UNIVERSITA' DEGLI STUDI DI SALERNO

Dipartimento di Scienze Economiche e Statistiche

Dottorato di ricerca in Economia del Settore Pubblico

VIII ciclo (nuova serie)

Tesi di Dottorato
in

The Italian banking industry: efficiency, market power, role in the local economies

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ANNO ACCADEMICO 2009/2010

TABLE OF CONTENTS

ACKNOWLEDGEMENTS 4

INTRODUCTION 5

CHAPTER ONE - Estimating Scale and Scope Economies in Banking: Evidence from a Multi-output Symmetric Generalized McFadden Cost Function

1.1 Introduction 7
1.2 A brief review of the literature 8
1.3 Methodology 11
1.4 Data and definition of the variables 15
1.5 Estimation results 17
1.6 Conclusion 21

CHAPTER TWO - Testing the "Quiet Life" Hypothesis in the Italian Banking Industry

2.1 Introduction 22
2.2 Market power, efficiency, and their relationship: a review of the banking literature 24
2.3 Estimation of cost efficiency and market power 29
2.4 Testing the "quiet life" hypothesis 31
2.5 Data and variables 34
2.6 Estimation results 35
2.7 Conclusions 48

CHAPTER THREE - Local Economic Growth and the Role of Banks

3.1 Introduction 50
3.2 Banking market structure, financial development and growth: review of the literature 51
3.3 The econometric model 56
3.4 Estimating efficiency and market power 64
3.5 Data 67
3.6 Estimation results 75
3.7 Summary and conclusions 82

REFERENCES 83

ACKNOWLEDGEMENTS

I am deeply grateful to my advisor, Prof. Paolo Coccorese, for his guidance, help and encouragement.

I would also like to thank the coordinator of the Ph.D. program, Prof. Sergio Pietro Destefanis, for his support and suggestions.

All remaining errors are my own.

INTRODUCTION

In the last twenty years the banking sector of many countries has undergone a period of consolidation and restructuring. This has raised concerns about the welfare implications of larger credit institutions, given that the banking industry is vital for the whole economic system.

From a theoretical point of view, one should expect two “direct” effects from these structural transformations. First of all, consolidation may allow banks to achieve a higher level of efficiency thanks to the exploitation of scale and scope economies. Secondly, mergers and acquisitions among credit institutions could lead to an increase in local market concentration and thus, as maintained by the Structure-Conduct Performance (SCP) paradigm, to an increase in banks’ market power.

In turn, market power in banking is the channel through which the consolidation process could have some “indirect effects” on other economic phenomena. Indeed, as shown by recent empirical works, the degree of competition in banking markets is a key explanatory variable of banks’ X-efficiency, as well as credit availability for small firms, relationship banking, economic growth and financial stability.

In this dissertation we empirically explore some of the consequences of the consolidation process, focusing on the Italian banking industry. More precisely, *Chapter One* studies the effect on banks’ cost efficiency. Starting from a Multi-output Symmetric Generalized McFadden cost function, we estimate a system of factor demand equations in order to assess the degree of scale and scope economies of Italian banks in the period 1992-2007. We find evidence of slight economies of scale and significant economies of scope. Our main conclusion is that the efficiency gains coming from merger and acquisition operations could be an explanation of the consolidation process; at the same time, they could translate into beneficial effects for consumers and firms, provided that they are not offset by an increased market power.

In the following chapters we turn to the possible indirect effects of banking consolidation. The focus of *Chapter Two* is on the impact of banks’ monopoly power on their X-efficiency. Particularly, we test the so-called “quite life” hypothesis (QLH), according to which firms with market power are less efficient. Using data for the period 1992-2007, we apply a two-step procedure. First, we estimate bank-level cost efficiency scores and Lerner indices. Then we use the estimated market power measures, as well as a vector of control variables, to explain cost efficiency. Unlike the existing literature on the subject, to this end we employ a logistic regression that, in our opinion, is better suited to model cost efficiency scores. Our empirical evidence supports the QLH, although the impact of market power on efficiency is not particularly remarkable in magnitude.

Finally, in *Chapter Three* we assess the impact of banks' market power, and other structural variables characterizing banking markets, on local economic growth. Using a dataset on the Italian provinces for the period 1999-2006, as well as banks' balance sheets data, we estimate a dynamic panel data model, also taking into account the possible spatial dependence among observations. This is a novelty in the empirical literature on the finance-growth nexus. Moreover, the use of data on local economies, allows us to control more easily for heterogeneity. Our results show a positive and statistically significant relationship between banks' market power and economic growth, thus supporting the view according to which competition in banking can be detrimental to growth because it tends to reduce credit availability for informationally opaque firms. This evidence can have important implications on the Italian economy, where the presence of small (usually more opaque) firms is quite relevant. Besides, when spatial interactions are accounted for, the impact of local financial development disappears, and provincial growth is positively linked to how fast contiguous provinces grow.

Although the three chapters, as explained above, are to some extent linked, they have been organized and written as self-contained works.

CHAPTER ONE

Estimating Scale and Scope Economies in Banking: Evidence from a Multi-output Symmetric Generalized McFadden Cost Function

1.1 Introduction

The estimation of scale and scope economies in banking has a long tradition in applied economics and the methodology has evolved according to the introduction of new functional forms. Not all of these, however, are well suited for assessing cost economies and, in particular, economies of scope.

The most used flexible functional form,[1] the translog cost function (TCF),[2] suffers from two weaknesses. On one hand, it often violates the theoretical property of concavity in prices. Although global concavity can be imposed, this destroys the flexibility of the TCF.[3] On the other hand, it does not admit zero values of outputs, since all variables enter in logarithmic form. Then it is not possible to assess economies of scope. Several solutions have been proposed to deal with this undesirable characteristic of the TCL, none of which is completely satisfactory (Pulley and Humphrey, 1993).

The quadratic cost function, originally proposed by Lau (1974), admits zero output values but it cannot be restricted parametrically in order to impose homogeneity and/or concavity in input prices without sacrificing its flexibility. The same applies for the Generalized-CES-Quadratic cost function introduced by Roller (1990).

Caves et al. (1980) proposed to use the Box-Cox transformation of the outputs in the translog model in order to accommodate zero values. However, empirical applications using this cost function show that the parameter of the transformation is nearly zero, so that the estimated Generalized translog cost function is a close approximation to the

[1] For the definition of flexibility, see Diewert (1974).
[2] The translog functional form has been introduced by Christensen et al. (1973).
[3] See Diewert and Wales (1987). Concavity can also be imposed locally as showed by Ryan and Wales (2000). Using Berndt and Khaled (1979) dataset (which consists of 25 observations), they find that

translog form. Conversely, the Symmetric Generalized McFadden cost function, introduced by Diewert and Wales (1987) and extended to the multi-output framework by Kumbhakar (1994), admits zero values for outputs and is globally concave in input prices.[4]

In this paper we assess scale and scope economies in the Italian banking industry over the period 1992-2007. We estimate a system of factor demand equations derived from a Multi-product Symmetric Generalized McFadden (MSGM) cost function.[5] Using a panel of banks, we are also able to control for technical change.

Reliable estimates cost economies in banking are very relevant from a policy point of view, due to the consolidation process that has taken place in Italy (as in many other countries) in the last twenty years.[6] Indeed, an effect (and at the same time a cause) of the consolidation could be the exploitation of scale and scope economies by larger and more diversified institutions and then lower interest rates on loans. If this is the case, to the extent to which those effects are not offset by an increased market power of banks, we should expect welfare gains from the ongoing consolidation in the banking industry.

The paper is organized as follows. Section 1.2 offers a brief review of the empirical literature on banking costs. Section 1.3 discusses the properties of the MSGM and the related measures of economies of scale, economies of scope and technical change. The dataset is described in Section 1.4, while in Section 1.5 results are presented and interpreted. Finally, Section 1.6 draws some conclusions.

1.2 A brief review of the literature

Early studies on costs in the banking industry date back to the mid-1950s. An excellent review on this first stage of research can be found in Gilbert (1984). Since

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imposing curvature conditions locally results in concavity at all points. However, this is less likely to happen for larger dataset.

[4] Anyway, concavity can be imposed through a simple reparametrization, without destroying the flexibility of the cost function.

[5] To our best knowledge no previous attempts have been made to assess cost economies in banking using a MSGM cost function. Barnett et al. (1995) employ this functional form to model banks' technology but in a macroeconomic framework.

[6] To give an idea, in Italy the number of banks reduced from 922 in 1998 to 806 in 2007, while in the same period the assets of the whole banking system increased from 1936.71 to 3871.32 billions euro (Bank of Italy data).

then, the methodology has quickly evolved, stimulated by the introduction of new functional forms.

One of the first studies employing a flexible functional form, namely the translog, is Benston et al. (1982). They use an aggregated measure of deposits and loans as output to estimate economies of scale for U.S. banks over the period 1975-1978. However, if one uses a single output specification, the finding of economies of scale could actually be due to the presence of economies of scope (Mester, 1987). Moreover, Kim M. (1986) tests the existence of a consistent output aggregate for a sample of Israeli banks, concluding that a composite measure of output is not able to adequately represent the banking technology.

Murray and White (1983) employ a translog cost function with multiple outputs. Using cross-section data on 61 credit institutions in British Columbia for the period 1976-1977, they find evidence of economies of scale for all banks in the sample, with a weak inverse relationship between returns to scale and asset size. Moreover, they find strong evidence of cost complementaries between mortgage lending and consumer lending.

Another study using a multi-product translog specification is that of Gilligan et al. (1984). The authors use the same data as Benston et al. (1982) but don't find evidence of economies of scale. However, like Murray and White (1983), they conclude that economies of scope exist, although they define bank output quite differently and use data with a lower level of disaggregation.

Using the parameter estimates of Murray and White, Kim H.Y. (1986) performs a richer analysis of credit institution in British Columbia. He observes that the authors omit to consider product-specific economies of scale that arise from the production of a specific subset of products. Moreover, they estimate cost complementaries, which are a sufficient but not necessary condition for economies of scope. Kim finds almost constant return to scale for mortgage lending and investments, diseconomies of scale for consumer lending, and strong evidence of both overall and product-specific economies of scope.

Cebenoyan (1988) estimates only economies of scale of U.S. banks for the period 1980-1983. Running different regressions for each year and separately for unit and multi-branching banks, he finds evidence of slight diseconomies of scale except for 1983.

Using data on 149 Saving and Loans institutions operating in California in 1982, Mester (1987) finds no evidence of both economies of scale and scope, but evidence of strong substitutability between capital and labour and between labour and demand deposits. Moreover, she shows that there are no cost advantages for institutions with larger branch networks.

One of the drawbacks of the translog cost function is that it is not defined at value zero for one or more outputs. An alternative is to employ the Generalized translog cost function. Lawrence (1989) adopts this type of flexible form to estimate economies of scale and scope for a sample of U.S. banks. Using data for the period 1979-1982, he cannot reject the hypothesis that there are no economies of scope.

None of the studies discussed so far control for technical change, being based on cross-section data. A study taking into account technical change is due to Hunter and Timme (1986). Using a balanced panel of U.S. bank for the period 1972-82 and a single-output translog specification, they find that, on average, costs reduced by 15 per cent during the sample period because of technical progress. Particularly, these benefits were obtained to a larger extent by banks with more branches or higher levels of output.

Another flexible functional form used in the banking literature is the Fourier cost function.[7] For example, Mitchell and Onvural (1996) use it to estimate scale and scope economies on a sample of about 300 U.S. banks for the years 1986 and 1990. They do not find evidence of neither economies of scale nor economies of scope.

More recent studies, based on models that take into account banks' risk preferences and financial capital, find scale economies for largest banks.[8]

Although the cost structure of European banks has not been so extensively studied as that of the U.S., the empirical research available is quite mixed. For example, Glass and McKillop (1992) use data from a single Irish bank to estimate economies of scale, economies of scope and the rate of technical change for the period 1972-1990. They find overall diseconomies of scale, but product-specific economies for lending.

[7] This functional form, introduced by Gallant (1981), combines a translog form with a truncated non-parametric Fourier series.
[8] See Mester (2008) for a review.

Estimation results suggest the presence of diseconomies of scope. As regarding technical change, they estimate an average annual rate of about 5%, except for the period 1975-1977.

A more comprehensive study on technical change is that of Altunbas et al. (1999). The authors estimate a Fourier cost function in a stochastic frontier framework. Using a large panel of European banks for the period 1989-1996, they find that the reduction in costs due to technical change varied between 2.8% and 3.6% over the sample period, with larger banks gaining more benefits.

Regarding single country studies, Zardkoohi and Kolari (1994) use data on 615 branch offices of Finnish bank in 1988 to estimate a translog cost model. The findings are that larger branches operate more efficiently, especially if they belong to banks with large branch networks. Conversely, they do not find evidence of economies of scope.

Two other studies on European country are Dietsch (1993), who finds scale economies for French banks, and Rime and Stiroh (2003), who reports economies of scale for small-medium banks and weak evidence of economies of scope in Switzerland.

For the Italian banking system, the works of Cossutta et al. (1988), Baldini and Landi (1990) and Conigliani et al. (1991) show the presence of economies of scale but not of economies of scope. The last finding, however, has not been confirmed by more recent studies. Cavallo and Rossi (2001) estimate economies of scale and scope on a panel data of banks of six European countries. For Italy, they conclude that global economies of scale exist especially for small banks. Product specific economies of scale are found for deposits and financial investments, and there is evidence of economies of scope both global and product specific.

1.3 Methodology

In order to estimate scale and scope economies in the Italian banking industry, we employ a MSGM cost function. This functional form has been introduced by Kumbhakar (1994), building on the single output specification of Diewert and Wales

(1987), who in turn generalized the McFadden (1978) cost function. It has been used, among others, by Asai (2006), Stewart (2009), and Ivaldi and McCullough (2008).[9]

The MSGM with *M* outputs and *N* inputs can be written as:

$$C = g\left(W\right)\sum_{k=1}^{M}\beta_k Q_k + \sum_{i=1}^{N} b_i W_i + \left(\sum_{i=1}^{N} b_{ii} W_i\right)\sum_{k=1}^{M}\beta_k Q_k + \sum_{i=1}^{N}\sum_{k=1}^{M} a_{ik} W_i Q_k t$$
$$a_t t \sum_{i=1}^{N}\alpha_i W_i + \left(\sum_{i=1}^{N}\lambda_i W_i\right)\sum_{j=1}^{M}\sum_{k=1}^{M} d_{jk} Q_j Q_k + a_{tt} t^2 \left(\sum_{i=1}^{N}\delta_i W_i\right)\sum_{k=1}^{M}\beta_k Q_k \qquad (1)$$

where Q_k is the *k*-th output, W_i is the *i*-th input, *t* is a time trend,[10] and $d_{jk} = d_{kj}$. The scalar function $g\left(W\right)$ is defined as:

$$g\left(W\right) = \frac{W' S W}{2\theta' W} \qquad (2)$$

where W is the *N* x 1 vector of inputs, *S* is an *N* x *N* negative semidefinite matrix of parameters, and θ is an *N* x 1 vector of non-negative constants not all zero.

In order to identify the parameters some restrictions are needed. Firstly, we must have $SP^* = 0$ for some vector P^* of strictly positive prices. If P^* is chosen to be the unit vector, this implies the set of restrictions $\sum_{j=1}^{N} s_{ij} = 0$ for $i = 1,...,N$. Secondly, setting $\theta_i = \alpha_i = \lambda_i = \delta_i = \bar{X}_i$, where $\bar{X}_i$ is the sample mean of the *i*-th input quantity, one needs to normalize to unity one of the β_k parameters.[11] In spite of these restrictions, there are still enough free parameters for the cost function to be flexible.[12]

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[9] The single output specification has been employed, for example, by Kumbhakar (1990), Rask (1995) and Nemoto and Goto (2004).

[10] The terms involving *t* account for technical progress.

[11] Alternatively, one can set $\sum_{k=1}^{M}\beta_k = 1$.

[12] See Kumbhakar (1994) for details. Moreover, the MSGM could be made even more flexible – in the sense that the number of free parameters is larger than those necessary to ensure flexibility - setting $\theta_i = \bar{X}_i$ and estimating separately the α_i, λ_i and δ_i parameters after normalizing to unity a_t, a_{tt} and one of the d_{jk} parameters.

Regarding the theoretical properties that a cost function should satisfy, the MSGM is linear homogeneous in prices by construction and, as shown by Diewert and Wales (1987), the negative semidefiniteness of the *S* matrix ensures the global concavity in prices. If the estimated *S* is not negative semidefinite, one can easily impose it through the reparametrization $S = -HH'$, where H is an *N* x *N* lower triangular matrix, while at the same time maintaining flexibility.[13]

By the Shephard's lemma, $X_i = \partial C / \partial W_i$. Then, starting from (1) we can write the input demand system as:

$$X_i = \frac{\partial g(W)}{\partial W_i} \sum_{k=1}^{M} \beta_k Q_k + b_i + b_{ii} \sum_{k=1}^{M} \beta_k Q_k + \sum_{k=1}^{M} a_{ik} Q_k t + a_t \alpha_i t + \lambda_i \sum_{j=1}^{M} \sum_{k=1}^{M} d_{jk} Q_j Q_k + a_{tt} \delta_i t^2 \sum_{k=1}^{M} \beta_k Q_k, \qquad (i = 1, \ldots, N) \tag{3}$$

where

$$\frac{\partial g(W)}{\partial W_i} = \left[\frac{S^{(i)} W}{\theta' W} - \frac{\theta_i W' S W}{2(\theta' W)^2} \right] \tag{4}$$

and $S^{(i)}$ is the *i*-th row of the *S* matrix. Adding a random error u_i to each equation, and assuming that $E(u) = 0$ and $E(uu') = \Sigma$, where $u = [u_1 \quad \ldots \quad u_N]'$, one gets a system of seemingly unrelated regressions that can be estimated by either the nonlinear and iterative version of the Zellner (1962) 's method or by maximum likelihood.

With the estimated parameters at hand, and following Baumol et al. (1982), the degree of scale economies is measured by:

$$ESC = \frac{C}{\sum_{k=1}^{M} Q_k \frac{\partial C}{\partial Q_k}} = \frac{1}{\sum_{k=1}^{M} \eta_k} \tag{5}$$

[13] Monotonicity in output and prices has to be checked after estimation or imposed locally.

where η_k is the elasticity of the cost function with respect to the *k*-th output. ESC is the generalization of the conventional measure of scale economies to multi-product firms, assuming that all outputs proportionally change. Returns to scale are increasing, constant or decreasing according to whether ESC is, greater than, equal to, or less than 1, respectively. For the MSGM cost function (1) we have:

$$\begin{aligned}\frac{\partial C}{\partial Q_k} &= g\left(W\right)\beta_k + \beta_k \sum_{i=1}^{N} b_{ii} W_i + \sum_{i=1}^{N} a_{ik} W_i t + \\ &\qquad 2\left(\sum_{i=1}^{N} \lambda_i W_i\right) \sum_{j=1}^{M} d_{jk} Q_j + a_{tt} t^2 \left(\sum_{i=1}^{N} \delta_i W_i\right)\beta_k, \quad \left(k = 1,\dots,M\right)\end{aligned} \tag{6}$$

Economies of scope come from the joint production of several outputs. They are defined as (Bailey and Friedlaender, 1982):

$$ESCP = \frac{\sum_{k=1}^{M} C\left(0,\dots,0,Q_k,0,\dots,0\right) - C}{C} \tag{7}$$

Thus, $ESCP$ measures the relative variation in costs due to the combined production of the *M* outputs. There exist economies of scope if $ESCP > 0$; indeed, if this is the case, the cost of producing the outputs separately is larger than the cost of producing them jointly, so the numerator is positive. By the same reasoning, if $ESCP < 0$, there exist diseconomies of scope. Finally, if the outputs are disjoint in the production process, $ESCP = 0$.

The rate of technical change is given by (minus) the growth rate of costs with respect to time, that is:

$$RTC = -\frac{\partial C / \partial t}{C} \tag{8}$$

If this quantity is positive, costs reduce over time at rate *RTC* thanks to technical change. For the MSGM cost function (1):

$$\frac{\partial C}{\partial t} = \sum_{i=1}^{N}\sum_{k=1}^{M} a_{ik} W_i Q_k + a_t \sum_{i=1}^{N} \alpha_i W_i + 2 a_{tt} t \left(\sum_{i=1}^{N} \delta_i W_i \right) \sum_{k=1}^{M} \beta_k Q_k \tag{9}$$

To better characterize the production process of Italian banks, we also estimate price elasticities of inputs. By definition, the elasticity of input *i* with respect to the price of input *j* is given by:

$$\varepsilon_{ij} = \frac{\partial X_i}{\partial W_j} \frac{W_j}{X_i} \tag{10}$$

Starting from (1), we can write:

$$\frac{\partial X_i}{\partial W_j} = \left[\frac{s_{ij}}{\theta' W} - \frac{\left(S^{(i)} \theta_j + S^{(j)} \theta_i \right) W}{\left(\theta' W \right)^2} + \theta_i \theta_j \frac{W' S W}{\left(\theta' W \right)^3} \right] \sum_{k=1}^{M} \beta_k Q_k \tag{11}$$

1.4 Data and definition of the variables

The sample of Italian banks has been drawn from the database Bankscope,[14] and covers the years 1992-2007. We have selected banks' balance sheet and profit and loss account data only in unconsolidated form (thus treating holding banks and their affiliates as separate decisional units). Besides, we have considered only commercial, cooperative and popular banks, dropping those observations for which relevant variables were not available. As consistency check, the sample has been matched to the official list of banks operating in Italy in each year, available from the Bank of Italy. We dropped the observations that did not pass this test.

