone and concave frontier functions”, *Journal of the American Statistical Association*, 94, pp. 220-228.

Giordano L., Lopes A. (2006), “Risk preference and investments quality as determinants of efficiency in the Italian banking system”, *Quaderni DSEMS 2006*, Dipartimento di Scienze Economiche, Matematiche e Statistiche, Università di Foggia, 12/2006.

Goldschmidt A. (1981), “On the definition and measurement of bank output”, *Journal of Banking and Finance*, 5, pp. 555-585.

Goldsmith R.W. (1969), *Financial Structure and Development*, New Haven, CT, Yale University Press.

Greene W. (1990), “A gamma distributed stochastic frontier model”, *Journal of Econometrics*, 46, pp. 141-164.

Greene W. (1993), “The econometric approach to efficiency analysis”, in Fried H.O., Lovell K.A.L., Schmidt S.S. (Eds.), *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford University Press, New York, pp. 68-119.

Greene, W. (2005), “Reconsidering heterogeneity in panel data estimators of the stochastic frontier model”, *Journal of Econometrics*, 126, pp. 269-303.

Guiso L., Sapienza P., Zingales L. (2004a), “The role of social capital in financial development”, *American Economic Review*, 94, pp. 526-556.

Guiso L., Sapienza P., Zingales L. (2004b), “Does local financial development matter?”, *The Quarterly Journal of Economics*, 119, pp. 929-969.

Gurley J., Shaw E. (1967), “Financial structure and economic development”, *Economic Development and Cultural Change*, 15, pp. 257-268.

Hall P., Simar L. (2002), “Estimating a changepoint, boundary, or frontier in the presence of observation error”, *Journal of the American Statistical Association*, American Statistical Association, 97, pp. 523-534.

Hasan I., Hunter W.C. (1996), “Efficiency of Japanese multinational banks in the United States”, *Research in Finance*, 14, pp. 157-173.

Hasan I., Koetter M., Wedow M. (2009), “Regional growth and finance in Europe: is there a quality effect of bank efficiency?”, *Journal of Banking and Finance*, 33, pp. 1446-1453.

Hassan M.B., Sanchez B., Yu G-S (2011), “Financial development and economic growth: new evidence from panel data”, *The Quarterly Review of Economic and Finance*, 51, pp. 88-104.

Huang C.J., Liu J.-T. (1994), “Estimation of a non-neutral stochastic frontier production function”, *Journal of Productivity Analysis*, 5, pp. 171-180.

Hughes J.P., Lang W.W., Mester L.J., Moon C.G. (1996), “Safety in numbers? Geographic diversification and bank insolvency risk,” *Proceedings*, Federal Reserve Bank of Chicago, pp. 202-218.

Hughes J.P., Lang W.W., Mester L.J., Moon C.G. (1999), “The dollars and sense of bank consolidation," *Journal of Banking and Finance*, 23, pp. 291-324.

Hughes J.P., Mester L.J. (1993), "A quality and risk-adjusted cost function for banks: evidence on the "Too-Big-To-Fail" doctrine," *Journal of Productivity Analysis*, 4, pp. 293-315.

Hughes J.P, Mester L.J., (2008), ''Efficiency in banking: theory, practice and evidence'', Working Papers 08-1, Federal Reserve Bank of Philadelphia.

ISTAT (2005), *Sistemi Locali del Lavoro available*, at: http://www.istat.it/salastampa/comunicati/non calendario/20050721 00/

Jayaratne J., Strahan P. (1996), "The finance-growth nexus: evidence from bank branch deregulation", *The Quarterly Journal of Economics*, 111, pp. 639-670.

Jondrow J., Lovell C.A.K., Materov I.S., Schmidt P. (1982), "On the estimation of technical inefficiency in the stochastic frontier production function model", *Journal of Econometrics*, 19, pp. 233-38.

Jung W.S. (1986), "Financial development and economic growth: international evidence", *Economic Development and Cultural Change*, 34, pp. 336-346.

Kaparakis E., Miller S, Noulas P (1994), Short-run cost inefficiency of commercial banks: a flexible stochastic frontier approach, *Journal of Money, Credit and Banking*, 26, pp. 875-893

Khan A. (2001), "Financial development and economic growth", *Macroeconomics Dynamics*, 5, pp. 413-433.

King R.G., Levine R. (1993a), "Financial intermediation and economic development", in *Mayer, C., Vives, X. (cur), "Capital Markets and Financial Intermediation"*, Cambridge University Press, pp. 156-89.