We follow the intermediation approach to banking costs (Sealey and Lindley, 1977) and consider a three outputs-three inputs specification of the system (3). The outputs are loans (Q_1), other earning assets (Q_2), which consist basically of financial assets, and

[14] The Bankscope database is distributed by Bureau van Dijk Electronic Publishing (BvDEP) and is one of the most used dataset in empirical banking.

non-traditional activities (Q_3), which generate non-interest income. To get an asset equivalent measure of non-traditional activities, we use an approach similar to that of Boyd and Gertler (1994).[15] Assuming that the net non-interest income (*NINC*) is generated from off-balance-sheet assets and that these non-traditional activities yield the same rate of return on assets (*ROA*) of other activities (loans and financial assets), we compute Q_3 as:

$$Q_3 = ROA \cdot NINC \tag{12}$$

where $ROA = \text{net interest income} \big/ \left(Q_1 + Q_2 \right)$.

The three inputs are: deposits and other funds (X_1), labour (measured as the number of employees) (X_2), and physical capital (X_3).[16] The corresponding cost figures are therefore interest expenses, personnel expenses, and other operating costs, respectively. In order to calculate the last figure, we have subtracted labour costs from all operating costs (which are net of financial expenses).

The price of deposits (W_1) is equal to the ratio between interest expenses and the sum of deposits, money market funding and other funding. The price of labour (W_2) has been computed dividing personnel expenses by the number of employees. Finally, the price of capital (W_3) has been proxied by the ratio between residual operating costs and fixed assets.

We have also checked for the presence of outliers. Observations for which the factor prices were lower than the 1st centile or larger than the 99th centile have been dropped. Finally, we excluded banks for which less then three observations were available. The final sample consists of 6265 observations on 703 banks. The panel is unbalanced, and includes about 9 observations for each bank. Table 1.1 provides some descriptive statistics of the sample.

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[15] This approach has also been used by Allen and Liu (2007) and Feng and Serletis (2009).

[16] Following an acknowledged approach in the banking literature, we consider physical capital as a variable input. Moreover, Hunter and Timme (1995) found that estimated scale economies are not affected if capital is considered as a quasi-fixed input.

It is worth nothing that Q_3 represents, on average, the 26% of total outputs,[17] showing the importance of non-traditional activities in the production process of Italian banks. Then, omitting this type of activities could lead to biased results.

TABLE 1.1 – *Descriptive statistics of the sample*

Variable	Obs.	Mean	Median	Minimum	Maximum	Std. Dev.
C (a)	6265	165.43	13.18	0.56	15585.94	726.18
Q_1 (a)	6265	1421.12	137.09	2.45	164391.00	6304.28
Q_2 (a)	6265	948.63	80.23	2.40	140662.90	4625.04
Q_3 (a)	6265	1391.24	69.44	1.76	273951.50	8418.92
$Q_1 + Q_2 + Q_3$	6265	3760.99	299.62	13.69	569518.80	18649.69
W_1 (b)	6265	0.0310	0.0246	0.0100	0.0792	0.0167
W_2 (c)	6265	55.00	54.52	35.69	79.83	6.45
W_3 (c)	6265	1.57	1.11	0.31	15.13	1.66
X_1 (a)	6265	2194.90	201.65	5.90	274522.60	10015.33
X_2 (d)	6265	640.16	71	3	48295	2394
X_3 (a)	6265	39.66	3.88	0.08	3117.17	167.99
S_1 (b)	6265	0.4062	0.3963	0.0698	0.7708	0.1096
S_2 (b)	6265	0.2849	0.2828	0.0904	0.5040	0.0634
S_3 (b)	6265	0.3089	0.3056	0.0988	0.7674	0.0754
SQ_1 (b)	6265	0.4395	0.4364	0.0431	0.9651	0.1172
SQ_2 (b)	6265	0.3047	0.3012	0.0077	0.7777	0.1263
SQ_3 (b)	6265	0.2558	0.2500	0.0034	0.6949	0.0869

(a) Millions euro (2000 values) - (b) Ratio - (c) Thousands euro (2000 values) - (d) Units
S_i = cost share of input i
SQ_i = share of output i with respect to total output ($Q_1 + Q_2 + Q_3$)

1.5 Estimation results

The system (3) has been estimated by maximum likelihood.[18] Table 1.2 shows the parameter estimates.[19] In a preliminary estimation, the S matrix was found to be not negative semidefinite, then the concavity of the cost function has been imposed by reparametrizing and re-estimating the model, as discussed in Section 1.3. However, the log-likelihoods of the two models are almost the same.[20] Most of the 28 parameters are statistically significant at the 1% level.

[17] Since all outputs are expressed in (constant) monetary values, we can add them, and compute the share of each output to total output.
[18] Note that the cost function does not contain additional parameters with respect to (3); so estimating it along with the input demand system is useless.
[19] Estimations have been performed using a program written in GAUSS.
[20] For the unconstrained model, the log-likelihood is 6731.45.

Table 1.3 shows the R^2 for each estimated equation and for the cost function. The lower value (0.86) is that of the capital equation, probably because of the imperfect measurement of this factor of production by the book value of the fixed assets. Although the cost equation has not been included in the estimated system, its goodness of fit measure reaches a satisfactory value of about 0.92.

TABLE 1.2 – *Parameter estimates*

Parameter	Coeff.	*t*-value
s_{11}	-0.04499	*-23.51* ***
s_{21}	0.04828	*24.12* ***
s_{22}	-0.05180	*-24.76* ***
β_2	1.00584	*84.92* ***
β_3	0.00725	*1.25*
b_1	-0.05269	*-7.00* ***
b_2	0.08231	*12.96* ***
b_3	0.00316	*3.88* ***
b_{11}	0.94745	*170.45* ***
b_{22}	0.27736	*130.03* ***
b_{33}	0.02609	*107.87* ***
a_{11}	-0.00185	*-2.78* ***
a_{21}	-0.00079	*-2.36* **
a_{31}	-0.00059	*-15.18* ***
a_{12}	0.00175	*3.03* ***
a_{22}	-0.02187	*-44.23* ***
a_{23}	-0.00224	*-35.71* ***
a_{13}	0.00064	*1.23*
a_{23}	0.00153	*6.95* ***
a_{33}	0.00014	*6.07* ***
a_t	0.00142	*4.35* ***
d_{11}	0.00059	*13.04* ***
d_{21}	-0.00089	*-17.83* ***
d_{22}	0.00130	*13.93* ***
d_{31}	0.00005	*2.31* **
d_{32}	-0.00011	*-2.75* ***
d_{33}	0.00002	*1.73* *
a_{tt}	-0.00007	*-5.29* ***
Log-likelihood	6730.67	
N. of observations	6265	
N. of banks	703	

Dependent variable: *C*.
*** = significant at the 1% level ; ** = significant at the 5% level;
* = significant at the 10% level.
Standard errors computed on the basis of the estimated Hessian of the log-likelihood.

Table 1.4 reports the cost elasticities with respect to outputs, scale and scope economies, and the rate of technical change, all computed at the sample means of the variables. Among the three outputs considered, loans show the higher cost elasticity. More precisely, a 1% increase in the production of loans translates into a 0.66% increase in total costs. Conversely, the percentage increase generated by a 1% increase in non-traditional activities is very low (0.03%). The sum of cost elasticities with respect to output equals to 0.94, implying an estimated value of *ESC* around 1.07, which is very similar to the result (1.09) obtained for Italy by Cavallo and Rossi (2001). This indicates that Italian banks have been characterized by slight economies of scale during the period under study. However, it is interesting to note that at the average total output, which equals to about 3.8 billions euro, economies of scale are not still exhausted.

The value of ESCP is positive (see Table 1.4), implying the presence of economies of scope. Our estimate suggests that producing the three outputs separately translates into an increase in total cost of 13.21% with respect to the cost that would result from the joint production of all outputs. The sign of this finding is consistent with that of Cavallo and Rossi (2001).[21] Scope economies, along with a lowering of risk, could explain the trend toward a diversification of activities and income sources followed by many banks in the last years, even through mergers and acquisitions.

Finally, the cost of banks reduced over time at an annul rate of 3.63%. This value is the same as that estimated by Altunbas et al. (1999) when considering the whole European banking system in the period 1989-1996. Then, banks have benefited substantially from technical progress.

Price elasticities of input demands are reported in Table 1.5. Every input demand is inelastic with respect to its own price. Labour seems to be the most sensitive factor of production to changes in price (-0.11). Conversely, deposits show an elasticity that is very close to zero. Regarding cross price elasticities, labour and capital turn out to be substitutes; according to our estimates, if the price of capital increases by 1%, the demand for labour increases by 0.12%. In the opposite case, that is if the price of labour increases by 1%, the demand for capital increases by 0.08%. Also deposits and capital

[21] Regarding economies of scope, they report a value of 71.8% (for the whole European banking system), that seems unreasonably high.

are substitutes, but the associated elasticities are much lower. Finally, deposits and labour appear to be complements, although the elasticity is nearly equal to zero.

Overall, we observe that our model generates lower price elasticities (in absolute terms) than those obtained in other studies, such as Hunter and Timme (1995) and Lang and Welzel (1998), both employing a translog specification. However, our price elasticities are comparable to those estimated by Glass and McKillop (1992) and Featherstone and Moss (1994) who used a generalized translog and a normalized quadratic cost function, respectively.

TABLE 1.3 – *Goodness of fit*

Equation	$\mathbf{R^2}$
Total Cost (C)	0.9210
Deposits (X_1)	0.9995
Labour (X_2)	0.9626
Capital (X_3)	0.8643

The R^2 values was calculated for each equation as 1- var(u)/var(Y) where var(u) is the variance of the residuals and var(Y) is the variance of the dependent variable.

TABLE 1.4 – *Cost economies and technical change*

Cost elasticities (CE)	
Loans (Q_1)	0.6677
Other earning assets (Q_2)	0.2339
Non traditional activities (Q_3)	0.0336
Economies of scale (ESC)	1.0693
Economies of scope ($ESCP$)	0.1321
Technical change (RTC)	0.0363

TABLE 1.5 – *Price elasticities*

	Deposits (X_1)	*Labour* (X_2)	*Capital* (X_3)
Deposits (X1)	-0.0002	-0.0034	0.0037
Labour (X_2)	-0.0068	-0.1139	0.1207
Capital (X_3)	0.0045	0.0751	-0.0796

1.6 Conclusion

In this paper we have analyzed the production process of the Italian banking industry in the period 1992-2007. Using a large dataset on 703 banks, we have estimated a MSGM system of factor demand equations in order to assess the degree of scale and scope economies and the rate of technical change.

The major findings can be summarized as follows. There is evidence of slight economies of scale. Conversely, cost economies from the joint production of several outputs are quite substantial. Finally, we find a reduction in costs due to technical change of about 3.63% per year.

Based on these findings, we can conclude that Italian banks obtained significant efficiency gains from the consolidation process. Specifically, this process appears to have been driven by cost economies associated to diversification, rather than a reduction in costs due to a larger size. From a policy point of view, this result suggests that the consolidation process should be beneficial to consumers, especially in view of the not remarkable anticompetitive effects of mergers and acquisitions, highlighted by research on market power in the banking industry.

CHAPTER TWO

Testing the "Quiet Life" Hypothesis in the Italian Banking Industry

2.1 Introduction

During the last two decades the banking sector of many countries has experienced a huge consolidation process. This is due to several reasons, such as technological progress, globalization, and deregulation of banking markets.[1] Regarding Europe, crucial factors stimulating the M&A operations have been also the adoption of the Second Banking Directive in 1989 and the implementation of the Economic and Monetary Union.

In Italy the number of banks reduced from 922 in 1998 to 806 in 2007, while in the same period the assets of the whole banking system increased from 1936.71 to 3871.32 billions euro.[2] This consolidation trend has raised concerns about its welfare implications, given that the banking market is vital for the whole economic system. Actually, from a theoretical point of view a more concentrated industry could lead to greater market power for banks. Thus, many empirical studies have attempted to estimate the degree of competition of the banking sector, often using the methodologies proposed by the so-called New Empirical Industrial Organization (NEIO).[3]

However, there is a related potential problem stemming from the exploitation of market power. It is the possibility, first stressed by Hicks (1935) and known in the literature as the "quiet life" hypothesis (QLH), that firms with higher market power put less effort in pursuing cost efficiency: instead of taking advantage of their favourable position by also cutting costs, in order to gain higher profits, they prefer to enjoy a "quite life". However, as pointed out by Berger and Hannan (1998), there are several

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[1] See Berger et al. (1999) for a review on causes and implications of consolidation in the financial services industry.
[2] Bank of Italy data (current values).
[3] With reference to the European countries see, among others, Molyneux et al. (1994), De Bandt and Davis (2000), Shaffer (2001), Bikker and Haaf (2002), and, for Italy, Coccorese (2005, 2008b).

other reasons for which firms with more market power would be less efficient. For example, their managers could overexpand some expenses, especially in order to preserve market power.

Surprisingly, this issue has received relatively little attention in the empirical literature, and only some recent studies have tried to test the QLH in banking. The aim of this paper is to contribute to this stream of literature focusing on the Italian banking industry for the period 1992-2007.

Using a two-step procedure, we first estimate bank-level cost efficiency scores and Lerner indices by means of a stochastic frontier model. Then we use the estimated market power measures, as well as a vector of control variables, to explain cost efficiency, also dealing with the potential endogeneity of the Lerner index. Our results support the prediction of the QLH, as banks' market power appears to negatively affect their cost efficiency, even if the overall impact is not particularly remarkable in magnitude. This means that the "quiet life" behaviour of Italian banks, although existing, does not lead to a noteworthy loss of efficiency.

Our analysis is characterized by a number of worthy features. First, it considers a single country, so that the results of the empirical analysis are more reliable because of the homogeneity of various factors (legal, historical, cultural, social) that usually play a crucial role in influencing firms' behaviour but are more difficult to be caught in a cross-country framework. Second, we estimate efficiency scores making use of two different stochastic frontier models, namely the standard Battese and Coelli (1992) methodology and the Aigner et al. (1977) approach, and perform the second step estimation by means of both a tobit model (the most widely adopted approach) and a logistic model (which, in our view, is more appropriate in this framework). The use of various techniques allows to check the robustness of our empirical evidence. Finally, we carry out some estimations also for sub-samples of banks, in order to assess possible different behaviours according to their type, location and size.

The paper is organized as follows. Section 2.2 offers a review of the literature on the estimation of market power in banking and the relationship between market power and efficiency. The methodologies used to estimate both banks' market power and cost efficiency, and to test the QLH, are described in Sections 2.3 and 2.4, respectively.

Section 2.5 illustrates data and variables, while the results are presented and discussed in Section 2.6. Finally, Section 2.7 draws some conclusions.

2.2 Market power, efficiency, and their relationship: a review of the banking literature

At the start, the assessment of competition in banking has been essentially based on the "structure-conduct-performance" (SCP) paradigm, first proposed by Mason (1939) and Bain (1951), according to which the performance of an industry depends on the behaviour of incumbent firms, which in turn is determined by the market structure, usually proxied by the level of concentration.

For the empirical implementation, this paradigm has taken a "structure-performance" (SP) form, since the standard practice has been to estimate a relationship between a measure of performance (in terms of profits or prices) and a concentration index.[4] In this framework, a statistically significant and positive coefficient of the concentration variable is interpreted as evidence of a cooperative behaviour among firms that allows them to exploit their market power at expense of customers.

While such a simplified version of the model can be theoretically justified (e.g. Cowling and Waterson, 1976), it has led to undervalue the role of firms' conduct in determining the equilibrium of the industry. The most important challenge to the SP hypothesis is the contestability theory of Baumol et al. (1982). According to these authors, an industry can reach competitive outcomes, whatever the level of concentration, if potential entrants are able to exert an adequate competitive pressure on incumbent firms.

Another criticism to the SP paradigm comes from the "efficient structure" (ES) hypothesis, suggested by authors like Demsetz (1973) and Peltzman (1977). They remark that a higher level of market concentration could be the result of differences in efficiency among firms or across markets. Firms that are more efficient get both higher market shares and profits, so that we observe a spurious positive relationship between profits and concentration. In other words, the SP and ES hypotheses take different

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[4] For an extensively review of the early banking studies on this topic, see Gilbert (1984).

variables as exogenous: concentration and efficiency, respectively (Berger and Hannan, 1989).

Based on the shortcomings of the SCP approach, the New Empirical Industrial Organization (NEIO) has developed several methodologies to derive a conduct parameter as a measure of the market power exerted by firms. One possibility is to estimate a simultaneous model of demand and supply equations, where the conduct parameter is represented by a conjectural variation coefficient that can assume different values depending on the degree of market power prevailing in the industry. Pioneered by Iwata (1974), this approach has been developed by Bresnahan (1982) and Lau (1982),[5] and applied to the banking sector by many authors.

Along the line of NEIO, Panzar and Rosse (1987) propose a methodology based on the estimation of a reduced form revenue equation, which includes the prices of the inputs among the regressors. The sum of the estimated elasticities of revenues to factor prices provides the so-called *H*-statistic, representing a conduct parameter that can range from negative values (monopoly or collusion) to one (perfect competition). The *H*-statistic only allows to discriminate among different market hypotheses, but it has been shown that, under specified assumptions, this index can be interpreted as a continuous measure of competition (Vesala, 1995, p. 56; Bikker and Haaf, 2002, p. 2203).

Another NEIO approach for assessing the degree of market power in banking is based on the calculation of the Lerner index, where the marginal cost (needed for its assessment) is obtained by means of the estimation of a cost function.[6] One advantage of this methodology is to provide a bank-level measure of market power, whose evolution over time can also be easily traced.

While several empirical studies have focused on the estimation of market power of banks, the attention towards its influence on efficiency is much more recent and leads to assorted results.

In general terms, the link between market structure and efficiency was first postulated by Hicks (1935), who argued that monopoly power allows managers to enjoy

[5] See also Appelbaum (1982).
[6] Examples in this regard are, among others, Fernández de Guevara et al. (2005), Oliver et al. (2006), and Fernández de Guevara and Maudos (2007).

a share of the monopoly rents in the form of discretionary expenses or less effort, which generates inefficiencies and justifies the evidence of a negative relationship between market power and efficiency as a consequence of managers' "quiet life" (i.e. free from hard competitive pressures): actually, in a more relaxed environment the search for cost efficiency is less severe, at the expense of somewhat lower profits. Because of this slack management, firms with greater market power are more inefficient.

This idea has been challenged on the ground that the owners of monopolistic firms could nonetheless exert some control on managerial effort. Therefore, other theories have been developed on this subject. For example, Leibenstein (1966) suggests that inefficiencies may result from the existence of imperfections in the internal organization of firms ("X-inefficiencies"), e.g. due to informational asymmetries or the incompleteness of labour contracts. These inefficiencies could be reduced through market competition, which provides incentives to managers to exercise more effort and also allows the owners to make a better assessment of firm (and managerial) performance relative to other companies. An alternative theory is the above mentioned "efficient structure" hypothesis by Demsetz (1973), for which there could be a reverse causality between competition and cost efficiency. This hypothesis maintains that the best-managed firms have the lowest costs and thus gain the largest market shares, which leads to an increase in the level of market concentration. In other words, (higher) efficiency determines (higher) concentration and (probably lower) competition.

By means of a theoretical model, Schmidt (1997) shows that an increase in competition has two effects on managerial incentives: it increases the probability of liquidation, which positively affects managerial effort, but it also reduces firm's profits, which may make the provision of high effort less attractive. Hence, the total effect is ambiguous. Empirical evidence of a "quiet life" preference of managers when they are protected from takeover threats is found by Bertrand and Mullainathan (2003), Zhao and Chen (2008), Giroud and Mueller (2009), and Qiu and Yu (2009).

Turning to the banking sector, Berger and Hannan (1998) start from the original standpoint of Hicks, according to which «the best of all monopoly profits is a quiet life» (Hicks, 1935, p. 8), and are the first to ask whether banks operating in more concentrated markets exhibit lower cost efficiency as a consequence of slack management. Again, the idea is that the market power exercised by banks in concentrated markets could allow them to avoid minimizing costs without necessarily exiting the industry. This behaviour might result in lower cost efficiency because of shirking by managers, the pursuit of objectives other than profit maximization, political or other activities to defend or gain market power, or simple incompetence that is obscured by the extra profits made available by the exercise of market power (Berger and Hannan, 1998, p. 464). In order to test the QLH, Berger and Hannan employ a sample of about 5000 U.S. banks for the years from 1980 to 1989, and find that credit institutions operating in more concentrated markets (in terms of Herfindahl-Hirschman index) are characterized by a lower cost efficiency.

To our knowledge, there are few other papers that try to explicitly test the presence of a “quiet life” behaviour in banking. These studies have generally replaced the HHI with the Lerner index as a proxy of market power. Working on a large sample of European banks, Maudos and Fernández de Guevara (2007) reject the QLH for the period 1993-2002. However, unlike Berger and Hannan, they do not take into account the potential endogeneity of the Lerner index.

Koetter et al. (2008) estimate the impact of market power on both cost and profit efficiency by means of a sample of about 4,000 U.S. banks from 1986 to 2006, finding a significant positive relation between Lerner indices and efficiency: accordingly, the evidence is that margins have increased in connection with banks’ effort to improve cost and profit efficiency, which implies a rejection of the QLH. Solis and Maudos (2008) analyze the Mexican banking system in the period 1993-2005, and are able to reject the QLH in the deposits market but not in the loans market.

Koetter and Vins (2008) consider the German savings banks between 1996 and 2006, and cannot reject the QLH, since the impact of market power is positive when they use profit efficiency scores while it is negative when considering cost efficiency. In the latter case, however, the estimated effects of the QLH are small in magnitude.

Al-Muharrami and Matthews (2009) focus on the Arab Gulf Cooperation Council (GCC) banking industry in the period 1993-2002. Their results do not support the QLH, since there is little evidence that banks in the more concentrated GCC markets exhibit lower technical efficiency. On the contrary, they find confirmation of the basic SCP version of the market power hypothesis, where market structure helps to explain performance even in the presence of technical efficiency.

Finally, Fu and Heffernan (2009) study the relationship between market structure and performance in China's banking system from 1985 to 2002, also testing the hypothesis of whether the big four banks enjoy a "quiet life". No evidence supports this conjecture, probably because the rigid regulatory rules governing their activities (e.g. branch expansion) and the strict control over interest rates prevented the state banks from earning monopoly profits.

Other papers focusing on efficiency in banking markets also recall and consider the possibility of a "quiet life" conduct of credit institutions. While testing the SCP and the ES hypotheses for the Taiwan banking market before and after the 1991 liberalization policy, Tu and Chen (2000) find that in the years prior to the 1991 this industry has appeared to exhibit a kind of regulation-induced quiet-life type of market structure (while for the subsequent period their results tend to support the efficiency hypothesis).

Weill (2004) investigates the link between competition (measured by the Panzar-Rosse *H*-statistic) and efficiency in the banking industries of 12 European countries for the period 1994-1999. The empirical results provide support to a negative relationship between these two variables, and therefore do not corroborate the QLH.

Using bank level balance sheet data for commercial credit institutions in the major European banking markets in the years 2000-2005, Casu and Girardone (2007) employ a Granger-type causality test and find a negative causation from efficiency to competition, while the reverse causality, although positive, is relatively weak.

Pruteanu-Podpiera et al. (2008) consider the banking industry of the Czech Republic and, after measuring the level and evolution of banking competition between 1994 and 2005, perform a Granger-causality-type analysis in order to assess the relationship and causality between competition and efficiency. Their results reject the QLH and indicate a negative relationship between these two variables. Particularly, as competition negatively Granger-causes efficiency, they maintain that greater competition, leading to an increase in monitoring costs through both a reduction in the length of the customer relationship and the presence of economies of scale in the banking sector, determines a reduction of banks' cost efficiency.

Delis and Tsionas (2009) provide an empirical methodology for the joint estimation of efficiency and market power for a sample of European and U.S. banks (years 1999-2006). By using the local maximum likelihood technique, they obtain bank-specific estimates of market power that are negatively correlated with efficiency, in line with the predictions of the QLH.

Using data from 821 banks in 60 developing countries over the period 1999-2005, Turk Ariss (2010) computes proxies for the degree of market power, bank efficiency and bank stability, all estimated at the bank level, with the purpose of investigating how different degrees of market power affect bank efficiency and stability in these economies. In terms of "quiet life behaviour", the results are mixed. Regarding costs, a positive relationship between the level of costs and market power emerges, which seems to support the QLH. On the other side, there is evidence of a direct association between market power and profit efficiency, and hence of its confutation. It should be noted that an opposite result is reported by Schaeck and Cihak (2008), who work on a large dataset of European and U.S. banks covering the years 1995-2005 and establish a positive effect of competition on profit efficiency.

2.3 Estimation of cost efficiency and market power

Given the panel structure of our data, we employ the stochastic frontier model of Battese and Coelli (1992), which allows to estimate time-varying cost efficiency scores. To model costs, we employ a translog function with one output and three inputs:

$$\begin{aligned}\ln C_{it} &= \alpha_0 + \alpha_1 \ln Q_{it} + \sum_{h=1}^{3} \alpha_h \ln W_{hit} + \alpha_T \ln TREND \\ &+ \frac{1}{2}\left\{ \alpha_{QQ} \left(\ln Q_{it}\right)^2 + \sum_{h=1}^{3}\sum_{k=1}^{3} \alpha_{hk} \ln W_{hit} \ln W_{kit} + \alpha_{TT} \left(\ln TREND\right)^2 \right\} \\ &+ \sum_{h=1}^{3} \alpha_{Qh} \ln Q_{it} \ln W_{hit} + \alpha_{TQ} \ln TREND \ln Q_{it} \\ &+ \sum_{h=1}^{3} \alpha_{Th} \ln TREND \ln W_{hit} + \varepsilon_{it}\end{aligned} \tag{1}$$

where $i = 1,...,N$ and $t = 1,...,T$ index banks and time, respectively, C is the total cost, Q is the output, W_h are the factor prices, and $TREND$ is a time trend included to take into account technical change. Finally, $\varepsilon_{it} = v_{it} + u_{it}$ is a two-components error term, where v_{it} is the usual error term – with $v_{it} \sim N(0,\sigma_v^2)$ – and u_{it} is the inefficiency term. The latter is modelled as a function of time, i.e. $u_{it} = u_i \exp[-\gamma(t-T_i)]$, where u_i is a truncated normal distribution with mean μ and variance σ_u^2.

One shortcoming of the above specification is that it imposes an a priori time path to the efficiency scores, which depends on the estimation of the γ parameter. Therefore, as robustness check, for the pooled sample we also estimate the stochastic frontier model as suggested by Aigner et al. (1977) and Meeusen and van Der Broeck (1977), where the u_{it} term – assumed to be distributed as a half-normal random variable – is free to vary over time without any a priori assumption.

Regarding the cost function, by symmetry of the Hessian we have $\alpha_{hk} = \alpha_{kh}$. In order to correspond to a well-behaved production technology, the cost function needs to be linearly homogeneous, non-decreasing and concave in factor prices, and non-decreasing in output. With the symmetry restrictions imposed, necessary and sufficient conditions for our translog cost specification to be linearly homogeneous in input prices are:[7]

$$\sum_{h=1}^{3}\alpha_h = 1,\ \sum_{k=1}^{3}\alpha_{hk} = 0\ \ (h = 1,2,3),\ \sum_{h=1}^{3}\alpha_{Qh} = 0,\ \sum_{h=1}^{3}\alpha_{Th} = 0\,.$$

The cost efficiency scores have been estimated as $CE_{it} = E\left[\exp\left(-u_{it}\right) \mid \varepsilon_{it}\right]$.[8] Since $u_{it} \geq 0$, CE_{it} ranges between 0 and 1, with $CE_{it} = 1$ characterizing the fully efficient firm.

Employing the parameters resulting from the estimation of the cost function, we can compute the marginal cost for each bank and time period as

$$\begin{aligned} MC_{it} &= \frac{\partial C_{it}}{\partial Q_{it}} = \frac{\partial \ln C_{it}}{\partial \ln Q_{it}}\frac{C_{it}}{Q_{it}} \\ &= \left(\alpha_Q + \alpha_{QQ}\ln Q_{it} + \sum_{h=1}^{3}\alpha_{Qh}\ln W_{hit} + \alpha_{TQ}\ln TREND\right)\frac{C_{it}}{Q_{it}} \end{aligned} \tag{2}$$

and the Lerner index as

[7] We imposed symmetry and homogeneity restrictions during the estimation process, and checked the other properties after estimation.
[8] For details on this point, see Kumbhakar and Lovell (2000), Chapter 4.

$$LERNER_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \qquad (3)$$

where P_{it} is the price charged on the output. Theoretically, the Lerner index can vary between 0 (in case of perfect competition) and 1.

2.4 Testing the "quiet life" hypothesis

We implement the test of the QLH for Italian banks by regressing the cost efficiency scores (*CE*) on the estimated Lerner index (*LERNER*) as well as a set of market-level and bank-level control variables. A negative and statistically significant coefficient of the variable *LERNER* can be interpreted as evidence of the validity of the QLH.

As market-level variables we consider:

- the growth rate of GDP (*GDPGROWTH*). It is included to take into account the influence of the business cycle on efficiency. In expanding and dynamic markets, banks can count on an increasing flow of demand that, if captured, could help to better exploit their (branch and/or network) size and hence improve efficiency. At the same time, competition among banks is expected to be stronger, so banks need to be prepared to take every opportunity that allows to enlarge the clientele, and could be forced to forgo efficiency on the grounds of short-run profitability. As a result, we can not anticipate the sign of this variable;
- the population density (*POPDENS*), given by the number of inhabitants per square kilometre. On one hand, in markets with high density of people it should be less costly to offer banking services; on the other hand, dealing with more customers could generate inefficiencies because of the difficulty of meeting all customers' requirements with good standards. Hence, the sign of this variable is not a priori determinable.

In order to have one value for each of the previous regressors, for all banks that operate in more than one geographical market the corresponding data have been weighted according to the distribution of branches.[9] As relevant markets, we consider the 20 Italian regions.

The bank-level variables are:

- the ratio between loans and total assets (*LOANASS*). Contrary to other bank assets (e.g. securities), lending requires more effort and organizational capabilities by the staff. If not properly performed, it could therefore generate inefficiencies;
- the deposits to assets ratio (*DEPASS*). Deposits are the main source of financing for banks, but they also ask for a good organization in order to be gathered and well managed. For the same reasoning as above, a higher fraction of deposits among liabilities could then produce inefficiencies on the cost side. As a result, we expect a negative coefficient for this variable too;
- the natural logarithm of the number of branches (ln*BRANCHES*). A widespread branch network involves the creation and management of a retail organization and the work of a possible large number of people. This could have a negative (or positive) impact on cost efficiency, depending on the coordination and organizational problems (or opportunities) linked to a bigger dimension. Under this point of view, branches can be also regarded as a good proxy for banks' size;[10]
- the natural logarithm of total assets per branches (ln*ASSBR*). This variable measures the average degree of capacity utilization of banks' branches. If economies of scale at the branch level exist, banks that are able to manage more assets per office should be more efficient, and this would involve a positive sign for the estimated coefficient.

In addition to these bank-level variables, we also control for the influence of bank type and bank location on efficiency. To this purpose, we introduce two groups of zero-one dummy variables: the first considers whether a given credit institution is a commercial, popular or cooperative bank (the latter representing our reference group);

[9] For an analogous choice, see Maudos (1998) and Coccorese and Pellecchia (2009).
[10] We prefer to proxy size with branches rather than total assets also because the latters are employed as a measure of the output Q in the cost function (see below).

the second records its location (North-West, North-East, Centre, South; here the first variable is assumed as reference).[11]

Given that CE_{it} lies between 0 and 1, an estimation using OLS would not be appropriate. Hence, some authors[12] employ a double-censored tobit specification, in accordance with what is suggested by Kumbhakar and Lovell (2000).[13]

As discussed in Section 2.2, the ES hypothesis postulates a causal relationship going from efficiency to market power. Thus, in our econometric model the variable *LERNER* could be endogenous. To deal with this possibility, besides a standard tobit specification, we also estimate an instrumental variables (IV) tobit model, where the Lerner index is instrumented using its first lag. Possible endogeneity can be tested by means of a Wald test (Wooldridge, 2002, pp. 472 ss.).

However, the tobit model is appropriate only when bounds on the dependent variable stem from non-observability. The fact that the dependent variable can take values in a given range is not per se a good motivation to use this type of model (Maddala, 1991). This is also the view of McDonald (2009), who shows that, if there are no observations for which $CE_{it} = 0$ or $CE_{it} = 1$ (as very often happens in empirical applications), estimating a double-censored tobit model is the same as estimating a linear regression model, since the two likelihood functions coincide.

Therefore, as an alternative specification, we also estimate the following logistic regression:

$$CE_{it} = \frac{\exp\left(x_{it}^{'}\beta\right)}{1+\exp\left(x_{it}^{'}\beta\right)} + \phi_{it} \ , \tag{4}$$

where x_{it} is the same vector of regressors used for the tobit model, β is the vector of parameters, and ϕ_{it} is an *i.i.d.* error term with mean zero and variance σ_{ϕ}^{2}.[14] Again, to

[11] Banks operating in more than one macro-region have been assigned to the area where they manage the higher fraction of branches.
[12] For example, see Koetter et al. (2008) and Turk Ariss (2010).
[13] «Since the dependent variable ... is bounded by zero and one, ... either the dependent variable must be transformed prior to estimation or a limited dependent variable estimation technique such as tobit must be employed». See Kumbhakar and Lovell (2000), p. 264.
[14] Another possibility would be to employ the fractional logit model of Papke and Wooldridge (1996).

cope with possible endogeneity problems, we estimate this model also instrumenting the Lerner index by its first lag.

2.5 Data and variables

Our sample of Italian banks is drawn from the database Bankscope,[15] and covers the period 1992-2007. In this database, balance sheet and profit and loss account figures are reported for each bank both in consolidated and unconsolidated form.[16] We have made use only of unconsolidated data, treating holding banks and their affiliates as separate decisional units. Since the organizational type was also available, we have selected only commercial, cooperative and popular banks, and dropped those observations for which relevant variables were not available.

As consistency check, and in order to include in the sample the number of branches of each bank (which is seldom reported in Bankscope), the data have been matched with those included in the yearly official lists of operating banks, available from the Bank of Italy. We dropped the observations that did not pass this test.

Following the intermediation approach to banking costs (Sealey and Lindley, 1977), the three inputs we consider in the cost function are: deposits, labour, and capital. Cost figures corresponding to these inputs are interest expenses, personnel expenses, and other operating costs, respectively. The last variable has been computed subtracting labour costs from all operating costs (which are net of financial expenses).

The price of deposits (W_1) has been computed dividing interest expenses by the sum of deposits, money market funding and other funding. The price of labour (W_2) is defined as the ratio between personnel expenses and total assets.[17] Finally, the price of capital (W_3) has been set equal to the ratio between the other operating costs and the value of the fixed assets.

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[15] This database is distributed by Bureau van Dijk Electronic Publishing (BvDEP) and is a widely used data source in empirical studies on banking.
[16] The consolidated data refer to holding banks and their affiliates.
[17] In Bankscope the number of employees is not available for many banks, so we proxy it by total assets.

As in Shaffer (1993) and Angelini and Cetorelli (2003), the output (*Q*) is proxied by the value of the total assets. The (single) output price (*P*) is computed as the ratio between total revenues (interest income plus net non-interest income) and total assets.

In order to correct for outliers, the observations for which the output and/or factor prices were lower than the 1st centile or larger than the 99th centile have been dropped. We have also discarded those banks for which less then three observations were available. After the data selection process, we have been left with 7168 observations on 714 banks. The panel is unbalanced, due to sample selection, consolidation, new entries and bankruptcies. On average, it includes 10 observations for each bank (see Table 2.1).

Some descriptive statistics regarding the variables used in the two estimation steps are provided in Table 2.2.

2.6 Estimation results

Consistent with the standard procedure characterizing the stochastic frontier analysis, Equation (1) has been estimated by maximum likelihood. Results for both the Battese-Coelli and the pooled stochastic frontier models (Model 1 and 2, respectively) are reported in Table 2.3. Almost all the estimated parameters are statistically significant at the 1% level.

Yearly averages of the efficiency scores and the Lerner indices for both models are presented in Table 2.4. As expected, cost efficiency scores derived from the Battese-Coelli model exhibit a clear (decreasing) trend, while those coming from the pooled estimation show an irregular pattern over time (see Figure 2.1).

In contrast, the trend of the Lerner index is clearly upward, indicating that the market power of the Italian banks has increased during the time interval under study (see Figure 2.2).[18] More precisely, the yearly average of the Lerner index ranges between 0.16 (in 1992) and 0.34 (in 2007) when considering Model 1, and between 0.15 and 0.27 for Model 2.

[18] This finding is consistent with the results (for Italy) of Maudos and Fernández de Guevara (2007), who employ the Lerner index as a measure of market power, and of Van Leuvensteijn et al. (2007), who use the Boone indicator.

TABLE 2.1 – *Number of observations (banks) by year*

Year	Obs.
1992	104
1993	149
1994	214
1995	251
1996	298
1997	553
1998	557
1999	611
2000	595
2001	604
2002	576
2003	556
2004	551
2005	539
2006	519
2007	491
TOTAL	**7168**
N. of banks	714
N. of obs. per bank	10

TABLE 2.2 – *Descriptive statistics of the sample*

Variable	Obs.	Mean	Median	Minimum	Maximum	Std. Dev.
C [a]	7168	162433.5	12223.95	600	15585940	732111.1
Q [a]	7168	2547782	226353.3	9964.4	330407800	11969220
W_1 [b]	7168	0.0305	0.0242	0.0098	0.0808	0.0169
W_2 [b]	7168	0.0165	0.0161	0.0069	0.0308	0.0042
W_3 [b]	7168	1.5481	1.0922	0.2989	15	1.6162
P [b]	7168	0.0704	0.0644	0.0384	0.1284	0.0198
LOANS [a]	7168	1399569	129349.7	2452.01	164391000	6441203
DEPOSITS [a]	7168	1551341	126141	3690.64	169595700	7226437
GDPGROWTH [c]	7168	1.6691	1.5024	-3.2685	9.8626	1.8363
POPDENS [d]	7168	0.2039	0.1802	0.0357	0.4276	0.1036
LOANASS [b]	7168	0.5584	0.5536	0.0426	0.9615	0.1497
DEPASS [b]	7168	0.5738	0.5696	0.0469	0.9130	0.0996
BRANCHES [e]	7168	48.10	8	1	3142	154.90
ASSBR [a]	7168	31527.7	27614.4	4982.2	323423	18124.1

[a] Thousands euro (2000 values) - [b] Ratio - [c] Percentage - [d] Thousands units - [e] Units

TABLE 2.3 – *Maximum likelihood estimates of the cost function*

Parameter	**Regressor**	**MODEL 1 (Battese-Coelli)**		**MODEL 2 (pooled)**	
		Coeff.	***t*-value**	**Coeff.**	***t*-value**
α_0	Constant	0.5145	*4.93* ***	0.5055	*6.64* ***
α_Q	$\ln Q$	1.0018	*76.23* ***	1.0259	*133.71* ***
α_1	$\ln W_1$	0.3028	*11.01* ***	0.2924	*10.26* ***
α_2	$\ln W_2$	0.5957	*19.09* ***	0.6713	*22.00* ***
α_3 (= $1-\alpha_1-\alpha_2$)	$\ln W_3$	0.1015	*6.26* ***	0.0362	*2.43* **
α_T	$\ln TREND$	0.1090	*3.99* ***	0.0901	*3.15* ***
α_{QQ}	$(\ln Q)^2/2$	-0.0002	*-0.19*	-0.0023	*-4.25* ***
α_{11}	$(\ln W_1)^2/2$	0.1968	*21.50* ***	0.1992	*20.46* ***
α_{12}	$\ln W_1 * \ln W_2$	-0.1900	*-21.34* ***	-0.2015	*-21.61* ***
α_{13} (= $1-\alpha_{11}-\alpha_{12}$)	$\ln W_1 * \ln W_3$	-0.0067	*-1.86* *	0.0023	*0.61*
α_{22}	$(\ln W_2)^2/2$	0.1712	*17.17* ***	0.1998	*19.53* ***
α_{23} (= $1-\alpha_{12}-\alpha_{22}$)	$\ln W_2 * \ln W_3$	0.0188	*4.77* ***	0.0017	*0.43*
α_{33} (= $\alpha_{11}+2\alpha_{12}+\alpha_{22}$)	$(\ln W_3)^2/2$	-0.0121	*-4.08* ***	-0.0039	*-1.49*
α_{TT}	$(\ln TREND)^2/2$	-0.0524	*-7.02* ***	-0.0019	*-0.29*
α_{Q1}	$\ln Q * \ln W_1$	0.0038	*2.40* **	0.0038	*2.39* **
α_{Q2}	$\ln Q * \ln W_2$	-0.0053	*-3.06* ***	-0.0061	*-3.91* ***
α_{Q3} (= $-\alpha_{Q1}-\alpha_{Q2}$)	$\ln Q * \ln W_3$	0.0015	*1.64*	0.0024	*3.10* ***
α_{TQ}	$\ln TREND * \ln Q$	-0.0057	*-3.58* ***	-0.0049	*-3.05* ***
α_{T1}	$\ln TREND * \ln W_1$	0.0049	*0.68*	0.0032	*0.39*
α_{T2}	$\ln TREND * \ln W_2$	-0.0090	*-1.32*	-0.0034	*-0.45*
α_{T3} (= $-\alpha_{T1}-\alpha_{T2}$)	$\ln TREND * \ln W_3$	0.0041	*1.09*	0.0003	*0.06*
Log-likelihood		8727.62		7704.11	
R^2		0.9844		0.9914	
N. obs.		7168		7168	
N. banks		714		714	

Dependent variable: ln*C*.
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.