King R.G., Levine R. (1993b), "Finance and growth: Schumpeter might be right", *The Quarterly Journal of Economics*, 108, pp. 717-38.

King R.G., Levine R. (1993c), “Finance, entrepreneurship, and growth: theory and evidence”, *Journal of Monetary Economics*, 32, pp. 513-42.

Kittelsen S.A.C. (1999), “Monte Carlo simulations of DEA efficiency measures and hypothesis tests”, *Memorandum n. 9*, Department of Economics, University of Oslo.

Kneip A., Park B.U., Simar L. (1998), “A note on the convergence of nonparametric DEA estimators for production efficiency scores”, *Econometric Theory*, 14, pp. 783-793.

Kumbhakar S.C., Ghosh S., McGuckin J.T. (1991), “A generalized production frontier approach for estimating determinants of inefficiency in U.S. dairy farms”, *Journal of Business and Economic Statistics*, 9, pp. 279-86.

Kumbhakar S.C., Lovell C.A.K, (2000). *Stochastic Frontier Analysis*, New York, Cambridge University Press.

Kumbhakar S.C., Sarkar S. (2003), “Deregulation, ownership, and productivity growth in the banking industry: evidence from India”, *Journal of Money, Credit and Banking*, 35, pp. 403-24.

Kwan S.H., Eisenbeis R.A. (1996), “An analysis of inefficiencies in banking: a stochastic cost frontier approach”, *Economic Review*, Federal Reserve Bank of San Francisco, pp. 16-26.

La Porta R., Lopez-de-Silanes F., Shleifer A., Vishny R.W. (1997), **“**Legal Determinants of External Finance”, *Journal of Finance*, 52, pp. 1131-50.

La Porta R., Lopez-de-Silanes F., Shleifer A., Vishny R.W. (1999), “The Quality of Government”, *Journal of Law, Economics and Organization*, 15, pp. 222-79.

Levine R. (1997), “Financial development and economic growth: views and agenda”, *Journal of Economic Literature*, 35, pp. 688-726.

Levine R. (2005), “Finance and growth: theory and evidence”, in *Philippe Aghion and Steven*

Durlauf (eds.), Handbook of Economic Growth, edition 1, volume 1, chapter 12, pp. 865-934.

Levine R., Loayza N., Beck T. (2000), “Financial intermediation and growth: causality and causes”, *Journal of Monetary Economics*, 46, pp. 31-84.

Levine R., Zervos S. (1998), “Stock markets, banks, and economic growth”, *American Economic Review*, 88, pp. 537-558.

Lewin A.Y., Lovell C.A.K (1990), “Frontier analysis: parametric and nonparametric approaches”, *Journal of Econometrics*, 46, pp. 1-245.

Lovell C.A.K. (1993), “Production frontiers and productive efficiency”, in Fried H., Lovell C. A. K., Schimdt S. (eds.), *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford: Oxford University Press.

Lozano-Vivas A., Pastor J., Pastor J.M. (2002), “An efficiency comparison of European banking systems operating under different environmental conditions”, *Journal of Productivity Analysis*, 18, pp. 59-77.

Lucchetti R., Papi L., Zazzaro A. (2001), “Bank inefficiency and economic growth: a micro–macro approach”, *Scottish Journal of Political Economy*, 48, pp. 400-424.

Maietta O.W. (2007), *L'Analisi dell'Efficienza: Tecniche di Base ed Estensioni Recenti*, Esi, Napoli.

Maudos J., Pastor J.M., Perez F., Quesada J. (2002), “Cost and profit efficiency in European banks”, *Journal of International Financial Markets, Institutions and Money*, 12, pp. 33-58.

McKinnon R.I. (1973), “Money and capital in economic development”, *Journal of International Economics*, 4, pp. 223-224.

Meeusen W., Van den Broeck J. (1977), “Efficiency estimation from Cobb-Douglas production functions with composed error”, *International Economic Review*, 18, pp. 435-444.

Mester L.J., (1996), “A study of bank efficiency taking into account risk-preferences”, *Journal of Banking and Finance*, 20, pp. 1025-1045.

Neusser K., Kugler M. (1998), “Manufacturing growth and financial development: evidence from OECD countries”, *Review of Economics and Statistics*, 80, pp. 638-646.

Niehans J. (1978), *The Theory of Money*, Baltimore, Johns Hopkins University Press.

Park B., Sickles R.C., Simar L. (1998), “Stochastic panel frontiers: a semiparametric approach”, *Journal of Econometrics*, 84, pp. 273-301.