TABLE 2.4 – *Yearly averages 1992-2007 of the cost efficiency scores (CE) and the Lerner indices (LERNER)*

Year	Battese-Coelli model		Pooled model	
	CE	***LERNER***	***CE***	***LERNER***
1992	0.9135	0.1600	0.9395	0.1500
1993	0.9128	0.2190	0.9025	0.2151
1994	0.9085	0.1561	0.9165	0.1481
1995	0.9030	0.2102	0.9198	0.1935
1996	0.8971	0.2089	0.9290	0.1839
1997	0.8923	0.2059	0.9271	0.1776
1998	0.8866	0.2512	0.9226	0.2216
1999	0.8810	0.2318	0.9076	0.2030
2000	0.8749	0.2758	0.9135	0.2395
2001	0.8669	0.2655	0.9171	0.2202
2002	0.8616	0.2507	0.9230	0.2005
2003	0.8551	0.2858	0.9085	0.2368
2004	0.8466	0.3051	0.9106	0.2534
2005	0.8383	0.3179	0.9002	0.2586
2006	0.8316	0.3449	0.9125	0.2793
2007	0.8225	0.3414	0.9165	0.2656

FIGURE 2.1 – *Yearly averages of the efficiency scores (1992 -2007)*

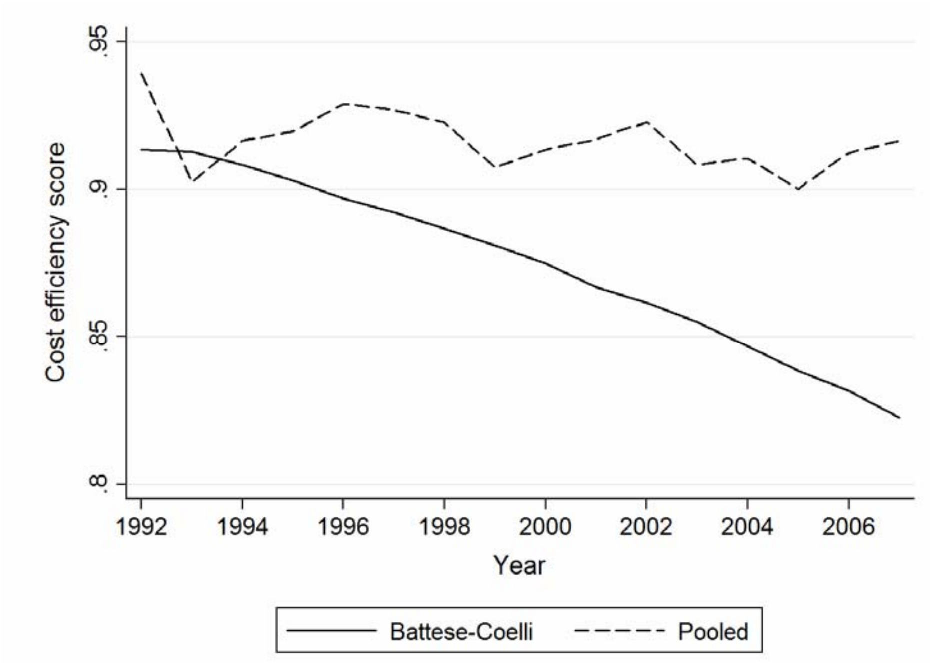
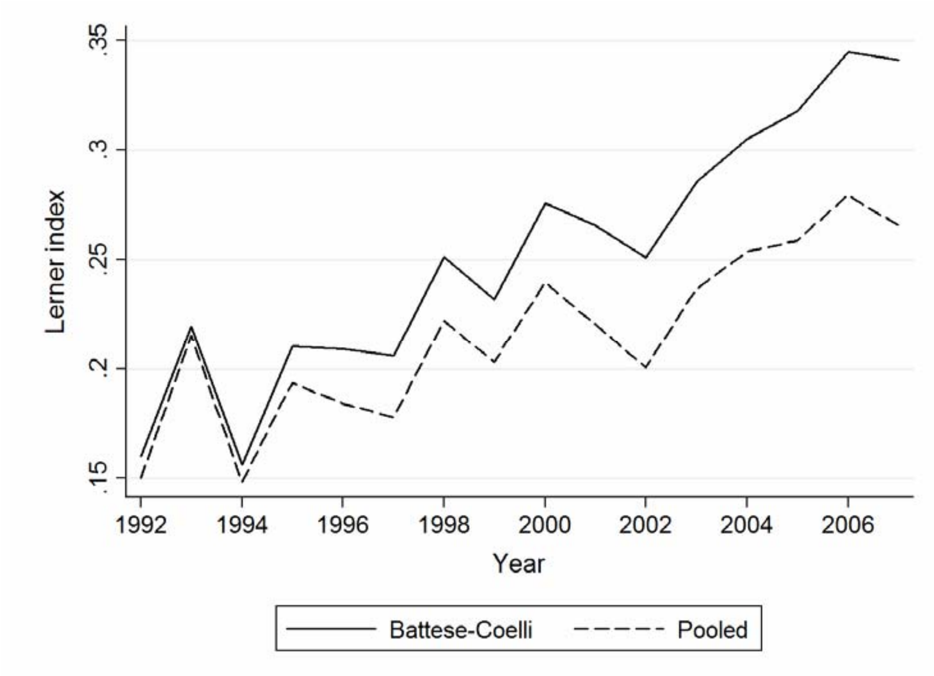


FIGURE 2.2 – *Yearly averages of the Lerner indices (1992 -2007)*



From Figure 2.3 we can also note that the sample correlation between efficiency scores and Lerner indices is negative for both models, foreseeing an inverse relationship between these two variables.

To deepen this issue, which after all represents the core of our paper, we use the cost efficiency scores and the Lerner indices, as calculated in the first step from the Battese-Coelli and the pooled models, so as to estimate the tobit specification by maximum likelihood (Tables 2.5 and 2.7) and the logistic specification by non linear least squares (Tables 2.6 and 2.8).[19]

First of all, in both tobit regressions with instrumental variables the Wald test rejects the null hypothesis of exogeneity of the Lerner index, confirming that our measure of market power is endogenous. Moreover, the significance of the regressors is only slightly influenced by either the first step estimation (Battese-Coelli model vs. pooled model) and the second step model specification (tobit vs. logistic).

For the above reasons, in what follows we mainly focus on the findings of the logistic specification with instrumental variables that employs the results derived from the Battese-Coelli model (namely, Table 2.6, second and third columns).

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[19] We estimated the logistic model by means of a program written in GAUSS.

FIGURE 2.3 – *Cost efficiency scores and Lerner indices – Scatter diagrams*

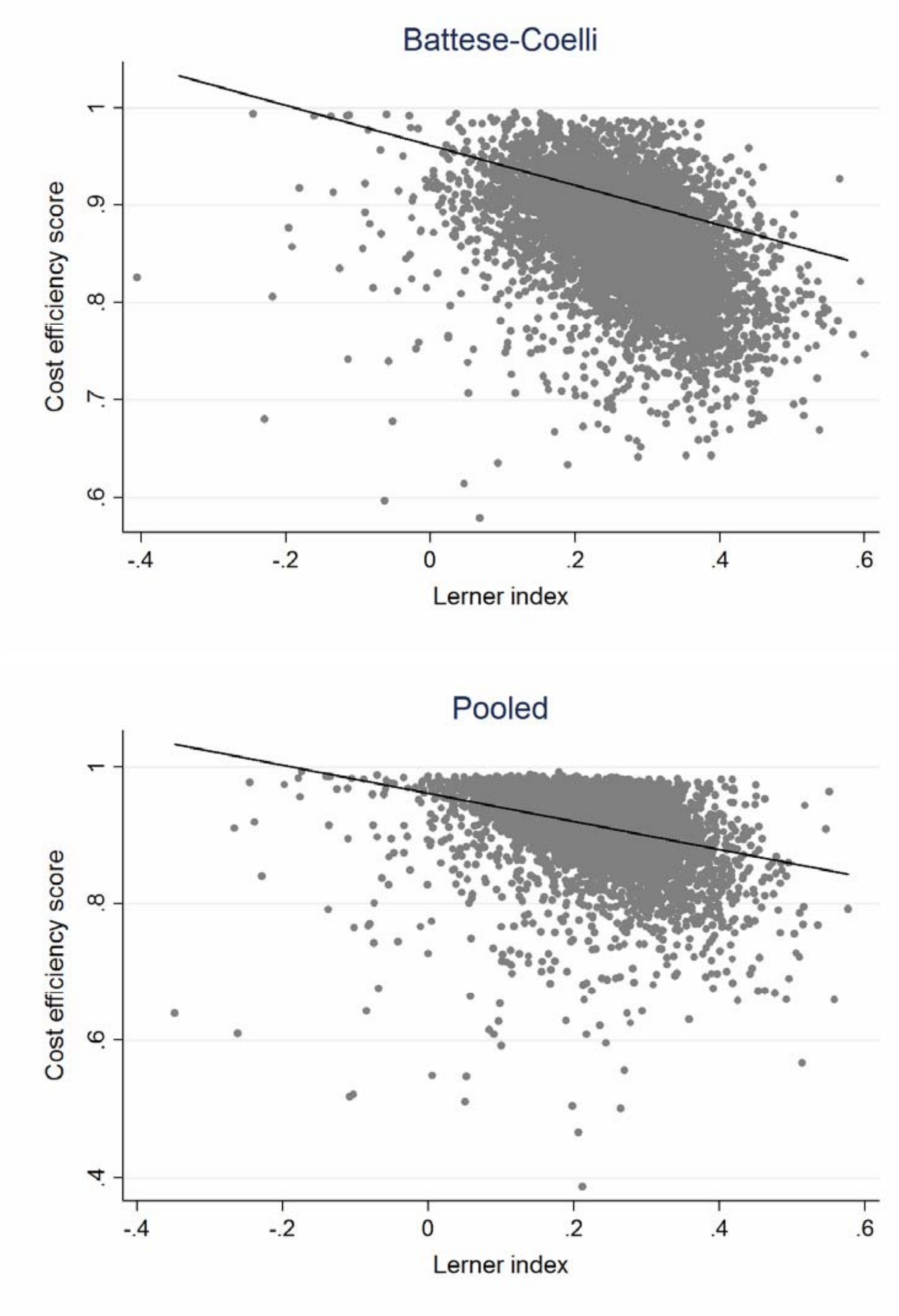

TABLE 2.5 – *Estimation results for Model 1 (Battese-Coelli): tobit regression*

VARIABLE	TOBIT	IV TOBIT	ELASTICITIES [a]
LERNER	-0.1821 *** (*0.0100*)	-0.2858 *** (*0.0129*)	-0.0901 *** (*0.0041*)
GDPGROWTH	0.0003 (*0.0004*)	0.0003 (*0.0005*)	0.0007 (*0.0010*)
POPDENS	-0.0464 *** (*0.0066*)	-0.0414 *** (*0.0072*)	-0.0098 *** (*0.0017*)
LOANASS	-0.0937 *** (*0.0060*)	-0.0843 *** (*0.0064*)	-0.0558 *** (*0.0042*)
DEPASS	-0.0250 *** (*0.0073*)	-0.0187 ** (*0.0083*)	-0.0124 ** (*0.0055*)
ln*BRANCHES*	0.0067 *** (*0.0006*)	0.0059 *** (*0.0007*)	0.0168 *** (*0.0020*)
ln*ASSBR*	0.0022 (*0.0014*)	0.0028 * (*0.0016*)	0.0334 * (*0.0189*)
COMMERCIAL	-0.0186 *** (*0.0018*)	-0.0179 *** (*0.0020*)	-0.0054 *** (*0.0006*)
POPULAR	-0.0217 *** (*0.0024*)	-0.0207 *** (*0.0028*)	-0.0019 *** (*0.0003*)
NORTHEAST	0.0186 *** (*0.0017*)	0.0187 *** (*0.0018*)	0.0084 *** (*0.0008*)
CENTRE	-0.0070 *** (*0.0018*)	-0.0068 *** (*0.0019*)	-0.0016 *** (*0.0005*)
SOUTH	-0.0138 *** (*0.0021*)	-0.0144 *** (*0.0023*)	-0.0036 *** (*0.0006*)
Wald test	-	89.95 (*0.0000*)	-
Log-likelihood	12340.65	20697.23	-
N. obs.	7168	6248	6248
N. banks	714	713	713

Dependent variable: *CE*
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level. Standard errors (in parenthesis) are robust to heteroschedasticity. This Wald test is distributed as a chi-square distribution with 1 degree of freedom (*P*-value in parenthesis). A constant and time dummies are included in all estimations but are not reported. In the IV tobit model, *LERNER* has been instrumented by its first lag.
[a] Elasticities refer to the IV tobit model.

TABLE 2.6 – *Estimation results for Model 1 (Battese-Coelli): logistic regression*

VARIABLE	LOGISTIC	IV LOGISTIC	ELASTICITIES [(a)]
LERNER	-1.6408 *** (*0.0798*)	-2.4307 *** (*0.1156*)	-0.0871 *** (*0.0040*)
GDPGROWTH	0.0031 (*0.0041*)	0.0026 (*0.0045*)	0.0006 (*0.0010*)
POPDENS	-0.3696 *** (*0.0552*)	-0.3342 *** (*0.0602*)	-0.0090 *** (*0.0016*)
LOANASS	-0.8103 *** (*0.0532*)	-0.7615 *** (*0.0549*)	-0.0573 *** (*0.0041*)
DEPASS	-0.1895 *** (*0.0641*)	-0.1277 * (*0.0702*)	-0.0096 * (*0.0053*)
ln*BRANCHES*	0.0601 *** (*0.0052*)	0.0475 *** (*0.0061*)	0.0154 *** (*0.0020*)
ln*ASSBR*	0.0152 (*0.0128*)	0.0240 * (*0.0137*)	0.0323 * (*0.0185*)
COMMERCIAL	-0.1357 *** (*0.0153*)	-0.1325 *** (*0.0175*)	-0.0045 *** (*0.0006*)
POPULAR	-0.1692 *** (*0.0202*)	-0.1673 *** (*0.0233*)	-0.0018 *** (*0.0003*)
NORTHEAST	0.1715 *** (*0.0152*)	0.1694 *** (*0.0158*)	0.0086 *** (*0.0008*)
CENTRE	-0.0501 *** (*0.0156*)	-0.0525 *** (*0.0164*)	-0.0014 *** (*0.0005*)
SOUTH	-0.1184 *** (*0.0174*)	-0.1210 *** (*0.0192*)	-0.0035 *** (*0.0006*)
Sum of squared residuals	13.2621	11.7117	-
N. obs.	7168	6248	6248
N. banks	714	713	713

Dependent variable: *CE*
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.
Standard errors (in parenthesis) are robust to heteroschedasticity. A constant and time dummies are included in all estimations but are not reported. In the IV logistic model, *LERNER* has been instrumented by its first lag.
[(a)] Elasticities refer to the IV logistic model. Their standard errors have been computed by the delta method.

TABLE 2.7 – *Estimation results for Model 2 (pooled): tobit regression*

VARIABLE	TOBIT	IV TOBIT	ELASTICITIES [a]
LERNER	-0.1984 *** (*0.0132*)	-0.2395 *** (*0.0135*)	-0.0597 *** (*0.0034*)
GDPGROWTH	-0.0006 (*0.0005*)	-0.0003 (*0.0005*)	-0.0006 (*0.0010*)
POPDENS	-0.0413 *** (*0.0076*)	-0.0340 *** (*0.0080*)	-0.0076 *** (*0.0018*)
LOANASS	-0.0747 *** (*0.0067*)	-0.0735 *** (*0.0071*)	-0.0459 *** (*0.0044*)
DEPASS	-0.0346 *** (*0.0085*)	-0.0337 *** (*0.0093*)	-0.0210 *** (*0.0058*)
ln*BRANCHES*	0.0079 *** (*0.0007*)	0.0071 *** (*0.0008*)	0.0193 *** (*0.0020*)
ln*ASSBR*	0.0086 *** (*0.0016*)	0.0085 *** (*0.0018*)	0.0950 *** (*0.0196*)
COMMERCIAL	-0.0193 *** (*0.0023*)	-0.0166 *** (*0.0022*)	-0.0047 *** (*0.0006*)
POPULAR	-0.0194 *** (*0.0030*)	-0.0169 *** (*0.0032*)	-0.0015 *** (*0.0003*)
NORTHEAST	0.0128 *** (*0.0020*)	0.0130 *** (*0.0021*)	0.0055 *** (*0.0009*)
CENTRE	-0.0074 *** (*0.0021*)	-0.0072 *** (*0.0022*)	-0.0016 *** (*0.0005*)
SOUTH	-0.0183 *** (*0.0023*)	-0.0187 *** (*0.0026*)	-0.0044 *** (*0.0006*)
Wald test	-	7.77 (*0.0053*)	-
Log-likelihood	11665.18	19754.19	-
N. obs.	7168	6248	6248
N. banks	714	713	713

Dependent variable: *CE*
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.
Standard errors (in parenthesis) are robust to heteroschedasticity. This Wald test is distributed as a chi-square distribution with 1 degree of freedom (*P*-value in parenthesis). A constant and time dummies are included in all estimations but are not reported. In the IV tobit model, *LERNER* has been instrumented by its first lag.
[a] Elasticities refer to the IV tobit model.

TABLE 2.8 – *Estimation results for Model 2 (pooled): logistic regression*

VARIABLE	LOGISTIC	IV LOGISTIC	ELASTICITIES [(a)]
LERNER	-2.9253 *** (*0.1365*)	-3.0212 *** (*0.1713*)	-0.0559 *** (*0.0031*)
GDPGROWTH	-0.0061 (*0.0061*)	-0.0054 (*0.0066*)	-0.0007 (*0.0009*)
POPDENS	-0.5121 *** (*0.0896*)	-0.4338 *** (*0.0968*)	-0.0072 *** (*0.0016*)
LOANASS	-0.9931 *** (*0.0918*)	-0.9807 *** (*0.0892*)	-0.0455 *** (*0.0041*)
DEPASS	-0.4595 *** (*0.1048*)	-0.3934 *** (*0.1172*)	-0.0183 *** (*0.0054*)
ln*BRANCHES*	0.1039 *** (*0.0092*)	0.0869 *** (*0.0099*)	0.0174 *** (*0.0020*)
ln*ASSBR*	0.1258 *** (*0.0205*)	0.1104 *** (*0.0225*)	0.0917 *** (*0.0187*)
COMMERCIAL	-0.2009 *** (*0.0276*)	-0.1873 *** (*0.0273*)	-0.0039 *** (*0.0006*)
POPULAR	-0.2016 *** (*0.0351*)	-0.1966 *** (*0.0384*)	-0.0013 *** (*0.0003*)
NORTHEAST	0.1849 *** (*0.0261*)	0.1800 *** (*0.0271*)	0.0057 *** (*0.0009*)
CENTRE	-0.0768 *** (*0.0265*)	-0.0889 *** (*0.0282*)	-0.0015 *** (*0.0005*)
SOUTH	-0.2021 *** (*0.0287*)	-0.2202 *** (*0.0312*)	-0.0039 *** (*0.0006*)
Sum of squared residuals	15.6550	13.3568	-
N. obs.	7168	6248	6248
N. banks	714	713	713

Dependent variable: *CE*
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.
Standard errors (in parenthesis) are robust to heteroschedasticity. A constant and time dummies are included in all estimations but are not reported. In the IV logistic model, *LERNER* has been instrumented by its first lag.
[(a)] Elasticities refer to the IV logistic model. Their standard errors have been computed by the delta method.

The coefficient of *LERNER* is negative and statistically significant at the 1% level in all specifications. This finding strongly supports the “quiet life” hypothesis: as for Italian banks higher Lerner indices are associated with cost inefficiencies, market power seems to reduce the incentives to minimize costs. This can be due to the fact that managers put less effort in their working activities, or even pursue objectives other than cost minimization.

For the logistic regression based on the Battese-Coelli model, the estimated value of the *LERNER* coefficient amounts to -2.43 (-0.29 when employing the tobit specification). Since this figure is not easily interpretable as a measure of the impact of market power on efficiency, it is preferable to take into consideration the elasticity of the cost efficiency scores (*CE*) with respect to the Lerner index, and in general to the covariates, at their sample means (last columns of Tables from 2.5 to 2.8).

The elasticity associated to *LERNER* shows that a 1% increase in the Lerner index determines a decrease in the efficiency score, on average, of 0.087% (0.09% for the tobit model). This value is similar to those obtained by Koetter and Vins (2008) for German banks, which range between 0.072% and 0.092%, depending on their model specification. Maudos and Fernández de Guevara (2007) and Solis and Maudos (2008) obtain smaller (absolute) values for the loan market (0.0029% and 0.013%, respectively), while Turk Ariss (2010) finds that for developing countries a 1% increase in the degree of market power reduces bank cost efficiency by 2.26%.

Still considering Table 2.6, the above value of elasticity implies that, if the Lerner index increases by 22% from 0.2660 (the overall mean of the estimated Lerner index for our sample) to 0.3245 (the third quartile), all else equal, cost efficiency scores should fall of about 1.91%, i.e. it should decrease from about 0.8670 (again the overall mean) to 0.8504, a value corresponding to the 35th centile. This implies that the effects of a "quiet life" behaviour from banks (econometrically supported by our estimations) are, however, not remarkably large in magnitude. In other words, even if Italian banks gained a considerable degree of market power, this would not generate a notable loss of efficiency.

Regarding the control variables, the coefficient of *GDPGROWTH* is never significant, implying that the rate of local GDP growth does not affect cost efficiency of banks. On the contrary, population density (*POPDENS*) appears to have a significant negative impact on cost efficiency: so, given that more crowded markets are associated to lower levels of efficiency, the positive effect linked to the possibility of reaching larger groups of customers in an easier way is more than offset by the greater complexity of such packed markets.

Turning to the bank-level variables, the coefficient of the loans to assets ratio (*LOANASS)* is negative and highly significant. Thus, there is evidence that banks with a higher proportion of loans experience a lower cost efficiency, probably as a consequence of the tougher organizational problems that lending entails. The impact of the deposits to assets ratio (*DEPASS*) is negative as well, also if sometimes only at the

10% level, confirming the idea that, as their size increases, they impose efficiency losses to banks. Quite to contrary, the ownership and management of a wider retail activity, proxied by the number of branches, positively affects banks efficiency, as the sign of ln*BRANCHES* shows: this is an evidence that a larger network size allows banks to reach higher levels of efficiency, at least on the cost side. This is probably due to the fact that Italian banks are generally small-size enterprises, so a bigger dimension allows an improvement in the quality of organization and management. Finally, the variable ln*ASSBR* shows a positive sign, which is however significant only at the 10% level when using the Battese-Coelli efficiency score: overall, this result seems to support the idea that banks are more efficient also when they are able to exploit scale economies at the branch level.

Considering the institutional dummy variables, both *COMMERCIAL* and *POPULAR* exhibit negative and significant coefficients: it follows that, *ceteris paribus*, they are less efficient than cooperative banks. With regard to the geographical localization, from the estimated coefficients (all significant at the 1% level) it emerges that banks operating in the North-East are the most efficient, followed by those located in the North-West, Centre and South, respectively. This result confirms that being positioned in more developed regions (both in infrastructural and economic terms) helps banks to improve cost efficiency, and once more stresses that in Italy there is a sharp contrast between Northern and Southern regions in terms of social and economic development.

To investigate whether the impact of market power on cost efficiency changes according to type, location or size of banks, we have also estimated the instrumental variables version of the logistic model on several sub-samples of our data.

Regarding the type, we have considered three different groups of banks (commercial, cooperative, popular). About location, we have divided banks along with the macro-region where they operate (North-West, North-East, Centre, South). With reference to size, we have classified banks in three groups: small (when total assets are less than 100,000 euro, in constant values), medium (total assets between 100,000 and 500,000 euro), large (total assets exceeding 500,000 euro).

Tables 2.9, 2.10 and 2.11 report the elasticities of *LERNER* with respect to *CE* (again computed at the sample means) and the corresponding standard errors for each sub-sample.

TABLE 2.9 – *Elasticity of LERNER by bank type*

TYPE	BATTESE-COELLI	POOLED	N. obs.
COMMERCIAL	-0.0548 *** (*0.0068*)	-0.0407 *** (*0.0053*)	1615
COOPERATIVE	-0.1219 *** (*0.0054*)	-0.0703 *** (*0.0036*)	4132
POPULAR	-0.0344 *** (*0.0119*)	-0.0219 (*0.0142*)	501

Elasticities refer to the IV logistic model.
Standard errors (in parenthesis) are robust to heteroschedasticity.

TABLE 2.10 – *Elasticity of LERNER by bank location*

LOCATION	BATTESE-COELLI	POOLED	N. obs.
NORTHWEST	-0.0720 *** (*0.0068*)	-0.0610 *** (*0.0069*)	1179
NORTHEAST	-0.0816 *** (*0.0068*)	-0.0512 *** (*0.0049*)	2417
CENTRE	-0.0883 *** (*0.0120*)	-0.0602 *** (*0.0083*)	1298
SOUTH	-0.1078 *** (*0.0081*)	-0.0613 *** (*0.0068*)	1354

Elasticities refer to the IV logistic model.
Standard errors (in parenthesis) are robust to heteroschedasticity.

TABLE 2.11 – *Elasticity of LERNER by bank size*

SIZE	BATTESE-COELLI	POOLED	N. obs.
SMALL	-0.1246 *** (*0.0084*)	-0.0671 *** (*0.0059*)	1607
MEDIUM	-0.0958 *** (*0.0059*)	-0.0565 *** (*0.0046*)	2563
LARGE	-0.0562 *** (*0.0059*)	-0.0505 *** (*0.0049*)	2078

Elasticities refer to the IV logistic model.
Standard errors (in parenthesis) are robust to heteroschedasticity.

All elasticities based on the Battese-Coelli model are negative and statistically significant at the 1% level: this means that the QLH holds whatever the type or location or size of banks. We note that for cooperative banks the elasticity (-0.122) is more than twice as that of commercial and popular banks. Hence, this group of banks, even though more efficient on average (see before), performs worse in presence of market power. The reason could be that they are generally small-sized banks with a strong propensity to long-term lending relationships with small businesses within the local markets: in case of an increase of their market power they would be therefore characterized by a greater loss of efficiency, because they can nonetheless count on a stable clientele. Actually, in Italy the historical role of cooperative banks (and also rural banks) has always been to provide credit to information-intensive borrowers (Usai and Vannini, 2005, p. 703). As a consequence, they are able to benefit of consolidated and close relationships with customers, due to private information and repeated interactions over time. This result is coherent with the fact that the elasticity for cooperative banks is broadly comparable in magnitude with that characterizing small banks (-0.125). Quite to contrary, large banks appear to be those who benefit less from a "quiet-life" behaviour, since their elasticity amounts to -0.056; not surprisingly, this value is very close to the elasticity of commercial banks (-0.055), because big credit institutions are mostly classified as such.

In terms of location, we discover an increase of elasticity moving from Northern to Southern regions. This means that market power in banking is able to generate cost inefficiencies in the South of Italy to a larger extent, while Northern banks are more efficient both as a whole (see above) and notwithstanding the possible exploiting of market power.

The previous findings are confirmed by the results based on the pooled model. All the estimated elasticities are negative and highly significant, except for popular banks. The elasticity of cooperative banks is again larger than that of both commercial and popular banks, although the gap is less evident. The difference between elasticities is also smaller when considering location and size. However, the largest elasticities again concern Southern banks and small banks, respectively.

2.7 Conclusions

The aim of this paper was to empirically verify the so-called "quiet life" hypothesis, according to which firms with higher market power are less efficient due to slack in management behaviour. We have considered the Italian banking system in the period 1992-2007, during which a huge process of consolidation has taken place: among the others, it could have strengthened banks' market power, inducing, in turn, a fall in the level of cost efficiency in a sector of great importance for the whole economic system.

To this purpose, we have followed a two-step procedure. First, we have estimated bank-level cost efficiency scores and Lerner indices through a translog stochastic frontier model, finding that, while cost efficiency seems to have remained stable (or even decreased), market power has been characterized by an increasing tendency over time.

Second, we have used the Lerner indices, along with a set of both market-level and bank-level variables, to explain the efficiency scores, dealing at the same time with possible endogeneity of this market power measure by means of instrumental variables. Moreover, together with a tobit regression, we have estimated also a logistic model, which is, in our opinion, more suitable when dealing with dependent variables that range between 0 and 1 but are not censored.

Our findings are however robust with respect to model specification, and suggest a negative and highly significant relationship between cost efficiency and market power, therefore confirming the "quite life hypothesis". On average, cost efficiency scores fall by about 0.09% as the Lerner index rises by 1%. We also find that small banks, cooperative banks and Southern banks exhibit a more pronounced "quite life" conduct.

Since the impact of market power on efficiency does exist, even if small in magnitude, our results suggest that Antitrust authorities should be however watchful about possible anticompetitive effects of the recent process of consolidation in the Italian banking industry, not only because of the reduced degree of competition that a greater concentration could induce, but also for the reason that an increase in market power could imply lower levels of cost efficiency for banks belonging to a particular category or operating in specific regions.

CHAPTER THREE

Local Economic Growth and the Role of Banks

3.1 Introduction

The role of the financial system in promoting economic growth has been the subject of many studies since a long time. While from a theoretical point of view there is no consensus on the sign of the relationship, a large body of empirical research supports the idea that countries with more developed financial systems grow more rapidly.

However, cross-country studies suffer from several shortcomings. First, it is hard to control for heterogeneity in legal, political and institutional factors, even when panel data techniques are employed. Second, the mechanism through which a higher financial development should foster economic growth has not been clearly identified, especially when the role of the banking system is not explicitly accounted for. Actually, many theoretical models show that the structure of the banking markets or the degree of monopoly power exerted by banks can affect economic growth. Moreover, the ability of banks in allocating resources to good investment projects may be a crucial factor for economic development. Third, the spatial aspects of the phenomenon are generally not considered. While the literature on convergence abounds in studies that take into account the possibility of diffusion and spillover effects, the analyses on the finance-growth nexus almost completely ignore them.

The novelty of this paper is to assess the impact of financial development on growth tackling all the three above mentioned shortcomings. To this purpose, we employ a dataset concerning the Italian provinces[1] that covers the period 1999-2006. This allows us to focus on small economic areas that share the same institutional and macroeconomic environment, thus dealing more easily with heterogeneity.

[1] In Italy, the province (*provincia*) is an administrative district that comprises a larger town or city and several little neighbouring towns. Since 1995, in Italy the number of provinces has been 103. In 2001, four new provinces have been created in Sardinia (one of the 20 regions in which provinces are further grouped), but they have been considered in the statistics of ISTAT (the Italian National Institute of Statistics) only starting from 2006. Italian regions and provinces correspond to the Eurostat NUTS-2 and NUTS-3 regions, respectively. See Eurostat (2007).

Moreover, we control for market power and other variables characterizing the local banking markets, and model the potential transmission mechanisms among areas by means of a dynamic spatial panel model. From a policy point of view, it is worth studying economic growth at the local level because many countries show sharp differences among regions in terms of economic and social development, so that understanding the determinants of local growth can contribute to reduce such gaps.

The main result of our analysis is that economic growth is positively influenced by banks' market power. This evidence is consistent with some of the literature on relationship lending, which holds that credit institutions need to exert a certain degree of market power in order to keep long-term relations with informationally opaque customers, as is the case of small firms, which have been always considered the backbone of the Italian economy. We also find a positive impact of financial deepening on growth, which however disappears when spatial dependence is accounted in the model. The latter finding highlights the importance of controlling for this aspect when dealing with regional topics.

The paper is organized as follows. Section 3.2 reviews the literature on finance and growth, with particular emphasis on the contributions exploring the role of the banking systems. Section 3.3 introduces the model and the econometric methodology, while Section 3.4 illustrates how we construct the variables measuring banks' market power and efficiency. Data and estimation results are presented and discussed in Sections 3.5 and 3.6, respectively. Finally, Section 3.7 summarizes our main findings and draws some conclusions.

3.2 Banking market structure, financial development and growth: review of the literature

Economists discuss about the role of financial development in promoting growth since a long time.[2] From a theoretical point of view, several authors have shown that the financial system can promote economic growth through several channels, such as raising the proportion of resources allocated to capital and avoiding its premature

[2] For a review, see Levine (1997, 2004).

liquidation (Bencivenga and Smith, 1991), gathering and using information to direct funds towards the most profitable investments (Greenwood and Jovanovic, 1990), reducing, through diversification, the risk associated to specialization and productivity growth (Saint-Paul, 1992). Moreover, a large body of empirical literature has tried to test the role of financial development, showing that there exists a positive and statistically significant link between finance and economic growth.[3]

However, most of this literature assumes that the banking system is perfectly competitive, while monopoly power is implicitly considered as harmful to growth because it entails higher interest rates and a lower supply of credit. This conventional wisdom has been recently challenged. In this regard, two groups of models can be identified: partial equilibrium models and general equilibrium models (Guzman, 2000a; Coccorese, 2008a).

Partial equilibrium models focus on specific aspects of the lending relationship and are not concerned with the overall economic impact of the particular banking industry structure. Hence, they recognize the primary role played by banks when relationship lending matters, i.e. when closer ties between lenders (banks) and borrowers (firms or households) can help to overcome the informational asymmetries that characterize debt contracts.[4] In this framework, firms are able to get credit more easily, with beneficial effects on economic growth.

However, the effect of market power on this kind of relationships is ambiguous. As discussed by Petersen and Rajan (1995), banks with market power are more willing to lend, since they can extract rents from firms in the future and therefore overcome the initial uncertainty about the credit worthiness of their clientele; conversely, in more competitive banking markets this uncertainty is resolved by charging higher interest rates since the beginning of the relationship, with the consequence that young, distressed or, more generally, informationally opaque firms have to suffer higher funding costs or even the impossibility of accessing bank credit.

On the other hand, a higher level of banking competition, by reducing profit margins of credit institutions, could induce them to invest more heavily in relationship banking

[3] Among others, see King and Levine (1993), Levin and Zervos (1998), Rajan and Zingales (1998), Beck et al. (2000), Beck and Levine (2004), and Loayza and Rancière (2006).
[4] For a review of the literature on relationship banking, see Boot (2000).

in order to lock in their clients and alleviate the competitive pressure of other banks (Boot and Thakor, 2000; Yafeh and Yosha, 2001).

Caminal and Matutes (2002) highlight another effect of banks' market power on economic growth, still due to the informational asymmetries. In their model, in order to overcome moral hazard problems, banks can choose between restricting loan size and increasing monitoring effort. As banks' market power increases, the credit granted to unmonitored firms reduces, but the monitoring effort increases, thus reducing firms' credit constraints. Overall, the effect of market power on investments is therefore ambiguous.

The empirical evidence for this type of models is also mixed. Consistently with their theory, Petersen and Rajan (1995) find that U.S. young firms get more credit than old ones when banking markets are more concentrated. Moreover, in such markets interest rates increase with the age of firms. Likewise, Ogura and Yamori (2009), using data on Japanese prefectures, discover a negative correlation between lending competition and relationship banking, especially in the case of small firms. Quite the opposite, the evidence of other studies is that competition promotes relationship banking. For example, Neuberger et al. (2008) consider Swiss small and medium-sized enterprises in 1996 and 2002 and find that the number of banking relationships is essentially driven by the firm and industry structure, rather than the concentration of banking markets. Using data on loan contracts of five German banks, Elsas (2005) finds an inverted U-shaped link between concentration (measured by the Herfindahl-Hirschman index of local debt markets) and the probability for a bank to be engaged in a relationship banking. Hence, for low levels of the Herfindhal-Hirschman index (HHI), this probability reduces with concentration, while the opposite happens for high levels of the HHI.

General equilibrium models consider both loans and deposits, and emphasize the influence of the banking market structure on the economy at expense of details on the relationship between banks and borrowers. So, while the link between banking market structure and growth is explicitly modelled, they overshadow the informational asymmetries characterizing the borrower-lender relationship.

Among them, Cetorelli (1997) studies a dynamic model of capital accumulation and compares the economic performance of both a perfectly competitive credit market and a monopolistic one. In the competitive environment, banks choose not to screen because they are not able to establish long-lasting relationships with firms that could allow them to recover the selection costs. For opposite reasons, monopolistic banks perform a screening activity and thus allocate credit to better quality projects and borrowers; as a consequence, capital accumulation and growth are enhanced. If this positive effect is not offset by the inefficiencies due to monopoly, one should expect that market power in banking is beneficial to growth.[5]

An opposite conclusion is reached by Guzman (2000b), who proposes a model with monitoring and credit rationing. He shows that market power in banking reduces capital accumulation and growth because either credit rationing problems are exacerbated or, if credit rationing is not present, a monopolistic bank wastes resources in monitoring activity in order to meet the higher default probability of borrowers, given the higher interest rates it charges.

Deidda and Fattouh (2005) build a general equilibrium model without asymmetric information, where banking concentration impacts on growth through scale and specialization economies. As concentration decreases, the average cost of financial intermediation reduces with beneficial effects on growth; on the other hand, the increased number of banks associated with the lower level of concentration causes a duplication of fixed costs, which impacts negatively on growth. If the level of income is sufficiently high, the latter effect prevails, and less concentrated markets imply lower growth rates of the economy.

Turning to the (scarce) empirical evidence on the relationship between market power and efficiency in banking and economic development, Jayaratne and Strahan (1996) show that the removal of intrastate branching restrictions has boosted economic growth. However, they surprisingly find evidence of a post-reform better loan quality rather than an increase in lending, concluding that the better growth performance has been driven essentially by an improvement in the screening and monitoring of investment projects.

In order to test whether the structure of the banking industry impacts on growth, Cetorelli and Gambera (2001) make use of the cross-country approach of Rajan and Zingales (1998). They include the sum of market shares (measured in total assets) of the three and the five largest banks of the various countries in the original dataset, and find

[5] See also Cetorelli and Peretto (2000).

that, on the whole, a higher level of concentration is detrimental to growth, although this effect impacts differently across industrial sectors. Particularly, more concentrated banking markets facilitate access to credit to younger and more innovative firms, allowing them to grow faster. The authors interpret this finding as evidence that concentration promotes relationship lending.

Claessens and Laeven (2005) perform a similar analysis but employ an estimated measure of banking competition, i.e. the so-called *H*-statistic introduced by Panzar and Rosse (1987). Their results show a positive effect of banking competition on growth for those sectors that are more dependent from external finance.

Using a database considering companies of different size for 74 countries, Beck et al. (2004) focus on the effect of concentration on access to credit for firms. They find that entrepreneurs face more difficulties in accessing to credit when banking markets are more concentrated, although this effect decreases with firms' size and is not significant for more developed countries.

On the whole, the empirical literature reviewed so far seems to support the view according to which banks' market power causes higher costs and less availability of credit for firms, with the result that it negatively impacts on economic development and growth. A contrasting result is obtained by Maudos and Fernández de Guevara (2006). They use data on 53 sectors in 21 countries for the years 1993-2003 and several measures of market power (concentration index, *H*-statistic, Lerner index). The evidence is that market power enhances growth of those sectors that are more dependent from external finance, thus giving support to the literature on relationship lending. Fernández de Guevara and Maudos (2009) apply the same methodology to firm-level data for 52 Spanish provinces in the period 1997-2003, and find an inverted-U relationship between market power and sectors' growth, so that the positive effect of the former on economic growth is the highest at intermediate values.

Turning to Italy, Lucchetti et al. (2001) observe that the traditional measures of financial development are able to capture the role of banks in channelling saving into capital accumulation, but omit to consider their importance in screening investment projects. Hence, they suggest to proxy this crucial function of banks by considering their efficiency as an autonomous determinant of economic growth. Using a panel of

Italian regions for the period 1982-1994, they prove that regional economies in which banks are less cost-efficient grow slower.

Another single-country study focusing on Italy, and trying to assess the role that specific categories of banks have played in the economic growth of Italian regions, is that of Usai and Vannini (2005). They concentrate on regional data for the years 1970-1993, and discover that, unlike larger banks, cooperative banks and special credit institutions have had a special importance in favouring the growth of local economies.

Finally, Coccorese (2008a) studies the link between concentration in banking and economic growth for the Italian regions by means of a Granger-causality test. He finds that in the short-run higher levels of concentration negatively affect the economic performance of local areas, while in the long-run this causality is reversed since economic growth is found to reduce banks' market shares and hence concentration.

3.3 The econometric model

To assess the impact of banks' market power and other banking variables on regional growth, we start from the following model:

$$y_{m,t} - y_{m,t-1} = \alpha y_{m,t-1} + \beta' x_{m,t} + \mu_m + \gamma_t + \varepsilon_{m,t} \quad (m = 1,...,M;\ t = 2,...,T) \qquad (1)$$

where M is the number of provinces, T is the number of time periods, $y_{m,t}$ is the natural logarithm of real per capita value added in province m at year t,[6] $x_{m,t}$ is a $K\times1$ vector of variables affecting economic growth, μ_m is a province-specific fixed effects, γ_t is a vector of time dummy variables, and $\varepsilon_{m,t}$ is an error term with mean zero and variance σ_ε^2.

The vector x includes the following variables:

- the ratio between the credit to the private sector and the valued added (*FINANCE*);

[6] It follows that the left-hand side of Equation (1) is an approximation of the per capita value added growth rate.

- the degree of market power exerted by banks operating in a given province (*LERNER*);[7]
- the level of cost efficiency of the provincial banking system (*EFF*);[8]
- the bad loans to total loans ratio (*BADLOANS*);
- the number of branches per 100 square kilometer (*BRDENS*);
- the ratio between the sum of import and export and the value added (*TRADE*);
- the ratio between the number of students enrolled at upper secondary school and the population aged between 14 and 19 years (*HUMCAP*);[9]
- the ratio between the number of crimes denounced to the judicial authorities and local population (*CRIME*).

In line with the evidence of the existing literature, we expect the variable *FINANCE* to positively affect the growth rate of the per capita value added. The variables *LERNER*, *EFF*, *BADLOANS* and *BRDENS* are included to capture some factors that could affect the role of banks in directing savings toward investment projects. As already discussed, the market power of banks is regarded as a crucial determinant of both cost and availability of credit for firms, and thus of economic growth. The variables *EFF* and *BADLOANS* aim at catching the ability of local banks to turn deposits into profitable investments by means of effective screening and monitoring activities. Particularly, higher levels of cost efficiency are expected to foster economic growth, while a larger fraction of bad loans may reflect banks' poor ability to select good projects, with a negative impact on growth. Finally, the variable *BRDENS* is added to capture the potential of lending throughout the province. Degryse and Ongena (2005), for instance, provide evidence that the cost of credit increases with the distance between firms and banks. Accordingly, in our framework a higher density of branches should positively affect investment and growth.

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[7] Recent studies on banking competition have shown that concentration and the degree of monopoly are not interchangeable. Then, in order to proxy for market power we avoid the use of a concentration index.
[8] Details about the methodology used to construct both this variable and the previous one (*LERNER*) can be found in Section 3.4.
[9] In Italy, the secondary education consists of a lower secondary school, which is compulsory and provides a basic level of education, and an upper secondary school, which is more advanced and intended for students usually aged between 14 and 19 years old.

The variables *TRADE*, *HUMCAP* and *CRIME* help to consider additional features of local economies that could influence growth: *TRADE* measures the provincial openness to trade, and should therefore exhibit a positive coefficient; *HUMCAP* is a proxy of the human capital, whose impact on the level of economic activity is generally positive; *CRIME* is added because it is by and large believed to negatively affect economic growth by influencing return on investments and business profitability.

We can rewrite Equation (1) as:

$$y_{m,t} = \tilde{\alpha} y_{m,t-1} + \beta' x_{m,t} + \mu_m + \gamma_t + \varepsilon_{m,t} \quad (m = 1,...,M;\ t = 2,...,T) \tag{2}$$

where $\tilde{\alpha} = \alpha + 1$.

Equation (2), which is our basic specification, represents a dynamic panel data model. Standard assumption for this model are: 1) $\tilde{\alpha} < 1$; 2) $E(\mu_m) = E(\varepsilon_{m,t}) = E(\mu_m\ \varepsilon_{m,t}) = 0$, i.e. both the individual effect and the error term have mean zero and are uncorrelated each other; 3) $E(\varepsilon_{m,t}\ \varepsilon_{m,s}) = 0$, $\forall\ t \neq s$, i.e. there is no serial correlation (Blundell and Bond, 1998).