Pasiouras F., Tanna S., Zopounidis C. (2009),”The impact of banking regulations on banks’ cost and profit efficiency: cross country evidence”, *International Review of Financial Analysis*, 18, pp. 294-302.

Pestieau P., Tulkens H. (1993), “Assessing the performance of public sector activities: some recent evidence from the productive efficiency viewpoint”, *Finanzarchiv*, 50, pp. 293-323.

Pitt M.M., Lee L.F. (1981), “Measurements and sources of technical inefficiency in the Indonesian weaving industry”, *Journal of Development Economics*, 9, pp. 43-64.

Rajan R.G., Zingales L. (1998), “Financial dependence and growth”, *American Economic Review*, 88, pp. 559-86.

Reifschneider D., Stevenson R. (1991), “Systematic departures from the frontier: a framework for the analysis of firm inefficiency”, *International Economic Review*, 32, pp. 715-723.

Resti A. (1997), “Evaluating the cost efficiency of the Italian banking system: what can be learned from the joint application of parametric and non-parametric techniques”, *Journal of Banking and Finance*, 21, pp. 221-50.

Richmond J. (1974), “Estimating the efficiency of production”, *International Economic Review*, 15, 2, pp. 515-521.

Rogers K.E., (1998), "Nontraditional activities and the efficiency of US commercial banks", *Journal of Banking and Finance*, 22, pp. 467-482.

Rossi S.M., Schwaiger S., Winkler G. (2009), "How loan portfolio diversification affects risk, efficiency and capitalization: a managerial behaviour model for Austrian banks", *Journal of Banking and Finance*, 33, pp. 2218-2226.

Rousseau P.L., Wachtel P. (1998), "Financial intermediation and economic performance: historical evidence from five industrial countries", *Journal of Money, Credit and Banking*, 30, pp. 657-678.

Schmidt P. (1986), "Frontier production functions", *Econometric Reviews*, 4, pp. 289-328.

Sealey C.W., Lindley J. (1997), "Inputs, outputs, and a theory of production and cost at depository financial institutions", *Journal of Finance*, 32, pp. 1251-1266.

Shan J., Morris A., Sun F. (2001), "Financial development and economic growth: an egg-chicken problem?", *Review of International Economics*, 9, pp. 443-454.

Simar L., Wilson P.W., (2007). "Estimation and inference in two-stage, semi-parametric models of production processes", *Journal of Econometrics*, 136, pp. 31-64.

Simar L., Wilson P.W., (2011), "Two-stage DEA: caveat emptor", *Journal of Productivity Analysis*, 36, pp. 205-218.

Stevenson R.E. (1980), "Likelihood functions for generalized stochastic frontier estimation", *Journal of Econometrics*, 13, pp. 57-66.

Stiroh K.J., (2000), "How did bank holding companies prosper in the 1990s?", *Journal of Banking and Finance*, 24, pp. 1703-1745.

Sylla R. (1969), "Federal policy, banking market structure, and capital mobilization in the United

States, 1863-1913”, *Journal of Economic History*, 29, pp. 657-686.

Sylla R. (1972), “The United States 1863-1913”, Rondo Cameron (ed.), *Banking and Economic Development: Some Lessons of History*, New York: Oxford University Press, pp. 232-262.

Sylla R. (2002), “Financial systems and economic moderization”, *Journal of Economic History*, 62, pp. 277-292.

Tørgersen A.M., Førsund F.A., Kittelsen S.A.C. (1996), “Slack-adjusted efficiency measures and ranking of efficient units”, *Journal of Productivity Analysis*, 7, pp. 379-398.

Tortosa-Ausina E., (2003), “Nontraditional activities and bank efficiency revisited: a distributional analysis for Spanish financial institutions”, *Journal of Economics and Business*, 55, pp. 371-395.

Tortosa-Ausina E., Grifell-Tatjé E., Armero C., Conesa D. (2008), “Sensitivity Spanish savings banks”, *European Journal of Operational Research*, 184, pp. 1062-1084.

Tulkens H. (1993), “On FDH efficiency analysis: some methodological issues and applications to retail banking, courts and urban transit”, *Journal of Productivity Analysis*, 4, pp. 183-210.

Van Hoose D. (2010), *The Industrial Organization of Banking*, Berlin-Heidelberg, Springer-Verlag.

Weill L. (2004), “Measuring cost efficiency in European banking: a comparison of frontier techniques”, *Journal of Productivity Analysis*, 21, pp. 133-152.

Williams B., Sturm J. (2004), “Foreign bank entry, deregulation and bank efficiency: lesson from the Australian experience”, *Journal of Banking and Finance*, 28, pp. 1775-1799.

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