Taking first differences of both sides of Equation (2) allows to remove the unobserved heterogeneity. The model thus becomes:

$$\Delta y_{m,t} = \tilde{\alpha} \Delta y_{m,t-1} + \beta' \Delta x_{m,t} + \Delta\gamma_t + \Delta\varepsilon_{m,t} \quad (m = 1,...,M;\ t = 3,...,T) \tag{3}$$

Since $\Delta y_{m,t-1}$ and $\Delta\varepsilon_{m,t}$ are correlated, estimating (3) by means of OLS would lead to biased and inconsistent results (Nickell, 1981). As proposed by Anderson and Hsiao (1981, 1982), one possible solution is to instrument the first difference of the lagged dependent variable, $\Delta y_{m,t-1}$, by $y_{m,t-2}$ or $\Delta y_{m,t-2}$ (which, under the above assumptions, are valid instruments) and apply the 2SLS estimator.

Developing this idea and the work of Holtz-Eakin et al. (1988), Arellano and Bond (1991) note that the Anderson-Hsiao estimator lacks of efficiency because it does not make use of all the available instruments, and suggest the use of a GMM framework to obtain more efficient estimates of the model parameters. This technique is known as

"Difference GMM" because it consists in applying GMM after first-differencing the data in order to eliminate the fixed effects.

In the case of a simple AR(1) model,[10] the following $(T–2)(T–1)/2$ moment conditions can be used for each m:

$$E\left(y_{m,t-j}\ \Delta\varepsilon_{m,t}\right)=0 \quad (t=3,...,T; j=2,...,t–1)\ , \tag{4}$$

which lead to the following instruments matrix:

$$Z_m=\begin{bmatrix} y_{m,1} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & y_{m,2} & y_{m,1} & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 0 & 0 & y_{m,3} & y_{m,2} & y_{m,1} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & y_{m,T-2} & \cdots & y_{m,1} \end{bmatrix}. \tag{5}$$

Given this matrix, the one step and the two-step GMM estimators can be applied along the lines developed by Hansen (1982).[11] Both are consistent and asymptotically normal for large N and fixed T, but the two-step estimator is more efficient when errors are not i.i.d.

Additional endogenous covariates other than the lagged dependent variable can be easily handled in the same way, i.e. using their second and higher order lags as instruments.[12] The validity of the overidentifying restrictions, and thus of the instruments, can be tested by the Sargan/Hansen statistic, which is given by the value of the GMM objective function at the efficient GMM estimator. Under the null of joint validity of all overidentifying restrictions, the statistic is distributed as χ^2 with $L–K$ degrees of freedom, where L is the number of instruments.

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[10] One example of an AR(1) model is Equation (2) without both the x covariates and time dummies.

[11] Particularly, given the MA serial correlation of the differenced errors, the weight matrix of the one-step estimator is given by

$$W=\left(N^{-1}\sum_{m=1}^{N} Z_m^{'}HZ_m\right)^{-1},$$

where H is a $(T–2)\times(T–2)$ matrix with 2's on the main diagonal, –1's on the first off-diagonals, and 0 elsewhere.

[12] On the contrary, for predetermined variables the first available instrument is their first lag.

However, if the $\varepsilon_{m,t}$'s are serially correlated, some lags would be endogenous and could not be used as instruments. For this reason, Arellano and Bond (1991) develop a test for autocorrelation in the differenced errors. Since $\Delta\varepsilon_{m,t}$ and $\Delta\varepsilon_{m,t-1}$ are negatively correlated by construction, the validity of second and higher order lags as instruments requires the absence of serial correlation of order 2 in the differenced errors. If this is not the case, one should start from higher order lags than the second in building the instruments matrix Z_m (Bond, 2002).

Blundell and Bond (1998) show that the lagged-level instruments in the Difference GMM estimator become weak as the autoregressive process happens to be too persistent or the ratio of the variance of the panel-level effect, μ_m, to the variance of the idiosyncratic error, $\varepsilon_{i,t}$, becomes too large. Hence, under mild additional assumptions, they develop a "System GMM" estimator that augments Difference GMM by estimating simultaneously in differences and levels, the two equations being distinctly instrumented. More precisely, the System GMM employs moment conditions in which lagged differences are used as instruments for the level equation in addition to the moment conditions of lagged levels as instruments for the differenced equation.

Both the Difference and System GMM easily allow to deal with multiple endogenous variables, because there is no need to look for the "right" instruments. All one has to do is to use lagged values of the potentially endogenous variables, and then test their validity.

However, this approach can lead to an instruments proliferation, since their number increases with the number of the instrumented variables and with T. As discussed by Roodman (2009), this has two main practical consequences on the small sample performance of the two estimators. First, as already noted by Arellano and Bond (1991), too many instruments can cause a downward bias in the two-step standard errors. Secondly, the Sargan/Hansen test is weakened in the sense that it does not reject the null too often.

While the first problem can be dealt with using the small sample correction proposed by Windmeijer (2005), the second necessarily calls for a reduction of the number of instruments. This can be done either using a limited number of lags as instruments or "collapsing" all the available lags. The latter approach is preferable since no information is lost. Operationally, it amounts to exploiting the following moment conditions:

$$E\left(y_{m,t-j}\ \Delta\varepsilon_{m,t}\right)=0 \quad (j=2, ..., t-1), \tag{6}$$

so that the instrument matrix (5) writes:

$$Z_i=\begin{bmatrix} y_{m,1} & 0 & 0 & 0 & \cdots & 0 \\ y_{m,2} & y_{m,1} & 0 & 0 & \cdots & 0 \\ y_{m,3} & y_{m,2} & y_{m,1} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ y_{m,T-2} & y_{m,T-3} & y_{m,T-4} & y_{m,T-5} & \cdots & y_{m,1} \end{bmatrix}. \tag{7}$$

One innovative feature of our analysis is that we try to take into account the geographic nature of our dataset by also estimating a spatial augmented version of Equation (2). Actually, when dealing with regional data the presence of either spatial heterogeneity or spatial dependence among cross-sectional units is an aspect that needs careful consideration.

Spatial heterogeneity refers to the possibility that the economic relationships are not stable over space. Essentially, this is the well known econometric notion of heterogeneity extended to a geographic framework; so, spatial heterogeneity can be handled by way of tools such as random coefficients, switching regressions, space varying parameters, or panel data techniques.

Spatial dependence implies that observations at a given location depend on observations at other locations. This may occur because of measurement error problems or, more importantly, because human activities are naturally linked across space, giving rise to diffusion and spillover effects.[13]

Spatial unobserved heterogeneity should not be a concern in our model, thanks to the inclusion of provincial-level fixed effects, and to the fact that we employ a dataset on small local economies that share the same social and institutional environment.

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[13] See Anselin (1988) for an outstanding treatment of these and related concepts, as well as the models commonly used in the spatial econometrics literature.

Spatial dependence is modeled by including the spatial lag of the dependent variable in Equation (2). In other words, we consider the following dynamic spatial panel model:

$$y_{m,t} = \tilde{\alpha} y_{m,t-1} + \rho \sum_{n=1}^{M} w_{m,n} y_{n,t} + \beta' x_{m,t} + \mu_m + \gamma_t + \varepsilon_{m,t} \quad (m = 1,...,M;\ t = 2,...,T)\ , \tag{8}$$

where ρ is the spatial autoregressive parameter, and $w_{m,n}$ is the generic element of the $M \times M$ matrix W that describes the exogenous spatial interactions among the various cross-sectional units. We can rewrite Equation (8) in the following more compact form:

$$y_{m,t} = \tilde{\alpha} y_{m,t-1} + \rho [WY_t]_m + \beta' x_{m,t} + \mu_m + \gamma_t + \varepsilon_{m,t} \quad (m = 1,...,M;\ t = 2,...,T)\ , \tag{9}$$

where $Y_t = \begin{bmatrix} y_{1,t} & \cdots & y_{M,t} \end{bmatrix}'$, while $[WY_t]_m$ denotes the m-th row of the WY_t matrix.

In spatial econometrics, it is a common practice to standardize the rows of W, so that each of them sums to one. As a consequence, the spatial lag, $[WY_t]_m$, is nothing but a weighted average of the per capita value added of the neighboring provinces, with the ρ parameter measuring its impact on the per capita value added of the m-th province. Rewriting Equation (9) in reduced form makes evident that the spatial lag is endogenous, since it is a linear combination of the error terms.

Taking first differences of (9) allows to remove the individual fixed effects, so we get:

$$\Delta y_{m,t} = \tilde{\alpha} \Delta y_{m,t-1} + \rho \Delta [WY_t]_m + \beta' \Delta x_{m,t} + \Delta \gamma_t + \Delta \varepsilon_{m,t} \quad (m = 1,...,M;\ t = 3,...,T) \tag{10}$$

Although ML or QML estimators are available for dealing with models like (10) (Elhorst, 2005; Yu et al., 2008), both suffer from the drawback that they do not allow endogenous covariates other than time and spatial lags.

An alternative approach would be that of Badinger at al. (2004), who apply the GMM estimator after a first-step filtering procedure on the data in order to remove spatial autocorrelation. However, as noted by Abreu et al. (2005), the properties of this two-stage estimator are not known; in addition, the filtering procedure could remove to some extent the data variability.

Given the non-availability of proper estimators for dynamic spatial lag models, Kukenova and Monteiro (2008) investigate the finite sample properties of several estimators for such models using Monte-Carlo simulations, and suggest to apply a system-GMM estimator, instrumenting the spatial lag like any other endogenous variable in the model.

This approach has been used, for instance, by Madariaga and Poncet (2007), Hong et al. (2008) and Bode et al. (2009) to study the spatial effects of foreign direct investments, by Foucault et al. (2008) for checking possible public spending interactions between neighbouring municipalities, and by Mitze (2009) to model migration flows.

We conform to this recent literature and estimate Equation (9) by means of a system-GMM procedure (relying on its good small sample properties for spatial dynamic panel models). Since the results could depend on the specification of the spatial interactions matrix, W, we consider the following three alternatives:

1) a matrix W_1 with generic element $w_{m,n}^{(1)} = \exp(-d_{m,n})$, where $d_{m,n}$ is the Euclidean distance between the capitals of provinces m and n;
2) a matrix W_2 with generic element $w_{m,n}^{(2)} = 1$ if provinces m and n share a common border, and $w_{m,n}^{(2)} = 0$ otherwise;
3) a matrix W_3 whose generic element, $w_{m,n}^{(3)}$, equals to the length of the border shared by provinces m and n.

Using W_1 means to assume that the per capita value added of province m is influenced by the per capita value added of *all* other Italian provinces, although this influence decreases with distance. In the case of W_2 and W_3, only the neighboring provinces impact on value added of the m-th province. Particularly, while the former implies that the weights used in computing the spatial lag are the same for all neighboring provinces, i.e. only contiguity matters, in the latter the impact of a given neighboring province on province m is proportional to the length of the border they share.

3.4 Estimating efficiency and market power

To get *LERNER* and *EFF* variables on a provincial basis, we first estimate bank-level measures of market power and efficiency.

Cost efficiency scores and technology parameters are estimated using the following translog stochastic frontier model with one output and three inputs:

$$\begin{aligned}\ln C_{it} &= \alpha_0 + \alpha_1 \ln Q_{it} + \sum_{h=1}^{3} \alpha_h \ln W_{hit} + \alpha_T \ln TREND + \\ &\frac{1}{2}\left\{\alpha_{QQ}\left(\ln Q_{it}\right)^2 + \sum_{h=1}^{3}\sum_{k=1}^{3} \alpha_{hk} \ln W_{hit} \ln W_{kit} + \alpha_{TT}\left(\ln TREND\right)^2\right\} + \\ &\sum_{h=1}^{3} \alpha_{Qh} \ln Q_{it} \ln W_{hit} + \alpha_{TQ} \ln TREND \ln Q_{it} + \sum_{h=1}^{3} \alpha_{Th} \ln TREND \ln W_{hit} + \varepsilon_{it}\end{aligned} \tag{11}$$

where $i = 1,...,N$ and $t = 1,...,T$ index banks and time, respectively, C measures the total cost, Q the output, W_h the factor prices, and *TREND* is a time trend included to account for technical change. Finally, $\varepsilon_{it} = v_{it} + u_{it}$ is a two-components error term, where v_{it} is the usual error term – with $v_{it} \sim N(0,\sigma_v^2)$ – and u_{it} is the inefficiency term. Given the panel structure of our data, the latter is modelled using the Battese and Coelli (1992) parametrization, i.e. $u_{it} = u_i \exp[-\gamma\,(t-T_i)]$, where u_i is a truncated normal distribution with mean μ and variance σ_u^2.

One shortcoming of this specification is that it imposes an a priori time path to the efficiency scores, which depends on the estimation of the γ parameter. Therefore, we check the robustness of results by estimating for the pooled sample also the stochastic frontier model as proposed by Aigner et al. (1977) and Meeusen and van Der Broeck (1977), where the u_{it} term – assumed to be distributed as a half-normal random variable – is free to vary over time without any previous assumption.

With reference to the cost function, the symmetry of the Hessian implies that $\alpha_{hk} = \alpha_{kh}$. In order to conform to a well-behaved production technology, the cost function needs to be linearly homogeneous, non-decreasing and concave in factor prices, and non-decreasing in output. With the symmetry restrictions imposed, necessary and sufficient conditions for our translog cost specification to be linearly homogeneous in input prices are:[14]

$$\sum_{h=1}^{3}\alpha_h = 1,\ \sum_{k=1}^{3}\alpha_{hk} = 0\ \ (h = 1,2,3),\ \sum_{h=1}^{3}\alpha_{Qh} = 0,\ \sum_{h=1}^{3}\alpha_{Th} = 0\,.$$

The cost efficiency scores are estimated as $EFF_{it} = E\left[\exp(-u_{it}) \mid \varepsilon_{it}\right]$.[15] Since $u_{it} \geq 0$, EFF_{it} ranges between 0 and 1, with $EFF_{it} = 1$ characterizing the fully efficient firm.

We compute the marginal cost for each bank and time period by means of the parameters resulting from the cost function estimation:

$$\begin{aligned} MC_{it} &= \frac{\partial C_{it}}{\partial Q_{it}} = \frac{\partial \ln C_{it}}{\partial \ln Q_{it}}\frac{C_{it}}{Q_{it}} = \\ &= \left(\alpha_Q + \alpha_{QQ}\ln Q_{it} + \sum_{h=1}^{3}\alpha_{Qh}\ln W_{hit} + \alpha_{TQ}\ln TREND\right)\frac{C_{it}}{Q_{it}} \end{aligned} \tag{12}$$

The Lerner index can be now calculated as:

$$LERNER_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \tag{13}$$

where P_{it} is the observed price (i.e. interest rate) charged on the output by bank i in year t. Theoretically, the Lerner index can vary between 0 (in case of perfect competition) and 1.

Once obtained the bank-level efficiency scores and Lerner indices, we compute the corresponding provincial-level measures as weighted averages based on the

[14] We imposed symmetry and homogeneity restrictions during the estimation process, and checked the other properties after estimation.
[15] For details on this point, see Kumbhakar and Lovell (2000), ch. 4.

geographical distribution of banks' branches. More formally, the market power exerted by banks operating in province *m* in year *t* is defined as:

$$LERNER_{mt} = \sum_{i=1}^{N_{mt}} \left(\frac{BR_{it}}{\sum_{i=1}^{N_{mt}} BR_{it}} \right) LERNER_{it} \,, \tag{14}$$

where BR_{it} is the number of branches of bank *i* in year *t*, and N_{mt} is the number of banks operating in province *m* in year *t*.

Similarly, the cost efficiency score of the *m*-th province's banking system in year *t* is calculated as:

$$EFF_{mt} = \sum_{i=1}^{N_{mt}} \left(\frac{BR_{it}}{\sum_{i=1}^{N_{mt}} BR_{it}} \right) EFF_{it} \ . \tag{15}$$

The above expressions are based on the assumption that pricing behaviour, technology and cost efficiency of each bank are the same for every province where it operates. We understand that this is a quite strong assumption. Unfortunately, balance-sheet data at a local level are not available. Moreover, it is rather common in studies regarding the banking systems of European countries to rely on the branch distribution in order to investigate the conditions of local markets. For instance, several authors[16] have computed local HHI indexes considering branches, rather than loans or deposits, while others[17] have used the distribution of branches to disaggregate balance-sheet items. On the other hand, our approach resembles that of Lucchetti et al. (2001), who employ it to build an efficiency index of Italian regional banking systems.

[16] For example, see Maudos (1998), Degryse and Ongena (2005), and Coccorese and Pellecchia (2009).
[17] This is the case of Carbó Valverde et al. (2003) and Agostino and Trivieri (2008).

3.5 Data

The sample of Italian banks used to estimate the bank-level cost efficiency scores and Lerner indices is drawn from the database Bankscope,[18] and covers the years 1996-2006. We have selected banks' balance sheet and profit and loss account data only in unconsolidated form (thus treating holding banks and their affiliates as separate decisional units). Besides, we have considered only commercial, cooperative and popular banks, dropping those observations for which relevant variables were not available. In order to record the number of branches of each bank (which is seldom reported in Bankscope), the data have been matched with those yearly available from the Bank of Italy. We dropped the observations that did not pass this test.

We follow the intermediation approach to banking costs,[19] and consider three inputs in the cost function: deposits, labour, and capital. The corresponding cost figures are therefore interest expenses, personnel expenses, and other operating costs, respectively. In order to calculate the last figure, we have subtracted labour costs from all operating costs (which are net of financial expenses).

The price of deposits (W_1) is equal to the ratio between interest expenses and the sum of deposits, money market funding and other funding. The price of labour (W_2) has been computed dividing personnel expenses by total assets.[20] Finally, the price of capital (W_3) has been proxied by the ratio between residual operating costs.

In assessing the level of output Q, we have conformed to Shaffer (1993) and Angelini and Cetorelli (2003), and set it equal to the value of the total assets. The output price P has been then computed as the ratio between total revenues (interest income plus net non-interest income) and total assets.

We have corrected for outliers by dropping those observations for which the output and/or factor prices were lower than the 1st centile or larger than the 99th centile. We have also discarded those banks for which less then three observations were available. After the data selection process, 4473 observations on 631 banks were available. The

[18] The Bankscope database is distributed by Bureau van Dijk Electronic Publishing (BvDEP) and is a common data source for empirical studies on banking.
[19] See Sealey and Lindley (1977).
[20] In Bankscope the number of employees is not available for many banks, so we proxy it by total assets.

panel is unbalanced, and includes about 7 observations for bank (see Table 3.1). Descriptive statistics of the sample of banks are provided in Table 3.2.

TABLE 3.1 – *Number of observations (banks) by year*

Year	Obs.
1999	547
2000	563
2001	586
2002	578
2003	562
2004	563
2005	547
2006	527
TOTAL	**4473**
N. of banks	631
N. of obs. per bank	7.1

TABLE 3.2 – *Descriptive statistics of the sample (bank-level variables)*

Variable	Obs.	Mean	Median	Minimum	Maximum	Std. Dev.
C [(a)]	4473	92870.55	9498.27	613.15	10442791	472540.4
Q [(a)]	4473	1896699	198711.8	10251.95	199886016	9985811
W_1 [(b)]	4473	0.0204	0.0201	0.0088	0.0381	0.0054
W_2 [(b)]	4473	0.0153	0.0151	0.0064	0.0270	0.0035
W_3 [(b)]	4473	1.6343	1.1176	0.2958	18.0000	1.8434
P [(b)]	4473	0.0588	0.0584	0.0356	0.0914	0.009
LOANS [(a)]	4473	1145054	117380.20	2816.54	116151816	5640632
DEPOSITS [(a)]	4473	1120592	107818.20	5173	110769440	5888268
BRANCHES [(c)]	4473	41.65	8	1	2845	147.67

[(a)] Thousands euro (2000 values) - [(b)] Ratio - [(c)] Units

The coverage of the sample, in terms of branches by province and year, is reported in Table 3.3. This information is crucial for assessing the reliability of our provincial market power and efficiency measures, as calculated by (14) and (15). If the coverage were low, these measures would not be accurate. As Table 3.3 shows, there is a very small number of pairs province/year for which the branch share of the banks included in our sample is less than 50 percent. Overall, the coverage is about 80%.

TABLE 3.3 – *Coverage of the sample in terms of branches (percentages)*

PROVINCE	1999	2000	2001	2002	2003	2004	2005	2006
Agrigento	83.24	60.23	74.57	69.82	92.98	92.81	91.07	97.60
Alessandria	83.78	66.42	75.18	81.82	70.32	75.35	76.04	93.22
Ancona	93.08	84.56	84.93	91.97	84.76	85.19	87.72	88.98
Aosta	82.56	**46.15**	76.34	82.29	**47.92**	63.16	65.63	91.75
Arezzo	96.70	66.31	72.02	95.00	96.60	75.48	94.31	62.27
Ascoli Piceno	93.78	86.89	87.67	94.22	93.01	94.09	95.51	91.86
Asti	96.45	77.62	93.84	90.73	77.63	79.33	80.54	97.39
Avellino	79.66	66.12	75.41	81.30	67.20	71.77	72.66	74.81
Bari	75.70	58.46	65.48	88.14	74.69	74.83	74.27	79.19
Belluno	77.25	80.34	82.12	88.59	57.59	59.90	60.42	93.91
Benevento	92.31	60.00	68.75	54.88	57.83	53.01	64.63	79.07
Bergamo	81.36	69.23	82.26	94.19	68.53	72.12	91.27	89.77
Biella	69.35	56.45	61.90	60.32	50.39	52.76	53.54	68.75
Bologna	85.17	66.05	69.94	94.17	72.69	74.26	73.68	88.40
Bolzano	90.36	67.00	70.30	94.28	92.59	94.06	93.09	93.61
Brescia	77.55	70.10	77.31	86.66	79.97	82.27	80.12	81.63
Brindisi	80.95	65.42	68.47	92.86	74.36	76.27	76.27	76.67
Cagliari	83.13	64.82	64.20	91.22	87.07	86.89	84.01	**48.16**
Caltanissetta	77.01	73.33	79.78	72.83	100.00	95.83	98.98	100.00
Campobasso	88.51	61.70	70.87	76.92	83.02	80.19	84.26	79.25
Caserta	83.61	57.53	57.14	81.25	56.61	56.99	56.70	57.00
Catania	77.32	70.25	74.10	66.57	88.60	89.34	87.43	89.52
Catanzaro	89.13	63.83	60.82	95.92	84.69	84.69	85.00	89.22
Chieti	92.59	82.64	79.61	91.08	91.98	92.26	93.60	86.36
Como	68.58	**48.08**	60.95	85.45	85.07	92.54	92.69	75.36
Cosenza	86.31	78.36	72.53	94.62	89.42	89.01	88.27	90.50
Cremona	69.53	**40.42**	74.10	85.43	84.25	84.82	85.93	85.09
Crotone	94.74	85.00	80.00	100.00	86.84	86.84	87.18	92.11
Cuneo	93.98	82.20	90.24	88.55	78.11	79.88	80.78	94.01
Enna	93.55	75.81	79.03	61.54	90.91	100.00	100.00	100.00
Ferrara	82.98	86.29	87.44	95.73	86.32	86.73	86.05	59.45
Firenze	89.89	69.98	75.30	89.08	88.50	88.52	88.91	69.67
Foggia	91.47	74.19	78.26	90.72	74.79	69.87	70.12	84.30
Forlì-Cesena	86.81	91.52	92.20	97.67	80.52	81.23	80.31	91.27
Frosinone	78.57	**26.54**	**37.20**	**40.96**	81.55	85.47	74.72	75.96
Genova	69.37	**45.88**	**24.17**	**44.99**	55.76	83.33	82.93	90.04
Gorizia	84.09	75.28	86.32	95.88	82.86	84.91	85.98	97.17
Grosseto	95.69	55.00	56.10	90.63	88.46	85.29	91.30	83.10
Imperia	68.69	51.52	**36.54**	61.68	54.72	79.09	79.31	89.08
Isernia	93.10	53.13	60.61	71.88	78.79	78.79	78.79	85.29
La Spezia	79.51	68.80	59.06	72.87	68.99	87.69	85.50	93.94
L'Aquila	80.83	84.09	84.56	92.31	95.14	94.44	95.97	84.31
Latina	96.45	**40.14**	**44.74**	64.74	90.80	86.67	73.81	86.63
Lecce	89.29	78.02	80.66	94.80	73.02	73.31	72.66	82.81
Lecco	55.91	68.39	55.67	90.34	90.34	92.49	95.31	62.39
Livorno	91.19	62.28	63.64	85.80	61.67	64.29	92.06	86.29
Lodi	91.45	59.66	82.79	96.00	91.60	92.42	95.59	96.45
Lucca	90.74	74.56	73.50	92.80	65.84	93.12	90.73	82.94
Macerata	95.43	90.27	89.90	96.10	91.24	91.74	91.48	93.53
Mantova	86.96	74.66	82.06	91.80	81.31	82.90	83.23	84.33
Massa-Carrara	92.31	77.17	75.79	92.78	81.00	93.00	91.09	85.05
Matera	80.77	73.42	76.54	87.95	82.14	83.13	83.33	86.05
Messina	69.06	56.25	60.09	68.89	89.24	92.38	86.09	90.79
Milano	67.01	52.15	59.38	85.46	77.33	83.81	83.44	89.49
Modena	93.53	83.29	84.94	92.71	75.71	76.87	68.96	69.18
Napoli	80.39	53.20	55.88	85.47	54.52	55.94	54.90	62.53

TABLE 3.3 (continued) – *Coverage of the sample in terms of branches (percentages)*

PROVINCE	1999	2000	2001	2002	2003	2004	2005	2006
Novara	77.96	65.96	72.02	68.21	50.76	55.38	51.78	94.50
Nuoro	93.04	87.07	87.18	95.80	93.33	94.17	93.28	**20.69**
Oristano	91.36	84.15	85.37	95.24	92.86	93.98	91.46	**27.16**
Padova	86.31	82.49	84.60	94.95	85.18	86.29	86.23	90.40
Palermo	77.81	69.52	69.11	52.37	87.53	90.58	87.53	93.67
Parma	87.73	53.24	87.38	93.83	86.67	90.03	88.52	88.44
Pavia	74.54	**45.42**	70.03	85.15	77.02	83.44	83.96	94.70
Perugia	96.40	80.46	82.68	90.08	94.01	90.39	74.22	87.44
Pesaro Urbino	95.38	93.20	93.44	96.65	90.94	88.38	91.36	80.06
Pescara	88.14	76.92	**47.76**	64.03	63.45	63.95	90.67	76.58
Piacenza	94.48	52.08	82.65	92.54	87.80	91.83	91.83	92.02
Pisa	92.69	81.14	81.55	59.15	64.05	77.82	77.78	86.69
Pistoia	94.20	85.23	85.35	89.44	84.52	92.40	94.41	90.76
Pordenone	71.43	75.00	79.60	95.73	81.40	81.78	82.24	93.09
Potenza	64.58	51.68	58.28	70.97	65.38	82.69	82.91	84.57
Prato	85.22	70.49	73.39	87.60	80.30	86.36	86.36	81.20
Ragusa	79.00	73.79	75.70	71.56	96.30	98.20	98.25	70.34
Ravenna	94.87	91.10	92.12	97.64	78.95	80.25	78.86	90.09
Reggio di Calabria	89.92	67.42	66.42	97.78	81.88	81.62	80.43	83.57
Reggio nell'Emilia	67.38	67.55	72.46	79.55	72.02	73.91	71.96	67.79
Rieti	98.67	63.64	64.56	83.54	84.81	74.07	86.75	85.54
Rimini	94.24	88.38	88.79	97.00	82.23	82.54	84.19	76.07
Roma	81.39	**39.92**	**45.84**	71.88	81.17	81.19	81.07	87.41
Rovigo	83.01	80.00	80.25	89.70	81.98	82.08	81.82	84.18
Salerno	77.07	68.57	69.44	85.89	74.55	76.40	75.87	76.19
Sassari	86.17	72.92	71.50	93.91	88.89	90.00	88.35	**43.48**
Savona	80.38	60.71	62.35	67.44	71.18	82.86	83.52	93.99
Siena	93.79	52.78	52.41	95.79	96.92	91.88	97.49	83.82
Siracusa	67.89	58.33	64.35	64.10	94.78	93.91	91.38	82.79
Sondrio	86.61	81.42	86.44	64.75	97.46	97.48	97.54	**23.20**
Taranto	80.74	58.22	69.93	93.63	74.52	76.40	76.88	82.53
Teramo	96.35	88.19	89.26	95.48	95.57	95.63	92.31	77.09
Terni	94.34	75.70	79.28	90.43	90.91	88.43	82.64	98.40
Torino	78.73	**44.58**	67.66	81.43	52.61	55.58	58.23	85.31
Trapani	66.28	66.86	69.32	74.58	92.98	94.35	91.53	97.69
Trento	85.38	89.38	91.99	96.36	82.27	83.76	81.99	92.60
Treviso	70.06	78.56	83.25	95.07	73.61	77.29	78.58	92.21
Trieste	74.02	64.39	66.67	89.78	65.69	68.42	67.18	93.28
Udine	60.95	67.30	79.13	97.31	82.34	83.48	84.12	95.59
Varese	79.33	61.63	70.91	81.90	61.77	73.64	83.81	88.40
Venezia	84.47	75.00	77.26	91.65	84.36	85.71	86.13	86.44
Verb.-Cusio-Ossola	82.50	69.14	74.70	70.59	57.32	63.75	62.96	91.76
Vercelli	86.61	71.88	82.95	66.67	57.14	58.65	60.15	89.63
Verona	90.81	81.70	83.92	91.86	67.62	70.59	71.81	69.65
Vibo Valentia	94.74	87.18	82.93	97.56	87.80	87.80	85.71	85.71
Vicenza	85.21	79.21	80.65	96.01	72.79	75.50	75.61	88.63
Viterbo	88.89	60.11	66.48	80.11	95.77	94.24	94.85	91.79

Values lower than 50 per cent in bold.

When studying the determinants of economic growth with panel techniques, most of the authors average the data over non-overlapping sub-periods in order to smooth them and reduce the influence of the business cycle on the estimation results. However, this approach has been criticized by Attanasio et al. (2000)[21] on the ground of several reasons. First, averaging does not necessarily eliminate business cycle influences, since it could well be the case that economic fluctuations are not synchronized across regions or countries; also, there is no guide as to the length of the non-overlapping periods to be used for averaging. Second, averaging implies a loss of information and does not allow to take into account short-run effects that could offset long-run ones.

Since market power and the other banking structural variables could have short-run as well as long-run effects on growth, we estimate the models using low-frequency (annual) data,[22] also considering that in our case the averaging approach would not be viable due to the unavailability of long time series at a provincial level.

Table 3.4 lists the sources of the variables needed for the estimation of Equations (2) and (9). The value added has been deflated by the Consumer Price Index (CPI) of the capital of the region that the province belongs to;[23] averages of the monthly series have been considered. Yearly averages of the real per capita value added (*PCVAD*) are shown in Figure 3.1. A clear increasing trend emerges, with no evidence of business cycle effects in spite of the relatively short time period under consideration.
Summary statistics of all variables (both estimated and calculated) are reported in Table 3.5. Overall, *PCVAD* ranges between 9.65 thousands euro (Crotone in 1999) and 39.91 thousand euro (Milano in 2006).[24] It is worth noting that the first value refers to a province located in the South of the country, while the second concerns the leading economic and financial province of Italy, which is located in the North. These figures are probably emblematic of the long-lasting gap between the North and the South of Italy in terms of economic development. Panel (a) of Figure 3.2 helps to have a clearer

[21] See also Loayza and Rancière (2006) and Wan et al. (2006).
[22] For an analogous choice regarding studies on growth, see Rosseau and Wachtel (2000), Soto (2003) and Hasan et al. (2009). The use of annual data to assess the determinants of growth is also a standard practice when dealing with transition countries, for which long economic series are often not available (see, for example, Krueger and Ciolko, 1998, and Bennet et al., 2007).
[23] Over the sample period, the CPI at the provincial level was available only for 60 provinces out of 103.
[24] Figures are in constant 1998 values.

idea of this aspect by showing the spatial distribution of the averages of *PCVAD* for the whole period 1999-2006.

As one can easily see, *PCVAD* reduces moving from the North to the South of Italy, and three well defined clusters of provinces can be detected: the first consists of all the Northern provinces, whose average *PCVAD* in most cases exceeds the third quartile of the distribution; the second includes the provinces located in the Center of the country, with values of *PCVAD* mainly ranging between the first and the second quartile; finally, the third cluster comprises the Southern provinces and the Islands, both characterized by very low values of the per capita value added (largely below the first quartile).

However, it appears that during the period under study this gap could have reduced, at least partially. As shown in panel (b) of Figure 3.2, many Southern provinces have experienced a significant average growth rate of the valued added over the sample period, sometimes comparable to that of other more wealthy areas.

Levine et al. (2000) have stressed the importance to accurately deflate the variables needed to compute the financial development indicator. Since the amount of credit to the private sector[25] was available on a quarterly basis, we first deflated it using the average of the monthly CPI's of the corresponding quarter, and then computed the annual value averaging over quarters. The value added, available on a yearly basis, was deflated by means of the averages of the monthly CPI's. We have been then able to calculate our variable *FINANCE* as the ratio between real credit to private sector and real value added.[26]

The spatial pattern of this financial development indicator is shown in panel (c) of Figure 3.2, and looks very similar to that of *PCVAD*. Clearly, more developed provinces show a higher level of the variable *FINANCE*, whose values range between 0.22 (Vibo Valentia in 2002) and 1.32 (Milano in 2006).

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[25] The Bank of Italy provides the geographical distribution (at the provincial level) of banks' loans disaggregated by sector. Our proxy of the credit to the private sector has been set equal to the credit granted to private firms, thus excluding that regarding public administration and households.

[26] It is worth to note that our measure of financial development is very similar to the *PRIVATE CREDIT* variable of Levine et al. (2000).

TABLE 3.4 – *Data sources (provincial-level variables)*

Variable	Source
Value added	National Institute of Statistic (ISTAT)
Regional Consumer Price Index (CPI)	National Institute of Statistic (ISTAT)
Population	National Institute of Statistic (ISTAT)
Credit to the private sector	Bank of Italy
Bad loans	Bank of Italy
Imports	National Institute of Statistic (ISTAT)
Export	National Institute of Statistic (ISTAT)
Students enrolled at secondary schools (1)	Ministry of Education, University and Research (MIUR)
Crimes denounced to the judicial authorities	National Institute of Statistic (ISTAT)

(1) Data for the provinces of Bolzano and Trento have been gathered from publications of the local statistical departments.

FIGURE 3.1 – *Yearly averages of the real per capita value added (1999 - 2006)*

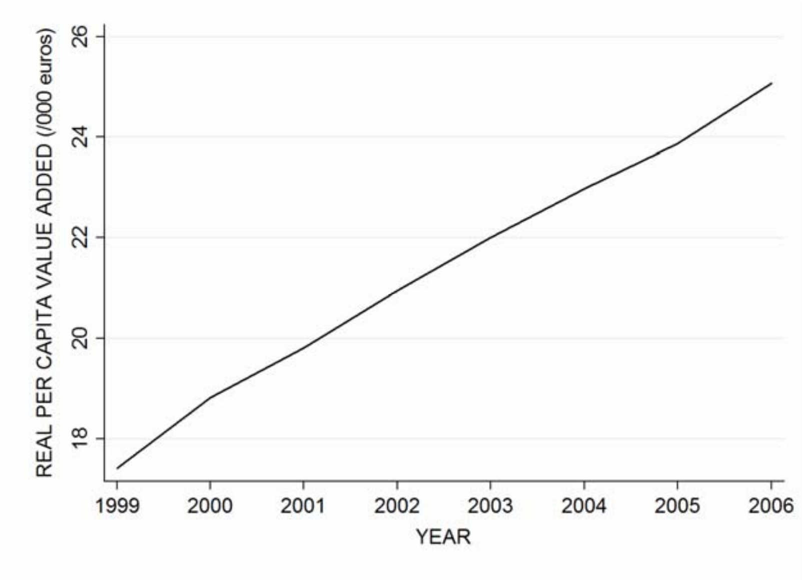


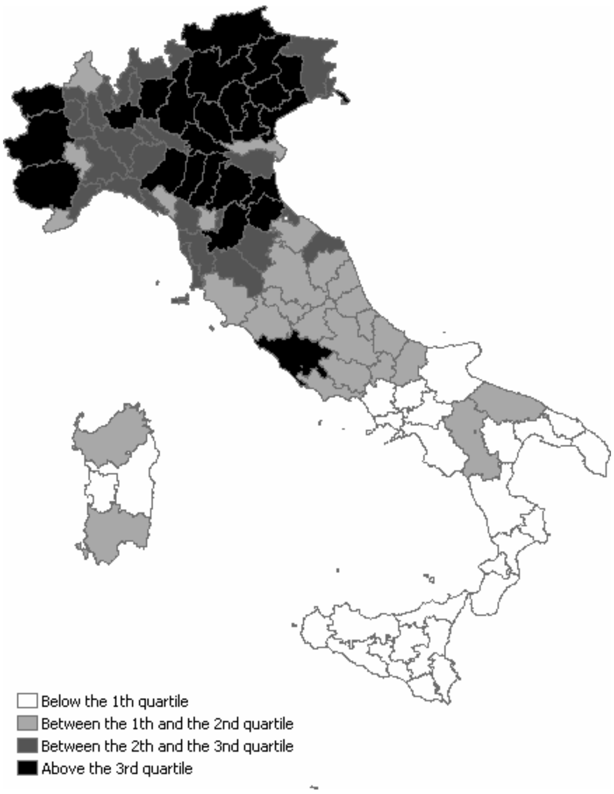
TABLE 3.5 – *Descriptive statistics of the sample (province-level variables)*

Variable	Obs.	Mean	Median	Minimum	Maximum	Std. Dev.
PCVAD (a)	824	21.3633	21.3155	9.6538	39.9109	5.8570
GROWTH (b)	721	0.0545	0.0528	-0.1205	0.2011	0.0340
FINANCE (b)	824	0.5434	0.5297	0.2247	1.3202	0.1775
LERNER1 (b)	824	0.3425	0.3482	0.1824	0.4767	0.0455
LERNER2 (b)	824	0.2348	0.2373	0.0862	0.3811	0.0433
EFF1 (b)	824	0.7808	0.7817	0.6782	0.8371	0.0230
EFF2 (b)	824	0.9146	0.9180	0.7108	0.9510	0.0211
BADLOANS (b)	824	0.0808	0.0577	0.0145	0.3326	0.0619
BRDENS (b)	824	0.1282	0.0822	0.0163	1.2387	0.1509
TRADE (b)	824	0.3974	0.3824	0.0158	2.2935	0.2607
HUMCAP (b)	816	0.7312	0.7352	0.5074	0.9390	0.0774
CRIME (b)	824	0.0362	0.0334	0.0108	0.1326	0.0122

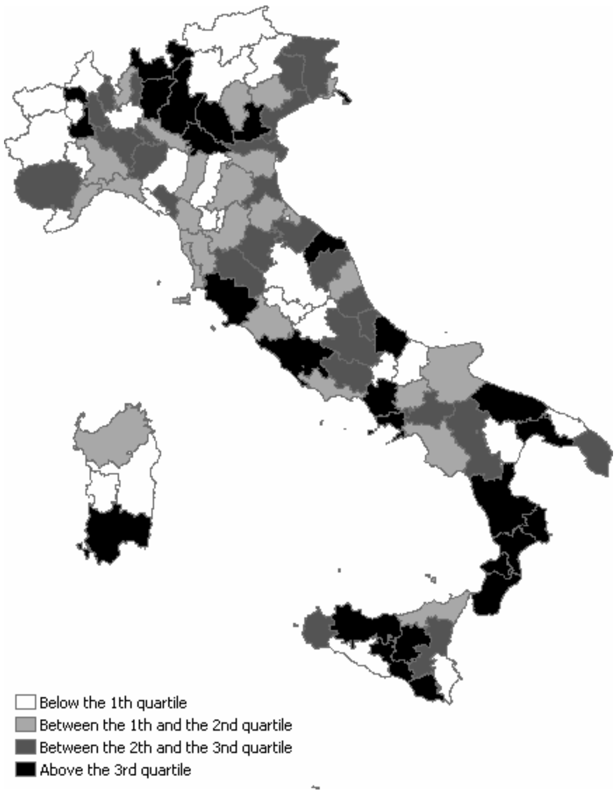
(a) Thousands euro (1998 values) - (b) Ratios

FIGURE 3.2 – *Per capita value added (PCVAD), growth rate (GROWTH) and financial development (FINANCE) – Averages 1999 – 2006*

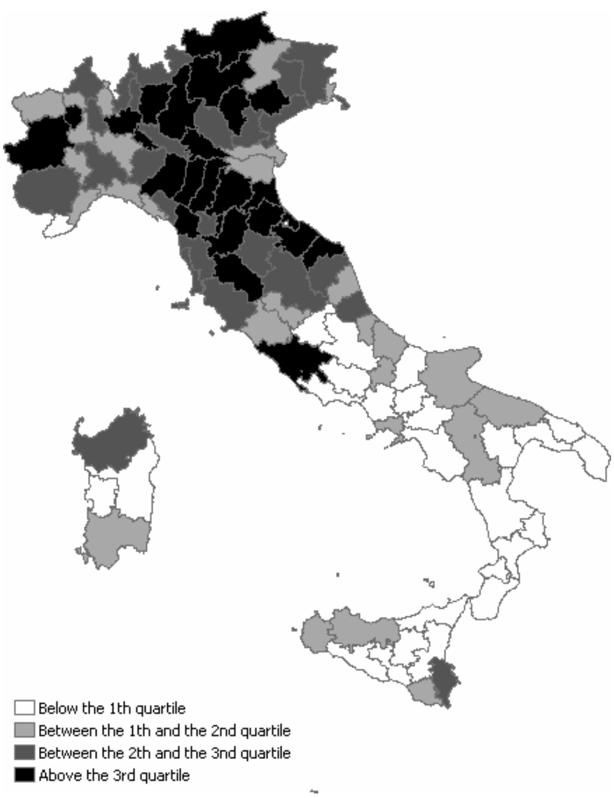
(a) PCVAD



(b) GROWTH



(c) FINANCE



3.6 Estimation results

Equation (11) has been estimated by maximum likelihood. Results for both the Battese-Coelli and the pooled stochastic frontier models are shown in Table 3.6. Many of the estimated parameters are statistically significant at the 1% level.

Starting from the bank-level estimates of cost efficiency scores and Lerner indices, we have then calculated the respective provincial-level values, EFF_{mt} and $LERNER_{mt}$, using Expressions (14) and (15). We report the averages of these variables over the sample period in Figure 3.3. Considering the results based on the Battese-Coelli model - panels (a) and (b) - we can see that the estimated market power of banks located in the Northern area of the country is higher. As happened for the per capita value added and the financial development index, three clusters of provinces can be therefore detected, each largely corresponding to one of the three geographical areas in which Italy is usually divided (see also above). A similar conclusion holds when looking at panels (c) and (d), which show the same averages obtained from the pooled model.

However, the two models provide results that are different under some respects, and this evidence gives reason for estimating the growth regressions for both.

As already stressed, Equations (2) and (9) have been estimated by means of the two-step System GMM method, treating all the right-hand side variables as endogenous and using as instruments all the available lags in collapsed form. In computing the standard errors, the Windmeijer (2005)'s finite-sample correction has been used.[27] We first estimate the basic specification, then introduce spatial effects based on each of the three weight matrices defined above. Given the potential nonlinearity of the link between economic growth and its determinants, natural logarithms of regressors have been used.[28] Among the explanatory variables, we include the provincial-level values of *LERNER* and *EFF*, as calculated above.

Estimation results are presented in Tables 3.7 and 3.8, depending on whether the weighted Lerner indices and efficiency scores have been obtained, respectively, from the Battese-Coelli model (Model 1) or the pooled model (Model 2).[29]

[27] Estimations have been carried out using the Stata routine *xtabond2*, provided by Roodman (2006).
[28] Levine et al. (2000) make the same choice.
[29] Note that the estimation results were obtained using 102 provinces (instead of 103), since we were not able to get the number of students enrolled at secondary schools for the province of Aosta.

TABLE 3.6 – *Maximum likelihood estimates of the cost function*

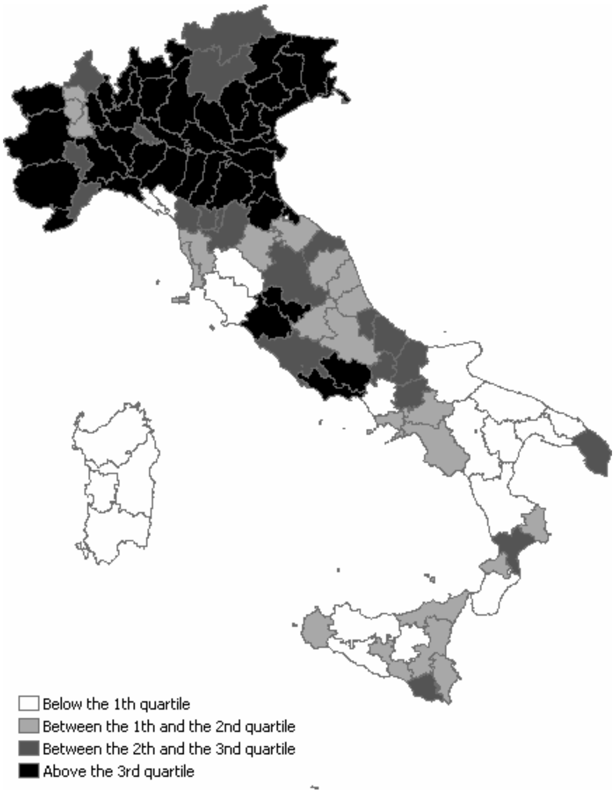
Parameter	Regressor	Battese-Coelli		Pooled	
		Coeff.	***t*-value**	**Coeff.**	***t*-value**
α_0	Constant	1.2239	*5.22* ***	1.2014	*4.86* ***
α_Q	ln$Q$	0.9778	*51.49* ***	1.0079	*78.21* ***
α_1	lnW_1	0.2268	*4.29* ***	0.1647	*2.91* ***
α_2	lnW_2	0.6198	*11.55* ***	0.7231	*12.86* ***
α_3 (= $1-\alpha_1-\alpha_2$)	lnW_3	0.1535	*6.13* ***	0.1122	*4.24* ***
α_T	ln*TREND*	-0.5156	*-3.36* ***	-0.5438	*-3.14* ***
α_{QQ}	$(\ln Q)^2/2$	0.0032	*2.19* **	-0.0010	*-1.32*
α_{11}	$(\ln W_1)^2/2$	0.1930	*12.49* ***	0.2109	*13.87* ***
α_{12}	lnW_1*lnW_2	-0.2104	*-14.20* ***	-0.2282	*-15.97* ***
α_{13} (= $1-\alpha_{11}-\alpha_{12}$)	lnW_1*lnW_3	0.0174	*3.32* ***	0.0174	*3.28* ***
α_{22}	$(\ln W_2)^2/2$	0.2116	*13.45* ***	0.2370	*15.80* ***
α_{23} (= $1-\alpha_{12}-\alpha_{22}$)	lnW_2*lnW_3	-0.0012	*-0.22*	-0.0088	*-1.71* *
α_{33} (= $\alpha_{11}+2\alpha_{12}+\alpha_{22}$)	$(\ln W_3)^2/2$	-0.0163	*-4.18* ***	-0.0086	*-2.53* **
α_{TT}	$(\ln TREND)^2/2$	0.1624	*2.44* **	0.2624	*3.82* ***
α_{Q1}	ln$Q$*lnW_1	-0.0038	*-1.44*	-0.0004	*-0.16*
α_{Q2}	ln$Q$*lnW_2	0.0082	*2.96* ***	-0.0001	*-0.05*
α_{Q3} (= $-\alpha_{Q1}-\alpha_{Q2}$)	ln$Q$*lnW_3	-0.0044	*-3.64* ***	0.0005	*0.49*
α_{TQ}	ln*TREND**ln$Q$	-0.0035	*-0.89*	-0.0002	*-0.03*
α_{T1}	ln*TREND**lnW_1	0.0338	*1.94* *	0.0504	*2.43* **
α_{T2}	ln*TREND**lnW_2	-0.0540	*-3.19* ***	-0.0371	*-1.85* *
α_{T3} (= $-\alpha_{T1}-\alpha_{T2}$)	ln*TREND**lnW_3	0.0202	*2.26* **	-0.0133	*-1.30*
Log-likelihood			5241.79	4522.24	
R^2			0.9493	0.9895	
N. of observations			4473	4473	
N. of banks			631	631	

Dependent variable: *lnC*.

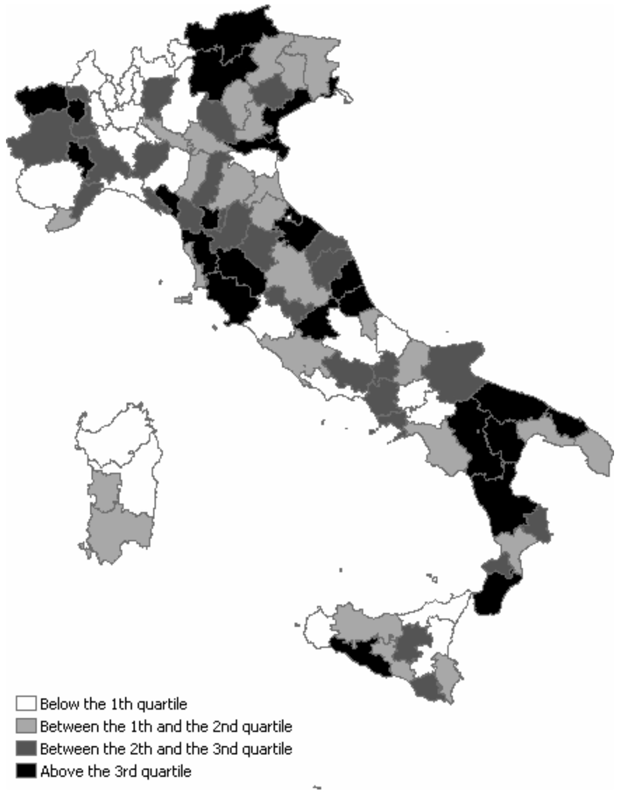
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.

FIGURE 3.3 – *Market power (LERNER) and efficiency (EFF) – Averages 1999 – 2006*

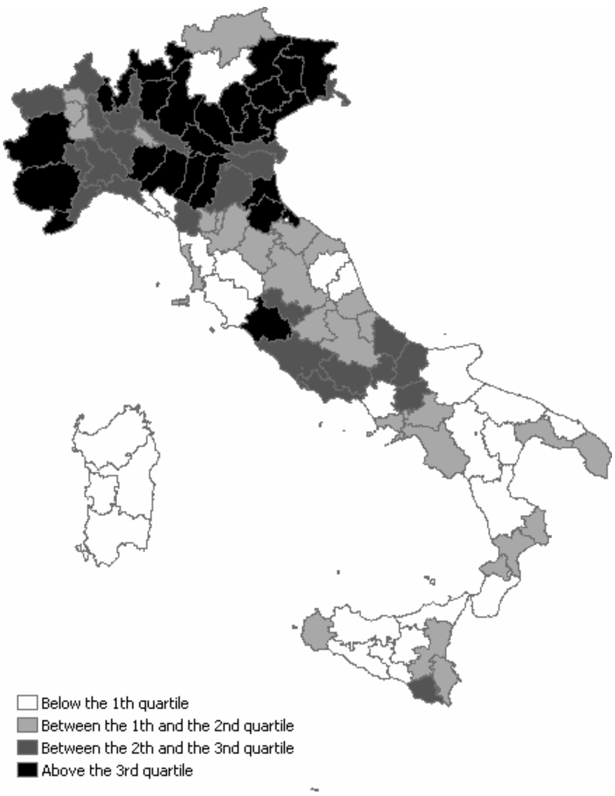
(a) LERNER



(b) EFF



(c) LERNER



(d) EFF

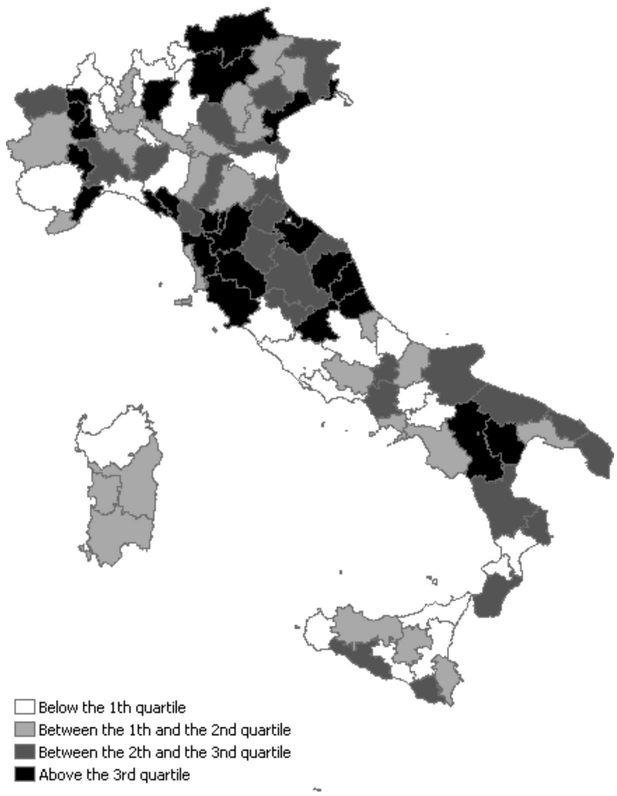


TABLE 3.7 – *Estimation results for Model 1*

VARIABLE	NO SPATIAL EFFECTS	SPATIAL EFFECTS		
y_{t-1}	0.7703 *** (*0.0598*)	0.6535 *** (*0.0689*)	0.6355 *** (*0.0658*)	0.6357 *** (*0.0634*)
$W_1 Y_t$	-	0.2481 ** (*0.1203*)	-	-
$W_2\ Y_t$	-	-	0.2748 *** (*0.0998*)	-
$W_3\ Y_t$	-	-	-	0.2685 *** (*0.0850*)
FINANCE	0.0605 *** (*0.0196*)	0.0268 (*0.0311*)	0.0161 (*0.0318*)	0.0173 (*0.0295*)
LERNER	0.0807 ** (*0.0345*)	0.0975 *** (*0.0369*)	0.0846 ** (*0.0355*)	0.0827 ** (*0.0361*)
EFF	0.3349 (*0.2277*)	0.4301 * (*0.2441*)	0.4206 (*0.2585*)	0.4121 (*0.2602*)
BADLOANS	-0.0039 (*0.0133*)	0.0088 (*0.0136*)	0.0078 (*0.0134*)	0.0060 (0.0128)
BRDENS	0.0090 (*0.0210*)	0.0297 (*0.0215*)	0.0256 (*0.0216*)	0.0259 (*0.0225*)
TRADE	0.0319 ** (*0.0161*)	0.0133 (*0.0184*)	0.0126 (*0.0149*)	0.0081 (*0.0141*)
HUMCAP	0.0023 (*0.0727*)	-0.0085 (*0.0945*)	0.0238 (*0.0833*)	0.0216 (*0.0800*)
CRIME	-0.0414 * (*0.0244*)	-0.0239 (*0.0276*)	-0.0166 (*0.0270*)	-0.0155 (*0.0264*)
Hansen test	57.14 (*0.359*)	68.01 (*0.223*)	64.91 (*0.310*)	66.49 (*0.264*)
First order autocorrelation test	-5.55 *** (*0.000*)	-4.93 *** (*0.000*)	-4.91 *** (*0.000*)	-5.01 *** (*0.000*)
Second order autocorrelation test	-1.34 (*0.180*)	-1.30 (*0.195*)	-1.29 (*0.196*)	-1.21 (*0.228*)
N. of observations	714	714	714	714
N. of provinces	102	102	102	102
N. of instruments	70	77	77	77

Dependent variable: *PCVAD*
Estimation method: System GMM
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level.
All regressors have been instrumented by their second and higher order lags. Instruments matrix has been collapsed. Standard errors are based on Windmeijer (2005)'s finite-sample correction. *p*-values of the tests in parenthesis. Time dummies have been included in the difference equation but are not reported.

TABLE 3.8 – *Estimation results for Model 2*

VARIABLE	NO SPATIAL EFFECTS	SPATIAL EFFECTS		
y_{t-1}	0.7409 *** (*0.0631*)	0.6287 *** (*0.0673*)	0.6245 *** (*0.0614*)	0.6198 *** (*0.0601*)
$W_1 Y_t$	-	0.2932 *** (*0.1137*)	-	-
$W_2\ Y_t$	-	-	0.2914 *** (*0.0800*)	-
$W_3\ Y_t$	-	-	-	0.2950 *** (*0.0808*)
FINANCE	0.0695 *** (*0.0272*)	0.0208 (*0.0282*)	0.0174 (*0.0291*)	0.0189 (*0.0272*)
LERNER	0.0509 *** (*0.0197*)	0.0582 *** (*0.0184*)	0.0524 *** (*0.0179*)	0.0475 *** (*0.0183*)
EFF	0.1826 (*0.1668*)	0.2371 (*0.1524*)	0.2357 * (*0.1433*)	0.2603 * (*0.1530*)
BADLOANS	0.0012 (*0.0130*)	0.0136 (*0.0134*)	0.0133 (*0.0131*)	0.0113 (*0.0121*)
BRDENS	0.0283 (*0.0239*)	0.0442 ** (*0.0218*)	0.0375 * (*0.0226*)	0.0365 (*0.0228*)
TRADE	0.0262 * (*0.0159*)	0.0064 (*0.0164*)	0.0067 (*0.0119*)	0.0019 (*0.0125*)
HUMCAP	-0.0087 (*0.0918*)	0.0250 (*0.0979*)	0.0495 (*0.0930*)	0.0454 (*0.0884*)
CRIME	-0.0516 * (*0.0291*)	-0.0279 (*0.0294*)	-0.0220 (*0.0256*)	-0.0224 (*0.0262*)
Hansen test	61.30 (*0.231*)	74.07 (*0.105*)	69.68 (*0.184*)	68.98 (*0.200*)
First order autocorrelation test	-5.32 *** (*0.000*)	-4.84 *** (*0.000*)	-4.96 *** (*0.000*)	-5.01 *** (*0.000*)
Second order autocorrelation test	-1.43 (*0.152*)	-1.44 (*0.148*)	-1.44 (*0.151*)	-1.34 (*0.179*)
N. of observations	714	714	714	714
N. of provinces	102	102	102	102
N. of instruments	70	77	77	77

Dependent variable: *PCVAD*
Estimation method: System GMM
*** = significant at the 1% level ; ** = significant at the 5% level; * = significant at the 10% level. All regressors have been instrumented by their second and higher order lags. Instruments matrix has been collapsed.
Standard errors are based on Windmeijer (2005)'s finite-sample correction. *p*-values of the tests in parenthesis. Time dummies have been included in the difference equation but are not reported.

First we consider the specification without spatial effects (first two columns of the tables). Based on the Hansen test, the null hypothesis of validity of the instruments cannot be rejected at the usual significance levels in both models. Moreover, there is no evidence of second order serial correlation in the difference errors. When significant, all coefficients have the expected sign.

Since the results are broadly similar, in what follows we focus mainly on Model 1. The lagged value of the per capita value added is positive and statistically significant at the 1% level. Its magnitude (about 0.77) is similar to that estimated by Vaona (2008) for the Italian provinces between 1986 and 2003.

Consistently with most of the previous empirical research, the level of financial development (*FINANCE*), highly significant as well, positively impacts on growth. Since all variables are in logarithms, the estimated parameters can be interpreted as (short-run) elasticities. Thus, the magnitude of 0.06 for the *FINANCE* coefficient suggests that a 1% increase in the financial development index produces an increase in the real per capita value added, on average, of 0.06%. For example, if *FINANCE* increases from of 0.31 (the median value of the corresponding distribution) to 0.43 (the third quartile), that is by 38%, the real per capita value added would increase by 2.3%.

Among the variables included to account for the role of banks in the growth process, only *LERNER* is significant (at the 5% level). Interestingly, the sign of the coefficient is positive, meaning that, contrary to the conventional view, a higher market power of banks operating in given local economy reveals to be beneficial to growth. In Model 1 this impact is even larger than that of the financial development. Taking the same exercise as before, the estimated parameter of 0.08 implies that if the market power increased again by 38% from the median value of 0.35 (i.e. to 0.48), the real per capita value added would rise by 3.07%. This finding is coherent with those of Maudos and Fernández de Guevara (2006) and Fernández de Guevara and Maudos (2009) for Spain, in spite they use a different methodology.

This result is also highly consistent with the Italian context, where there is a notable presence of small firms, usually characterized by information opacity. Our empirical evidence indicates that banks' market power and specific credit relationships may represent a decisive factor for making available adequate investment funds to such firms and thus favoring economic growth.

As regards the other variables in Model 1, *TRADE* is significant at the 5% level and shows that trade openness has a positive impact on local growth, while the level of criminality (*CRIME*) is inversely related to *PCVAD*, although its coefficient is different from zero only at the 10% level. Both results are somehow expected. The lack of significance of the proxy of human capital (*HUMCAP*) indicates that the level of schooling is not a key factor for the growth of provincial value added, in spite of regular migration flows from the South to the North of Italy (due to the economic gap between the two areas).

Turning to the estimations with spatial effects, again the Hansen and autocorrelation tests do not signal any sort of misspecification. Besides, the spatial autoregressive parameter is highly significant whatever the weight matrix is. The positive sign makes evident that the growth of a given province benefits from the growth of the surrounding local economies.

However, explicitly adding the spatial effects in our regressions determines that the coefficient of the variable *FINANCE* is no longer significant. Thus, when we control for the diffusion and spillover effects, the level of financial development seems not to be relevant in explaining economic growth anymore. One possible explanation for this evidence is that spatial links among areas are enough to explain local growth rates. In more developed areas it is easier to reach adequate levels of economic activity because of positive transmission effects among households and firms and, just as a natural consequence, financial markets are more developed as well. This would be in line with the view of Joan Robinson, according to which “where enterprise leads finance follows” (Robinson, 1952, p. 86). In turn, in more depressed regions local communities suffer from a negative contagion from the other neighboring, also disadvantaged zones.

Quite to contrary, the positive impact of banks’ market power on growth is confirmed, being statistically significant at least at 5% level in all specifications, and again stresses the importance of regulating banking competition in order to boost provincial economies.

We can therefore conclude that improving local economic growth in Italy requires especially the establishment and preservation of longstanding relationships between banks and firms, so that entrepreneurs can count on a stable supply of credit to finance their investment projects. This is particularly true for small firms, given their difficulties in accessing to capital markets.

3.7 Summary and conclusions

In this paper we have tried to contribute to the literature on financial development and growth from a regional perspective by accounting explicitly for both the role of banks and the possible diffusion and spillover effects among local economies, the latter aspect being largely overlooked in the literature on the finance-growth nexus. Using a dataset on Italian provinces for the period 1999-2006, we have estimated two dynamic panel models – both without and with spatial effects – using GMM techniques.

Our findings are of considerable importance for at least two reasons. First, we discover a positive, robust and statistically significant link between market power and economic growth. This gives support to the view according to which bank competition can be harmful to growth especially when it reduces the credit availability for informationally opaque (usually small) firms, i.e. when the local economy calls for specific and long-lasting credit relationships with firms. Such a landscape well portrays the Italian productive system, where the role of small-sized firms is quite important. Second, the positive role of financial development in promoting growth, which is a customary evidence in many cross-country studies, is not confirmed when we control for spatial effects. This means that for local areas it is easier to grow especially when they belong to more vital territories, which should also involve, as a natural corollary, well developed financial backgrounds.

We conclude that local economic growth is affected not so much by the amount of credit, as by the establishment of longstanding relationships between banks and firms, which allow the latters to count on durable credit provisions for their productive investments. However, growing is more difficult in less dynamic contexts.

Although further research about this topic is surely needed, our findings cast some shadows on the current tendency of policymakers to generally promote banking competition.

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